CHANGES IN CROP MANAGEMENT SYSTEMS IN DANE COUNTY: EXTRACTING MORE VALUE FROM ROADSIDE TRANSECT SURVEYS

By

KYLE D. KETTNER

A thesis submitted in partial fulfillment of the requirements for the degree of

Masters of Science

(Soil Science)

at the

UNIVERSITY OF WISCONSIN-MADISON

2021

APPROVED:

Francisco J. Arriaga, Associate Professor

Department of Soil Science

DATE: ___June 10, 2021___________________

ACKNOWLEDGMENTS

My thanks to Amy Piaget and Curt Diehl of the Dane County Land and Water Department for providing access to Dane county's Cropland Roadside Survey dataset, inspiring the research, and providing assistance throughout. An abundance of credit goes to my loving spouse, Jessica, who both permitted and enabled this work while keeping my sanity intact. My thanks also to my advisor, Dr. Francisco J. Arriaga, for his guidance and mentorship and for having confidence in my work. Carol Duffy, Ekrem Ozlu, Julie Garvin, Maria Kamenetsky, Rick Wayne, and Paul Karaaka, all contributed to the success of this work through their advice, technical assistance, and kind patronage of my curiosity.

TABLE OF CONTENTS

TABLE OF CONTENTS (continued)

TABLE OF CONTENTS (continued)

LIST OF FIGURES

LIST OF FIGURES (continued)

Page

LIST OF FIGURES (continued)

LIST OF TABLES

LIST OF TABLES (continued)

Page

SUPPLEMENTAL DOCUMENT 1

ABSTRACT

This work explores the opportunities and limitations of the Cropland Roadside Survey in Dane County, Wisconsin. The Cropland Roadside Survey is a transect crop and tillage survey developed by the Conservation Information and Technology Center and conducted by many counties throughout the United States to monitor and assess the adoption of conservation tillage practices. The Dane County Land and Water Resources Department has conducted this survey since 1994, providing a vast historic dataset on crop and tillage practice throughout the county. Presently only annual summaries of crop and tillage practice are produced from this dataset. The objective of this work is therefore to expand the utility and value of these Cropland Roadside Survey data. This is achieved through an assessment of survey design and data structure to determine the potential for new data products from existing data and to provide recommendations to improve survey design. An examination of alternative survey methods and technologies is presented. To further improve the utility of the dataset, ancillary data such as soil and field physical are added to survey data through geospatial analysis.

Results from this work demonstrate the versatility and depth of information that can be extracted from the Cropland Roadside Survey datasets. Analysis of survey data demonstrates an increased adoption of both crop residue cover and no-tillage practices, both important components of conservation tillage. Beyond crop and tillage trends, crop rotation data, crop tenure, and double cropping information was generated from the original survey data. The addition of soil characteristics, particularly the Highly Erodible Lands status of soils, demonstrated the ability of Cropland Roadside Survey data to be

used to explore the relationship between agricultural practices, conservation adoption, and field level physical phenomena.

Key challenges in expanding the utility of the Cropland Roadside Survey are the lack of metrics on measurement accuracy for crop residue cover estimates and the need to increase the efficiency of data collection. Dressing et al. (2017) provides recommendations on conducting in-situ accuracy assessments of crop residue cover estimates at the cost of increased labor and time, but utilization of imagery and novel technology platforms offer the greatest opportunity for improving efficiency and accuracy of the Cropland Roadside Survey. Improvements in efficiency and accuracy creates substantial value from Cropland Roadside Survey data, as it allows for comparison and aggregation of data between counties and regions, improves responsiveness, and enables use of the data for more advanced statistical analysis. Additionally, validation of Cropland Roadside Survey data could provide a robust dataset for improving existing remote sensing platforms for monitoring crop residue cover. This integration would help bridge the gap between regional remote sensing products and the need for high quality, localized data across multiple spatial scales.

CHAPTER 1

A Critical Review of County Transect Surveys for Residue Estimates

Abstract

The Cropland Roadside Survey is a county-scale crop and tillage survey developed to monitor adoption of conservation tillage practices throughout the United States. The survey was in active use by the Conservation Technology and Information Center (CTIC) from the early 1980s to 2004. Many counties throughout the United States still conduct the Cropland Roadside Survey, offering a large, underutilized, database on crop and tillage practices during the past three decades. This work presents a detailed examination and evaluation of the Cropland Roadside Survey and its application in Dane County, Wisconsin. Remote sensing alternatives for collecting crop and tillage data are also considered, along with opportunities to improve the Cropland Roadside Survey with new technologies. An analysis of the original survey methodology and the statistical foundations of the survey revealed the lack of a robust measurement accuracy assessment. This creates uncertainty in comparisons and aggregations of survey data across counties. A method for accuracy assessment is identified along with an examination of unmanned aerial systems (UAS) and computer assisted technologies to aid in the rapid collection and assessment of crop and tillage survey data. The technologies of remote sensing, UAS platforms, and image processing augment rather than replace the Cropland Roadside Survey and there is still the need for systematic ground surveys.

Crop Residue and Tillage Data Collection

The conservation of soil has been a long-standing issue in the United States' agricultural production. The Dust Bowl of the 1930s prompted the creation of the Soil Erosion Service within the U.S. Department of the Interior, which was a few years later incorporated into the Soil Conservation Service under the U.S. Department of Agriculture. Soil conservation again became a prominent national policy topic with the passage of the Food Security Act in 1985 that included specific programs for the conservation of soil and water resources (McGranahan et al., 2013); however, some Midwestern states such as Illinois in 1980 and Wisconsin in 1982 had adopted "T-by-2000" programs earlier in the decade. These past efforts to ensure food security and to conserve soil and water resources are echoed in more recent years by calls for sustainable food and water resources, both highly dependent on the sustainable conservation of soil as a natural resource (Keesstra et al., 2016).

As initiatives focused on conserving soil resources proliferated, the need arose to characterize and quantify the impact these programs had on farmer's adoption of conservation agriculture practices. The most common and well-established methods for gathering cropping practice and crop data were through self-reporting mail questionnaires and in-person interviews, with the National Agriculture Statistics Service (NASS) and Economic Research Service (ERS) spearheading such efforts (USDA ERS, 2020). The Conservation Technology Information Center (CTIC) at Purdue was established in 1982 with the purpose of recording and analyzing adoption of conservation tillage and crop practices on a county-by-county basis at a national scale. The creation of the CTIC represented a major step in standardizing residue and tillage data collection and making this information widely available through the Crop Residue Management survey (CRM). Between 1983 and 1998, CTIC collected residue and tillage data by crop through best estimates made after consultation with local and regional partners (Hill, 1996; Baker, 2011). In 1994, the Soil Conservation Service was renamed the Natural Resources Conservation Service (NRCS) to reflect the broader scope of this agency's work and programs beyond soil conservation.

The 1990s saw significant improvement in the collection of crop residue and tillage information. The USDA implemented the Agricultural Resource Management Survey (ARMS), administered by NASS and provides multi-county scale crop and tillage data (USDA NASS, 2020). Meanwhile the CTIC, in conjunction with local and regional partners, developed an in-situ field survey to acquire crop residue and tillage data. The Cropland Roadside Survey Method of Collecting Residue and Tillage Data (Hill, 1996) represents a formalized presentation of a transect survey design developed by Hill and others since the late 1980s. Dane County in Wisconsin, the primary subject of this review, uses the term "Crop and Tillage Survey" – or CT survey, while other states such as Minnesota refer to this survey as the "Tillage Transect Survey" or TTS to describe their implementation of the Cropland Roadside Survey Method. The term most commonly found in the literature is that of Tillage Transect Survey (Gowda et al., 2001; Thoma et al., 2004; Zheng et al., 2014; Dressing et al., 2017). This chapter will use Cropland Roadside Survey throughout to avoid any ambiguity about which specific method is being employed, especially to avoid confusion with the similarly named line-transect method measuring crop residue values in fields (Morrison et al., 1993).

The Cropland Roadside Survey approach was widely adopted in the early-to-mid 1990s by county conservation offices across the Midwest, with Minnesota adopting the method in 1989, Indiana, Ohio, and Iowa since at least 1990, and Illinois in 1994 (Illinois Agric. Dept., 2018; Fisher and Moore, 2008). The Cropland Roadside Survey method gained national application when the CTIC utilized it for CRM survey data collection in 17 states for 2000, 2002, and 2004 (Revised Cropland Survey, 2002; Baker, 2011). Wisconsin adopted the Cropland Roadside Survey method on a voluntary county-by-county basis in 1994. In 1998, the Wisconsin Department of Agriculture, Trade and Consumer Protection (DATCP) recommended statewide adoption of this survey for generating the T-By-2000 Report (DATCP, 1999). Although many counties throughout the United States participated in the CTIC's CRM survey and continued to collect data using the Cropland Roadside Survey for their own use, access to the vast majority of these data is restricted to individual water and soil conservation districts and counties. Typically, data are used internally and/or compiled for the CTIC's CRM survey reports. The data maintained by CTIC as part of the CRM survey are propriety and available in aggregated form at the HUC 8 watershed scale. Nationwide data collection for the CRM survey ended in 2004 when federal funding and NRCS involvement ended (CTIC, 2020).

While some states and local governments have continued to gather crop and tillage data through field work like the Roadside Cropland Survey, there has been a pivot to remotely sensed data acquisition. Since 2008, the NASS' Crop Data Layer is developed by classifying Landsat satellite imagery with data layers at the national scale available. The CTIC has initiated the Operational Tillage Information System, a remote sensing-based program for classification of crop residues (Hagen et al., 2016; Hagen et al., 2020). These new approaches will be discussed later in this chapter.

Roadside Cropland Survey Methodology

and the Dane County Crop and Tillage Survey

Dane County adopted the Crop and Tillage Survey based on the Cropland Roadside Survey in 1994 in cooperation with P. Hill and the CTIC to assess the effectiveness of soil conservation efforts. Administered by the county's Land and Water Resources Department (LWR), the survey has been conducted annually since 1994 with a 2-year gap from 2008 to 2009. The resulting crop and tillage survey dataset represents over 23 years of data on agricultural practices collected at the field level across Dane County.

Establishing the roadside survey path, or transect, involved mapping out a driving route through the county that was representative of the county's agricultural soils and conditions, while avoiding urban areas and heavily trafficked roads. This route was recommended to be determined by someone unfamiliar with conservation and cropping efforts in the area of interest to avoid biasing the route. At half-mile intervals along this route, the vehicle is to stop and collect observations on either side of the road if an agricultural field is present. These sample points were denoted by their stop number and their position on the left or right side of the transect path. Determination of these routes involved the use of soil survey map hard copies and recording of the route on hard copies, with detailed notes of the sampling sites and odometer readings used to determine the correct sampling point along the transect for subsequent survey years. In 1996, a GPS receiver was used to attribute GPS coordinates to each survey stopping points, with in-field observation points assumed to be 10 to 15 feet interior of the field's edge and beyond end rows. Observations were made at each point by stopping the vehicle along the route to get a clear and steady view of the field.

The Dane County Roadside Cropland Survey maintained the same sampling points every year (Fig. 1) and the same person within the county conservation staff has conducted the survey for every data point collected. Although Dane County utilizes the same sample points year-to-year, some jurisdictions utilizing the Cropland Roadside Survey method forgo this step and instead record the data as they pass by the sample point (Hagen et al., 2016). The Dane County database has the potential to provide consistent observations of agricultural land use and tillage practices from one year to the next for each sampling point along the transect given the manner in which the data have been collected. The transect survey is conducted in the spring of every year, after planting and initial crop growth but before canopy closure. Fields are revisited if no crop is observed during the first visit.

The initial design for the Roadside Cropland Transect Survey collected information on the current crop, the previous year's crop (inferred from residues if any), tillage system, residue cover, and the presence or absence of ephemeral erosion (Fig. 2). Initially the number of crop categories in the Dane County survey was limited to eight but was expanded in 2010 with over 65 distinct crop descriptors recorded in the survey. Crop residue cover was recorded in five broad categories and the best estimate of tillage system is recorded,

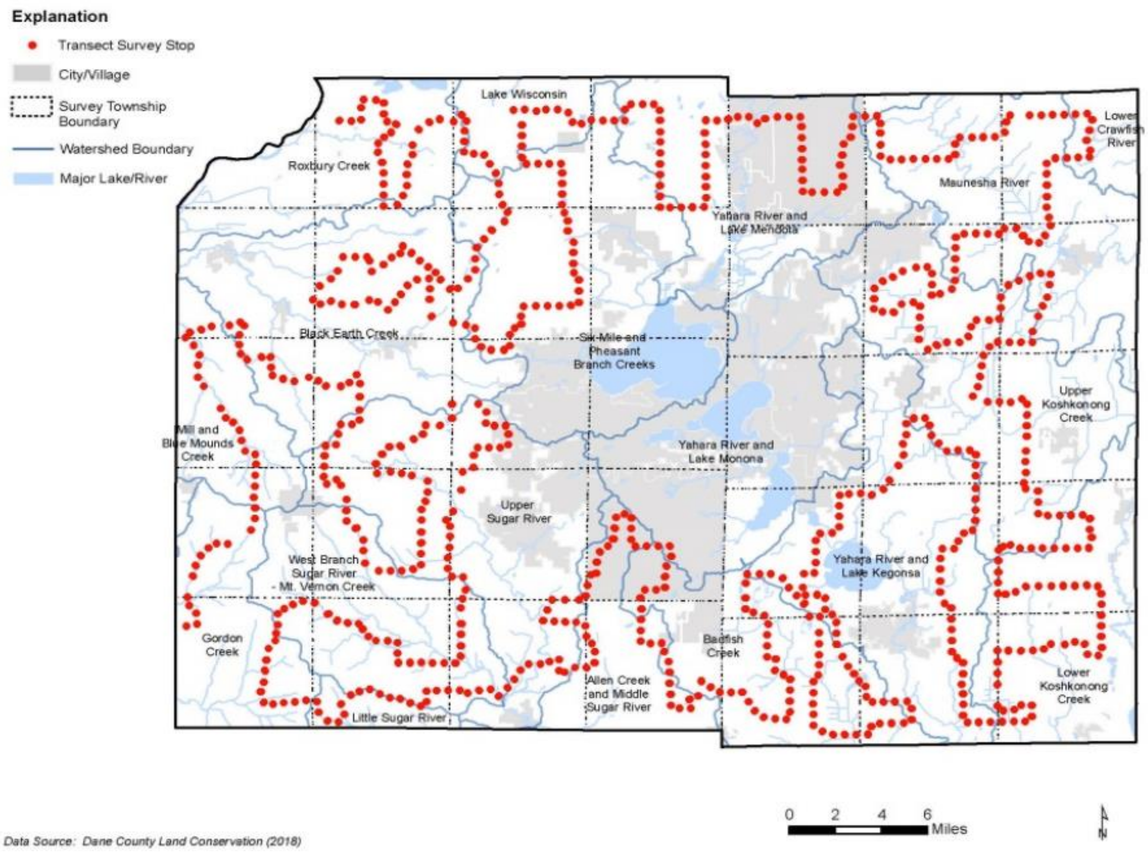


Figure 1. Map of Dane County, Wisconsin showing the route of the Cropland Roadside Survey. Each red dot marks an observation site. The survey starts in the northwest corner of the county every year (Dane County Land and Water Resources 2018).

Tillage Systems Definitions

As featured in the National Crop Residue Management Survey

The following set of definitions was established by CTIC and is recognized as a standard. They are used nationwide by government agencies and private industry.

Conservation Tillage Types

(30 percent or more crop residue left, after planting. Conservation tillage systems include no-till, ridge-till and mulch-till)

Any tillage and planting system that covers 30 percent or more of the soil surface with crop residue, after planting, to reduce soil erosion by water. Where soil erosion by wind is the primary concern, any system that maintains at least 1,000 pounds per acre of flat, small grain residue-equivalent on the surface throughout the critical wind erosion period.

No-till - The soil is left undisturbed from harvest to planting except for nutrient injection. Planting or drilling is accomplished in a narrow seedbed or slot created by coulters, row cleaners, disk openers, in-row chisels or roto-tillers. Weed control is accomplished primarily with herbicides. Cultivation may be used for emergency weed control.

Ridge-till - The soil is left undisturbed from harvest to planting except for nutrient injection. Planting is completed in a seedbed prepared on ridges with sweeps, disk openers, coulters, or row cleaners. Residue is left on the surface between ridges. Weed control is accomplished with herbicides and/or cultivation. Ridges are rebuilt during cultivation.

Mulch-till - The soil is disturbed prior to planting. Tillage tools such as chisels, field cultivators, disks, sweeps or blades are used. Weed control is accomplished with herbicides and/or cultivation.

Other Tillage Types:

(less than 30 percent crop residue left after planting)

Tillage and planting systems that may meet erosion control goals with or without other supporting conservation practices (i.e. strip cropping, contouring, terracing, etc.).

Reduced-till - Tillage types that leave 15-30 percent residue cover after planting or 500 to 1,000 pounds per acre of small grain residue equivalent throughout the critical wind erosion period.

Conventional-till - Tillage types that leave less than 15 percent residue cover after planting, or less than 500 pounds per acre of small grain residue equivalent throughout the critical wind erosion period. Generally involves plowing or intensive tillage.

CODES FOR FILLING OUT TRANSECT SURVEY FORM:

Present Crop	Previous Crop	Tillage System	Percent Slope	P - Factor	Ephemeral Erosion
C = Corn	C = Corn	C = Conventional	1 = 1%	1 = 1.0	Y = Yes
R = Row Soybeans	B = Soybeans	M = Mulch-till (>30% cover)	2 = 2%	9 = 0.9	N = No
D = Drilled Soybeans	G = Small Grains	N = No-till	3 = 3%	8 = 0.8	
G = Small Grains	H = Hay	R = Ridge-till	4 = 4%	7 = 0.7	
H = Hay	V = Cover Crop	X = Other	5 = 5%	6 = 0.6	
F = Fallow (e.g., set-aside)	X = Other	/ = Doesn't Apply	6 = 6%	5 = 0.5	
X = Other	/ = Doesn't Apply		7 = 7%	4 = 0.4	
Z = CRP			8 = 8%	3 = 0.3	
			9 = 9%	2 = 0.2	
			X = 10%		
			Y = 11 - 15%		
			Z = 16 - 20%		

T-Level	K-Factor	Residue Cover	Slope Length (feet)	Watershed Code
1 = 1 t/a	a = .43	1 = 0 - 15%	a = 75 (50-100)	See individual county codes for letters a - n.
2 = 2 t/a	b = .37	2 = 16 - 30%	b = 125 (100-150)	
3 = 3 t/a	c = .32	3 = 31 - 50%	c = 175 (150-200)	
4 = 4 t/a	d = .28	4 = 51 - 75%	d = 250 (200-300)	
5 = 5 t/a	e = .24	5 = 76 - 100%	e = 400 (300-500)	
	f = .20	/ = Doesn't Apply		
	g = .17			
	h = .15			

Figure 2. Original information collected annually in the Cropland Roadside Survey. Includes present crop at time of survey, previous crop determined from residue, current tillage practice, residue cover, presence of ephemeral erosion, and P-factor. Other information that describes a particular field was attributed during the initial survey setup (Hill, 1996).

where tillage systems are attributed according the CTIC's conservation, reduced, and conventional tillage category definitions (Fig. 2). However, tillage systems are difficult to determine from surface disturbance alone, since practices such as disking, multiple tillage passes, and combinations of various implement attachments can create a similar degree of surface soil disturbance. Therefore, in practice, highly disturbed and inverted soils are described as conventional, direct evidence of the ridge till can be recorded as such, and no-till conditions are often distinctly identifiable by the lack of any soil surface disturbance in seeded fields. Additional information on each sample site was described during the initial transect setup in 1994 including factors for use with the Universal Soil Loss Equation, watershed, and topographical characteristics.

The primary statistical product of the Cropland Roadside Survey is an estimate of total cropping acres in a given crop and crop residue cover. These estimates are generated by taking a simple proportional count of observations for a given crop and crop residue cover class. For example, if there are 600 total observations of corn (*Zea mays* L.) from the roadside survey and 287 of these observations are classified as crop residue class 3 (31 to 50% crop residue) in any particular year, the percent of corn acres in Dane County with this crop residue class can be estimated by dividing these two values (e.g., 287/600 x 100 = 47.8%). Further, the number of acres of corn with this crop residue class in the county can be estimated by taking the number of acres in corn from NASS data (13,000 acres) and multiplying by the percentage (e.g., 13,000 total acres in corn x 47.8% = 6,214 corn acres with crop residue cover class 3 in Dane County). These estimate summaries are recorded over time, providing yearly snapshots allowing county conservationists to assess adoption of conservation practices (Hill, 1996; Baker, 2011). It is important to note that the definition of tillage systems includes estimates of crop residue cover but also includes direct observations of soil disturbance (CTIC, 2020). In this way tillage systems may be compared to crop residue cover, such as how often no-till results in a crop residue cover greater than 50%. For counties participating in the CRM survey estimates of acreage of crop type by crop residue cover estimates were submitted to the CTIC for compilation. Additional attributes for each field can be included, such as soil loss tolerance ("T-Factor") and field slope. The integration of further ancillary data expands the potential application and usefulness of the Cropland Roadside Survey.

Statistical Foundation and Reliability of the Cropland Roadside Survey

The Cropland Roadside Survey was designed to provide statistical estimates on crop residue and descriptive statistics of crop and tillage practices at the county scale. Hill (1996) emphasizes the desire for the highest level of confidence (at least a 90% confidence interval) for the survey design with the most important attribute being crop residue. In order to provide estimates with the appropriate statistical power, the minimum number of sample points required by the Cropland Roadside Survey was calculated based on the assumption of a multinomial population (Hill 1996). In this methodology, an increase in the number of categories would require an increase in the number of samples required to maintain the desired statistical power, thereby putting a practical upper limit on the number of different categories the survey can consider with a high confidence level (Dressing et al., 2017). This can be problematic when a survey is first developed, because the survey team must determine if they will spend additional time and resources to establish more sample points for future new or novel evaluation criteria. An expansion of data categories occurred for both the Dane County Cropland Roadside Survey and the Minnesota statewide initiative, where the need for more classification categories was recognized for crops and tillage systems, along with the addition of ancillary data such as watershed designations, soil characteristics, and the addition of cover crop monitoring (Fisher and Moore, 2008). Dressing et al. (2017) noted the need to add an additional buffer to survey sample size for anticipated loss of sample points through urban sprawl and conversion of agricultural sites. These two situations, the later need for additional categories and the loss of sample sites due to land conversion, highlight the importance of careful survey design to allow for adaptability when the intent is to collect information for long periods of time.

While these considerations of sample size address the matter of variance in the estimates, there is no provision within the Cropland Roadside Survey to provide a measure of accuracy or reliability. In the introduction of the method, Hill (1996) describes the transect survey as providing "90% or more confidence in the accuracy of the results" and equates this to a high level of reliability, with accuracy and reliability in this instance being used colloquially. Unfortunately, some documents based on this methodology repeat this provision with the assurance that the Cropland Tillage Survey provides a 90% level of accuracy in residue estimates (DATCP, 1999; Revised Cropland Survey, 2002). This may lead to confusion on the actual statistical strengths and limitations of the survey design. An examination of these strengths and weaknesses follows below, along with recommendations for improvement.

The primary source of error in the survey design is found in visual estimates of crop residue. This method of estimating crop residue is inherently subjective and depends on the individual observer to make accurate estimates. The survey design calls for periodic line-transect measurements of crop residue in field to create a visual reference for roadside estimates to minimize measurement error. However, there is no procedure for recording these self-evaluations of accuracy in the database. If these data are collected, they may provide a basis to evaluate the accuracy of a specific observer(s) associated with a recorded transect.

An assessment of accuracy in the Cropland Roadside Survey estimates would allow for statistical comparisons between years and between counties. This is particularly important when transect surveys are conducted by different observers between years. Without an accuracy assessment, it is not possible to statistically quantify if changes between one year and the next represent an actual change in crop and tillage practice or are the result of systematic measurement error if different observers collected data different years. Without a method to reduce this uncertainty, the Cropland Roadside Survey's most meaningful products are qualitative trends and frequency estimates. This is not to say the estimates provided by the Cropland Roadside Survey do not have a practical value, as they inform the expert knowledge of county conservationists and provide a unique perspective on agricultural practice within a county. However, the current uncertainty present in the Cropland Roadside Survey limits statistical comparison between counties or at state and regional scales. The reliability of the dataset is highly dependent on having the same observers carry out the operation each year. The development of an accuracy assessment would reduce this dependency and allow for description of anticipated variation between observers. Researchers conducting Minnesota's transect tillage survey in 2007 noted that potential inconsistencies in reported accuracy and protocol adherence made quality assurance of county-level summaries difficult and resulted in some estimates that stretched credibility, representing either remarkable adoption of conservation practice or a discrepancy in the reliability of data collection between counties (Fisher and Moore, 2008).

Independent assessments of the Cropland Roadside Survey method are extremely limited within the published literature and internal assessments conducted by initiatives utilizing the survey have not been made readily available to the public. Thoma et al. (2004) used the line-transect method of measuring in-situ crop residues to assess the accuracy of Cropland Roadside Survey estimates and found a 49% level of accuracy when residue values were binned in five groups (0 to 15, 16 to 30, 31 to 50, 51 to 75, and 75 to 100% crop residue cover). More accurate estimates were developed with fewer categories, with the greatest level of accuracy being 74% with two residue categories (0 to 30 and 31 to 100% crop residue cover). Beeson et al. (2016) similarly compared estimates from the Cropland Roadside Survey method to line-transect estimates of crop residue cover and found an overall accuracy of 74% when using two crop residue cover categories (0 to 30 and 31 to 100%). In a project report for the Canadian SWEEP (Soil and Water Environmental Enhancement Program) by Robert and Coleman (1987), a similar transect survey design to the Cropland Roadside Survey approach was described to provide residue estimate validations for a subset of their surveyed fields, with a reported overall accuracy of 96% using a cross tabulation of in-situ line-transect crop residue estimates with visual estimates.

The cross-tabulation approach used by Robert and Coleman (1987) was equivalent to the method employed by Thoma et al. (2004) and Beeson et al. (2016). Dressing et al. (2017) noted that in the Thoma et al. (2004) and Robert and Coleman (1987) assessments where the line-transect method was used to validate visual estimates, there was a general tendency of the visual estimates to overestimate crop residue for low crop residue categories (i.e., < 30%) and underestimate crop residue for higher crop residue categories (i.e., > 50%). This pattern of error in estimation was also reported by Beeson et al. (2016) in their assessment.

These findings suggest there may be a systematic bias in the Cropland Roadside Survey, but more rigorous evaluations are required to provide a quantification and possible correction for this systematic bias. In order to accomplish this, Dressing et al. (2017) provides validation procedures that allow for robust accuracy assessments using sample error matrices and unbiased estimators based on marginal proportions of the sample error matrix. Dressing et al. (2017) note that the validation procedures only function to model the accuracy of a given individual in a given year; however, this presents the opportunity for determining empirically the nominal accuracy (bias and variance) of visual crop residue estimates in a Cropland Roadside Survey. An expected conservative estimate of accuracy would necessitate that training and the method used be consistent across survey teams for comparisons, but it also would provide a structure for training and evaluating the performance of survey teams in a more robust fashion than the in-field visual assessment method originally proposed. Conservative estimates of accuracy would also help in data comparisons of decades of archival data across counties and states that have conducted these surveys.

Other sources of systematic bias within a survey design include the roadside position for making observations and the influence of "binning" crop residue estimates into categories with residue ranges covering intervals of 15 to 25%. The roadside position presents issues at oblique viewing angles and limited sight lines for determining crop residue level (Thoma et al., 2004; Beeson et al., 2016). The binning of crop residue estimates converts a population of observations with a continuous distribution into a multimodal distribution. This introduces a bias toward the middle value of each bin and, therefore, the number of bins used to represent the data increases or decreases the certainty that can be attributed to that estimate (Thoma et al., 2004; Hagen et al., 2016; Dressing et al., 2017). The trade-off in the roadside position is ease of access, which largely avoids the need to obtain field access permission from the field owner/operator except in cases of spot-checking estimates with in-field line transect estimates. Additionally, the roadside observations allow for a greater rate of data collection compared to infield measurements and a high level of continuity in sampling position from year-to-year. In general, the Cropland Roadside Survey design process provides careful consideration for survey route planning and consistent methodology for gathering data spatially along the transect route with inclusion and exclusion criteria for field observations.

The overall effect of these two methodological sources of potential bias is presently unknown, especially because accuracy and precision of residue estimates may not be consistent across all residue values within a bin, with Thoma et al. (2004) remarking that the greatest uncertainty in visual estimates was found around 30% crop residue cover, an important threshold for discriminating conservation tillage practice.

In practical application, expert knowledge and familiarity of the region may allow a county conservationist to use findings within a given year or between years to affirm a general trend in crop and tillage practices, and to call out plausible patterns. Given that the statistical product of the estimates still maintains a level of precision, changes between years can still be noted within a dataset captured by a given observer. In its capacity to provide a "snapshot" of cropping and tillage practices, the Cropland Roadside Survey serves a practical purpose and gives more credibility to the expert opinion and experience of county personnel beyond anecdotal evidence. With the implementation of a validation procedure, Cropland Roadside Survey results may be used to augment quantitative models that seek to describe the impact of statewide or federal initiatives and programs to conserve farmland and reduce erosion.

Application of Satellite Remote Sensing

A leading alternative to transect surveys like the Cropland Roadside Survey is the use of satellite remote sensing to estimate crop residue covers over large areas and at regional scales. Advantages of satellite remote sensing platforms include rapid and objective data acquisition over large spatial extents providing continuous statistical surfaces of crop residue estimates (Zheng et al., 2014). Satellite remote sensing technologies for crop residue estimation gained significant attention in the early 2000s with studies exploring the capabilities of satellite platforms for crop residue estimates at the field and local level (Gowda et al., 2001; Thoma et al., 2004; Daughtry et al., 2005; Daughtry et al., 2006). More recently, there have been a number of studies utilizing remote sensing technologies for regional and broad scale crop residue monitoring (Zheng et al., 2013a; Zheng et al., 2013b;

Hagen et al., 2016; Azzari et al., 2019; Beeson et al., 2020; Hagen et al., 2020). Presently, the most comprehensive efforts to map crop residue cover at broad scales have been undertaken by Hagen et al. (2016), Azzari et al. (2019), Beeson et al. (2020), and Hagen et al. (2020).

Hagen et al. (2016) and Hagen et al. (2020) describe a large-scale annual tillage mapping initiative utilizing satellite remote sensing with their Operational Tillage Information System (OpTIS); OpTIS is designed to provide crop residue cover estimates from a county-to-multistate scale. Thus far, they produced estimates for 645 counties in the American Corn Belt using a mix of MODIS and Landsat datasets (Hagen et al., 2016; Hagen et al., 2020). A comparison of OpTIS estimates to estimates from a modified Cropland Roadside Survey found a Pearson correlation coefficient of 0.683, with a statistically significant ($p < 0.05$) R^2 value of 0.467 (Hagen et al., 2020). Modifications to the Cropland Roadside Survey used to generate estimates made use of roadside imagery to serve as a visual record and for quality control. The difference between OpTIS and survey estimates varied greatly, from less than 10% to greater than 80%, but found an agreement of 42.3% between the two estimates and an overall weighted kappa statistic of 0.67 (Hagen et al., 2020). It is important to note that comparisons between OpTIS estimates and Cropland Roadside Survey estimates do not have accuracy metrics and therefore these comparisons provide a descriptive quantification of agreement and not a robust evaluation of accuracy.

The difficulty in validating large-scale estimates, from multiple states to nationwide, are demonstrated by Azzari et al. (2019) and Beeson et al. (2020). Beeson et al. (2020) carried out a multistate regional analysis of crop residue cover in the Midwest that parallels the analysis of the OpTIS project. In this study, the authors compared their regional estimates spanning 10 years from 2007 to 2016 to Agricultural Resource Management Survey (ARMS) results and reported an accuracy of 64 to 74% when remotely sensed estimates of crop residue cover were compared to the ARMS estimates. Azzari et al. (2019) produced estimates for crop residue cover in soybean (*Glycine max.*) fields across the Midwest from 2006 to 2016 using a mix of Landsat archive imagery and Sentinel-1 radar data. For validation Azzari et al. (2019) relied on producer surveys from throughout the region of interest and had a best reported accuracy of 75 to 79%. In both cases, the reference data available, either locally or at larger spatial extents, are limited and often fragmented both spatially and temporally. In evaluating their results, Beeson et al. (2020) cautions that comparisons using historical survey data can be problematic and should "be regarded as a rough guide at best." This sentiment is echoed by others, where the lack of reliable ground data for validation presents a particular challenge to broad-scale classification of crop residue cover (De Paul, 2012; Zheng et al., 2014; Azzari et al., 2019; Hagen et al., 2020).

When validated against local scale in-situ line-transect methods, satellite remote sensing estimates of crop residue ranged in accuracy from 19 to 90% and, as observed in the Cropland Transect Survey, reducing the number of categories greatly increased the accuracy of most models (Table 1). Azzari et al. (2019) notes that in the cases of Zheng et al. (2012) and Beeson et al (2016) clustered training data may result in an over estimation of accuracy. The ability of crop residue cover model to be widely applied is constrained by the training and validation data available, where locally develop models perform poorly when applied to

Table 1. Satellite remote sensing classification accuracies of crop residue cover estimates validated by line-transect method.

Accuracies vs. line transect method	Number of categories (residue cover)	Reference
90 to 91%	3 (< 30, 30 to 70, >70%)	Zheng et al. (2012)
69 to 79%	3 (< 30, 30 to 70, >70%)	Zheng et al. (2013b)
57 to 65%	4 (<15, 15 to 30, 30 to 60, >60%)	Daughtry et al. (2006)
66 to 68%	3 (<15, 15 to 30, >30%)	
80 to 82%	2 (<30 and >30%)	
59 to 73%	2 (0 to 30, 31 to 100%)	Thoma et al. (2004)
61 to 71%	3 (0 to 30, 31 to 75, 76 to 100%)	
19 to 40%	5 (0 to 15, 16 to 30, 31 to 50, 51 to 75, 76 to 100%)	
66 to 89%	2 (0 to 30, 31 to 100%)	Beeson et al. (2016)

broader regions. These comparisons focus on crop residue cover, although some remote sensing studies report these values as estimates of tillage practice, inferred from crop residue cover. This is different from the results of ground level cropland roadside surveys, which can infer tillage practice directly from observations of soil disturbance in addition to crop residue cover.

Challenges that contribute to a wide range of accuracy in remotely sensed estimates of crop residue cover are related to the still developing nature of remote sensing (Zheng et al., 2014), while atmospheric conditions, sensor and platform limitations, and ground conditions are additional complicating factors (Table 2). Zheng et al. (2014) presents an excellent review of satellite remote sensing for crop residue cover applications.

New satellite platforms offer a promising opportunity to improve on many of these challenges, with the Sentinel-1 and Sentinel-2 platforms providing a greatly improved spectral and temporal resolution that promises to increase the reliability of satellite remote sensing image capture, and a greater quality of remotely sensed crop and crop residue cover estimates (Zheng et al., 2014; Begue et al., 2018; Beeson et al., 2020; Hagen et al., 2020). However, development of these new technologies will still need to be paired with higher quality ground data, as any improvement in data quality for a model is still limited by the absence of an equally robust dataset for calibration and validation. Improvements in these supporting ground-level datasets would lead to even greater accuracy in regional crop residue cover models (Zheng et al., 2014; Azzari et al., 2019).

Table 2. Potential limitations for remotely sensed estimates of crop residue cover †.

Atmospheric effects	Sensor and platform	Ground conditions
• Atmospheric[3] reflectance and interference • Cloud cover[1,2,3,4,6]	• Long revisit times and timing issues with tillage[1,3,4,6] • Current sensors lack ideal spectral sensitivity[3,4] • By-pixel classification can under represent variability[4]	• Vegetation, including crop canopy[2,3,4,5,6] • Variable residue signature over time[4] • Soil moisture content[2,3,4,5,6] • Soil physical characteristics[3,4,5,6]

† [1]Beeson et al. (2020); [2]Begue et al. (2018); [3]Zheng et al. (2014); [4]De Paul (2012); [5]Serbin et al. (2009); [6]Thoma et al. (2004).

Alternative Methods and Discussion

There is an inherent tradeoff between generality and specificity in the spatial scale of models estimating crop residue cover. Identifying the appropriate scale and level of localized accuracy is important in determining which model of estimation is most suitable. The line transect method of in-field crop residue estimation provides a high degree of accuracy and precision, acting as a standard reference for other estimation methods (Morrison et al., 1993; Laamrani et al., 2017). However, the line transect method is limited in application to small spatial extends due to its time and labor costs. Roadside surveys provide a qualitative snapshot and data over a much larger spatial extent, but currently lacks validation to determine differences from different observers and other concerns discussed earlier. Increasing accuracy and precision in measurement would require additional steps and therefore require additional cost and time requirements. Satellite remote sensing addresses many of the shortcomings of these in-situ methods by covering vast areas of land quickly. Satellite remote sensing products, however, experience the inverse trade-off of the in-situ survey methods in that the larger the extent the more cost effective the methodology is, while achieving local level accuracy requires a far greater expenditure of resources. The fundamental challenge to satellite remote sensing is the need for accurate, localized, calibration and validation data. Thus, current methods in satellite remote sensing requires the type of rigorous field work that it is poised to replace (De Paul, 2012; Zheng et al., 2014). To meet this need, Zheng et al. (2014) suggests that a validated version of the Cropland Roadside Survey could provide the necessary local datasets. Validating these methodologies would then enable more advanced satellite remote sensing estimates as well as greatly increase the utility of the two decades of Cropland Roadside Survey data held across the country in county offices.

Technological advancements in proximal remote sensing and unmanned aerial systems (UASs) may provide improvements in both collection and spatial coverage of ground truth data. The OpTIS project is a modified Cropland Roadside Survey procedure that incorporated the collection of pictures of current field conditions at the time of data collection (Hagen et al., 2020). These images allowed for multiple independent estimates of crop residue cover and provide an archive of imagery for comparison to field reports. This method provides a more objective means of quality assurance and allows for peer-review of individual field estimates. In a similar method, Pilger et al. (2020) obtained roadside images, except instead of relying on the observer to capture the image, cameras were mounted to the outside of the vehicle and images were automatically captured in motion. In both instances, crop residue cover is estimated visually at a later time. However, these images are still taken at the same oblique angle as the in-situ visual estimates, and so share potential sources of error in estimations (Pilger et al., 2020). Imagery taken orthogonally to the ground can be utilized to estimate crop residue cover with similar accuracy and precision as the line transect method using a grid intercept method (Laamrani et al., 2017). In all cases, the imagery-based approach allows for estimates of crop residue cover to be determined at a later time by qualified personnel, providing more flexibility in the level of training and expertise required during the field campaign season. The method by Laamrani et al. (2017) would additionally provide the benefit of a very high degree of accuracy. However, to incorporate these orthogonal images in the cropland roadside survey the observer would need to enter the field adding additional collection time and requiring permission in advance from the field owner/operator.

Two studies (Kosmowski et al., 2017; Kavoosi et al., 2020) have explored the use of UASs to rapidly collect field scale imagery at the centimeter or greater resolution and then classified crop residue cover using segmentation (Kosmowski et al., 2017) or RGB indexes (Kavoosi et al., 2020). Comparison to line transect based estimates of crop and residue cover determined that these methods yielded results similar to satellite remotely sensed products; however, these images were taken on low-cost, consumer-grade cameras and UAS platforms and only provided RGB band imagery (Kosmowski et al., 2017; Kavoosi et al., 2020). Improved sensors or optimized classification methods may yield greater results, such as Laamrani et al. (2018) utilization of a script-based mobile app for automatic classification of crop residue coverage from orthogonal in-field imagery. Ding et al. (2020) utilized supervised SVM classification to estimate crop residue cover from UAS imagery with an overall accuracy of 98.1%. In addition, manual methods of visual estimation and grid intercept are applicable with UAS platforms as very high levels of image resolution can be maintained, up to and exceeding 0.5 cm (Kosmowski et al., 2017; Bansod et al., 2017).

Another potential advantage of the UAS platforms for gathering field level ground-truth data is that flight paths can be automated along pre-determined sampling paths, so that every field can be sampled at large spatial extent, and this sampling can be consistent from year-to-year utilizing precise GPS coordinates. This significantly reduces the likelihood of field mis-identification between survey years and allows for highly consistent data collection with an imagery archive for quality control. The pre-determined flight paths would also allow field crews carrying out the Cropland Roadside Survey the ability to make fewer stops, while collecting a greater number of data points per stop.

Conclusion and Recommendations

Remote sensing can efficiently provide continuous data over large areas but requires a high degree of expertise and is lacking in widely available application, whereas the inverse is true of remote sensing products that are best suited for large-scale, multi-county to regional application. A county conservation team may require specific information for their county, and to do so with the flexibility to adapt and change as priorities and project areas change the locations of interest. For a watershed scale, the CRS may serve perfectly well, providing a relatively rapid, low overhead snapshot of that region compared to the high level of expertise necessary for remote sensing products and the spatial and temporal resolution limitations inherent in remote sensed data. For larger-scale applications such as the multi-county or state level, remote sensing provides a very efficient methodology for tillage monitoring, particularly if initial start-up costs are offset by the production of multi-year datasets. However, neither of these practices are exclusive, as the validation needs of remote sensing approaches necessitate a localized field survey. Therefore, developing a uniform methodology to validate data collected by the Cropland Roadside Survey holds great promise to address the needs of both local conservation initiatives and state and regional actors. The CTICs effort to develop just such a system through its Crop Residue Management Survey and now its OpTIS initiative demonstrates that the key challenge lies in the lack of rapid field data acquisition that also delivers desirable levels of accuracy. New technologies such as UAS and roadside image capture platforms paired with automated accurate classification of high resolution proximally sensed imagery are poised to reduce these critical labor barriers. In the interim, collection of Cropland Roadside Survey data with a suitable validation framework can provide meaningful information for local soil conservation efforts while providing an archive of ground reference data for the rapidly developing field of remote sensing.

References

Azzari, G., P. Grassini, J.I.R. Edreira, S. Conley, S. Mourtzinis, et al. 2019. Satellite mapping of tillage practices in the North Central U.S. region from 2005 to 2016. Remote Sensing Environ. 221: 417–429. doi: 10.1016/j.rse.2018.11.010.

Baker, N.T. 2011. Tillage practices in the conterminous United States, 1989 – 2004: Datasets aggregated by watershed. Data Series 573. Natl. Water-Quality Assess. Progr. 13. https://pubs.usgs.gov/ds/ds573/ (accessed 13 Jan. 2020).

Bansod, B., R. Singh, R. Thakur, and G. Singhal. 2017. A comparison between satellite based and drone based remote sensing technology to achieve sustainable development: A review. J. Agric. Environ. Internatl. Develop. 111(2):383–407. doi: 10.12895/jaeid.20172.690.

Beeson, P.C., C.S.T. Daughtry, E.R. Hunt, B. Akhmedov, A.M. Sadeghi, et al. 2016. Multispectral satellite mapping of crop residue cover and tillage intensity in Iowa. J. Soil Water Conserv. 71(5):85–395. doi: 10.2489/jswc.71.5.385.

Beeson, P.C., C.S.T. Daughtry, and S.A. Wallander. 2020. Estimates of conservation tillage practices using landsat archive. Remote Sensing 12(16):2665–2665. doi: 10.3390/RS12162665.

Bégué, A., D. Arvor, B. Bellon, J. Betbeder, D. de Abelleyra, et al. 2018. Remote sensing and cropping practices: A review. Remote Sensing 10(2):99. doi: 10.3390/rs10010099.

Conservation Technology Information Center (CTIC). 2020. CRM. Conservation Technology Information Center. https://www.ctic.org/CRM (accessed 26 Dec. 2020).

Dane County Land and Water Resources. 2018. Management plan. Land and Water Resource Division. https://lwrd.countyofdane.com/plans-studies-reports/lwrm-plan (accessed 13 Dec. 2020).

Daughtry, C.S.T., P.C. Doraiswamy, E.R. Hunt, A.J. Stern, J.E. McMurtrey, et al. 2006. Remote sensing of crop residue cover and soil tillage intensity. Handbook of environmental chemistry, Vol. 5 – Water Pollution 91(1–2):101–108. doi: 10.1016/j.still.2005.11.013.

Daughtry, C.S.T., E.R. Hunt, P.C. Doraiswamy, and J.E. McMurtrey. 2005. Remote sensing the spatial distribution of crop residues. Agron. J. 97(3):864–871. doi: 10.2134/agronj2003.0291.

Department of Agriculture Trade and Consumer Protection (DATCP). 1999. Wisconsin County Transect Survey Procedures.

De Paul, V.O. 2012. Review article: Remote sensing, surface residue cover and tillage practice. J. Environ. Protect. 3:211–217. doi: 10.4236/jep.2012.32026.

Ding, Y., H. Zhang, Z. Wang, Q. Xie, Y. Wang, et al. 2020. A comparison of estimating crop residue cover from Sentinel-2 data using empirical regressions and machine learning methods. Remote Sensing 12(9). doi: 10.3390/RS12091470.

Dressing, S., T. Tech, J. Harcum, M. Dubin, and C. Watts. 2017. Recommendation report for the establishment of uniform evaluation standards for application of roadside transect surveys to identify and inventory agricultural conservation practices for the Chesapeake Bay Program Partnership's Watershed Model. https://www.chesapeakebay.net/documents/Transect_Survey_Recommendations_Report_3-16-17.pdf (accessed 11 Oct. 2020).

Fisher, S.J., and R. Moore. 2008. 2007 Tillage Transect Survey Final Report. Minnesota River Basin Data Center, Mankato, Minnesota. https://mrbdc.mnsu.edu/minnesota-tillage-transect-survey-data-center (accessed 28 Sept. 2020).

Gowda, P.H., B.J. Dalzell, D.J. Mulla, and F. Kollman. 2001. Mapping tillage practices with landstat thematic mapper based logistic regression models. J. Soil Water Conserv. 56(2):91–96. www.swcs.org (accessed 11 Oct. 2020).

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.

Hagen, S.C., G. Delgado, P. Ingraham, I. Cooke, R. Emery, et al. 2020. Mapping conservation management practices and outcomes in the Corn Belt using the Operational Tillage Information System (OpTIS) and the Denitrification–Decomposition (DNDC) Model. Land 9(11):408. doi: 10.3390/land9110408.

Hill, P. 1996. Cropland Roadside Survey Method. Conservation Technology and Information Center, West Lafyette Indiana. https://efotg.sc.egov.usda.gov/references/public/NM/ag45_transmittal_document.pdf (accessed 11 Oct. 2020).

Illinois Dept. Agric. 2018. Illinois soil conservation transect survey summary report. State of Illinois. 9 p. https://www2.illinois.gov/sites/agr/Resources/LandWater/Pages/Illinois-Soil-Conservation-Transect-Survey-Reports.aspx (accessed 27 Jan. 2019)

Kavoosi, Z., M.H. Raoufat, M. Dehghani, J. Abdolabbas, S.A. Kazemeini, et al. 2020. Feasibility of satellite and drone images for monitoring soil residue cover. J. Saudi Soc. Agric. Sci. doi: 10.1016/j.jssas.2018.06.001.

Keesstra, S.D., J. Bouma, J. Wallinga, P. Tittonell, P. Smith, et al. 2016. The significance of soils and soil science towards realization of the United Nations sustainable development goals. Soil 2(2):111–128. doi: 10.5194/soil-2-111-2016.

Kosmowski, F., J. Stevenson, J. Campbell, A. Ambel, and A. Haile Tsegay. 2017. On the ground or in the air? A methodological experiment on crop residue cover measurement in Ethiopia. Environ. Mgmt. 60(4):705–716. doi: 10.1007/s00267-017-0898-0.

Laamrani, A., P. Joosse, and N. Feisthauer. 2017. Determining the number of measurements required to estimate crop residue cover by different methods. J. Soil Water Conserv. 72(5):471–479. doi: 10.2489/jswc.72.5.471.

Laamrani, A., R.P. Lara, A.A. Berg, D. Branson, and P. Joosse. 2018. Using a mobile device “app” and proximal remote sensing technologies to assess soil cover fractions on agricultural fields. Sensors (Switzerland) 18(3):1–16. doi: 10.3390/s18030708.

McGranahan, D.A., P.W. Brown, L.A. Schulte, and J.C. Tyndall. 2013. A historical primer on the US farm bill: Supply management and conservation policy. J. Soil Water Conserv. 68(3):67–73. doi: 10.2489/jswc.68.3.67A.

Morrison, J.E., C.-H. Huang, D.T. Lightle, and C.S.T. Daughtry. 1993. Residue measurement techniques. J. Soil Water Conserv. 48(6).

Pilger, N., A. Berg, and P. Joosse. 2020. Semi-automated roadside image data collection for characterization of agricultural land management practices. Remote Sensing 12(14). doi: 10.3390/rs12142342.

Revised & Simplified Cropland Roadside Transect Survey. 2002. https://efotg.sc.egov.usda.gov/references/Delete/2003-10-06/nb_450_2_2_a1[1].pdf (accessed 30 June 2020).

Roberts, P., and C. Coleman. 1987. A survey of crop residue in Southwestern Ontario. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.516.3418&rep=rep1&type=pdf (accessed 11 Oct. 2020)

Serbin, G., C.S.T. Daughtry, E.R. Hunt Jr., D.J. Brown, and G.W. McCarty. 2009. Effects of soil spectral properties on remote sensing of crop residue cover. Soil Sci. Soc. Am. J. 73(5):1545-1558.

Thoma, D.P., S.C. Gupta, and M.E. Bauer. 2004. Evaluation of optical remote sensing models for crop residue cover assessment. J. Soil Water Conserv. 59(5):224–233.

USDA National Agricultural Statistics Service (NASS). 2020. About NASS History of agricultural statistics.

https://www.nass.usda.gov/About_NASS/History_of_Ag_Statistics/index.php (accessed 11 Oct. 2020).

USDA ERS. 2020 Documentation. https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/documentation/#about (accessed 11 Oct. 2020).

Zheng, B., J.B. Campbell, and K.M. de Beurs. 2012. Remote sensing of crop residue cover using multi-temporal Landsat imagery. Remote Sensing Environ. 117:177–183. doi: 10.1016/j.rse.2011.09.016.

Zheng, B., J.B. Campbell, G. Serbin, and C.S.T. Daughtry. 2013a. Multitemporal remote sensing of crop residue cover and tillage practices: A validation of the minNDTI strategy in the United States. J. Soil Water Conserv. 68(2):120–131. doi: 10.2489/jswc.68.2.120.

Zheng, B., J.B. Campbell, G. Serbin, and J.M. Galbraith. 2014. Remote sensing of crop residue and tillage practices: Present capabilities and future prospects. Soil Tillage Res. 138:26–34. doi: 10.1016/j.still.2013.12.009.

Zheng, B., J.B. Campbell, Y. Shao, and R.H. Wynne. 2013b. Broad-scale monitoring of tillage practices using sequential landsat imagery. Soil Sci. Soc. Am. J. 77(5):1755–1764. doi: 10.2136/sssaj2013.03.0108.

CHAPTER 2

Long-term Cropland Roadside Transect Survey Shows Increased Conservation Practice Adoption in Dane County, Wisconsin

Abstract

Conservation tillage has been an area of active research for it is potential to reduce soil loss through erosion, combat climate change, and improve food security. Conventionally conservation tillage is described as operations that leave greater than 30% crop residue cover in the field and includes no-tillage practice. This work utilizes annual crop and tillage data collected in Dane County, Wisconsin over a 22-year period using the Cropland Roadside Survey method. This same method was used by the Conservation Technology and Information Center (CTIC) in their national Crop Residue Management Survey. This work presents the relationships between crop type, crop residue cover, and no-tillage along with trends among these characteristics through time. We found an increase in conservation tillage practice from 1994 to 2017. This trend is apparent in increases of both crop residue cover levels and no-tillage practice. The most significant increase in no-tillage practice and crop residue cover levels was the result of changes in soybean (*Glycine max*.) tillage practices while corn (*Zea mays* L.) had a far more modest adoption of no-tillage and high crop residue cover. These results demonstrate the potential for the Cropland Roadside Survey to provide highly specific analysis of tillage and crop practices through time.

Introduction

Conservation tillage practices are an important strategy in mitigating the impacts of climate change, preventing soil erosion, facilitating water conservation, and promoting soil health (Busari et al., 2015; Claassen et al., 2018). Conservation tillage as a descriptive term covers a wide range of practices (Reicosky and Allmaras, 2003; Reicosky, 2015). For the purpose of this study, the conventions established by the Conservation Technology Information Center (CTIC) defining tillage systems are used. In this context, conservation tillage is defined as when greater than 30% of crop residue cover is left in the field after tillage and includes no-tillage, ridge-tillage, and mulch-tillage practices, among others. Reduced tillage includes crop residue cover levels from 15 to 30% and conventional tillage leaves between 0 to 15% crop residue cover (CTIC, 2020).

The adoption of conservation tillage has been an area of active research, with the most comprehensive tillage practice monitoring initiatives represented by the Agricultural Resource Management Survey (ARMS) of the Economic Research Service Agency within the U.S. Department of Agriculture, and the Crop Residue Management survey (CRM) conducted by the CTIC and local county governments. The CRM survey design is based on the Cropland Roadside Survey procedure developed by Hill (1996) and is discussed at length in Chapter 1. Despite a myriad of efforts to clearly understand the relationships and factors that drive adoption of conservation tillage practices over the past decades, there is not a strong consensus on what these factors are and the degree to which they contribute to adoption (Prokopy et al., 2019). Further, there is a high degree of variation in conservation tillage practices on a regional and crop basis (Lyon et al., 2004; Wade et al., 2015). While there is extensive research into the drivers of conservation tillage and the benefits it can provide, there is a lack of quantitative data on field level conservation practices. Data from ARMS are collected in multi-year intervals and rely on producer perceptions of their own present and historic practices. These accounts are collected primarily through mailed surveys and practices are summarized at the regional scale. The lack of direct observation of field conditions by an expert and relying on producer perceptions in ARMS introduces additional sources of observer bias and is potentially complicated by the broad and often ambiguous understanding of what constitutes conservation tillage (Reicosky and Allmaras, 2003; Reicosky, 2015). The lack of a predictive model for conservation tillage adoption and regional variability in conservation practices emphasizes the need and value of locally collected data on cropping and tillage practices.

The Cropland Roadside Survey methodology practiced at the county level provides the most comprehensive and most widespread dataset currently available for field level crop and tillage practice, which can help determine practice adoption. These datasets provide an advantage over ARMS data by providing yearly snapshots and trends over time at the field level when conducted in consecutive years. However, data from Cropland Roadside Surveys are typically only analyzed as summary reports for individual years, or broadly aggregated into regional scale summaries of year-on-year occurrences of crop and tillage practices. After 2004, broad scale and regional data reporting was curtailed by a lack of funding and the CTIC's national CRM initiative was largely abandoned. Although no longer supported on a national scale, many counties still carry out local surveys providing a vast but decentralized and underutilized archive of field level agricultural practices.

The Cropland Roadside Survey method defines tillage systems by ranges of crop residue cover left after tillage, rather than the specific implements used. Although this approach is less specific, it has the added benefit of describing a measure that directly relates to surface erosion. However, visual observations cannot clearly identify below surface soil disturbance. Therefore, in this study we consider crop residue cover and clear signs of soil disturbance to distinguish no-tillage as indicators of conservation tillage. The objective of this work was to summarize a 22-year crop and tillage monitoring database derived from the Cropland Roadside Survey conducted by the Dane County Land and Water Conservation Department in Wisconsin since 1994. A secondary objective was to provide a framework for exploration and analysis of these type of data.

Methods

Cropland Roadside Survey Design

The Cropland Roadside Survey is a windshield transect survey developed in the 1990s and utilized by county conservation offices and by the CTIC's Crop Residue Management Survey (Hill, 1996; Baker, 2011). Surveys were designed to sample agricultural fields at regular intervals along a predetermined road transect path. The transect path was designed to sample agricultural fields, and thus, avoided populated regions of the county and areas undergoing urban sprawl. The survey is conducted in the spring, includes 763 stops and covers about 410 driven miles. Visual estimates of crop type, tillage system, ephemeral erosion, and crop residue cover were made at approximately 100 feet into the field from the road at each stop on both sides of the road. This results in two field sampling points for most transect stops for a total of 1,161 sample observations. Transect points were excluded from sampling if they were not in agricultural production. For the purposes of this survey agricultural production was categorized by crop, such as corn (*Zea mays* L.), soybean (*Glycine max*.), small grains, forage crops, and included other crops such as tobacco and vegetable crops as "other crops." Transect points that were apparent to the observer as an agricultural field but that had no visible or emergent crop were categorized as idle if during a revisit on a later date no crop was observed.

Data Pre-Processing

The Cropland Roadside Survey data provided by Dane County Land and Water Resources Department covered 22 years from 1994 through 2017 with a gap in data collection in 2008 and 2009. These data are missing because staff were unavailable to conduct the survey in those 2 years. Crop category was inferred for 1993 by examining crop residue observed during data collection in the spring of 1994, expanding the crop dataset to 23 years, but there are no tillage or residue values for 1993. The Cropland Roadside Survey was designed to observe fields after tillage and planting, but before crop canopy cover obscures the soil surface, typically mid- to late-May. The survey in Dane County was conducted by the same person during the entire time from 1994 to 2017.

The original data were provided in .csv, .txt, and .dbf file formats for 1993 to 2007, while data from 2010 to 2013 were extracted from a WinTransect database. WinTransect was a custom user data collection interface and data analysis tool developed in 2008 for handling cropland roadside survey data by P. Kaarakka in the Department of Soil Science at the University of Wisconsin-Madison. The WinTransect software is no longer available and survey data for Dane County from 2010 to 2013 was only available as archived database exports (P. Kaarakka, pers. commun., 31 Jan. 2021). Data from 2014 to 2017 were provided as .snapDB files from the SnapPlus nutrient management software (https://snapplus.wisc.edu/) and is presently used to record and manage transect data (C. Diehl, pers. commun., 17 Jan. 2020). The .snapDB file format was based on the standard Structured Query Language (SQL) and data can be directly interacted with SQL command line instructions or a database browser. Notable changes in survey data collection are:

1994 – Data collected included year, field, present crop, tillage, residue, previous crop, slope

1995 – The following parameters were added: P factor, presence of ephemeral erosion, T level, K factor, slope length, drain out, if field present in a DNR priority watershed, soil loss estimates

1996 – DOS Transect software adopted for data collection

2000 – Wisconsin DATCP promotes statewide transect use

2010 – WinTransect Software adopted for data collection; previous crop data dropped

2014 – SnapPlus adopted for data collection

Information gathered by the Cropland Roadside Survey were recorded for each field within a year. Crop type data were initially collected as eight different categories in 1994, but after adoption of WinTransect and SnapPlus, over 64 distinct crop categories were added to the dataset. These included different codifications of the same crops (e.g., soybean and corn) with various row planting widths, or the end use of a crop such as the use of corn for silage or grain. Crop residue cover recording was held consistent across all survey years as five distinct levels: 1 = 0 to 15% crop residue cover, 2 = 16 to 30% crop residue cover, 3 = 31 to 50% crop residue cover, 4 = 51 to 75% crop residue cover, and 5 = 76 to 100% residue cover.

Tillage systems were defined broadly by a distinction in crop residue cover and the specific level of soil disturbance according to the standards established by the CTIC (CTIC, 2020; Hill, 1996). Tillage systems described by the Cropland Roadside Survey include no-tillage, ridge-till, mulch-till, reduced-till, conventional-till, and moldboard plow tillage. These tillage systems in turn correspond to the broader categories as defined by crop residue cover: conventional tillage (< 15% crop residue cover), reduced tillage (15 to 30% crop residue cover) and conservation tillage (> 30% crop residue cover). Additional information about initial survey categories and attribute codes can be found in Chapter 1 and Hill (1996).

The different data files formats for 1994 to 2007 were processed independently given their simple text document data structure and imported into an SQL database where the records for year, field, present crop, previous crop, residue, tillage, and ephemeral erosion were queried. These tables were then collated so that they represented one continuous dataset from 1993 to 2007. Both WinTransect and SnapPlus use a relational database structure. The exported WinTransect text files and SnapPlus data tables were imported into a SQL database where the relational databases were joined and queried to create a single dataset that contained the same attributes as the data structure for the 1994 to 2007 dataset. All crop and tillage data were then collated into a single dataset representing the period from 1997 to 2017 with years 2008 and 2009 missing as previously mentioned. The combined dataset was then cleaned to remove duplicate entries, empty values, and invalid entries within the SQL database.

Data Recoding

The combined database contained values that belonged to the same class but had different categories depending on the platform used to collect data. Classes were converted into a format that had the same categories for all the years in the database. For example, data from 1994 to 2007 used a one letter code for crop type and tillage system (Table 1), while data from SnapPlus used a three- or four-character code for each crop type. Common class values were assigned to crop type, for both present crop and previous crop, and tillage category. In addition, crop descriptors varied in the number of categories possible across the Transect, WinTransect, and SnapPlus platforms and required that crop categories be condensed homogenized into a format that contained five crop categories to span the entire dataset. The five categories used were corn, soybean, small grain and forage, idle, and other crops. The original crop attributes were maintained in the database for purposes of cross-checking or future uses.

The decision was made during database recoding process to include small grains and hay together in one category since they would appear similar at the time the survey was conducted in the spring and because the species or end use of the crop could not be validated with the available data. Within the Dane County Cropland Roadside Survey methodology, a field planted into a grain or hay crop in the same year as the survey year was recorded as small grains from 1994 to 2007 and as direct seeding or spring seeded in 2008 to 2017. Fields observed in the survey where it was apparent a small grain or forage crop was established the previous year were recorded as hay, alfalfa, or forage (C. Diehl, pers. commun., 17 Jan, 2020). This means that within a given survey year small grains could represent a wheat or barely grain crop, or it could represent a newly direct seeded hay field.

Table 1. Crop and tillage recoding categories from the original 1994 Transect Survey Design. Original values from the survey data format were recoded from a letter code format to descriptive names.

Crop categories	
Original values	New value
C	Corn
B	Soybean
F	Fallow
H	Hay
S	Small grain
G	Small grain
D	Drilled soybean
R	Rowed soybean
X	Other crop
Z	CRP
Tillage categories	
Original values	New value
C	Conventional
M	Mulch till
N	No till
R	Ridge till
X	Other
/	NA

Therefore, the greatest level of confidence in land cover type was obtained by combining the small grains and forage crop categories as single attribute.

Original data files also included slope, T factor, DNR priority watershed, and K factor variables that were derived from NRCS soil survey data using an analog overlay technique with printed National Agriculture Imagery Program orthophotographs. These attributes are incomplete as not all fields were assigned attributes with this method. Therefore, these attributes were not included in analyses within this study and are instead considered in Chapter 3, where geospatial analysis tools were used to populate an updated set of attributes describing each field.

Roadside observations describing tillage systems were limited to estimates of crop residue cover and soil disturbance. However, in most cases the type of tillage equipment used or the degree of below surface soil disturbance could not be inferred. To address this uncertainty, tillage system was reclassified to present a binary condition of either no-tillage or tillage. Crop residue cover data were used to determine conservation, reduced, or conventional tillage system classifications. The no-tillage classification was used to identify the most conservative method of conservation tillage.

Crop Classifications

The previous crop attribute for a given season were collected between 1994 and 2007 by inferring from the previous season crop residue remaining in a field at the time the survey was conducted in the spring. At the same time, current crop for a particular year was recorded if a crop had emerged and could be identified. This provided the opportunity for validating crop classifications in some situations. Similarly, crop residue present in a field from the previous year can indicate if a second crop was planted. A new attribute for the occurrence of a second crop and its crop category was created. A detailed list of corrections and changes made as a result of this approach, along with justifications, can be found in Supplemental document 1.

An established small grain or forage field will not have undergone tillage, and therefore there is no meaningful range in residue values to report. In these cases, established fields can be parsed from newly planted fields by filtering for the presence of tillage values. However, newly planted small grain or forage fields with no-tillage could be miss categorized using this approach since in both instances the soil is not disturbed by tillage and existing plant matter and root structures are maintained. Therefore, these two scenarios were assumed to be equivalent for purposes of this work. The data cleaning and recoding processes revealed a systematic data collection discrepancy in the WinTransect data. Small-grain-and-forage crops, along with idle fields, from 2010 to 2013 in the WinTransect dataset had abnormally high levels of crop residue cover (Fig. 1). In these instances, residue level was recorded as 5 (75 to 100% surface cover) with no observation for tillage recorded since there was no tillage and, as a result, these residue values appear to be anomalous. In the methodology for recording tillage and residue estimates utilized by Dane County Land and Water staff prior to WinTransect, these values would have been recorded as “NA” since tillage was not performed and no crop residue cover values were recorded. This includes the

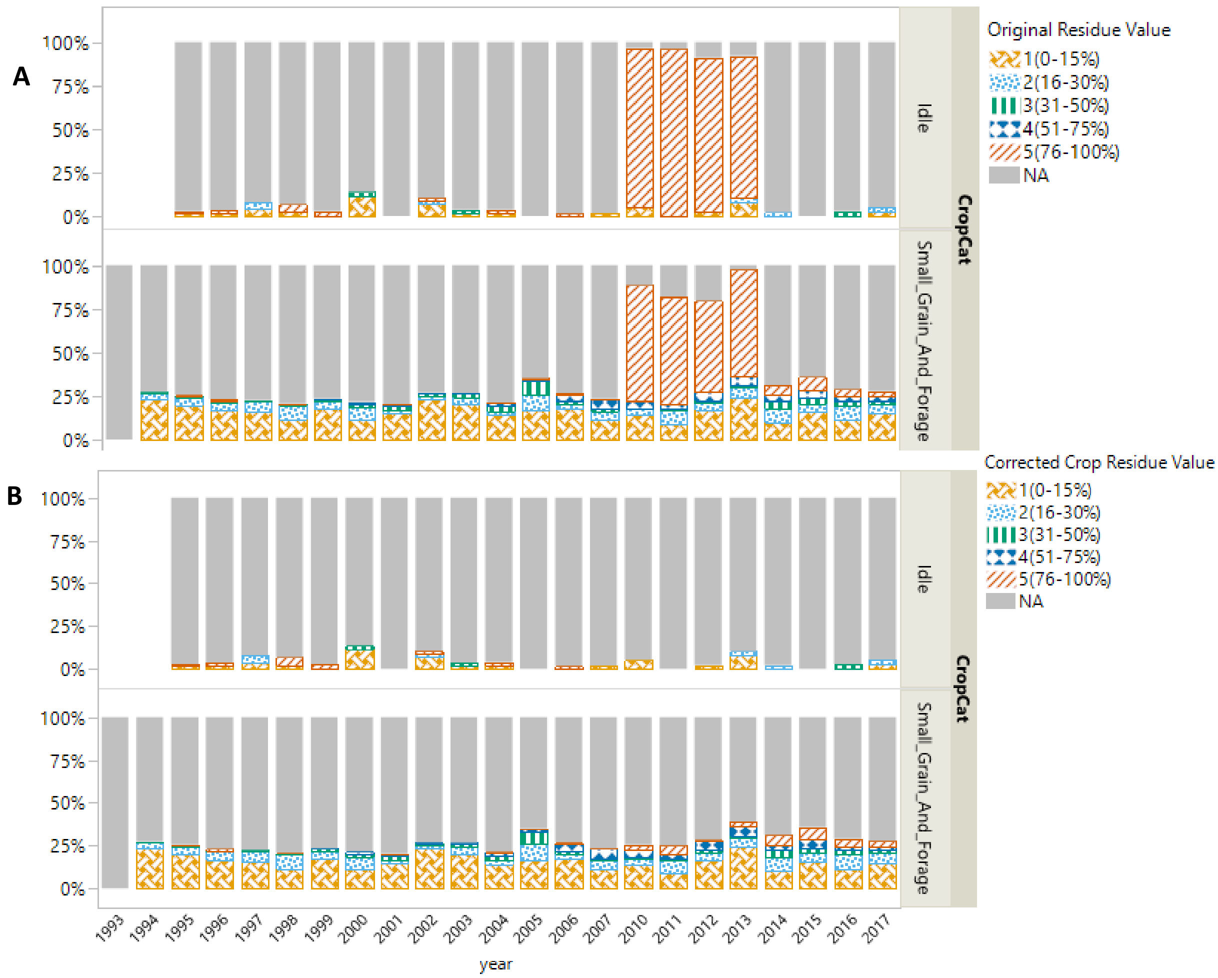


Figure 1. (A) Percent of crop residue cover values in idle crop, and small grains and forage classes demonstrating WinTransect database error between 2010 and 2013, and (B) percent of crop residue cover values after database error was resolved.

majority of years with data recorded in the Transect and SnapPlus datasets (1994 to 2007 and 2014 to 2017, respectively). The small grain and forage, and idle crop class attributes were processed through a conditional statement to assign NA values where tillage was also reported to be NA in the “small grain and forage” crop category and the “idle” crop category to resolve this discrepancy. This resulted in an update to 659 of 1,147 small grain and forage crop category entries, and 176 of 197 idle crop category entries in the WinTransect dataset. There was a small number of fields with residue and tillage values reported in both idle and small grain and forage categories. These are largely consistent across years which represented newly planted small grains or forage, or newly fallowed land.

Current year crop classifications using emerged crops in the spring were validated with the residue from the previous crop observation the following year. Crop classification accuracy was calculated by comparing of the current crop category to the crop residue in-field the following spring using a confusion matrix. The determination of a crop type from residue was assumed to be more robust than the visual classification of crop type by observing emerged plants in the spring since crop residue from matured and harvested plants is more distinctive from a distance than green shoots in the spring. The difficulty of using green shoot observations to determine current crop was compounded by variable planting dates and crop growth stages between fields during the survey period.

Field Attrition Data

Field attrition data describing the number of fields lost from the dataset by land conversion or field abandonment were derived from the dataset. Queries were used to call the number of fields that had no data recorded beginning with 2016 and working successively backwards. The year 2017 was excluded from this range because there is no subsequent year to confirm a given field is out of agricultural land use from 2017. This approach provided a record of fields which were likely removed from agricultural production over time as defined by survey criteria.

Statistical Analyses

Descriptive and summary statistics for crop residue cover, crop type, and tillage were generated using JMP version 15 statistical analysis software (SAS Institute Inc., Cary NC). A rate change of crop type and residue cover level were analyzed by tabulating occurrences of each crop type and crop residue cover level. This table was exported to a spreadsheet where rate of change between each year was calculated for all crop categories and crop residue cover levels greater than 30% were aggregated to express the rate of change for conservation tillage. The rate of change in conservation tillage was then set against the rate of change of each crop category with linear regression. Statistical significance of the relationship between change in crop type and residue cover was determined at an $\alpha = 0.05$.

A confusion matrix was used to determine the overall accuracy of crop classifications by comparing the present crop classification for a given year to a reference value, in this case the previous crop reported for that same field the following spring. The confusion matrix represents data from 1994 to 2006. Previous crop data were not collected after 2006. Overall accuracy was calculated as the total correct classifications across all classes divided by the total number of classifications.

Results and Discussion

Crop Classification and Field Attrition

The Dane County Cropland Roadside Survey extends across the county over a length of 410 miles as driven, with 763 stops and 1,526 potential sample points. Of these, 1,161 unique fields met survey criteria throughout the 22 years of sampling campaigns. This resulted in a total of 24,684 unique observations when crop data from 1993 is included. Accuracy assessment using a confusion matrix resulted in an overall 98% crop classification accuracy for corn, soybean, and idle crop values (Table 2). An accuracy assessment of small grain and forage and other crop categories was not possible using this methodology, as these crop categories could be explained by double cropping practices.

Overall, there was a decline in the number of fields sampled each year and a total of 127 fields lost throughout the duration of the survey. This decrease in total observations each year does not appear to be entirely explained by field attrition (Table 3). Rather the absence of an observation in a given year may reflect missing data or the field being temporarily removed from agricultural production (e.g., NRCS's Conservation Reserve Program). The data as provided were insufficient to determine the cause of missing or non-applicable data entries, or to parse between data points that were missing and those that were sampled but deemed to be non-applicable in a given year. Additionally, these data cannot be used to determine land conversion because the transect survey design intentionally avoided urban areas to avoid losing fields in the survey as a result of urban sprawl and land conversion. A description of the Cropland Roadside Survey design and criteria for sampling and gathering data can be found in Hill (1996) and Chapter 1.

Table 2. Crop classification error summary with a confusion matrix for visual crop classification from roadside stops from 1994 to 2006. Overall accuracy was estimated at 98%. Only cases where spring reported values are corn, soybean, or idle, are used for validation data. The other crop categories of small grains and forage and other crops could be explained as the result of double cropping.

		Crop classification from spring residue			
		Corn	Soybean	Idle	Total
Initial crop classification (present crop)	Corn	6403	54	7	6464
	Soybean	78	2296	1	2375
	Idle	34	18	311	363
	Total	6515	2368	319	9202

Table 3. Number of fields sampled each year (N) and field attrition. Each year a field was surveyed if it met the criteria as an agricultural field. The annual change in the number of fields from one year to the next does not reflect field attrition, but mainly corresponded with fields that were temporarily removed from agriculture or where data were missing. Survey data for 1993 was inferred from crop residue in the spring of 1994 and is therefore excluded from the data. NA – not available.

Year	N	Total attrition	Magnitude of change
1993	1056	NA	NA
1994	1130	0	0
1995	1124	3	-3
1996	1128	8	-5
1997	1125	12	-4
1998	1123	17	-5
1999	1112	29	-12
2000	1105	34	-5
2001	1100	44	-10
2002	1088	55	-11
2003	1065	73	-18
2004	1061	79	-6
2005	1057	86	-7
2006	1050	95	-9
2007	1038	97	-2
2010	1039	103	-6
2011	1049	103	0
2012	1048	107	-4
2013	1045	111	-4
2014	1044	115	-4
2015	1037	122	-7
2016	1033	127	-5
2017	1027	NA	NA

A

Crop category	Count
Corn	11726
Idle	987
Other crop	491
Small grain and forage	7037
Soybean	4443
Total	24684

B

Second crop category	Count
Corn	108
Other crop	27
Small grain and forage	129
Soybean	21
Total	285

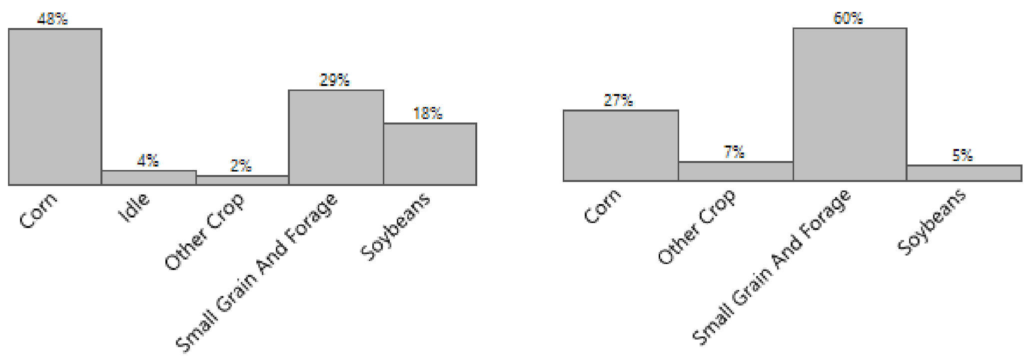


Figure 2. Distribution of (A) crop category across all data years and (B) second crop category inferred from spring reported crop residue from 1994 to 2017 in Dane County, Wisconsin.

<u>Crop Type Frequency Distribution and Double Cropping</u>

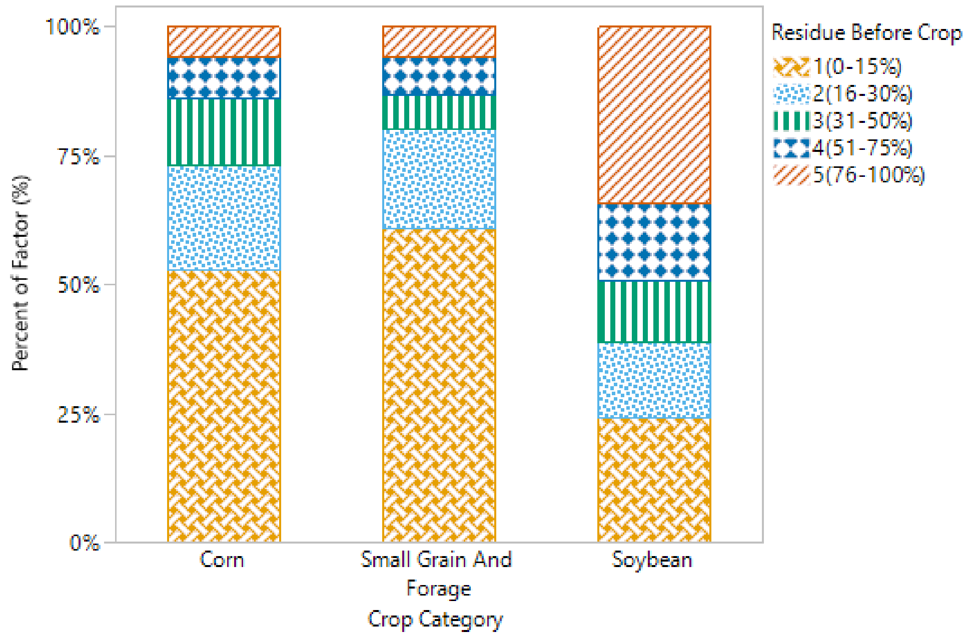
Across the surveyed fields and years, corn was the predominant crop where it was found 48% of the time (Fig. 2A). Small grain and forage crops category was found in 29% of the time, followed by soybean (18%). Idle and other crops represented a small proportion of the field during the survey period. Only 285 incidences of fields planted with a second crop were inferenced from the 14 survey years from 1994 to 2010 when this information was collected (Fig. 2B). These years with a reported second planting event include cases where a small grain crop was planted after a spring planting of soybean or corn, as well as cases where corn was planted after an early harvest of a small grain such as winter wheat. The most common second crop in a growing season was corn following small grains (n = 100), followed in occurrence by small grain planted within a season after corn (n = 85). The next most frequent double cropping practice observed was small grains following soybean (n = 32) and soybean following small grains (n = 20). Borchers et al. (2014) found that winter wheat was the most common crop to be planted in the same season as soybean, with a soybean-winter wheat rotation the most prevalent and rye was the most common winter crop species to be planted in combination with corn in northern U.S. latitudes. Growing two crops within a growing season was not a common practice during the survey period studied here. However, this may become more important as climate change drives an increase in growing season length and an increased potential for double and cover cropping (Borchers et al. 2014; Seifert and Lobell, 2015; Lant et al., 2016). A fall survey in addition to recording previous crop residues during the spring survey would expand the utility of the dataset for cover crop and double crop monitoring in Dane County.

Crop Residue Cover and Crop Type

A comparison of crop category and in-field crop residue cover revealed that soybean was most often planted into high levels of crop residue, with 61% of the observations planted into greater than 30% surface residue (Fig. 3A). Corn typically resulted in greater crop residue cover the following spring, with 36% of the observations having greater than 30% surface residue and 20% of the total observations falling within the surface residue classification for reduced tillage of 15 to 30% (Fig. 3B). This was expected as corn residue takes longer to decompose than soybean and small grain crop residues (Kumar and Goh, 1999; Hadas et al., 2004; Kriaučiuniene et al., 2012). However, there was a wide range in crop residue cover levels resulting from corn crops. This variation in crop residue levels in corn appear to be the result of different crop use between corn for silage and corn for grain. From 2010 to 2016, when observations were recorded to determine differences between corn for silage or grain, corn silage resulted in less than 15% surface residue cover in 81% of observations, and only 9% of corn silage instances resulted in conservation tillage levels of crop residue cover (> 30%). This compares to 55% of corn grain fields with conservation tillage levels of surface residue cover in the spring and 22% with levels within reduced tillage category for surface residue cover.

Soybean increased in the proportion of crop categories observed from 1 year to the next between 1993 and 2001, rising from a low of 6% of all crops to 23% with relatively small changes from 2002 onward (Fig. 4). This increase in soybean frequency aligns with a

A



B

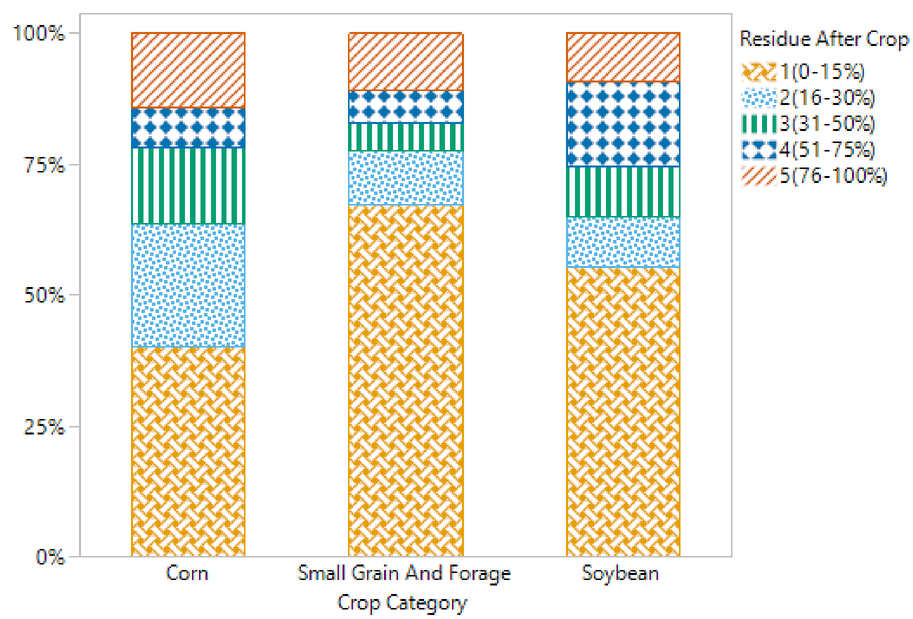


Figure 3. A) Percentage of each crop residue cover level in-field before a crop was planted, and (B) percentage of each residue level in-field after a crop was grown averaged from 1994 to 2017 in Dane County, Wisconsin.

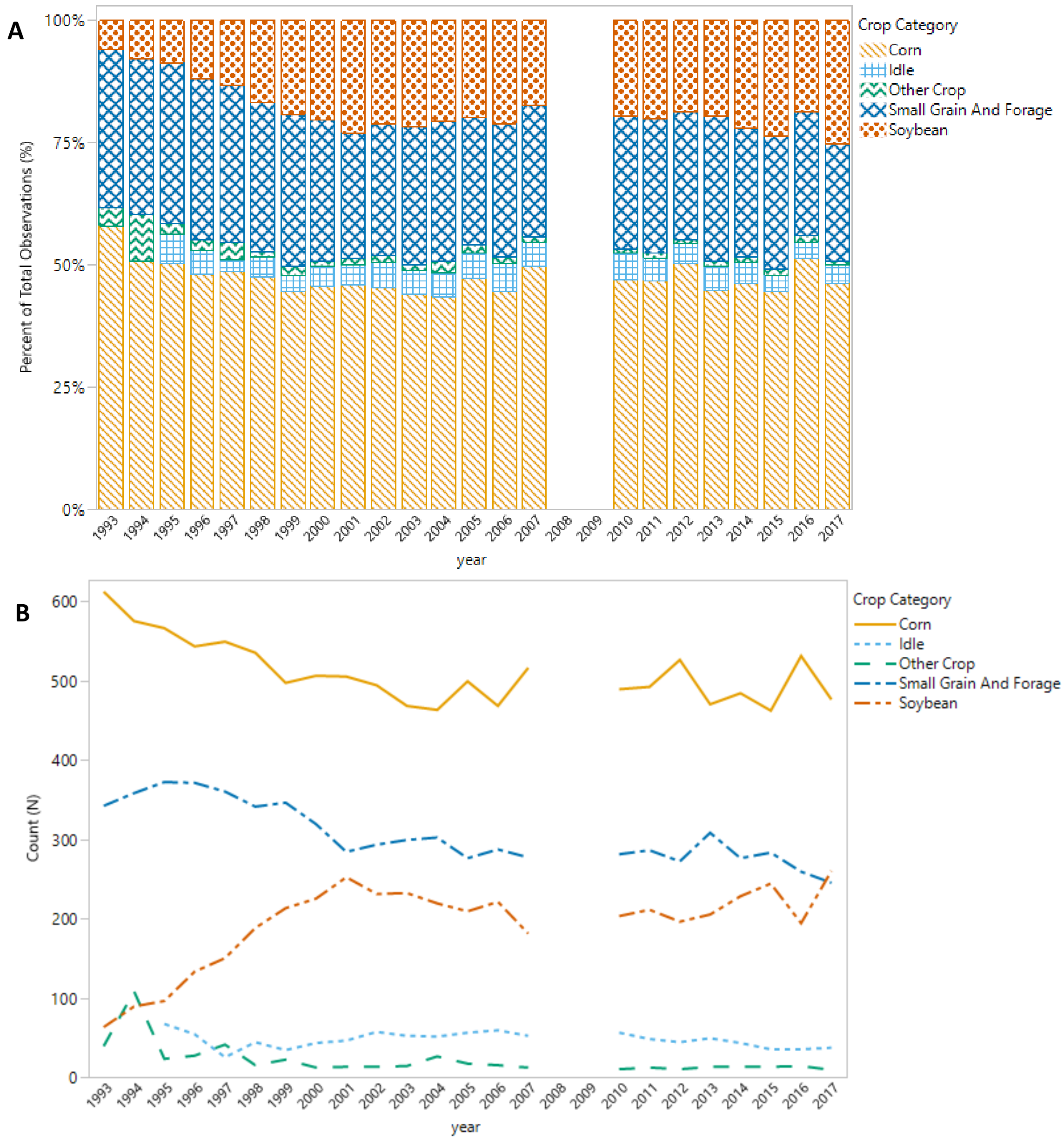


Figure 4. Proportional distribution of crop category by year for all fields as a (A) percent of observations and (B) as a numerical count of observations.

reduction in small grain and forage crops, and corn. Corn had the greatest reduction in its share of yearly crops during the period from 1993 to 1999, from a high of 58% in 1993 to 44% by 1999, and after that corn fluctuated in a range between 44 and 51%. Like corn, small grains and forage crops had their high in 1993 with a 32% share of all crops planted that year, and from 2001 onward represented between 28.5 and 24% of total crops planted annually. The crop categories of idle and other crop had the lowest degree of variability in addition to representing the smallest proportion of overall field observations.

The crop trends generated from the Cropland Roadside Survey data relate well with ARMS data estimates of corn and soybean crops for Dane County during the same period from 1994 to 2017 (NASS, 2021). Corn had a decrease in total acres from 1994 to 2000, while soybean increased in total acres during the same period, matching the trends seen in the Cropland Roadside Survey data (Fig. 5). Fluctuations in corn and soybean crop acres in the ARMS for Dane County after 2000 are also similar to the changes in the proportion of corn and soybean crops in the Cropland Roadside Survey. These similarities in trends occur despite that the ARMS data for Dane County reports total crop acres while the Cropland Roadside Survey primarily reports a count of fields for a given crop. These findings suggest that changes in frequency count of crops in the Cropland Roadside Survey are representative of general changes in crop acreage for Dane County.

Crop Residue Cover Trends

There was a general gradual increase in the proportion of crop surface residue levels of 51% or greater over time (Fig. 6A). As previously mentioned, the percent surface crop residue cover observed in the spring can be related to the type of crop grown the previous

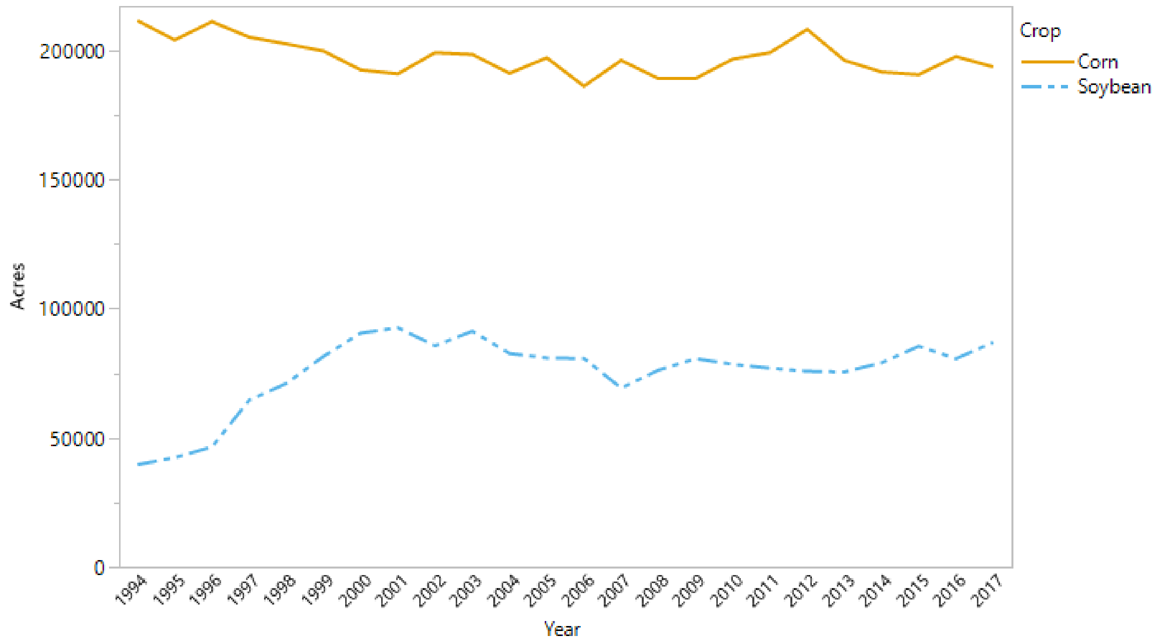


Figure 5. Acres of corn and soybean crops from 1994-2017 obtained from National Agricultural Statistics Service ARMS data (NASS, 2021).

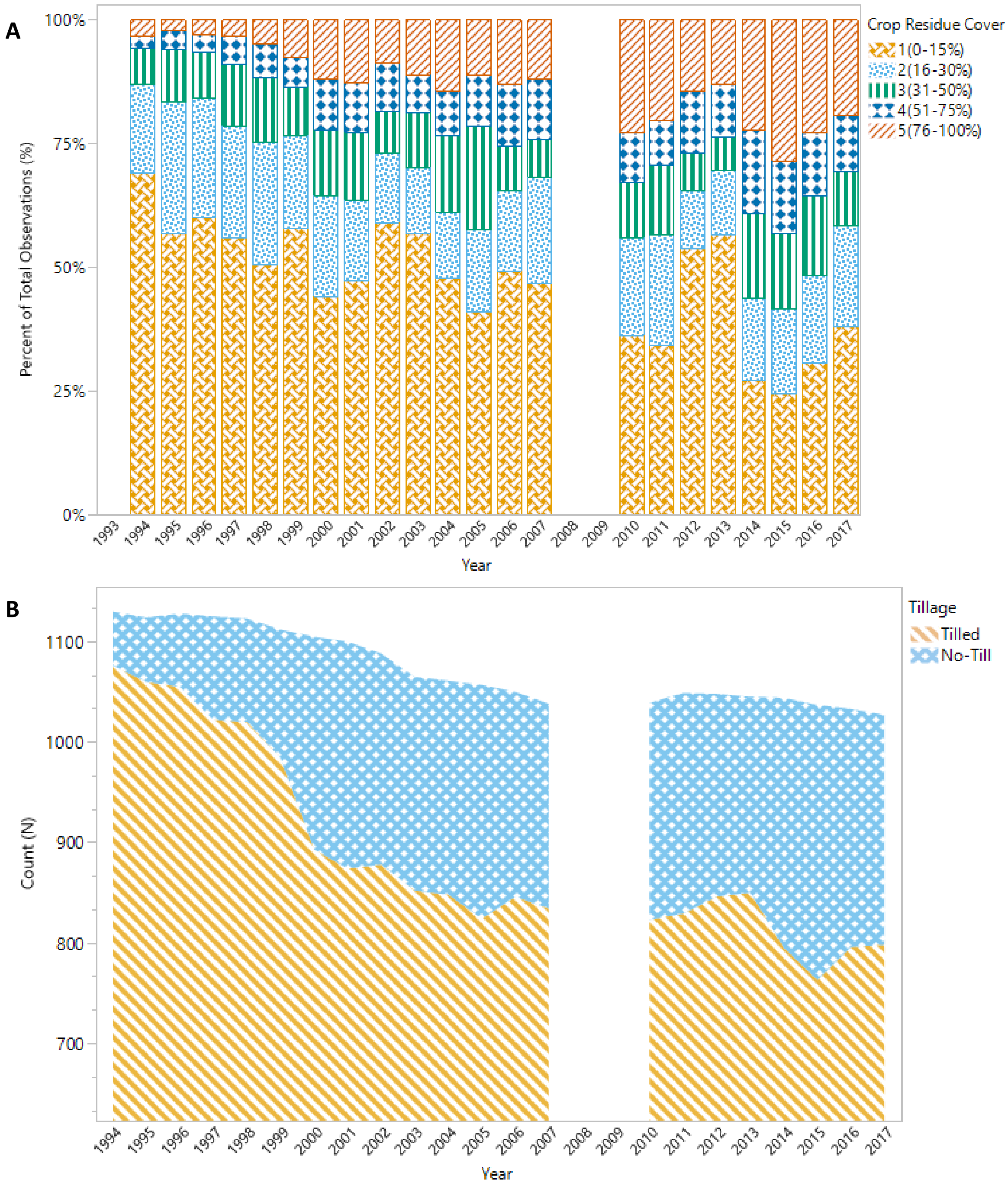


Figure 6. (A) Proportional distribution of surface crop residue cover categories and (B) occurrence of no-tillage by year in Dane County, Wisconsin.

year. However, no statistically significant relationship was found between the percent change in crop categories and percent change in crop residue cover greater than 30%. The percent change in crop residue cover over 30% was used for the regression as it represented the range of values where the most change was observed. This assessment quantitatively supports observations when comparing year on year changes in crop residue cover with changes in crop category (Fig. 6A and Fig. 4). These findings suggest that the overall increase in crop residue cover levels were the result of changes in agricultural conservation practices and not just a change in crop type. This observation is further supported by an increase of 17% in no-tillage, changing from 5% adoption in 1994 to 22% in 2017 (Fig. 6B).

On a crop-by-crop basis, the trend of increasing crop surface residue cover was not uniform. However, the amount of surface residue cover following all crops generally increased over time. Soybean had the greatest increase in surface crop residue the following spring across the survey period (Fig. 7). Corn had a lower increase in surface residue cover over time than soybean, while small grain and forage had a modest increase.

The amount of surface residue a particular crop was planted into increased over time for the three crop categories considered (Fig. 8). Soybean had the greatest increase in surface residue cover at the time of planting. This was somewhat expected since in 91% of cases soybean were preceded by corn the previous crop year. However, the most commonly planted crop after corn was corn (i.e., continuous corn) occurring 53% of the time, and soybean followed corn 35% of the time. The expected high surface residue levels following corn partially explains the high surface residue levels at the time of soybean planting. Nevertheless, surface residue levels after corn vary depending on crop usage. Between 2010

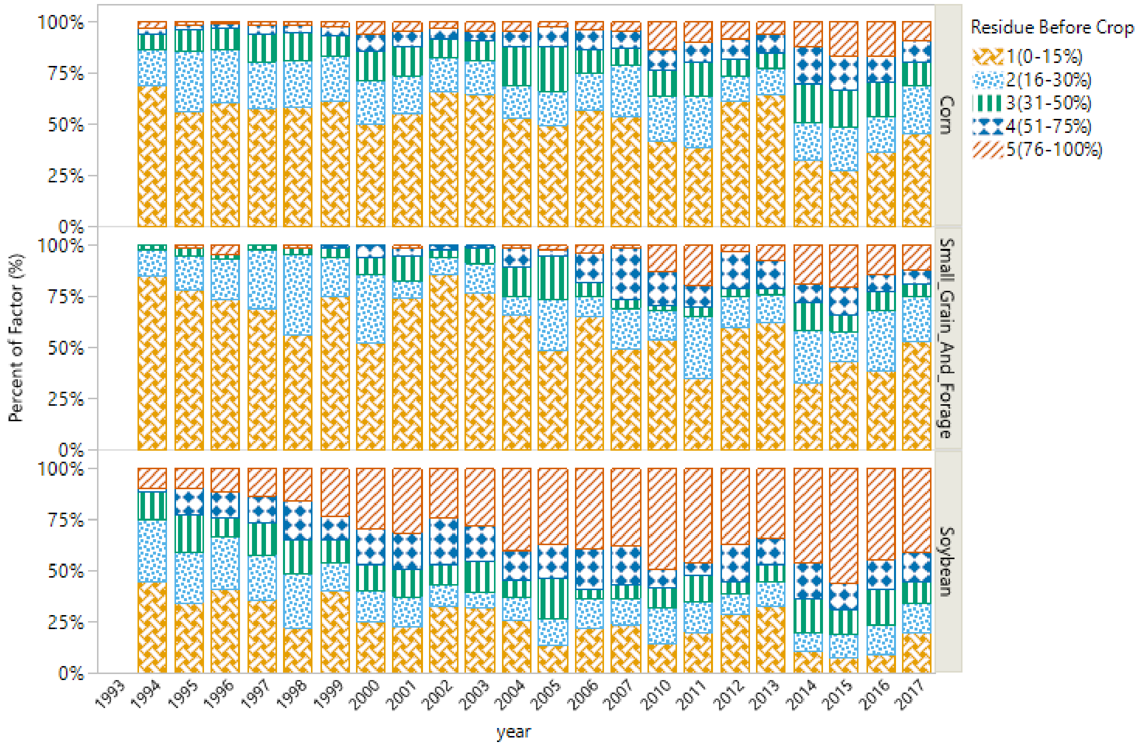


Figure 7. Annual proportion of surface residue the following spring after corn, soybean, and small grain and forage crop categories in Dane County, Wisconsin.

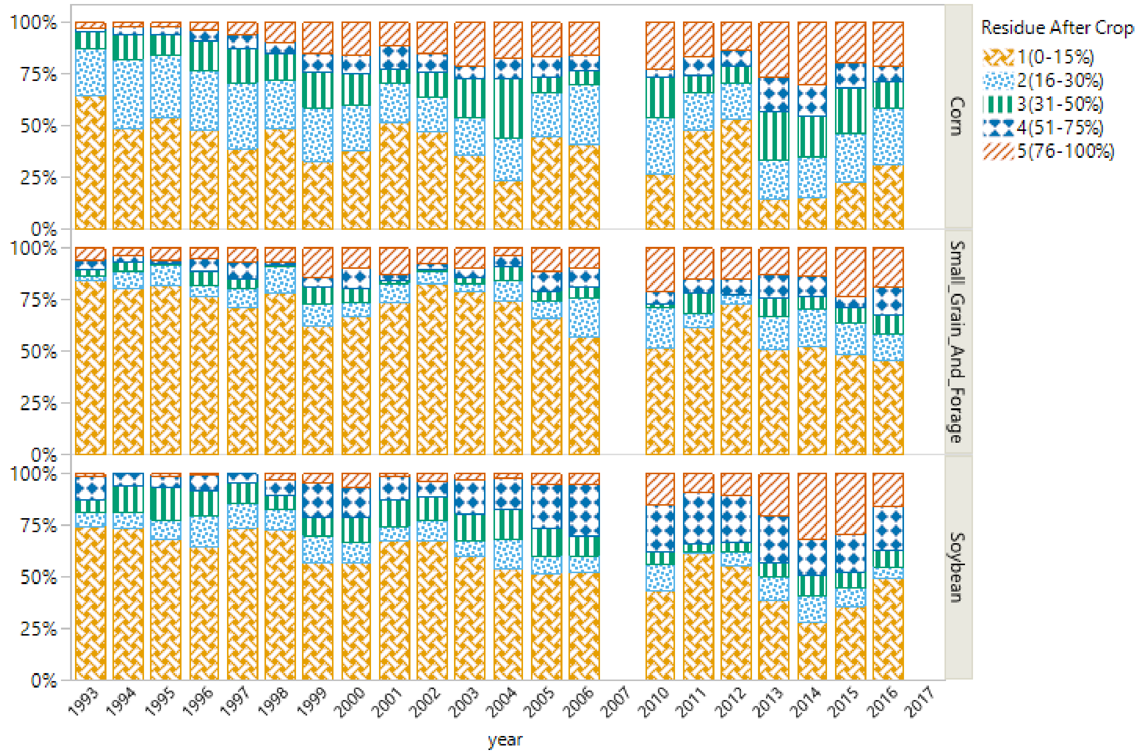


Figure 8. Annual proportion of surface residue cover that a particular corn, soybean, and small grain and forage crop was planted into in Dane County, Wisconsin.

and 2017, use of corn for grain resulted in conservation tillage surface residue levels in 55% of the observations, while residue levels after corn silage were in the conventional tillage range in 82% of the observations. Comparing surface residue levels after corn, corn grain was followed by no-tillage more frequently (26% of the time) than corn silage (10% of the time). This is noteworthy, as in addition to soybean crops almost always following corn, 96% of soybean crops were planted into corn grain residue during the 2010 to 2017 period these data were recorded.

These patterns were reflected in tillage practices between soybean and corn, where 45% of soybean crops were planted as no-tillage compared to 15% for corn across all data years (Fig. 9). Additionally, adoption of no-tillage demonstrates that this disparity has grown consistently since 1994, with no-tillage adoption in soybean having a rapid increase from 12 to 43% of crops with no-tillage by 2005 (Fig. 10). In contrast, there was an increase in no-tillage in corn to 20% in 2005 from a low of 7% in 1994. By 2017, no-tillage represented 45% of all soybean crops, and 19% of all corn crops.

Corn-soybean crop rotations are prevalent in the U.S. Corn Belt (Hill, 2001; Lyon et al., 2004) and represent the vast majority of 2-year crop rotations in the Cropland Roadside Survey dataset. Within these corn-soybean crop rotations, it is common for tillage practices to vary depending on the crop to be planted, where soybean tends to be no-tilled more frequently while corn is conventionally tilled (Hill, 1998, 2001; Wade and Claassen, 2017). The substantial difference between soybean and corn crop residue management was expected as developments in planting equipment, herbicide resistant cultivars, and favorable yield results from no-tillage in soybean are contrasted with mixed results in yields for no-

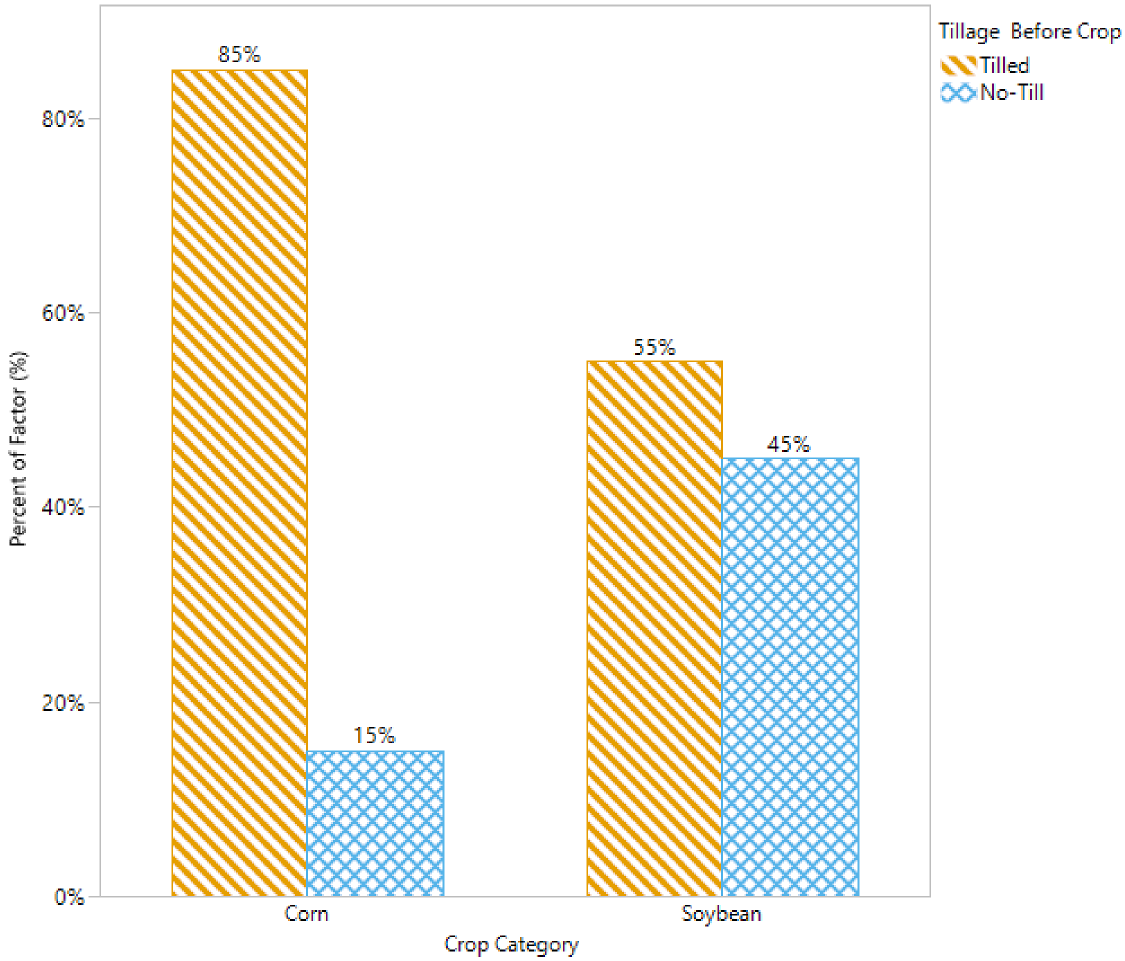


Figure 9. Tillage conditions at planting for corn and soybean from 1994 to 2017 in Dane County, Wisconsin.

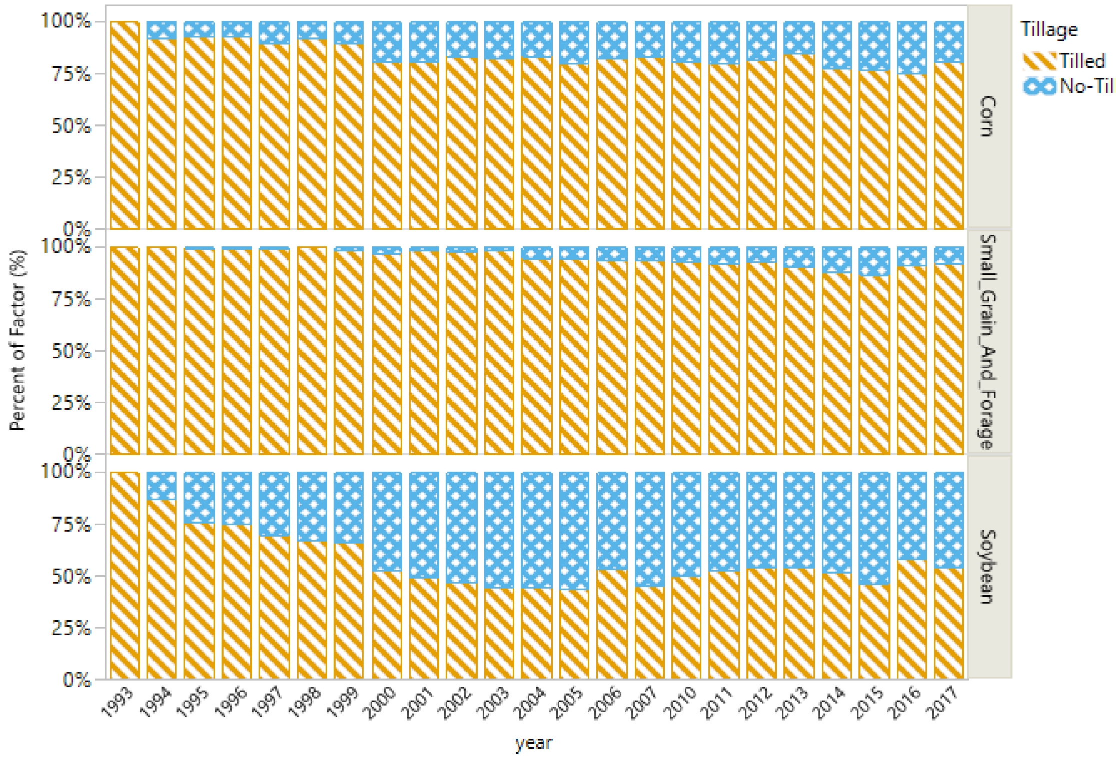


Figure 10. Annual proportion of no-tillage versus tilled fields in corn, soybean, and small grain and forage crops by year in Dane County, Wisconsin.

tilled corn in poorer drained soils and in northern, colder regions like Wisconsin (Hill, 2001; Lyon et al., 2004; Triplett and Dick, 2008; Duiker and Thomason, 2014). The pattern of conventional tillage corn and no-tilled soybean in rotation was likely an attempt to take advantage of these differing responses to no-tillage and optimize residue management in corn-soybean rotations (Hill, 2001; Lyon et al., 2004).

The small but increasing trend in crop residue cover for corn in this dataset differs in part from the national trend described by Claassen et al. (2018) from ARMS data, where it was found that conservation tillage in corn, including no-tillage, saw an increase from 2002 to 2006, but a general decline in total acres in following years. They also noted a similar pattern of growth followed by a modest decline for total acres of soybean planted in conservation tillage. Minnesota and Illinois have conducted state-wide Cropland Roadside Surveys. The Minnesota Cropland Roadside Survey reports their findings in acres, calculated as a proportion of total crop acres. Illinois reports its survey trends as proportions of sample point, which is similar to the Dane County Cropland Roadside Survey. Fischer and Moore (2008) describe the Minnesota Cropland Roadside Survey results, wherein they report an increase in conservation tillage from 18 to 35% of total acres from 1989 to 2007. In Illinois, there also was an increase in conservation tillage from 32 to 48% from 1994 to 2018 (Illinois Dept. Agric., 2018). This growth in conservation tillage adoption in Minnesota and Illinois is consistent with Dane County, although the increase in conservation tillage in Dane County was greater in magnitude. The smaller increase in conservation tillage practice in Illinois may reflect an already high degree of practice in Illinois at the beginning of the survey (Hill, 2001). On a crop-by-crop basis, there was a rapid and sizable increase in soybean with conservation tillage in Minnesota and Illinois. An increase in soybean acres in Minnesota was reported from 22% in 1989 to 56% in 2007 (Fischer and Moore, 2008). In Illinois, there was a rise in the proportion of soybean sample points with conservation tillage from 44% in 1994 to 70% in 2018 (Illinois Dept. Agric., 2018). Contrary to trends in Wisconsin and Illinois which reported increases, there was an overall decrease in corn with conservation tillage in Minnesota from 27 to 14%.

Comparisons between the Dane County datasets, ARMS, and Cropland Roadside Surveys from other states were done to illustrate general trends in the region; however, comparing findings between regional and local scales can be problematic given differences in soil conditions, dominant agricultural production systems, and differences in sampling and survey designs. Wade et al. (2015) notes a high degree of region and crop specific variation in conservation tillage practice within the ARMS data. Further, Lyon et al. (2004) reported distinctly different measures of conservation tillage adoption and practice between regions using CRM data. Direct comparisons between different Cropland Roadside Survey datasets, such as between different counties or states, share similar difficulties to those present in direct comparisons between ARMS data and Cropland Roadside Survey data discussed in Chapter 1. However, the Cropland Roadside Survey datasets have a common survey design and so provide a more reasonable comparison than to ARMS data and may provide some insight into broader regional trends.

Conclusions

Our findings demonstrate the potential value of robust, locally responsive data for describing and understanding trends and adoption of agricultural conservation practices. Results from analysis of these data connect increased crop residue cover to an increased adoption of conservation tillage practices, namely no-tillage. These changes were not uniform across crops, but were most pronounced in soybean, particularly following corn grain within corn-soybean rotations. Data analysis of previous and next year crop, tillage, and residue information was of particular value as it allowed for the evaluation of relationships from year to year, beyond simple crop and tillage summaries and year-on-year reports. These results demonstrate the type of specific questions conservationists and local organizers can answer with these data and how these data might be leveraged to address past and future crop and tillage data needs. Further work to develop a standard data structure for survey results is needed to reliably compare crop summaries and more detailed analyses between neighboring counties and broader regions. As demonstrated by this work, the result of such an effort would be a multi-scale dataset that allows for general summaries as well as detailed investigations of relationships between crop type, tillage, and residue management practices through time.

References

Baker, N.T. 2011. Tillage practices in the conterminous United States, 1989 to 2004. Datasets Aggregated by Watershed Data Series 573. National Water-Quality Assessment Program 13. https://pubs.usgs.gov/ds/ds573/ (accessed 13 Jan. 2020).

Borchers, A., E. Truex-Powell, S. Wallander, and C. Nickerson. 2014. Multi-cropping practices: Recent trends in double cropping. Rep. EIB-125. U.S. Department of Agriculture, Economic Research Service (May).

Busari, M.A., S.S. Kukal, A. Kaur, R. Bhatt, and A.A. Dulazi. 2015. Conservation tillage impacts on soil, crop and the environment. Internatl. Soil Water Conserv. Res. 3(2): 119–129. doi: 10.1016/j.iswcr.2015.05.002.

Claassen, R., M. Bowman, J. McFadden, D. Smith, and S. Wallander. 2018. Tillage intensity and conservation cropping in the United States. Rep. EIB-197. U.S. Department of Agriculture, Economic Research Service (Sept.).

Conservation Technology Information Center (CTIC). 2020. CRM: Conservation Technology Information Center. https://www.ctic.org/CRM (accessed 26 Dec. 2020).

Duiker, S.W., and W. Thomason. 2014. Conservation agriculture in the USA. p. 26–53. In R.A. Jat et al. (ed.) Conservation agriculture: Global prospects and challenges. CAB Internatl.

Fisher, S.J., and R. Moore. 2008. 2007 Tillage Transect Survey Final Report. Minnesota River Basin Data Center, Mankato, MN. https://mrbdc.mnsu.edu/minnesota-tillage-transect-survey-data-center (accessed 28 Sept. 2020).

Hadas, A., L. Kautsky, M. Goek, and E.E. Kara. 2004. Rates of decomposition of plant residues and available nitrogen in soil, related to residue composition through simulation of carbon and nitrogen turnover. Soil Biol. Biochem. 36(2):255–266. doi: 10.1016/j.soilbio.2003.09.012.

Hill, P. 1996. Cropland Roadside Survey Method. Conservation Technology and Information Center (CTIC), West Lafyette Indiana. https://efotg.sc.egov.usda.gov/references/public/NM/ag45_transmittal_document.pdf (accessed 11 Oct. 2020).

Hill, P.R. 1998. Use of rotational tillage for corn and soybean production in the eastern Corn Belt. J. Prod. Agric. 11(1):125–128. doi: 10.2134/jpa1998.0125.

Hill, P.R. 2001. Use of continuous no-till and rotational tillage systems in the central and northern Corn Belt. J. Soil Water Conserv. 56(4):286–290. https://www.jswconline.org/content/56/4/286.short (accessed 11 Oct. 2020).

Illinois Dept. Agric. 2018. Illinois soil conservation transect survey summary report. State of Illinois. 9 p. https://www2.illinois.gov/sites/agr/Resources/LandWater/Pages/Illinois-Soil-Conservation-Transect-Survey-Reports.aspx (accessed 27 Jan. 2019)

Kriaučiuniene, Z., R. Velička, and S. Raudonius. 2012. The influence of crop residues type on their decomposition rate in the soil: A litterbag study. Zemdirbyste 99(3):227–236.

Kumar, K., and K.M. Goh. 1999. Crop residues and management practices: Effects on soil quality, soil nitrogen dynamics, crop yield, and nitrogen recovery. Adv. Agron. 68(C): 197–319. doi: 10.1016/S0065-2113(08)60846-9.

Lant, C., T.J. Stoebner, J.T. Schoof, and B. Crabb. 2016. The effect of climate change on rural land cover patterns in the Central United States. Climatic Change 138(3-4):585–602. doi: 10.1007/s10584-016-1738-6.

Lyon, D., S. Bruce, T. Vyn, and G. Peterson. 2004. Achievements and future challenges in conservation tillage. 4th Internatl. Crop Science Congress: 1–19.

NASS (National Agricultural Statistics Service). 2021. Agricultural Resource Management Survey. https://quickstats.nass.usda.gov/ (accessed 30 March 2021).

Prokopy, L.S., K. Floress, J.G. Arbuckle, S.P. Church, F.R. Eanes, et al. 2019. Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. J. Soil Water Conserv. 74(5):520–534. doi: 10.2489/jswc.74.5.520.

Reicosky, D.C. 2015. Conservation tillage is not conservation agriculture. J. Soil Water Conserv. 70(5):103–108. doi: 10.2489/jswc.70.5.103A.

Reicosky, D.C., and R.R. Allmaras. 2003. Advances in tillage research in North American cropping systems. J. Crop Prod. 8(1-2):75–125. doi: 10.1300/J144v08n01_05.

Seifert, C.A., and D.B. Lobell. 2015. Response of double cropping suitability to climate change in the United States. Environ. Res. Letters 10(2). doi: 10.1088/1748-9326/10/2/024002.

Triplett, G.B., and W.A. Dick. 2008. No-tillage crop production: A revolution in agriculture! Agron. J. 100(3 Suppl.). doi: 10.2134/agronj2007.0005c.

Wade, T., and R. Claassen. 2017. Modeling no-till adoption by corn and soybean producers: insights into sustained adoption. J. Agric. Appl. Econ. 49(2):186–210. doi: 10.1017/aae.2016.48.

Wade, T., R. Claassen, and S. Wallander. 2015. Conservation-practice adoption rates vary widely by crop and region. Rep. EIB-147. U.S. Department of Agriculture, Economic Research Service (Dec.).

CHAPTER 3

Augmenting the Value of Cropland Roadside Transect Survey Data Through Spatial Analysis and Derived Data Products

Abstract

The Cropland Roadside Survey provides valuable observations on crop and tillage practices throughout a county. However, there are opportunities to increase the value of these data and increase the efficiency of the time and labor costs of the survey. An analysis of crop rotation is presented, followed by statistical characterization of the relationships between field physical characteristics and crop and tillage practices. Finally, considerations for spatial analysis of survey data are explored. Monoculture cropping was the most common practice while corn (*Zea mays* L.)-soybean (*Glycine max*) systems were the most common 2-year crop rotation. These 2-year crop rotations saw a marked increase between 1995 and 2001, displacing monocropping practices. Highly erodible land (HEL) soils had a significant relationship with crop type in all years, and with crop residue cover and field T-level from 2010 to 2017. Overall, there was an increase in no-tillage operations on HEL soils. Delineation of field boundaries would greatly increase field-level data description, but there is a lack of quality sources for field boundaries.

Introduction

The purpose of the Cropland Roadside Survey was principally to monitor crop residue management and tillage systems with the objective of providing information on the adoption of conservation tillage practices (Hill, 1996). In many instances, such as in Wisconsin and Illinois, the survey included the collection of field descriptive data such as K factor, slope, and slope length, and ephemeral erosion (DATCP, 1999; Illinois Dept. Agric., 2018). Hill (1996) describes the use of watershed identifiers so that data can be summarized at county and watershed scales. This broader record of attributes for each field allows for exploration of relationships between agricultural practices and the local characteristics where those practices were implemented. Developments in remote sensing technologies hold the potential to provide additional information on some crop and tillage practices at large scales (Zheng et al., 2014; Azzari et al., 2019; Waldner et al., 2019; Hagen et al., 2020). However, these technologies are dependent on ground truth data (Zheng et al., 2014; Begue et al., 2018). Roadside surveys allow for direct observation of field conditions and agricultural practices that may be otherwise difficult to quantify. The Cropland Roadside Survey methodology is a versatile tool for building a statistically and spatially representative dataset at the field level (Dressing et al., 2017; Waldner et al., 2019).

The primary challenges with ground surveys are the work hours and costs involved in data collection. Therefore, the objective of this work was to explore opportunities to improve the utility and value of the Cropland Roadside Survey in Dane County, Wisconsin for monitoring and assessing conservation agricultural practices. Several opportunities were explored, including trends in crop rotation, crop tenure, influence of the presence of highly erodible land (HEL) soil on conservation practices, and other landscape influenced properties.

Materials and Methods

Cropland Roadside Survey

The Cropland Roadside Survey is a windshield transect survey developed in the 1990s and utilized by county conservation offices and by the CTIC's Crop Residue Management Survey (Hill, 1996; Baker, 2011). Surveys were designed to sample agricultural fields at regular intervals along a predetermined road transect path. The survey is conducted in the spring, includes 763 stops and covers about 410 driven miles. Visual estimates of crop type, tillage system, ephemeral erosion, and crop residue cover were made at approximately 100 feet into the field from the road and on both sides of the road for most stops. This results in two field sampling points for most transect stops for a total of 1,161 sample observations transect points were excluded from sampling if they were not in agricultural production. For the purposes of this survey, agricultural production was categorized by crop, such as corn (*Zea mays* L.), soybean (*Glycine max*), small grain, forage crops, and included other crops such as tobacco and vegetable crops as "other crops." Transect points that were apparent to the observer as an agricultural field but that had no visible or emergent crop were categorized as idle if during a revisit on a later date no crop was observed.

Crop Rotation and Crop Tenure

Crop rotation and tenure information was derived from the Dane County Roadside Survey data to provide a description of the number of years a single crop was planted consecutively in the same field year-on-year. These data provide a description of duration and species diversity of mono-cropping practice. The rotation of crops, particularly high residue crops, and the duration of mono-cropping are recognized as important factors affecting soil health and erosion risk (Duiker and Thomason, 2014; Claassen et al., 2018).

Field, year, and crop type were queried from the survey data using SQL then grouped by field and ordered by year. This produced an ordered list of crops in chronological order for each field. A record of rotations and their duration for each field was generated from this list using the R statistical package. The resulting dataset was analyzed both as a standard table with variables in columns and attributes described in records and transposed using JMP 15.0 statistical software (SAS Institute Inc., Cary NC) to provide a chronological table where each record represents an individual field and each variable across the table represents a year. This transposition method was also used with survey crop data to create a field tally table. The field tally table was used to generate counts and summaries for individual fields and aggregate statistics describing survey data on a field basis.

Influence of Field Physical Attributes on Crop Practices and Survey Factors

Conservation practices implemented on highly erodible land (HEL) provide highly effective mitigation of soil loss from erosion and, therefore, are a priority for the adoption of conservation practices. Other soil physical and geographic factors, such as distance to water and field size influence conservation practice adoption (Prokopy et al., 2019). Hence, opportunities for characterization of soil properties and spatial relationships through field delineation and geospatial analysis were explored in this work.

Soils Data – The USDA-Natural Resources Conservation Service's Soil Survey Geographic Database (SSURGO) soil data for Dane County were downloaded using the Soil Data Development Toolbox in ArcMap. These data were converted into a gSSURGO format geodatabase. Soil maps for K factor, T factor, and representative slope were created using the create soil map tool in the Soil Data Development Toolbox. Wisconsin HEL soil map units were obtained from the Wisconsin NRCS website (https://www.nrcs.usda.gov/wps/portal/nrcs/main/wi/programs/farmbill/cc/). The SSURGO MUPolygon layer was then spatially joined with Cropland Roadside Survey transect points to assign a map unit key to each field. This key was then used to join the K factor, T factor, representative slope, and HEL data to the Cropland Roadside Survey transect points.

Distance to Water – Lakes and ponds, and rivers and streams data layers were obtained from the Dane County open data portal (https://gis-countyofdane.opendata.arcgis.com/). The Near tool in the Proximity Toolset in ArcMap was used to determine the nearest water feature to each Cropland Roadside Survey transect point.

Hydrologic Unit Code 10 and 12 – Hydrologic unit code (HUC) data layers for 12-digit (HUC 12) and 10-digit (HUC 10) watershed boundaries were obtained from the Wisconsin Department of Natural Resources (WDNR) Open Data Portal (https://data-wi-dnr.opendata.arcgis.com/). The HUC layers were then clipped in ArcMap to the WDNR 24k scale Dane County boundary layer to reduce data processing demand. The Cropland

Roadside Survey transect point data layer were spatially joined with the HUC 10 and HUC 12 layers in ArcMap to populate each field with a HUC 10 and HUC 12 attribute.

Common Land Units (CLU) Selection to Define Field Boundaries of Surveyed Points

All spatial products were derived using ArcMap version 10.8 software and all data layers were converted or transformed to the NAD 1983 (2011) Geographic Coordinate System and the Wisconsin Coordinate Reference Systems (WICRS) projection for Dane County (Wis. State Cartographers Office, 2009). For this work, CLU boundaries are considered as a potential source of field delineations for Cropland Roadside Survey transect points. Accuracy assessments were carried out to determine the suitability of CLU boundaries toward this purpose and to explore potential other uses of these geospatial data as described below.

An ESRI point-shape file of Cropland Roadside Survey stop points and estimated in-field observation locations was provided by the Dane County Land and Water Resource Department. These points were derived from GPS readings taken in 1996 at stops along the transect route and in-field locations were estimated as points at least 100 feet into the field based on roadside viewing angles and observer notes. Before using these points to develop spatial products, they were quality controlled by manual comparison to National Agriculture Imagery Program ortho-photographs from 2018 to ensure correct survey point placement when errors were identified. The spatial accuracy of the spatially differentiated GPS unit was at least 3 meters during initial collection of transect stop point coordinates. National Agriculture Imagery Program (NAIP) imagery from 2018 for Dane County has a spatial resolution of 0.6 m and allowed for digitization and correction of missing or erroneous point placements using feature editing in ArcMap 10.8.

Farm Service Agency (FSA) CLU from 2008 were used as an approximation of individual agricultural field extents. This is the most current dataset because of the enactment in May 2008 of The Food, Conservation, and Energy Act of 2008, Title I - Commodity Programs, Subtitle F - Administration, Section 1619, which prohibits FSA from sharing geospatial data. These CLUs were identified by selecting polygons that contained an in-field transect sample point. In some cases, CLUs contained more than one in-field sample point. In these instances, the second sample point was removed. The CLU boundaries were then spatially joined with the Cropland Roadside Survey transect points to attribute each field with an acreage estimate using the Field Calculator in ArcMap 10.8 and to identify the selected CLUs by which field they represent from the survey dataset. A total of 1,082 of 1,161 observed fields could be attributed CLU acreage data.

Common Land Units (CLU) Accuracy Assessment

A subset of 50 Cropland Roadside Survey in-field transect points were randomly selected in ArcMap. These 50 field locations were then manually digitized to create reference field boundaries using NAIP 2008 imagery at a fixed scale of 1:5,000. Field boundaries were identified and digitized using permanent features such as tree lines, roads, and fence lines and contained only one apparent crop type. This process mirrors that used when developing CLU boundaries (FSA, 2021). A total of 49 field locations were used for analysis; one location was removed as a result of land conversion to a residence since the original transect point was established. The Symmetrical Difference tool was then used to identify how the reference field boundaries differed from the CLU boundaries that contained the same sample point. The difference in acres between the reference field boundaries and the CLU extents were quantified by subtracting the acres of each symmetrical difference polygon from the corresponding CLU acres. Therefore, a positive value indicates that the digitized area for a specific field was smaller than the CLU value, whereas a negative value indicates that the digitized field area was greater than the CLU area. The magnitude of difference as a percentage of field size was determined by dividing the absolute value of the difference in acres for a given field by the total acres of the reference field boundary for that field.

Statistical Analysis

One-way ANOVA and Pearson's Chi-Squared tests were conducted using JMP 15 statistical package to determine relationships between field physical characteristics and agricultural practices. In all cases, tests were conducted at an α of 0.05. Box plots were used to describe the distribution and central tendency for field physical characteristics and cropping and tillage practices.

Results and Discussion

Crop Rotations

Overall mono-cropping was the most prevalent cropping pattern with 43% of all crop rotations. Within the mono-cropped rotation, corn accounted for 53% of the observations, followed by the small grain and forage category with 45%. Continuous corn accounted for 26% and continuous small grain and forage for 22% of all crop observations for the entire survey period. Two-year crop rotations were the second most common rotation, representing

37% of all crop rotations. Corn- and soybean-based rotations represented 73% of the 2-year rotations and accounted for 30% of all observed crops. Three-year crop rotations were the least common with only 3% of all crop rotations. Within 3-year crop rotations, instances of corn-soybeans/soybean-corn preceding or following small grains were more common than instances where corn and soybean were separated by a year of small grains.

From 1995 to 2001, there was a rapid increase in the use of 2-year crop rotations, displacing mono crop systems. Two-year crop rotations increased from 25 to 44% during this period while the prevalence of mono-cropping decreased from 59 to 40%. This increase in 2-year rotations was the result of the adoption of corn-soybean based rotations (Fig. 1). After 2001, 2-year crop rotations and mono-cropping maintained a similar proportion of overall crop rotations with fluctuations in one typically mirrored by a reciprocal change in the other (Fig. 2). Three-year crop rotations were relatively unchanged, increasing from 1 to 6% of crop rotations between 1993 and 2017.

The dominance of corn-soybean based rotations was consistent with national trends between 1993 and 2001 (Hill, 2001; Lyon et al., 2004). The increase of corn and soybean in rotation also helps explain the general increase in soybean cropping and decrease in corn cropping observed in Dane County during this same period. The pairing of these two crops in a rotation would tend to bring their yearly proportions closer together. The general equilibrium after 2001 between mono-cropping (predominantly corn) and 2-year crop rotations may have been a response to rising corn prices and ethanol production between 2001 and 2007 (Stern et al., 2012). Although the complex drivers that influence producer crop choice were beyond the scope of this work, the complexity inherent in agricultural

Figure 1. Annual count of fields with a specific type of 2-year crop rotation in Dane County, Wisconsin. CS – corn/soybean; CX – corn/small grain and forage; SC – soybean/corn; SX – soybean/small grain and forage; XC - small grain and forage /corn; XS - small grain and forage/soybean.

Figure 2. Annual occurrence of mono-, 2-year, and 3-year crop rotations in fields surveyed by the Cropland Roadside Survey in Dane County, Wisconsin.

systems emphasizes the need for timely and reliable reporting on changes in cropping practices such as crop rotations.

The development of crop rotation data expands the original scope of the Dane County Cropland Roadside Survey to better fit a more advanced understanding of conservation practices in agriculture (Duiker and Thomason, 2014; Reicosky, 2015). Increased diversity of crop rotations has been recognized for its potential to increase yields and manage pests in no-tillage systems (Triplett and Dick, 2008; Duiker and Thomason, 2014). Diverse crop rotations can further increase soil carbon capture and improve overall soil health (Claassen et al., 2018).

Crop Tenure

Crop tenure represents the number of consecutive years a single crop type was planted in the same field. Crop tenure was presented here as summary statistics describing crop tenure across all 1,162 fields for the years spanning 1993 to 2007. The 2-year disruption in data collection in 2008 and 2009 creates an artificial break in tenure counts, providing a maximum continuously observed crop tenure of 15 years (from 1993 through 2007). Across this 15-year period, small grain and forage crops had the greatest tenure with a mean of 3.1 years followed by idle field conditions with a mean crop tenure of 2.75 years. Small grain and forage had the greatest range in crop tenure followed by idle field conditions (Fig. 3). Corn was observed to have a mean crop tenure of 1.9 years, and soybean with a mean tenure of 1 year. When crop tenure was counted continuously from 1993 to 2017 for mono-cropped fields but omitting the missing data years 2008 and 2009, a total of 66 fields were observed having more than 15 years of monoculture. In these fields with mono-cropping, it seems

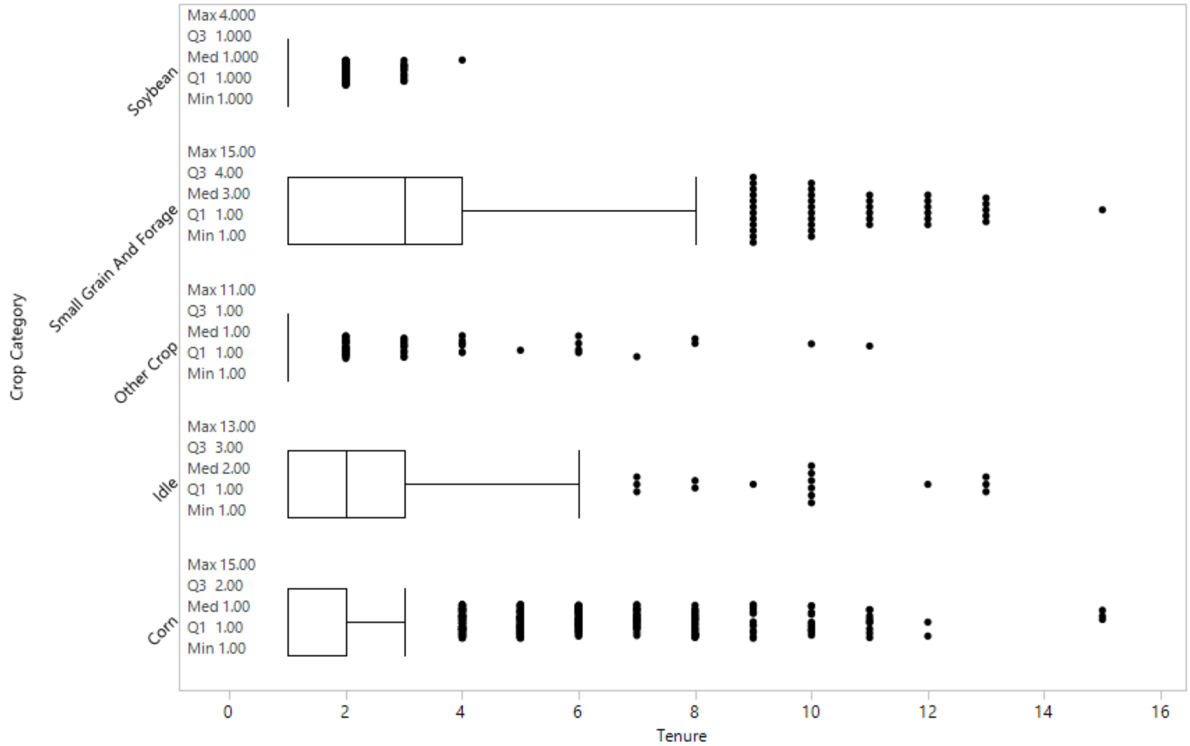


Figure 3. Years in a specific crop continuous tenure across all fields from 1993 to 2007 in Dane County, Wisconsin.

unlikely that the pattern of crop planted would have changed in the 2 years without observations. These 66 fields represent 5.6% of the total fields in the survey and consisted primarily of continuous small-grain and forage (n = 35) and continuous corn (n = 27). Data from 1993 to 2007 likely represent most crop tenure practices in addition to containing the majority of survey years. However, other sources of cropping information may be useful to fill in missing data from 2008 and 2009. For example, the National Crop Data Layer provides geospatial data on planted crops in Dane County beginning from 2008 onward and could be used to estimate field specific crop types in the missing data years. This approach may be of particular value for other cropland roadside surveys that only collected crop data periodically, such as the Illinois Tillage Transect Survey (Illinois Dept. Agric., 2018).

Field Physical Attributes and Cropping Practices

The relationship between HEL soils and crop management practices was explored using Chi-Square tests. Crop category had a statistically significant relationship with HEL soils in all years of the survey except for 2012. Tillage type (i.e., no-tillage versus tillage) had a statistically significant relationship with HEL soils from 2010 to 2015 and again in 2017 (Table 1). Crop residue cover was significantly associated with HEL designated soils in 11 of 23 years of the survey data, primarily after 2010. These findings are consistent with the relationship between tillage type and HEL soils, given that no-tillage conditions were statistically significant and crop residue cover exceeding 60% is expected in a no-tillage system (CTIC, 2020). Additionally, an examination of the relationship between T-level and crop residue cover using an ANOVA test revealed statistical significance for these two

Table 1. Summary of statistical significance for Pearson's Chi-Squared and One-Way ANOVA tests to compare various Cropland Roadside Survey parameters and derived field factors on an annual basis. Crop residue by HEL, crop category by HEL, and tillage by crop category were compared using Pearson's Chi-Square test of independence, while all other results were determined using a One-Way ANOVA. Significant = statistically significant at P ≥ 0.05; NS = not statistically significant.

Year	Crop residue by HEL	Crop category by HEL	Tillage by crop category	T-level by residue cover	K-factor by residue cover	CLU acres by residue cover	Distance to water by crop residue	K-factor by crop category
1993	NS	Significant	NS	NS	NS	NS	NS	NS
1994	NS	Significant	NS	NS	NS	NS	NS	Significant
1995	Significant	Significant	NS	Significant	NS	NS	NS	Significant
1996	NS	Significant	NS	NS	NS	NS	NS	NS
1997	NS	Significant	NS	NS	NS	NS	NS	NS
1998	NS	Significant	NS	NS	NS	NS	NS	NS
1999	NS	Significant	NS	NS	NS	NS	Significant	NS
2000	Significant	Significant	Significant	NS	NS	NS	Significant	NS
2001	Significant	Significant	NS	NS	NS	NS	NS	NS
2002	Significant	Significant	NS	Significant	NS	NS	NS	NS
2003	NS	Significant	NS	NS	NS	NS	NS	NS
2004	NS	Significant	NS	Significant	NS	NS	NS	NS
2005	Significant	Significant	NS	NS	NS	NS	Significant	NS
2006	NS	Significant	NS	Significant	NS	Significant	Significant	NS
2007	NS	Significant	NS	NS	NS	NS	NS	NS
2008	NS	Significant	NS	NS	NS	NS	NS	NS
2009	NS	Significant	NS	NS	NS	NS	NS	NS
2010	Significant	Significant	Significant	Significant	NS	NS	Significant	NS
2011	Significant	Significant	Significant	Significant	NS	Significant	NS	NS
2012	Significant	NS	Significant	Significant	NS	NS	Significant	NS
2013	Significant	Significant	Significant	Significant	NS	NS	NS	NS
2014	NS	Significant	Significant	Significant	Significant	NS	NS	NS
2015	Significant	Significant	Significant	Significant	NS	NS	NS	Significant
2016	NS	Significant	NS	Significant	NS	NS	NS	Significant
2017	Significant	Significant	Significant	Significant	NS	NS	NS	NS

factors in 2010 to 2017. Distance to water, and k-factor had no consistent statistical relationship with crop or tillage practices.

Fields representing HEL soils were planted into small grain and forage in greater proportion than into fields with non-HEL (NHEL) soils (Fig. 4). Corn and soybean were planted more frequently in soils classified as NHEL than HEL; however, this difference was less marked for soybean. These overall proportional differences were observed to be generally consistent through time between HEL and NHEL (Fig. 5), although for both land erodibility classifications there was a general increase of soybean planted as a proportion of total crops between 1994 and 2002 as noted in Chapter 2. Within HEL fields, there was an apparent decrease in the occurrence of small grain and forage crops and a rise in corn and soybean crops as a proportion of total crops over time. This was unexpected, as row cropping exposes HEL to a greater degree of erosion risk than perennial hay or forage crops. Interestingly there was an increase in no-tillage for all crops in both HEL and NHEL during the survey period (Fig. 6). This may presumably represent an increase in conservation practices in concurrence with an increase in row cropping on more vulnerable lands. Determining if the adoption of no-tillage has encouraged more row cropping of HEL is important for soil conservation as these soils are an area of priority for soil loss prevention. While the increase in row cropped HEL represents an increase in erosion potential, it may also demonstrate the influence of conservation compliance requirements for production on these soils (Wade et al., 2016; Wade and Claassen, 2017). Studies have found strong, positive, statistical relationships between HEL soil status and conservation tillage adoption (Wade et al. 2016; Wade and Claassen, 2017; Tran and Kurkalova, 2019). These results are

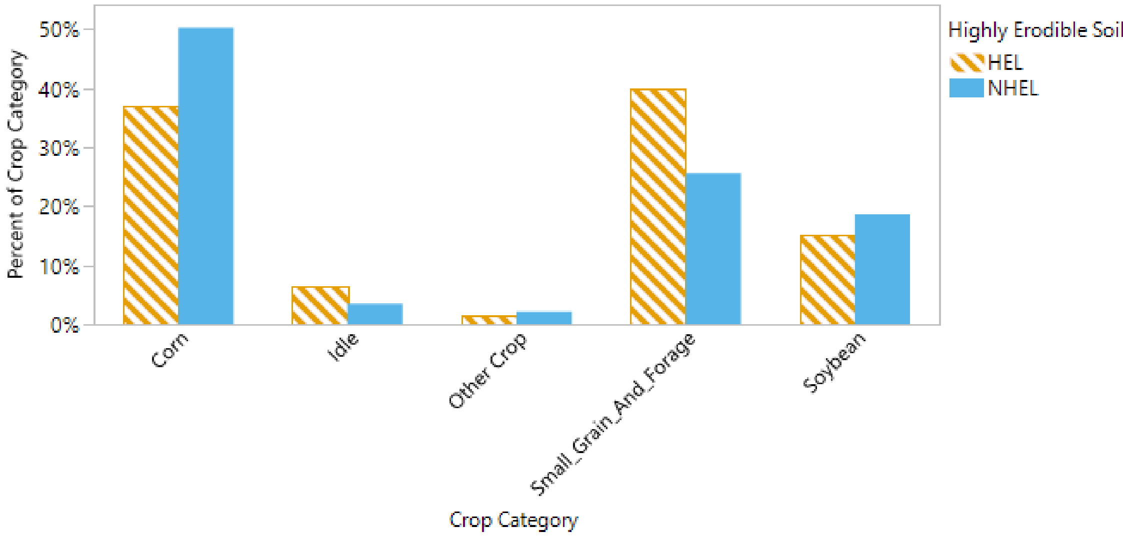


Figure 4. Proportion of each crop category observed in highly erodible land (HEL) and non-HEL (NHEL) classified soils for all years of the Cropland Roadside Survey in Dane County, Wisconsin.

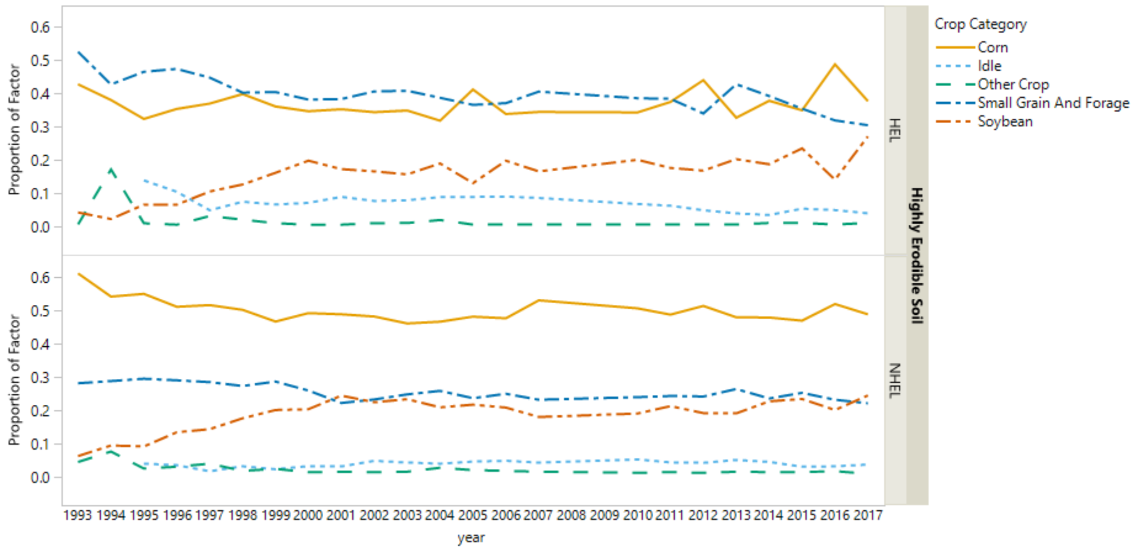


Figure 5. Annual proportion of each crop category observed in highly erodible land (HEL) and non-HEL (NHEL) classified soils in the Cropland Roadside Survey in Dane County, Wisconsin.

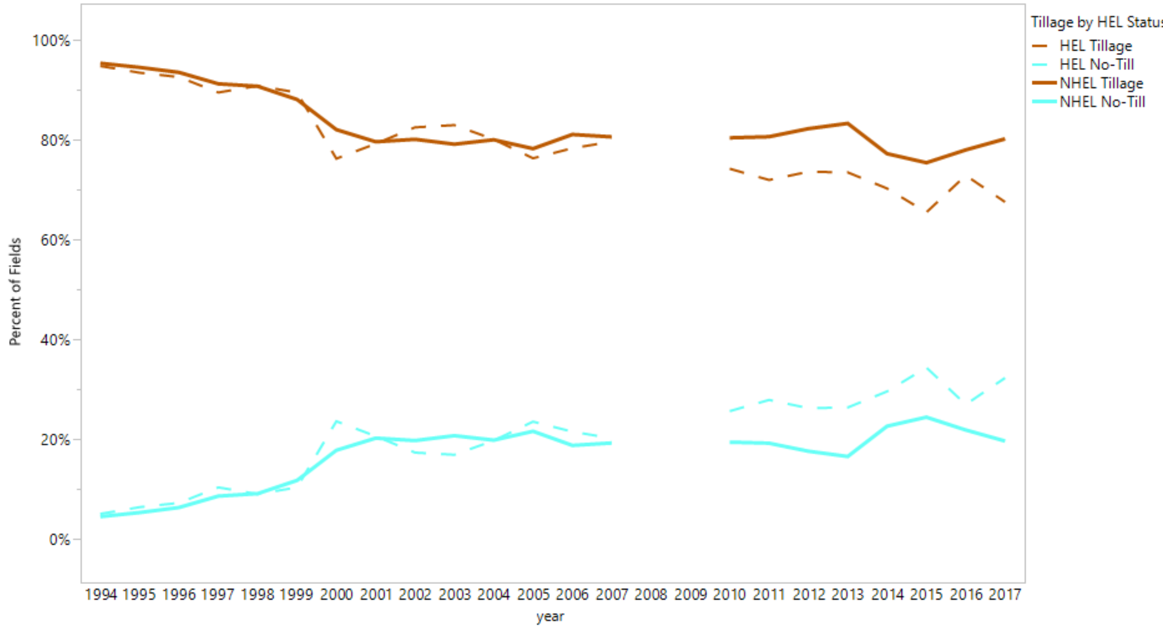


Figure 6. Annual percentage of fields with highly erodible land (HEL) and non-HEL (NHEL) soils with tilled and no-tilled conditions in Dane County, Wisconsin.

consistent with our findings using no-tillage and HEL soil classifications but differ from the inconsistent results with crop residue cover and HEL soil classification found in the Dane County survey data.

Wade et al. (2016) make use of CTIC Residue Management Survey data aggregated to the county level with addition factors derived from soils and CDL data for their evaluation of conservation tillage adoption. These authors suggest that less aggregated field data would further enhance an understanding of conservation tillage adoption and increase the effectiveness and efficiency of incentive programs. The field level data presented in this work, derived from direct survey observations of soil surface and crop conditions, serve as a valuable source of locally specific data for utilization in empirical models. Field delineations provide the opportunity to increase the quality of soil data associated with each transect point, while also providing a measure of acreage for each field, as well as crop and tillage practices. The Cropland Roadside Survey design includes attributes for slope, slope length, K factor, and T factor for each transect point. When the Dane County Cropland Roadside Survey was established in 1994, an analog method of overlaying transparencies was utilized to attribute these soil characteristics to each transect point. The assumption of the Cropland Roadside Survey was that each transect point was a representative sample of the broader agricultural field that contains the transect point. This sampling method may be suitable where a phenomenon such as crop type, residue cover and tillage may be uniform over the extent of a field. However, soil properties demonstrate no loyalty to field boundaries and a given field may have a very high degree of spatial variability of its soil properties. Moreover, the degree of spatial variability of soil units and their attending soil properties can differ significantly based on how a field is oriented in the landscape. Field delineation therefore provides a significantly greater quality of soil data and spatial characterization of each transect survey point. These spatial extents can also be utilized for extracting and attributing data from other sources such as raster datasets (Beeson et al., 2020).

Analysis of Field Delineations

The vast majority (81%) of CLUs in the accuracy testing subset represented an over estimation of actual field size (Fig. 7). The overall size of fields based on reference field boundaries was small, with a mean field size of 16 acres and a median of 9 acres. Field size estimated by CLU boundaries had a mean of 27.6 acres and a median of 16 acres (Fig. 8). The magnitude of difference between reference field boundaries and CLU-defined fields is relatively large, with a mean difference as a percentage of field size of 393%. In other words, mischaracterization of acreage was a factor of 3.93x on average and ranged from 2126 to 3%. The median magnitude of difference was 94%. This finding suggests that CLU boundaries are poorly suited to determine representative acreage estimates for a farmed field. However, the purpose of the CLU boundaries is to assist in the administration of FSA arm records and federal Farm Bill programs. This means that CLU boundaries are digitized to represent farmsteads, woodlots, and supporting land in addition to cropland. Additionally, CLU boundaries are often based on information from the producers themselves that informs the digitization process for specific use cases.

A more suitable application of these boundaries may be for validating remote sensing, where the spatial extent of the CLU can be used to validate multiple pixels in clusters. This

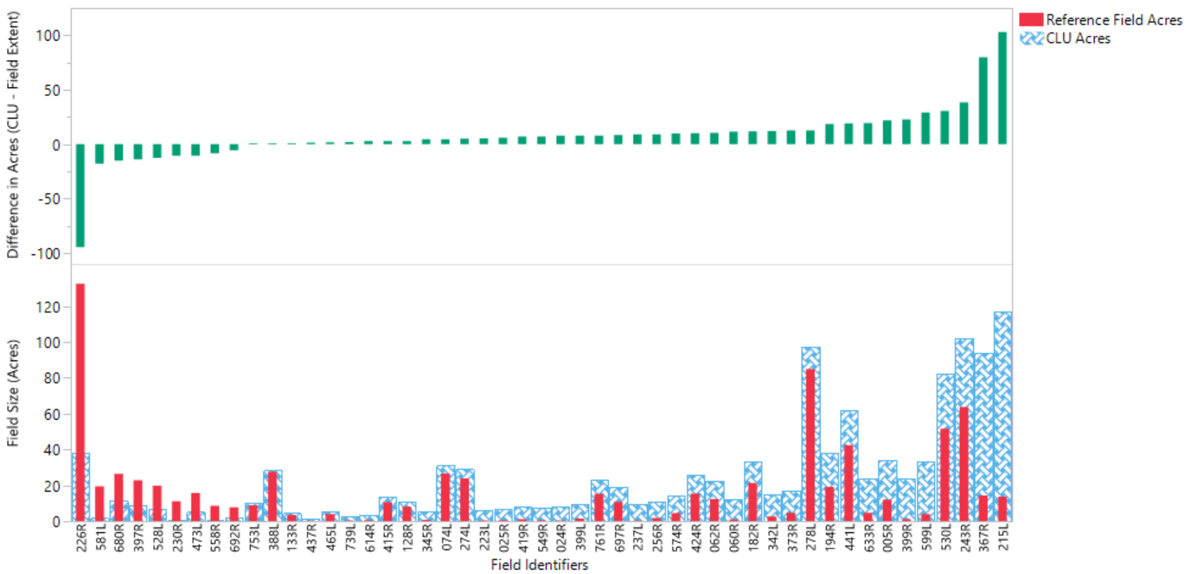


Figure 7. Difference between CLU acres and reference boundaries by field (Green) and a comparison of reference boundary estimated field size and CLU estimated field size.

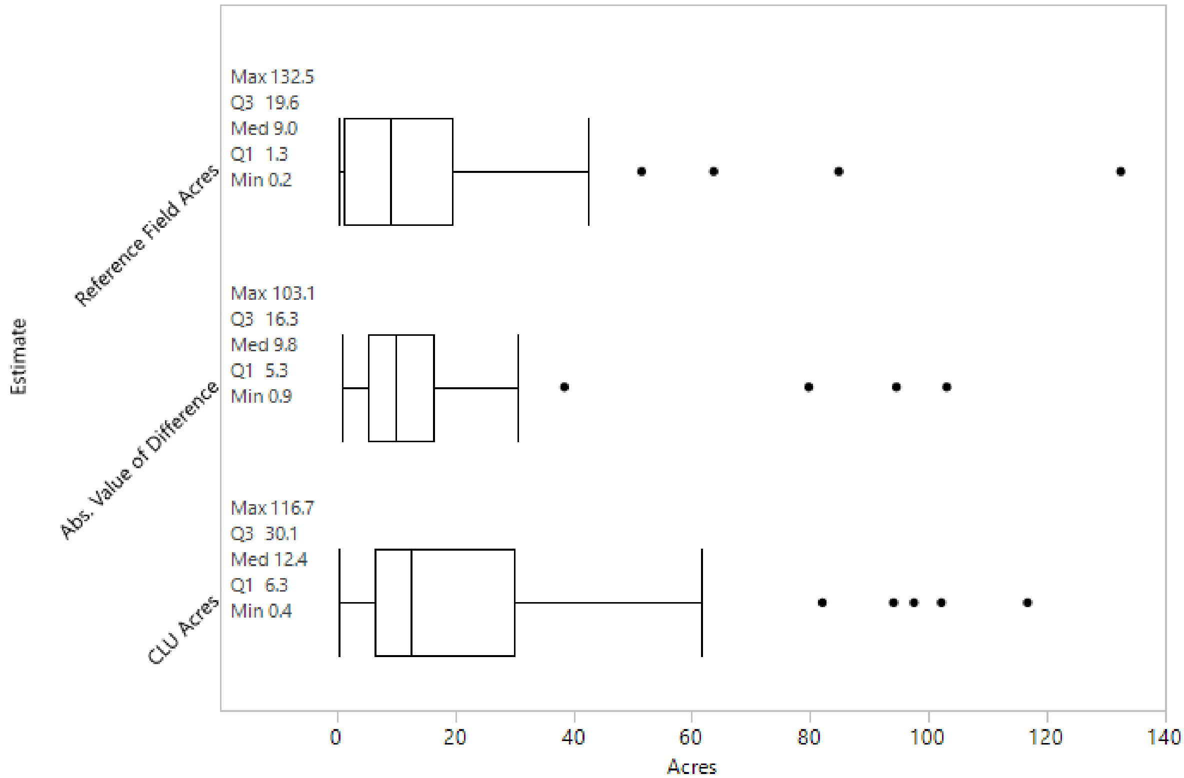


Figure 8. Distribution and central tendency of field size estimates for CLU and reference boundaries and absolute value difference between boundaries.

approach is used during the development of CDL data, where CLU boundaries are buffered 30 to 15 meters from the edges and used for ground truthing crop classifications. Beeson et al. (2020) presented considerations for the use of CLU boundaries for crop residue estimates using remote sensing technologies, but ultimately chose to use a region growing approach using CDL data. Key issues presented by Beeson et al. (2020) for not using the CLU data were the lack of availability, potential for accuracy issues, and the need to utilize new boundaries over time as practices within a field may change.

Advances in image segmentation and geographic object-based image analysis may provide a reliable and ready source of agricultural field delineations in the future (Li et al., 2016; North et al., 2019; Kucharczyk et al., 2020), while the in-situ field observations

Spatial Representation of the Cropland Roadside Survey

The Cropland Roadside Survey was designed to provide estimates of crop and tillage practices at the county scale (Hill, 1996). Utilizing these survey data at different spatial scales requires accuracy metrics to maintain consistency between datasets on larger scales, and sufficient spatial representation at scales smaller than the county level.

Baker (2011) used nationwide Cropland Roadside Survey data collected by the CTIC for their Crop Residue Management survey to generate a national dataset aggregated at the HUC8 watershed scale. In this approach, the goal was to characterize a larger population (the conterminous United States) from smaller subsamples (counties and watersheds). The primary challenge with this approach arises from the statistical uncertainty inherent in the Cropland Roadside Survey that can make comparisons and aggregations of different county's surveys difficult. These challenges were discussed in Chapter 1. Another consideration for use of the Cropland Roadside Survey is how well the survey represents cropland within the county.

The sampling method of the Cropland Roadside Survey inherently limits sample sites to roadside positions where a clear line of sight can be established. Additionally, the survey route was designed to survey areas under predominantly agricultural practice, particularly where conservation tillage practices were concentrated. This necessitates avoiding developed areas and introduces a constraint within the county itself, wherein the survey samples agricultural land within the county as a separate class from the county extent. When county-level data were aggregated to a smaller spatial extent the original dataset was effectively subsampled. This process may introduce uncertainty if the new descriptive zones do not contain a sufficient number of sample points, may contain points from multiple surveys, and may not be representatively distributed (Fig. 9).

Waldner et al. (2019) presents an evaluation of roadside survey methods for crop mapping. The authors concluded that roadside surveys had a similar representativeness and accuracy to random sampling and recommended a sampling density of one observation for every 30 to 40 hectares (~74 to 98 acres). The current Dane County survey design would provide an average of 1.6 observations per 1,000 acres within HUC 12 watersheds and an average of 1.5 observations per 1,000 acres within HUC 10 watersheds that contain at least one transect point. However, the acreage of individual watersheds includes all land uses and landforms while the Cropland Roadside Survey exclusively targets land in agricultural production, representing a smaller portion of the overall landscape (See HUC 12 and HUC 10 insets of Fig. 9). This suggests that a redesign of sampling routes and survey point

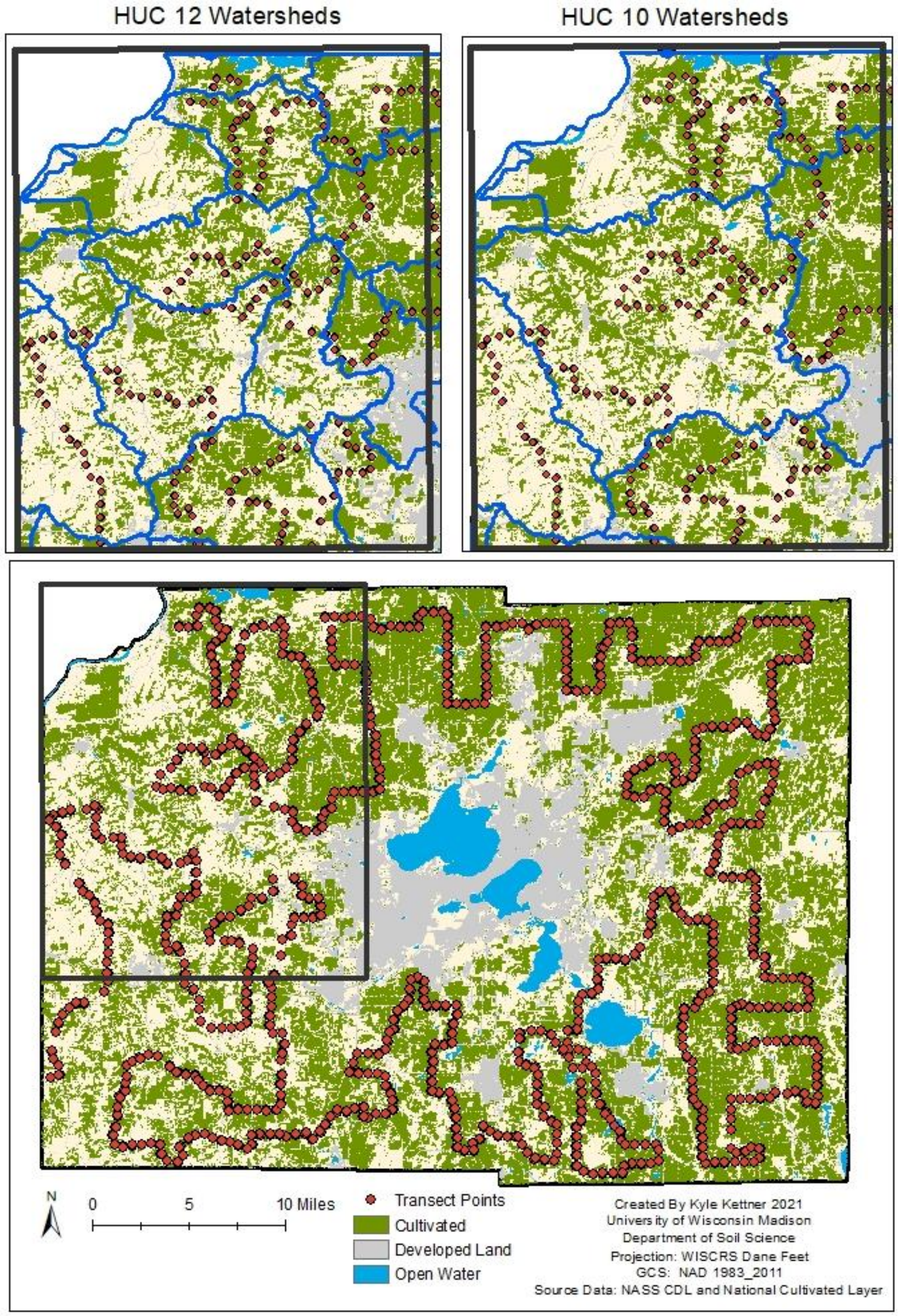


Figure 9. Map of Dane County with transect survey points of the Cropland Roadside Survey. This figure overlays NASS National Cultivated Layer data with Hydrologic Unit Codes (HUC) 12 and 10 watershed boundaries (blue lines).

density may be necessary for the application of survey data for crop mapping and spatial analysis. Modification of the existing Cropland Roadside Survey to satisfy these requirements would require the addition of sampling points. This may subsequently increase the cost of the survey procedure, although the density of sampling points may be reduced in favor of a more evenly distributed route. However, these changes also stand to improve the quality of survey products and enables novel opportunities, such as assessing the relationship between landscape scale change in agriculture and ecosystem services (Koschke et al., 2013).

Conclusions

The Cropland Roadside Survey provides a valuable historic dataset capturing crop, tillage, and conservation tillage trends. The survey data can also be explored and analyzed in novel ways to address more contemporary questions and changing paradigms such as conservation agriculture and soil health, greatly expanding survey data applications beyond its initial design. The addition of ancillary data, particularly soil physical characteristics, further increases the potential specificity of survey data applications. Geospatial analysis is an efficient and effective way to attribute additional data to transect points while field delineations may greatly increase the scope of the added information. Lastly, with some modifications the Cropland Roadside Survey may provide a valuable spatial dataset, where existing and ancillary data can be used for crop mapping and for training and developing empirical and remote sensing models. These novel approaches present a path to creating value added products, offsetting the initial costs in time and funds to establish and conduct surveys. Further development of local scale crop and tillage surveys is important, as the information these surveys provide informs our understanding of otherwise overlooked landscape scale processes.

References

Azzari, G., P. Grassini, J.I.R. Edreira, S. Conley, S. Mourtzinis, et al. 2019. Satellite mapping of tillage practices in the North Central US region from 2005 to 2016. Remote Sensing Environ. 221(November 2018):417–429. doi: 10.1016/j.rse.2018.11.010.

Baker, N.T. 2011. Tillage practices in the conterminous United States, 1989 – 2004 — Datasets aggregated by watershed. Data Series 573. National Water-Quality Assessment Program: 13. https://pubs.usgs.gov/ds/ds573/ (accessed 13 Jan. 2020).

Beeson, P.C., C.S.T. Daughtry, and S.A. Wallander. 2020. Estimates of conservation tillage practices using landsat archive. Remote Sensing 12(16):2665. doi: 10.3390/RS12162665.

Bégué, A., D. Arvor, B. Bellon, J. Betbeder, D. de Abelleyra, et al. 2018. Remote sensing and cropping practices: A review. Remote Sensing 10(2):99. doi: 10.3390/rs10010099.

Claassen, R., M. Bowman, J. McFadden, D. Smith, and S. Wallander. 2018. Tillage intensity and conservation cropping in the United States. Rep. EIB-197, U.S. Department of Agriculture, Economic Research Service (September).

Conservation Technology Information Center (CTIC). 2020. CRM. Conservation Technology Information Center. West Lafayette, Indiana. https://www.ctic.org/CRM (accessed 26 Dec. 2020).

Department of Agriculture Trade and Consumer Protection (DATCP). 1999. Wisconsin County Transect Survey Procedures. Madison, Wisconsin.

Dressing, S., T. Tech, J. Harcum, M. Dubin, and C. Watts. 2017. Recommendation report for the establishment of uniform evaluation standards for application of Roadside Transect Surveys to identify and inventory agricultural conservation practices for the Chesapeake Bay Program Partnership's Watershed Model. https://www.chesapeakebay.net/documents/Transect_Survey_Recommendations_Report_3-16-17.pdf (accessed 11 Oct. 2020)

Duiker, S.W., and W. Thomason. 2014. Conservation agriculture in the USA. p. 26–53. In R.A. Jat et al. (ed.) Conservation agriculture: Global prospects and challenges. CAB Internatl.

Farm Service Agency (FSA). 2021. Common Land Unit (CLU). https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-products/common-land-unit-clu/index (accessed 25 May 2021).

Hagen, S.C., G. Delgado, P. Ingraham, I. Cooke, R. Emery, et al. 2020. Mapping conservation management practices and outcomes in the Corn Belt using the Operational Tillage Information System (OpTIS) and the Denitrification–Decomposition (DNDC) Model. Land 9(11):408. doi: 10.3390/land9110408.

Hill, P. 1996. Cropland Roadside Survey Method. Conservation Technology and Information Center (CTIC), West Lafayette Indiana. https://efotg.sc.egov.usda.gov/references/public/NM/ag45_transmittal_document.pdf (accessed 11 Oct. 2020).

Hill, P.R. 2001. Use of continuous no-till and rotational tillage systems in the central and northern Corn Belt. J. Soil Water Conserv. 56(4):286–290. https://www.jswconline.org/content/56/4/286.short (accessed 11 Oct. 2020).

Illinois Dept. Agric. 2018. Illinois soil conservation transect survey summary report. State of Illinois. 9 p. https://www2.illinois.gov/sites/agr/Resources/LandWater/Pages/Illinois-Soil-Conservation-Transect-Survey-Reports.aspx (accessed 27 Jan. 2019)

Koschke, L., C. Fürst, M. Lorenz, A. Witt, S. Frank, et al. 2013. The integration of crop rotation and tillage practices in the assessment of ecosystem services provision at the regional scale. Ecol. Indicators 32:157–171. doi: 10.1016/j.ecolind.2013.03.008.

Kucharczyk, M., G.J. Hay, S. Ghaffarian, and C.H. Hugenholtz. 2020. Geographic object-based image analysis: A primer and future directions. Remote Sens. 12:1–33. https://doi.org/10.3390/rs12122012

Li, M., L. Ma, T. Blaschke, L. Cheng, and D. Tiede. 2016. A systematic comparison of different object-based classification techniques using high spatial resolution imagery in agricultural environments. Internatl. J. Appl. Earth Observ. Geoinform. 49:87–98. doi: 10.1016/j.jag.2016.01.011.

Lyon, D., S. Bruce, T. Vyn, and G. Peterson. 2004. Achievements and Future Challenges in Conservation Tillage. p. 1-19. In Proc. 4th International Crop Science Congress.

North, H.C., D. Pairman, and S.E. Belliss. 2019. Boundary delineation of agricultural fields in multitemporal satellite imagery. IEEE J. Selected Topics. Appl. Earth Observ. Remote Sensing 12(1):237–251. doi: 10.1109/JSTARS.2018.2884513.

Prokopy, L.S., K. Floress, J.G. Arbuckle, S.P. Church, F.R. Eanes, et al. 2019. Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. J. Soil Water Conserv. 74(5):520–534. doi: 10.2489/jswc.74.5.520.

Reicosky, D.C. 2015. Conservation tillage is not conservation agriculture. J. Soil Water Conserv. 70(5):103–108. doi: 10.2489/jswc.70.5.103A.

Stern, A.J., Doraiswamy, P.C., Raymond Hunt, E., 2012. Changes of crop rotation in Iowa determined from the United States Department of Agriculture, National Agricultural Statistics Service cropland data layer product. J. Appl. Remote Sens. 6:063590. https://doi.org/10.1117/1.jrs.6.063590.

Tran, D.Q., and L.A. Kurkalova. 2019. Persistence in tillage decisions: Aggregate data analysis. Internatl. Soil Water Conserv. Res. 7(2):109–118. doi: 10.1016/j.iswcr.2019.03.002.

Triplett, G.B., and W.A. Dick. 2008. No-tillage crop production: A revolution in agriculture! Agron. J. 100(S3). doi: 10.2134/agronj2007.0005c.

Wade, T., and R. Claassen. 2017. Modeling no-till adoption by corn and soybean producers: Insights into sustained adoption. J. Agric. Appl. Econ. 49(2):186–210. doi: 10.1017/aae.2016.48.

Wade, T., L. Kurkalova, and S. Secchi. 2016. Modeling field-level conservation tillage adoption with aggregate choice data. J. Agric. Resour. Econ. 41(2):266–285. doi: 10.22004/ag.econ.235190.

Waldner, F., N. Bellemans, Z. Hochman, T. Newby, D. de Abelleyra, et al. 2019. Roadside collection of training data for cropland mapping is viable when environmental and management gradients are surveyed. Internatl. J. Appl. Earth Observ. Geoinform. 80:82–93. doi: 10.1016/j.jag.2019.01.002.

Wisconsin State Cartographer's Office. 2009. Wisconsin Coordinate Reference Systems. 2nd ed. Revised June 2015. https://www.sco.wisc.edu/wp-content/uploads/2017/07/WisCoordRefSys_June2015.pdf (accessed 05 May 2019).

Zheng, B., J.B. Campbell, G. Serbin, and J.M. Galbraith. 2014. Remote sensing of crop residue and tillage practices: Present capabilities and future prospects. Soil Tillage Res. 138:26–34. doi: 10.1016/j.still.2013.12.009.

Supplemental Document 1

A comparison of present crop observations, those directly made of planted crops in the field, and the crop residue in the same field the following year allowed for inferences to be made about the presence of a second crop or to identify a classification error. Crop classifications for corn, soybean, and idle were determined when these crops were observed in both the present crop observation and when residue of that crop in the same field was observed the following year. If the crop residue in field the following year differed from the present crop observation it was assumed as either an incorrect classification or evidence of a second crop. Incorrect classifications were recorded for instances where difference full season row crops were observed for present crop and from crop residue the following spring. In these instances the crop determined from residue in the following year is assumed to be the correct crop type. This is because crop type is more easily distinguished from the mature plant residue than from recently planted crops when observations are made from the roadside vantage point. A second crop was recorded when the crop residue could be reasonably explained by a second crop, such as a fall planted small grain crop following harvest of spring planted corn. Second crop values were then used to identify when a field was double cropped. A record of misclassification and second crop assignments is included here (Table 1).

Table 1. Record of crop classification decisions for determining crop classification accuracy of corn, soybean, and idle crops and to inference a second crop.

Present Crop directly observed in field	**Crop determined from residue the following spring**	**Revised present crop value**	**New second crop value**	**Type of change**
Corn	cover crop	Corn	Cover_Crop	Second Crop
Corn	Hay	Corn	Hay	Second Crop
Corn	Idle	Idle	NA	Incorrect Classification
Corn	Other Crop	Corn	Other_Crop	Second Crop
Corn	Small Grain	Corn	Small_Grain	Second Crop
Corn	Soybeans	Soybeans	NA	Incorrect Classification
Drilled Soybeans	Corn	Corn	NA	Incorrect Classification
Drilled Soybeans	Hay	Drilled_Soybeans	Hay	Second Crop
Drilled Soybeans	Other Crop	Drilled_Soybeans	Other_Crop	Second Crop
Drilled Soybeans	Small Grain	Drilled_Soybeans	Small_Grain	Second Crop
Hay	Corn	Hay	Corn	Second Crop
Hay	cover crop	Hay	Cover_Crop	Second Crop
Hay	Idle	Idle	NA	Incorrect Classification
Hay	Other Crop	Hay	Other_Crop	Second Crop
Hay	Small Grain	Hay	Small_Grain	Second Crop
Hay	Soybeans	Hay	Soybeans	Second Crop
Idle	Corn	Corn	NA	Incorrect Classification
Idle	Hay	Hay	NA	Incorrect Classification
Idle	Other Crop	Other_Crop	NA	Incorrect Classification
Idle	Small Grain	Small_Grain	NA	Incorrect Classification
Idle	Soybeans	Soybeans	NA	Incorrect Classification
NA	Corn	Corn	NA	Incorrect Classification
NA	Hay	Hay	NA	Incorrect Classification
NA	Idle	Idle	NA	Incorrect Classification
NA	Other Crop	Other_Crop	NA	Incorrect Classification
NA	Small Grain	Small_Grain	NA	Incorrect Classification
NA	Soybeans	Soybeans	NA	Incorrect Classification
Other Crop	Corn	Other_Crop	Corn	Second Crop
Other Crop	Hay	Other_Crop	Hay	Second Crop
Other Crop	Idle	Idle	NA	Incorrect Classification
Other Crop	Small Grain	Other_Crop	Small_Grain	Second Crop
Other Crop	Soybeans	Other_Crop	Soybeans	Second Crop
Rowed Soybeans	Corn	Corn	NA	Incorrect Classification
Rowed Soybeans	Hay	Rowed_Soybeans	Hay	Second Crop
Rowed Soybeans	Idle	Idle	NA	Incorrect Classification
Rowed Soybeans	Small Grain	Rowed_Soybeans	Small_Grain	Second Crop
Small Grain	Corn	Small_Grain	Corn	Second Crop
Small Grain	Hay	Small_Grain	Hay	Incorrect Classification
Small Grain	Idle	Idle	NA	Incorrect Classification
Small Grain	Other Crop	Small_Grain	Other_Crop	Second Crop
Small Grain	Soybeans	Small_Grain	Soybeans	Second Crop