University of Nebraska - Lincoln

DigitalCommons@University of Nebraska - Lincoln

Papers in Natural Resources | Natural Resources, School of

2016

Quantification and Mapping of Surface Residue Cover for Maize and Soybean Fields in South Central Nebraska

Vivek Sharma
University of Florida, vsharma1@ufl.edu

Suat Irmak
University of Nebraska-Lincoln, sirmak2@unl.edu

Ayse Kilic
University of Nebraska-Lincoln, akilic@unl.edu

Vasudha Sharma
University of Nebraska-Lincoln

John E. Gilley
Adjunct Professor, Biological Systems Engineering, john.gilley@ars.usda.gov

See next page for additional authors

Follow this and additional works at: https://digitalcommons.unl.edu/natrespapers

Part of the Natural Resources and Conservation Commons, Natural Resources Management and Policy Commons, and the Other Environmental Sciences Commons

Sharma, Vivek; Irmak, Suat; Kilic, Ayse; Sharma, Vasudha; Gilley, John E.; Meyer, George; Knezevic, Stevan Z.; and Marx, D. B., "Quantification and Mapping of Surface Residue Cover for Maize and Soybean Fields in South Central Nebraska" (2016). *Papers in Natural Resources*. 1488.
https://digitalcommons.unl.edu/natrespapers/1488

This Article is brought to you for free and open access by the Natural Resources, School of at DigitalCommons@University of Nebraska - Lincoln. It has been accepted for inclusion in Papers in Natural Resources by an authorized administrator of DigitalCommons@University of Nebraska - Lincoln.

Authors

Vivek Sharma, Suat Irmak, Ayse Kilic, Vasudha Sharma, John E. Gilley, George Meyer, Stevan Z. Knezevic, and D. B. Marx

This article is available at DigitalCommons@University of Nebraska - Lincoln: https://digitalcommons.unl.edu/natrespapers/1488

QUANTIFICATION AND MAPPING OF SURFACE RESIDUE COVER FOR MAIZE AND SOYBEAN FIELDS IN SOUTH CENTRAL NEBRASKA

V. Sharma, S. Irmak, A. Kilic, V. Sharma, J. E. Gilley, G. E. Meyer, S. Z. Knezevic, D. Marx

ABSTRACT. *The area cultivated under conservation tillage practices such as no-till and minimal tillage has recently increased in Midwestern states, including Nebraska. This increase, consequently, resulted in changes in some of the impacts of cropping systems on soil, such as enhancing soil and water quality, improving soil structure and infiltration, increasing water use efficiency, and promoting carbon sequestration. However, there are no methods currently available to quantify the percent crop residue cover (CRC) and the area under conservation tillage for maize and soybean at large scales on a continuous basis. This research used Landsat-7 (ETM+) and Landsat-8 (OLI) satellite data to evaluate six tillage indices [normalized difference tillage index (NDTI), normalized difference index 7 (NDI7), normalized difference index 5 (NDI5), normalized difference senescent vegetative index (NDSVI), modified CRC (ModCRC), and simple tillage index (STI)] to map CRC in eight counties in south central Nebraska. A linear regression CRC model showed that NDTI performed well in differentiating the CRC for different tillage practices at large scales, with a coefficient of determination (R^2) of 0.62, 0.68, 0.78, and 0.07 for 25 March, 18 April, 28 May, and 6 June 2013 Landsat images, respectively. A minimum NDTI method was then used to spatially map the CRC on a regional scale by considering the timing of planting and tillage implementation. The measured CRC data were divided into training (calibration) and testing (validation) datasets. A CRC model was developed using the training dataset between minimum NDTI and measured CRC with an R^2 of 0.89 (RMSD = 10.63%). A 3 × 3 matrix showed an overall accuracy of 0.90 with a kappa coefficient of 0.89. About 26% of the maize area and 15% of the soybean area had more than 70% CRC in south central Nebraska. This research and the procedures presented illustrate that multi-spectral Landsat images can be used to estimate and map CRC (error within 10.6%) on a regional scale and continuous basis using locally developed tillage practice versus crop residue algorithms. Further research is needed to incorporate soil and residue moisture content into the CRC versus tillage index to enhance the accuracy of the models for estimating CRC.*

Keywords. *Crop residue cover, Landsat, Maize, Soybean, Tillage, Tillage index.*

The expansion of the crop production area under conservation tillage practices such as no-till (NT) and minimal tillage may result in changes in soil and water and in the cropping systems' behavior. Such practices have been adopted as best management practices (BMP) in cropping systems in the U.S. and other parts of the world. By definition, conservation tillage includes those practices that leave more than 30% crop residue cover (CRC) over the soil surface, compared to conventional tillage practices that greatly disturb the soil surface and leave crop surface residue of less than 30% (Gebhardt et al., 1985; CTIC, 2004) (fig. 1). Diverse cropping systems that support NT practices can dramatically affect hydrological properties, leading to benefits that include increased soil organic matter, improved soil structure, and enhanced water use efficiency (Sullivan et al., 2007); reduction in soil erosion (Ribeiro et al., 2007); water quality improvements (Dalzell et al., 2004); increased soil organic carbon (SOC) and sequestering of carbon (C) from the atmosphere (Ogle et al., 2012; Lal et al., 1998); and improved economics for farming (Soane et al., 2012). Ketcheson and Stonehouse (1983) found that a 15% corn residue cover can reduce erosion by 75% in comparison to bare soil. Sullivan et al. (2007) reported that adoption of conservation tillage practices can potentially reduce the statewide irrigation water requirement by 10% in Georgia. Other studies conducted by Dick and Van Doren (1985), Edwards et al. (1988), Halvorson et al. (1999, 2002), Hussain et al.

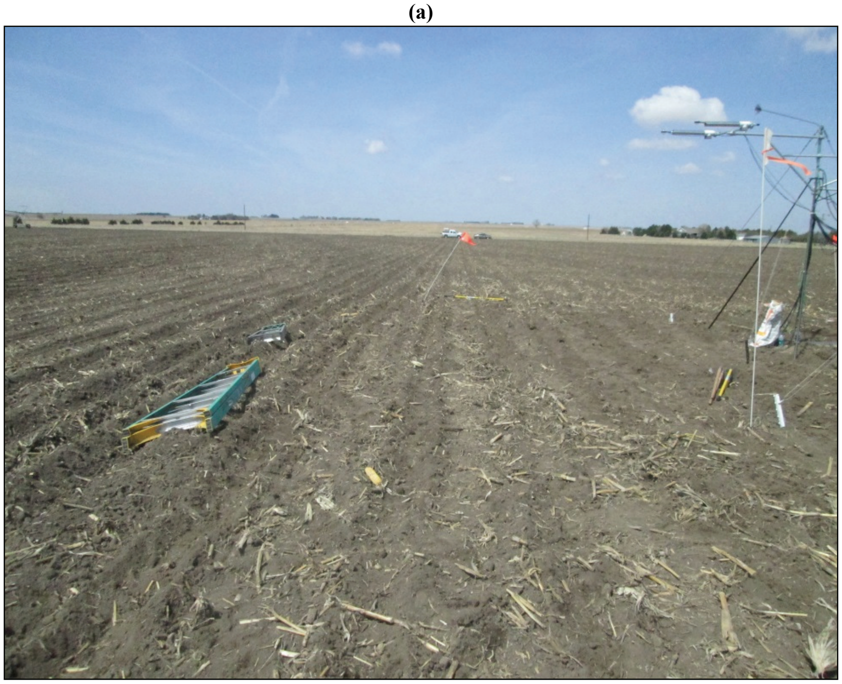
Submitted for review in August 2015 as manuscript number NRES 11489; approved for publication by the Natural Resources & Environmental Systems Community of ASABE in January 2016.

The mention of trade names or commercial products is for the reader's information and does not constitute an endorsement or recommendation by the University of Nebraska-Lincoln or the authors.

The authors are **Vivek Sharma, ASABE Member,** Post-Doctoral Research Associate, and **Suat Irmak, ASABE Member,** Distinguished Professor, Department of Biological Systems Engineering, University of Nebraska-Lincoln (UNL); **Ayse Kilic,** Associate Professor, School of Natural Resources and Department of Civil Engineering, UNL; **Vasudha Sharma, ASABE Member,** Graduate Student, Department of Biological Systems Engineering, UNL; **John E. Gilley, ASABE Member,** Research Agricultural Engineer, USDA-ARS Agroecosystem Management Research Unit, Lincoln, Nebraska; **George E. Meyer, ASABE Member,** Professor, Department of Biological Systems Engineering, UNL; **Stevan Z. Knezevic,** Professor, Department of Agronomy and Horticulture, UNL Northeast Research and Extension Center, Concord, Nebraska; **David B. Marx,** Professor Emeritus, Department of Statistics, UNL. **Corresponding author:** Suat Irmak, 239 L.W. Chase Hall, Lincoln, NE 68583-0726, phone: 402-472-4865; e-mail: sirmak2@unl.edu.

Vol. 59(3): 925-939 © 2016 American Society of Agricultural and Biological Engineers ISSN 2151-0032 DOI 10.13031/trans.59.11489

(a)



(b)

Figure 1. Photographs of agricultural fields: (a) conservation tillage (no-till, CRC > 90%) and (b) conventional tilled (disk tilled, CRC < 30%) near Holdrege, Nebraska, as part of the Nebraska Water and Energy Flux Measurement, Modeling, and Research Network (NEBFLUX; Irmak, 2010).

(1999), Nyakatawa et al. (2000), Beyaert et al. (2002), Dam et al. (2005), and Tarkalson et al. (2006) reported increases or no change in crop yield with the adoption of NT practices; however, no-till cropping systems are more profitable in terms of labor, farm equipment, and fuel and irrigation costs. Logan and Adams (1981) reported that adoption of conservation tillage practices can reduce soil and phosphorous losses by 89%, as compared to conventional tillage methods, because conservation tillage retains the crop residue after the crop is planted. CRC estimation can also be a critical parameter in assessing soil carbon and in modeling and monitoring the improvements in carbon sequestration that follow from adjustments in land management approaches and in various soil erosion models. Furthermore, information about tillage practices and CRC can be helpful in implementing policies and programs in BMPs (Pacheco and McNairn, 2010). Considering the impact of conservation tillage practices at field, watershed, and regional scales, it is therefore important to develop methodologies for continuous monitoring of CRC to meet the needs of policy and land management decision-makers.

Traditional methods of collecting tillage data (e.g., line transect methods; Morrison et al., 1993) and roadside surveys conducted by the USDA Natural Resources Conservation Service and the Conservation Technology Information Center (CTIC) over large regions are time-consuming, expensive (Sudheer et al., 2010), and are often unable to characterize the variability of CRC across an agricultural field. These surveys rely solely on the respondents' best qualitative judgment and estimates of the existing tillage practices and residue cover. Currently, no scientifically based, reliable, robust, and continuous conservation tillage database exists. CTIC provides estimates and assessment of conservation tillage by aggregating information on farm-scale tillage practices at county, state, and regional scales. However, these datasets can be biased, lack spatial and temporal variability (once every three to five years or longer), and may be prone to operator judgment error (South et al., 2004). For example, the latest no-till acreage map for the state of Nebraska was produced by NRCS in 2008. However, this dataset was survey-based and provided NT acreage at the county scale, which cannot reveal field-scale details or within-field variation of CRC. These spatial and temporal gaps in tillage datasets confine users' ability to study the impacts of conservation practices on crop management and their effect on water quality and carbon sequestration to regional scales.

In recent years, with the access to numerous space (Landsat, MODIS, etc.) and airborne data collection systems at different spatial, temporal, radiometric, and spectral resolutions, remote sensing techniques have emerged as a tool to evaluate and map tillage practices and residue cover over larger areas (Daughtry et al., 1996, 2004; Biard and Baret, 1997; Bannari et al., 2000, 2006; Daughtry, 2001; Sullivan et al., 2006; Serbin et al., 2009a; Zheng at al., 2012). Most of these techniques require development and validation of spectral indices to quantify green vegetation, CRC, soil characteristics, etc. These spectral indices are calculated by converting the digital number (DN) of the satellite images to top-of-atmosphere radiance and reflectance values using the modified methodology of Chander and Markham (2003) and Chander et al. (2007). Various spectral indices, such as normalized difference indices, spectral angle methods, and reflectance band height indices, are designed to map CRC specific to space and airborne sensors and classification techniques (linear spectral un-mixing analysis) when compared with measured values of CRC.

Normalized indices, such as normalized difference tillage index (NDTI) (van Deventer et al., 1997), NDI5 and NDI7 (McNairn and Protz, 1993), normalized difference senescent vegetation index (NDSVI) (Qi et al., 2002), modified CRC (ModCRC) (Sullivan et al., 2006), etc., are used with Landsat Thematic Mapper (TM) imagery. The spectral angle method includes the crop residue index multiband (CRIM) (Biard and Baret, 1997), which involves a combination of two or more spectral bands. Reflectance band height indices include cellulose absorption index (CAI) (Daughtry et al., 1996) and lignin cellulose absorption (LCA) (Daughtry et al., 2005) with their absorption featured near 2100 nm. Daughtry et al. (2006) used Landsat-TM and EO-1 Hyperion imaging spectrometer data to evaluate several spectral indices for measuring CRC and to categorize tillage intensity in agricultural fields in central Iowa. Their results showed that CAI and LCA performed best and had a linear relationship with CRC, with R^2 of 0.85 for May and 0.77 for June 2004, and an overall accuracy of 80% to 82% when using Hyperion data. CAI and LCA, with their absorption featured near 2100, nm can only be acquired from: EO-1 Hyperion (which suffers from bad detector lines); Advanced Space-borne Thermal Emission and Reflection (ASTER) platforms, which are past their planned operation lifetime (USGS, 2007); and Digital Globe WorkView-3 satellite platform (eight visible and near-infrared bands and eight shortwave infrared bands), which was not available for purchase at the time of analysis. Pacheco and McNairn (2010) evaluated the accuracy of spectral un-mixing classification to map and monitor CRC using multi-spectral Landsat and SPOT data and reported a root-mean squared difference (RMSD) between 17.3% and 20.7%. Their model performed best when estimating corn and small grain residues. However, higher error was observed in soybean fields due to lower spectral contrast between soil and soybean residue. On the other hand, high spatial and temporal resolution datasets, e.g., IKONOS, and SPOT, are expensive and inconvenient at regional scale due to their small swaths (Watts et al., 2011). Contrary to that, Landsat products [Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and the newly launched Landsat-8 Operational Land Imager (OLI)] are preferred due to their high spatial (30 m) and temporal (8-day) resolution, with a total swath of 185 km per scene. Thus, some studies have evaluated Landsat-5 TM and Landsat-7 (ETM+) for mapping CRC and tillage practices using different Landsat-based tillage indices (van Deventer et al., 1997; Daughtry et al., 2006; Gowda et al., 2008; Serbin et al., 2009b).

The aforementioned studies do not account for the timing of image acquisitions during the planting season. For example, in Nebraska, planting and tillage operations in maize and soybean fields generally vary from the last week of April to the last week of May. Thus, if images were acquired before the fields were tilled, using one Landsat image would interpret tilled fields as NT. Therefore, it is important to consider a high temporal resolution dataset for accurate mapping of CRC and tillage practices (Watts et al., 2011; Zheng et al., 2012, 2013). Watts et al. (2011) illustrated the importance of temporal sampling for capturing the tillage disturbance signature using the Random Forest Classification Model with high temporal MODIS (250 and 500 m) and Landsat (30 m) reflectance values and obtained an overall accuracy of 94%. Similar results were obtained by Zheng et al. (2012) using NDTI, who found that multi-temporal NDTI values can constantly capture surface disturbance by tillage or planting. They used linear regression between CRC and minimum NDTI (minNDTI) with an R^2 of 0.89 and reported an overall classification accuracy of 90%. However, the results of the aforementioned studies also indicated that the accuracy of different models can vary substantially for the same crop. Thus, the accuracy, robustness, and overall performance of various models should be validated on large scales under different soil, climatic, and crop management conditions. The objectives of this research were to: (1) evaluate the performance of different Landsat-based tillage indices for estimating

CRC using extensive field observations of tillage practices and measurements of residue cover data, and (2) develop maps of CRC in south central Nebraska using multi-temporal Landsat imagery.

Materials and Methods

Study Area and Field Measurements

The research focuses on CRC mapping in south central Nebraska, located between 40° 21′ 38.97″ N and 40° 31′ 5.22″ N and between 99° 38′ 40.73″ W and 96° 54′ 40.86″ W, for the years 2013 and 2014 (fig. 2). The research site is in a transition zone between subhumid and semiarid regions, and the average annual and seasonal precipitation of the region is 623 mm and 395 mm, respectively. About 70% of the land is under agricultural production with the main crops including irrigated and rainfed maize, soybean, sorghum, winter wheat, alfalfa, etc. Typical soil associations in the study region include Shell (deep, nearly level, well-drained, silty soils formed in alluvium on bottomlands), Muir (deep, nearly level, well-drained, silty soils formed in alluvium and loess on stream terraces), and Hobbs (deep, nearly level, well-drained, silty soils formed in alluvium on bottomlands) (Elder, 1969).

The tillage practices used by each producer significantly influence the amount of residue cover in the fields, which mainly depends on the previous years' crop type, type of tillage applied, and density of the plant material. Farmers use a variety of tillage practices, including moldboard plow, chisel, and disks. Ridge till, strip till, and NT are also practiced extensively, resulting in a considerable variation in CRC across the research area. For example, figures 1a and 1b show NT and disk-tilled fields in Phelps County, Nebraska, that are approximately 1 km apart and have a considerable difference in CRC. For this research, CRC ground measurements were acquired from 52 maize and soybean fields during 10 to 15 May 2013 and from 90 fields during the same period in 2014 (fig. 2). The distribution of fields under maize and soybean is presented in table 1. To further check the accuracy of measured crop type, crop data layers from the previous year were superimposed over the measured points (USDA-NASS, 2013). Figure 3 shows the distribution of crops across the study area for the years 2012 and 2013. On average, about 77% and 76% of the total land area was planted with maize and soybean in 2012 and 2013, respectively.

Gregory (1982) and Daughtry et al. (2006) reported that the average CRC after harvest was 98% for maize fields and 56% for soybean fields. However, CRC on the soil surface was reduced with time due to prolonged exposure to weather, resulting in decomposition, and due to various field operations. Al-Kaisi and Hanna (2009) reported 30% to 50% reduction in CRC when tilled by plows, and reductions of about 5% to 10% were estimated in NT field with the use of runner openers and staggered double disk openers. They estimated the change in CRC based on factors

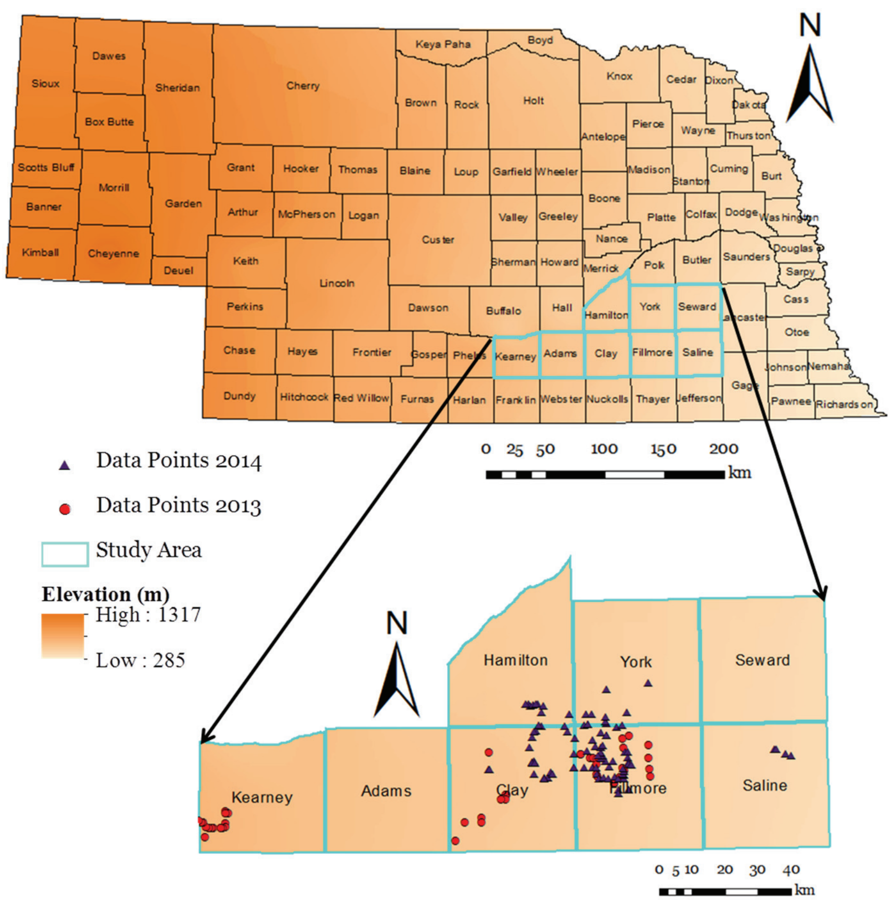


Figure 2. Locations of measured CRC sampling sites in south central Nebraska. Color represents elevation gradient across the study area.

Table 1. Crop residue cover (CRC) classification before planting from randomly selected fields for ground truth data of south central Nebraska during the 2013 and 2014 growing seasons.

Growing Season	CRC	Maize	Soybean	Maize/ Soybean	Total
2013	<30%	14	5	0	19
	30% to 70%	9	7	4	20
	≥70%	12	1	0	13
	Total	35	13	4	52
2014	<30%	16	23	3	42
	30% to 70%	11	3	8	22
	≥70%	19	3	4	26
	Total	46	29	15	90

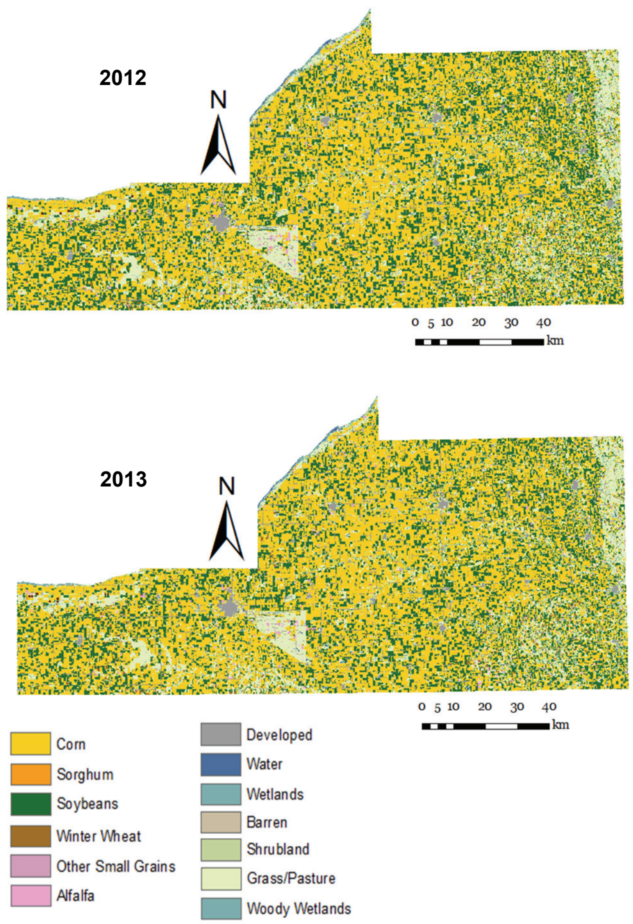


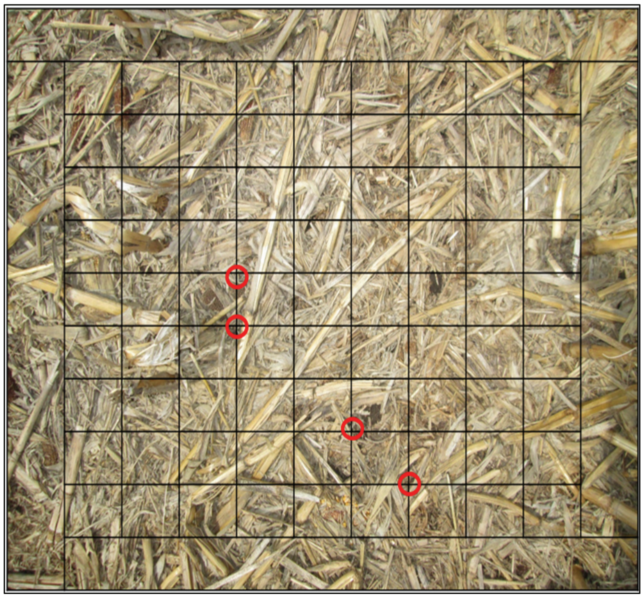
Figure 3. Cropland data layer from the USDA for 2012 and 2013 across the study area (USDA-NASS, 2013).

such as the total amount of residue, plant characteristics, degree of residue composition when disturbed, exposure to weather, and the action of field machinery. A similar observation was made in the present study, with measured values of CRC ranging from 6% to 94% for maize and from 5% to 80% for soybean before planting. Therefore, it is important to identify the actual variability in CRC from field to field and within fields within a relatively homogeneous agricultural region of south central Nebraska. For this study, CRC measurements were taken at four random locations within each field, >100 m from the edge of the field and from each other. Four random locations in each field were chosen to consider the within-field variation of CRC. At each location, four digital photographs were taken vertically downward from approximately 2 m height, and the coordinates were recorded using an eTrex Summit GPS unit (Garmin International, Inc.). Initial estimation of tillage management within each field included a visual examination of each field for CRC, crop residue type, soil disturbance, and residue position. For example, in many cases, it was observed that the residue in NT fields was relatively upright, while some reduced tillage fields were identified that had high levels of surface residue. To calculate the final CRC percentage, a digital grid of 10 × 10 points was superimposed on each digital photograph (fig. 4). The number of grid intersections overlapping a piece of crop residue was visually counted, and percent residue cover was calculated by summing the number of grid intersections falling on a piece of residue divided by the total number of intersections multiplied by 100. The estimates of ground residue cover from the four photos were then averaged to provide a single residue cover estimate per sampling site, following the procedures outlined by Pacheco and McNairn (2010).

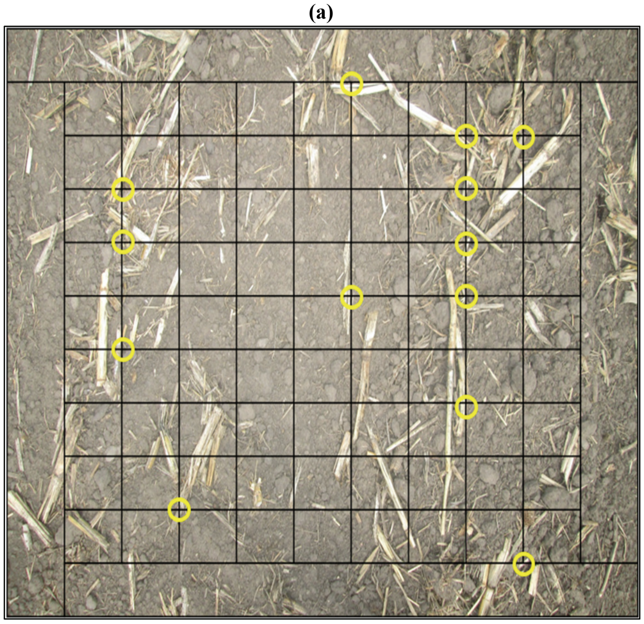
Remote Sensing Data

Significant variation in planting dates usually existed over the study area. Table 2 represents the Nebraska crop progress report for the years 2013 and 2014 (USDA-NASS, 2014). Warm temperatures and optimum moisture conditions in 2014 allowed producers to plant earlier, as compared to the 2013 crop growing season; however, for both years, about 95% of the maize and soybean area was planted by 25 May and 8 June, respectively. In normal conditions (in the absence of heavy precipitation and within-field runoff) after the field was planted, its CRC should remain stable for several weeks as the crop emerges and begins to grow (Daughtry et al., 2006). Therefore, using a single satellite image to assess the CRC cannot provide a good representation of the actual field conditions, as tillage and planting can happen any time from the last week of April to the first week of June in south central Nebraska. For example, in the present study, the measured values of CRC were observed between 10 to 15 May, and the fields that were tilled or planted before these dates could provide the correct status and representation of the tillage practice and CRC. However, fields that were tilled after the observation dates could misrepresent the actual CRC that existed in the field. It is important to account for the multi-temporal Landsat imagery to determine the correct CRC measurements of any given field. Therefore, a total of two images [17 May and 2 June (ETM+)] in 2013 and four images [25 March (OLI), 18 April (ETM+), 28 May (OLI), and 13 June (OLI)] in 2014 were used in the analysis. All the Landsat-7 (ETM+) and Landsat-8 (OLI) cloud-free and geo-rectified systematic terrain-corrected images for the overpass (path 29, row 32) were obtained from the USGS Earth Resources Observation and Science Center (EROS).

Table 3 shows the spectral bands of Landsat-7 and Landsat-8 in the visible near-infrared (VNI) and thermal infrared (TI) regions used for tillage index application. The Model Maker tool of ERDAS Imagine processing software (Leica Geosystems Geospatial Imaging, LLC) was used to model the spectral indices from raw digital numbers. Top-



(a)



(b)

Figure 4. Digital 1 cm × 1 cm transect grid superimposed over (a) no-till field image (CRC = 96%) and (b) disk-tilled field image (CRC = 13%) to calculate the CRC percentage. Red circles in (a) are locations where no residue was observed, and yellow circles in (b) are locations where residue was observed.

of-atmosphere (TOA) reflectance data were used to calculate various Landsat-based tillage indices because NASA has not yet released Landsat-8 (OLI) atmospherically corrected surface reflectance data. A case study presented by Exelis (2009) showed that in the absence of atmospherically corrected surface reflectance data, TOA reflectance could provide acceptable accuracy. Images acquired on 18 April 2014 were partially covered by clouds and cloud shadows; therefore, only cloud-free measured data points were used in the analysis. The scan line correction for the Landsat-7, band 5 dataset was carried out using the neighborhood function with a 5 × 5 pixel majority function. For path 29, row 32 images, neighborhood gap filling did not affect the pixels surrounding the measured data points, as there were no missing pixels. It is important to note that precipitation prior to the image acquisition date decreases the brightness of the maize residue and subsequently its reflectance and causes an underestimation of CRC (Pacheco and McNairn, 2010). Serbin et al. (2009a, 2009b) also reported that rain could encourage plant canopy growth in some cases, and the increase in total water content can also adversely affect Landsat band 5 and 7 reflectance. For this study, no large precipitation events occurred immediately prior to the image acquisition date; hence, the effect of the water content of the soil and crop residue was implicitly included in the analysis.

Tillage Indices

Six previously established Landsat-based tillage indices were used to estimate the CRC in this research: NDTI (van Deventer et al., 1997), NDI5 and NDI7 (McNairn and Protz, 1993), NDSVI (Qi et al., 2002), ModCRC (Sullivan et al., 2006), and STI (van Deventer et al., 1997), which are defined as:

$$\text{NDTI} = \frac{\rho_5 - \rho_7}{\rho_5 + \rho_7} \tag{1}$$

$$\text{NDI5} = \frac{\rho_4 - \rho_5}{\rho_4 + \rho_5} \tag{2}$$

$$\text{NDI7} = \frac{\rho_4 - \rho_7}{\rho_4 + \rho_7} \tag{3}$$

$$\text{NDSVI} = \frac{\rho_5 - \rho_3}{\rho_5 + \rho_3} \tag{4}$$

Table 2. Nebraska crop progress report for 2013 and 2014 maize and soybean growing season (USDA-NASS, 2014).

	2013				2014			
	Maize		Soybean		Maize		Soybean	
Date	% Planted	% Emerged	% Planted	% Emerged	% Planted	% Emerged	% Planted	% Emerged
13 April	0	0	0	0	1	0	0	0
20 April	0	0	0	0	4	0	0	0
27 April	3	0	0	0	20	2	6	0
4 May	14	0	1	0	44	7	11	0
11 May	43	2	7	0	77	18	36	0
18 May	84	26	33	2	91	43	65	13
25 May	96	61	63	17	97	74	88	42
1 June	99	84	81	47	100	90	96	72
8 June	100	90	94	71	100	98	100	92
15 June	100	100	100	90	100	100	100	97

Table 3. Band type, pixel resolution (m), and band width (μm) for Landsat-7 Enhanced Thematic Mapper (ETM+) and Landsat-8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS).

	Landsat-7 (ETM+)			Landsat-8 (OLI/TIRS)		
Band Number	Band Type[a]	Pixel Resolution (m)	Band Width (μm)	Band Type[a]	Pixel Resolution (m)	Band Width (μm)
1	Blue	30	0.45 to 0.52	Coastal aerosol	30	0.43 to 0.45
2	Green	30	0.52 to 0.60	Blue	30	0.45 to 0.51
3	Red	30	0.63 to 0.69	Green	30	0.53 to 0.59
4	Near infrared	30	0.77 to 0.90	Red	30	0.64 to 0.67
5	SWIR 1	30	1.55 to 1.75	Near infrared	30	0.85 to 0.88
6	Thermal infrared	60 (30)[b]	10.40 to 12.50	SWIR 1	30	1.57 to 1.65
7	SWIR 2	30	2.09 to 2.35	SWIR 1	30	2.11 to 2.29
8	Panchromatic	15	0.52 to 0.90	Pan chromatic	15	0.50 to 0.68
9	-	-	-	Cirrus	30	1.36 to 1.38
10	-	-	-	Band 10 - TIRS 1	100 (30)[b]	10.60 to 11.19
11	-	-	-	Band 11 - TIRS 2	100 (30)[b]	11.50 to 12.51

[a] SWIR = shortwave infrared.

[b] ETM+ band 6 and TIRS bands 10 and 11 were acquired at 60 m or 100 m resolution but resampled to 30 m in final delivered data product.

$$\text{ModCRC} = \frac{\rho_5 - \rho_2}{\rho_5 + \rho_2} \quad (5)$$

$$\text{STI} = \frac{\rho_5}{\rho_7} \quad (6)$$

where ρ_2, ρ_4, ρ_5, and ρ_7 are the reflectances of thematic bands 2, 4, 5, and 7 for Landsat-7 (ETM+) and bands 3, 5, 6, and 7 for Landsat-8 (OLI). The widths of each band for Landsat-7 (ETM+) and Landsat-8 (OLI) is presented in table 2. To avoid the interference of green vegetation, pixel values with normalized difference vegetation index (NDVI) values were calculated as:

$$\text{NDVI} = \frac{\rho_4 - \rho_3}{\rho_4 + \rho_3} \quad (7)$$

where ρ_3 and ρ_4 are the reflectances of thematic bands 3 and 4 for Landsat-7 (ETM+) and bands 4 and 5 for Landsat-8 (OLI), respectively. For CRC mapping, NDVI values greater than 0.30 were considered green vegetation and excluded from the analysis (Daughtry et al., 2005; Serbin et al., 2008). Linear models were developed to evaluate the performance of each tillage index using the coefficient of determination (R^2).

Training and Testing Datasets

The measured data were randomly divided into training (calibration) (67% of the total data) and testing (validation) (33% of the total data) datasets. Regression equations were developed using the training dataset, which were then applied to the testing dataset to predict the CRC. The root mean squared difference (RMSD) between the predicted and measured CRC for 2013 was used to evaluate the prediction performance:

$$\text{RMSD} = \sqrt{\frac{1}{n}(x-y)^2} \quad (8)$$

where n is the number of observed CRC data points, and x and y are the observed and predicted CRC, respectively. Further evaluation was conducted by calculating the percent classification accuracy. Error matrixes were developed for each tillage index between tillage classes as: CRC < 30% (conventional tillage), 30% < CRC < 70%, and CRC ≥ 70% (conservation tillage). For this study, fields with 30% < CRC < 70% were considered ridge tilled and/or strip tilled, and fields with CRC ≥ 70% were assumed to be managed as NT. The classification accuracy of the 3 × 3 matrix (<30%, 30% to 70%, and ≥70%), (estimation accuracy of tillage index relative to measured CRC data) was assessed using percent overall accuracy (correct sample/total number of test samples) and the kappa coefficient (Carletta, 1996). Even though other statistics such as RMSD were used in this study, these calculations provide a measure of agreement but do not take into account the agreement that would be expected purely by chance. If the observed and model-estimated CRC agree purely by chance, they are not really agreeing; only agreement beyond that expected by chance can be considered "true" agreement. The kappa coefficient (κ) is a measure of "true" agreement. It indicates the proportion of agreement beyond that expected by chance, that is, the achieved beyond-chance agreement as a proportion of the possible beyond-chance agreement (Sim and Wright, 2005). The kappa coefficient (κ) measures the pairwise agreement among a set of variables making category judgments and correcting for expected chance agreement:

$$\kappa = \frac{P(A) - P(E)}{1 - P(E)} \quad (9)$$

where $P(A)$ is the proportion of times that the variables (estimated vs. observed CRC; observed agreement) agree, and $P(E)$ is the proportion of times that estimated and observed CRC are expected to agree by chance (chance agreement), calculated along the lines of the intuitive argument presented above (Carletta, 1996). When there is no agreement between the estimated and observed CRC (other than that which would be expected by chance), κ = 0; when there is total agreement, κ = 1.0.

Results and Discussion

Model Performance

Simple linear regression models and associated coefficients of determination (R^2) were developed from measured CRC using each tillage index from the training dataset for each sampling date in 2013 and 2014 (table 4). Positive correlations were observed for NDI5, NDI7, NDTI, and STI. However, an inverse relationship was observed with CRC for ModCRC and NDSVI. For both years, maximum variation in CRC was explained by NDTI followed by STI and NDI7. However, on 6 June 2014, a low R^2 of 0.07 was observed between NDTI and measured CRC. In contrast, NDTI explained about 62% of the variation in CRC in 2013. This can be explained by the fact that only 84% of maize and 47% of soybean were emerged by that time in 2013, as compared to 90% and 72% emergence for maize and soybean, respectively, in 2014 (table 2 and fig. 6). To further evaluate the variation in CRC with different tillage indices, comparisons of CRC versus tillage index values with acquisition dates are presented in figure 5. Among all the dates, the maximum deviation in CRC was observed for the June images. Figures 5b, 5c, 5e, and 5f show that the slope of the regression line is almost parallel to the *x*-axis for all indices, except NDSVI and ModCRC, representing the dependence of tillage indices on acquisition date. Similar results were reported by Galloza et al. (2013), who observed a linear relationship between residue cover and Landsat-TM based NDTI with R^2 values of 0.73, 0.93, and 0.71 for fall 2008, spring 2009, and fall 2010 images, respectively, in central Indiana. Serbin et al. (2009a) developed a new index, the shortwave infrared normalized difference residue index (SINDRI), using ASTER bands 6 and 7, and compared the performance of the new index with the existing CAI, LCA, and NDTI tillage indices in Indiana, Illinois, Iowa, and Maryland. They observed that NDTI is highly affected by the image acquisition date, with a maximum R^2 of 0.64 (RMSD = 11%) observed on 19 May 2009 at Ames, Iowa, using NDTI. They calculated NDTI by averaging ASTER bands 5 to 8 into an equivalent Landsat-TM band 7. However, NDTI did not perform well at other locations. Daughtry et al. (2006) observed weak correlation with NDTI, NDI5, and NDTI, with R^2 of 0.11, 0.14, and 0.14, respectively. The low R^2 can be attributed to the fact that they used a Landsat image that was acquired on 12 June 2004, when 100% of maize and soybean had already emerged in central Iowa.

To evaluate the overall accuracy of each CRC model, regression equations were developed using the training dataset and then applied to the testing dataset. The R^2 and RMSD values between observed and measured CRC were evaluated. Considerable variation was observed between measured and predicted CRC, as well as between model performances, with R^2 ranging from 0.01 to 0.81 (table 5). The maximum R^2 was obtained for NDTI on 17 May 2013 (R^2 = 0.78 and RMSD = 19%) and 25 May 2014 (R^2 = 0.81 and RMSD = 10.5%). However, the minimum variation in CRC was observed for the June image, when most of the crops had emerged across the study area and confounded the tillage index signal. The performance of the 3 × 3 classification matrices for three CRC categories (<30%, 30% to 70% and ≥70%) was evaluated using the overall accuracy and kappa coefficient for each model. This process showed that the performance of NDTI was much better than the other indices in predicting CRC. The maximum accuracy with ground observation was observed for the 28 May 2014 image, with percent overall accuracy of 0.79 (κ = 0.78). However, for the June image, all indices did not classify tillage practices over the study area. The 2 × 2 classifications (i.e., conventional and conservation tillage) improved the overall accuracy for all the indices (data not shown). Among all models evaluated, the NDTI tillage index performed well and can be used as a practical tool to identify tillage practices. Therefore, NDTI was used or further evaluated to map CRC across the study region. Furthermore, Zheng et al. (2012) and Watts et al. (2011) reported that in the presence of multi-temporal Landsat images, it is better to evaluate the performance by calculating the minimum NDTI values, which represent the closest status of the field surface immediately after tillage or planting and which vary greatly from field to field over a homogeneous agricultural region. Therefore, in the next section, the minimum NDTI data were quantified and evaluated.

Table 4. Coefficient of determination (R^2) and models developed using simple linear regression for all tillage indices for 2013 and 2014 (*N* = 67% of observed CRC data points).

Tillage Index	*N*	R^2	Regression Equation	*N*	R^2	Regression Equation
	17 May 2013			2 June 2013		
ModCRC	34	0.24	$y = -812.93x + 418.06$	34	0.06	$y = -180.05x + 127.6$
NDI5	34	0.28	$y = 505.65x + 168.3$	34	0.04	$y = 209.98x + 86.597$
NDI7	34	0.58	$y = 361.82x + 85.945$	34	0.43	$y = 394.43x + 79.342$
NDSVI	34	0.49	$y = -793.8x + 358.53$	34	0.15	$y = -281.62x + 155.72$
NDTI	34	0.73	$y = 781.37x - 62.297$	34	0.62	$y = 802.74x - 51.203$
STI	34	0.6	$y = 254.67x - 290.37$	34	0.53	$y = 306.87x - 346.13$
	25 March 2014			18 April 2014		
ModCRC	60	0.36	$y = -502.73x + 262.41$	30	0.34	$y = -453.27x + 225.58$
NDI5	60	0.48	$y = 348.69x + 95.342$	30	0.57	$y = 443.67x + 125.66$
NDI7	60	0.55	$y = 220.96x + 50.172$	30	0.7	$y = 264.7x + 56.795$
NDSVI	60	0.45	$y = -359.59x + 167.25$	30	0.54	$y = -412.75x + 180.72$
NDTI	60	0.62	$y = 558.73x - 22.535$	30	0.68	$y = 593.86x - 37.08$
STI	60	0.55	$y = 217.19x - 233.12$	30	0.57	$y = 213.19x - 237.75$
	28 May 2014			6 June 2014		
ModCRC	60	0.57	$y = -792.9x + 433.56$	60	0.31	$y = -565.54x + 323.16$
NDI5	60	0.49	$y = 645.98x + 176.19$	60	0.05	$y = -73.172x + 43.568$
NDI7	60	0.65	$y = 415.45x + 87.66$	60	0.01	$y = -20.05x + 49.909$
NDSVI	60	0.59	$y = -615.64x + 306.68$	60	0.65	$y = -538.42x + 306$
NDTI	60	0.78	$y = 858.15x - 41.861$	60	0.07	$y = 200.06x + 17.468$
STI	60	0.63	$y = 308.53x - 334.29$	60	0.06	$y = 68.605x - 45.638$

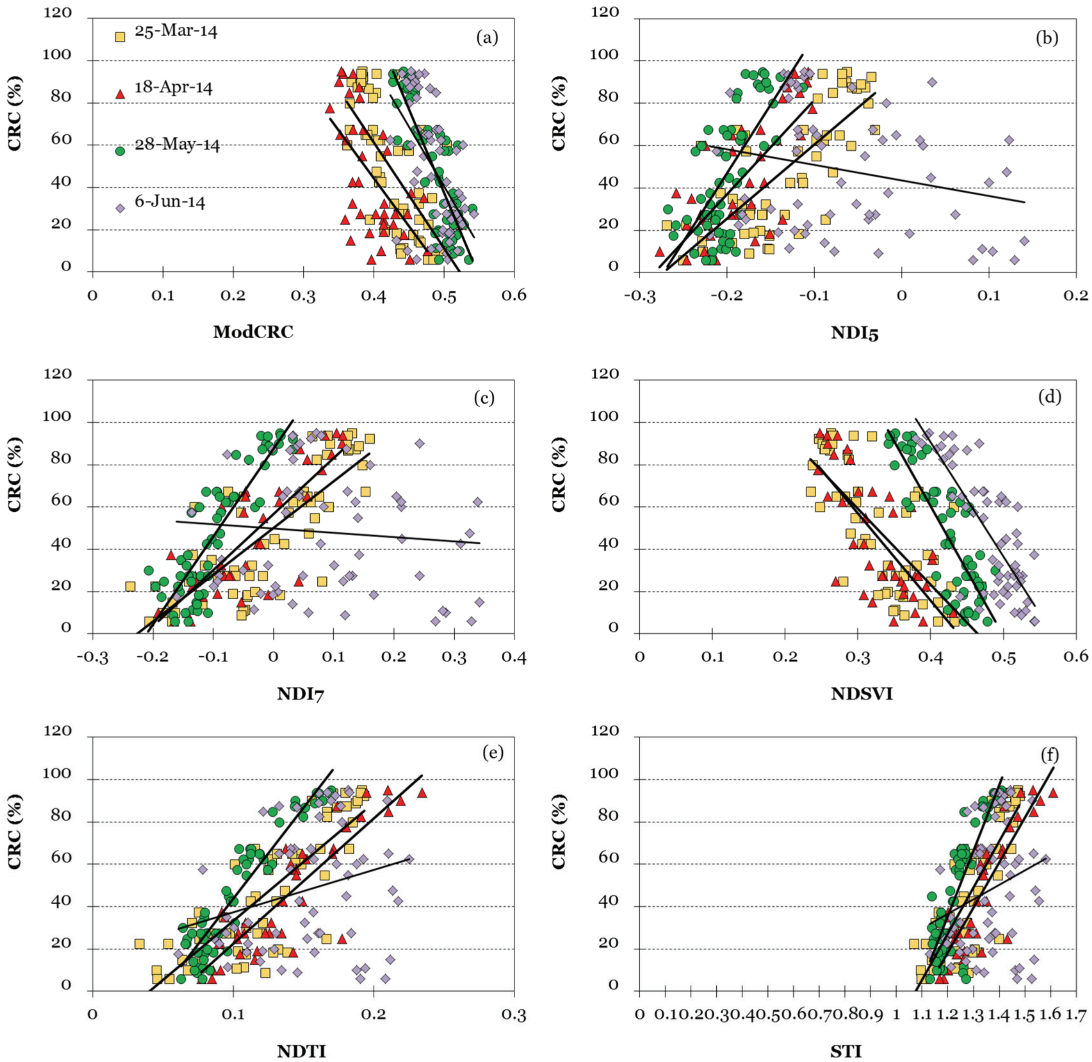


Figure 5. Crop residue cover (CRC, %) as a function of (a) ModCRC, (b) NDI5, (c) NDI7, (d) NDSVI, (e) NDTI, and (f) STI for training dataset on 25 March, 18 April, 28 May, and 6 June 2014.

Table 5. Comparison of ModCRC, NDI5, NDI7, NDSVI, NDTI, and STI tillage indices for the 2013 and 2014 maize and soybean planting seasons. *N* is the number of testing data, R^2 is the coefficient of determination, and RMSD is the root mean square difference between observed (ground truth) and predicted CRC. Classification accuracy of the 3 × 3 matrix (<30%, 30% to 70%, and ≥70%) was assessed using percent overall accuracy (correct sample/total number of test samples) and kappa coefficient (κ).

Tillage Index	*N*	R^2	RMSD (%)	Overall Accuracy (%)	Kappa Coefficient	xx	*N*	R^2	RMSD (%)	Overall Accuracy (%)	Kappa Coefficient
	17 May 2013						2 June 2013				
ModCRC	16	0.45	36.2	50	0.39		16	0.11	28.6	29	0.01
NDI5	16	0.52	31.1	63	0.48		16	0.11	28.6	29	0.01
NDI7	16	0.57	28.6	63	0.51		16	0.28	27.2	64	0.45
NDSVI	16	0.51	36.1	56	0.41		16	0.11	27.9	28	0.01
NDTI	16	0.78	18.7	69	0.64		16	0.38	26.5	57	0.53
STI	16	0.6	24.5	62	0.43		16	0.35	26.3	57	0.42
	25 March 2014						18 April 2014				
ModCRC	30	0.61	19.84	53	0.45		18	0.53	21.50	61	0.54
NDI5	30	0.52	21.98	60	0.53		18	0.64	18.35	56	0.48
NDI7	30	0.56	21.16	67	0.52		18	0.63	16.05	62	0.59
NDSVI	30	0.59	20.06	63	0.58		18	0.55	18.09	51	0.51
NDTI	30	0.63	20.40	68	0.63		18	0.69	15.57	68	0.69
STI	30	0.61	20.21	60	0.55		18	0.58	15.27	57	0.47
	28 May 2014						6 June 2014				
ModCRC	30	0.66	18.72	53	0.59		30	0.03	39.92	30	0.17
NDI5	30	0.47	23.31	47	0.38		30	0.01	34.96	17	0.01
NDI7	30	0.68	15.95	63	0.69		30	0.02	34.51	17	0.01
NDSVI	30	0.67	18.35	59	0.47		30	0.24	46.09	53	0.46
NDTI	30	0.81	10.47	79	0.78		30	0.03	35.20	17	0.01
STI	30	0.7	14.50	67	0.54		30	0.03	35.13	17	0.01

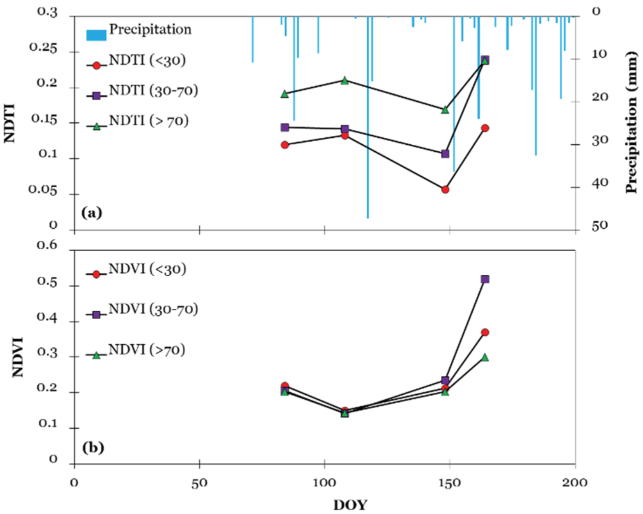


Figure 6. Time series of (a) NDTI and (b) NDVI values for three classifications (CRC < 30%, 30% < CRC < 70%, and CRC ≥ 70%). Vertical blue bars represent daily precipitation obtained from the Clay Center, Nebraska, weather station, which is a part of the High Plain Regional Climate Center (HPRCC) Automated Weather Data Network.

MINIMUM NDTI

Figure 6 shows the change in NDTI values with time over the study region for three CRC categories (<30%, 30% to 70%, and ≥70%) from March to June 2014. One field under each category was selected from the study region. Reduction in NDTI values from day of year (DOY) 108 to 145 was due to residue weathering and tillage and planting operations implemented in the field. For example, a high value of NDTI of 0.12 was observed for the low CRC (<30%) early in the season. Field measurements were taken between 10 and 15 May (at that time, the field was interpreted at CRC of 35%); however, the decline in NDTI to 0.05 after DOY 108 indicates the application of tillage in that field after data collection, which could mislead the correct estimation of CRC. Therefore, it was important to use multi-temporal Landsat imagery for correct estimation of CRC, as tillage or planting could have occurred anytime from the last week of April to the end of May (table 3) in the study region. A sharp increase after DOY 145 is due to emergence of maize and soybean green vegetation over the study area, resulting in high values of NDVI (fig. 6). Thus, for further CRC estimations, the minimum NDTI value was calculated from the available imagery. Zheng et al. (2013) reported that the multi-temporal method for mapping CRC was subject to failure with an insufficient number of remotely sensed images. For the minimum NDTI analysis, only the 2014 data were used, as 2013 had only two cloud-free images available in May and June, which may not be enough imagery to infer the changes in CRC caused by planting or tillage. The training dataset was then used to develop a simple linear regression model using minimum NDTI values and CRC, which was then evaluated with the testing dataset. As shown in figure 6, there was no apparent impact of precipitation events on NDTI values.

Figure 7 shows the linear relationship between CRC and minimum NDTI for the training dataset, with R^2 of 0.86 and RMSD of 11%. The relationship was then further applied to the testing dataset to predict CRC (fig. 8). Considerable variation in CRC was observed, with R^2 = 0.89 and RMSD of 10.6%; however, the slope and intercept did not differ significantly ($p > 0.05$) from one and zero, respectively, at the 5% significance level. Figure 9 shows the relationship between measured CRC with minimum NDTI using the pooled dataset (R^2 = 0.87; RMSD = 10.9%). Test results showed that the model overestimated CRC values for high amounts of residue (CRC > 70%), while underestimation was observed for data points in the lower residue range (CRC < 30% to 40%). Table 6 shows the 3 × 3 classification matric for three residue cover categories that resulted from the testing and pooled datasets. High overall accuracy of 90% with κ = 0.89 was observed for the testing dataset. Combining the training and testing datasets (pooled data) resulted in high overall accuracy of 87% and κ = 0.84. Similar results were observed by Zheng et al. (2012), who used five Landsat images to estimate CRC on a regional scale. They found a linear correlation between CRC and minimum

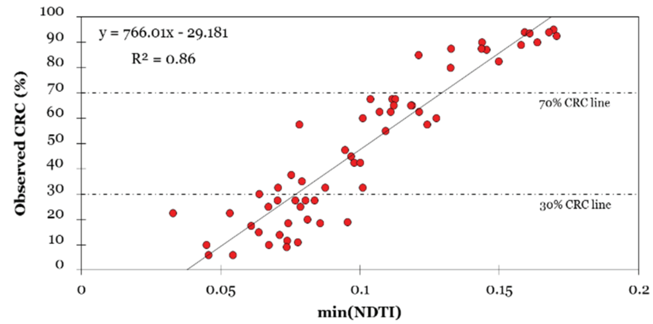


Figure 7. Observed crop residue cover (CRC, %) as a function of minimum NDTI for training dataset (*n* = 60).

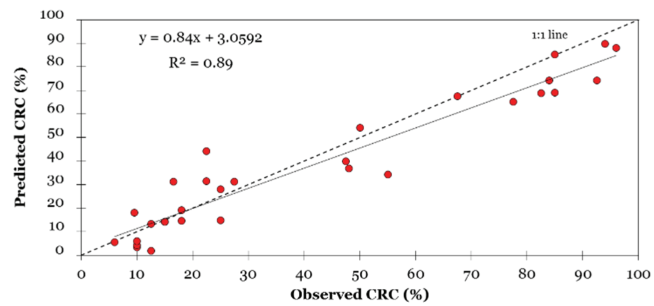


Figure 8. Observed vs. predicted crop residue cover (CRC, %) for the testing dataset (*n* = 30) for 2014.

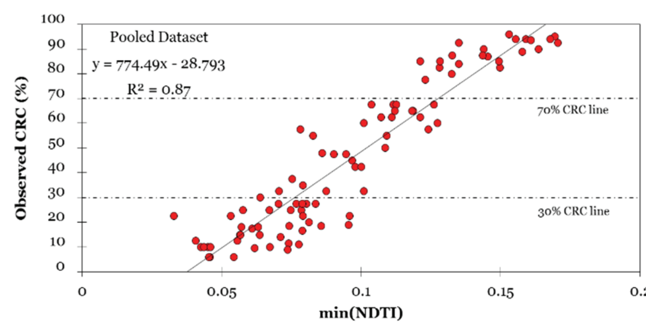


Figure 9. Observed crop residue cover (CRC, %) as a function of minimum NDTI for the pooled dataset (*n* = 90) for year 2014.

Table 6. Classification matrix for three CRC categories derived using linear regression for the testing and pooled datasets.

	<30%	30% to 70%	≥70%	Total	Accuracy (%)
Testing dataset					
<30%	15	1	0	16	94
30% to 70%	1	4	0	5	80
≥70%	0	1	8	9	89
Total	16	6	8	30	
Overall accuracy = 0.9					
Kappa coefficient = 0.89					
Pooled dataset					
<30%	36	4	0	40	90
30% to 70%	4	23	0	27	85
≥70%	0	4	19	23	83
Total	40	31	19	90	
Overall accuracy (%) = 87					
Kappa coefficient = 0.84					

NDTI with R^2 of 0.89 and RMSD of 10.5% for the calibration dataset and R^2 of 0.87 (RMSD = 11.5%) for the pooled dataset. They further applied the regression equation from the calibration dataset to the test dataset, which yielded an R^2 of 0.85 and RMSD of 12.6% when compared with the ground measurements, with an overall accuracy of 91% and 90% for the test and pooled datasets, respectively. To further evaluate the performance of the model developed using training data, the model equation was applied to the 17 May 2013 dataset (fig. 10). Overall, a good correlation was observed between measured and predicted CRC, with R^2 = 0.84 (RMSD = 18.5%). However, in most cases, the model overestimated CRC, and the overestimations were greater for the lower range of CRC (i.e., <60% to 70%). The lower correlation as compared to 2014 might be due to an insufficient number of multi-temporal Landsat images in 2013 and the differences in CRC and management practices between years. An additional dataset is required to test the accuracy of the model for different years and locations.

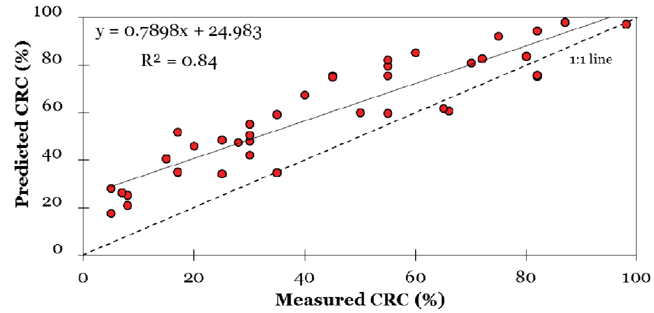


Figure 10. Measured vs. predicted crop residue cover (CRC, %) for the testing dataset for 2013.

Large-Scale Spatial Mapping of CRC

In order to map the CRC for the study area, two Landsat images from 25 March and 28 May 2014 were selected, and the training model was then applied. For mapping CRC, we divided CRC into three categories: <30%, 30% to 70%, and ≥70%. Figure 11 shows the spatial variation of CRC on 25 March and 28 May 2014 over the study region.

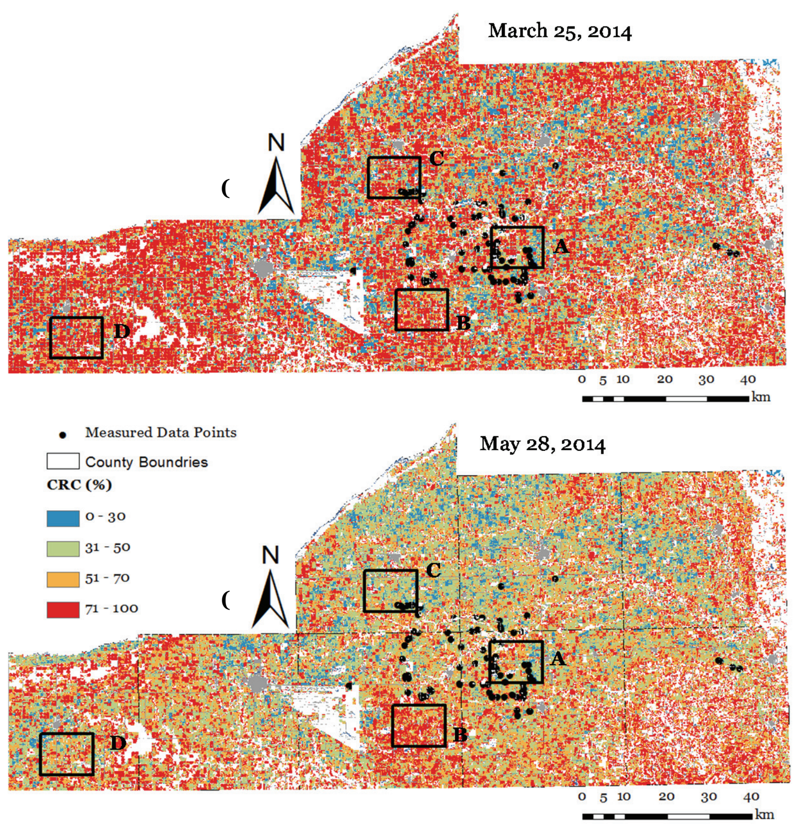


Figure 11. Crop residue cover (CRC) classification into four categories (0 < CRC < 30%, 31% to 50%, 51% to 70%, and >71%) using minimum NDTI index values from multi-temporal Landsat images for (a) 25 March 2014 and (b) 28 May 2014 in south central Nebraska. Areas A, B, C, and D were selected for detailed analysis.

Non-agricultural fields and developed (urban) areas with NDVI > 0.3 were excluded from the image. Red color in figure 11 represents areas with very high CRC values. Relatively large values of CRC were observed (more red color) for the March 2014 image when the residue from the last season maize and soybean harvest remained on the soil surface and planting and tillage operations had not yet begun. Planting and tillage operations in the fields led to reductions in CRC, which can be clearly seen in the May 2014 image. To further evaluate the changes that occurred between the two dates, four small areas (A, B, C, and D) were randomly selected from the study area, as shown in

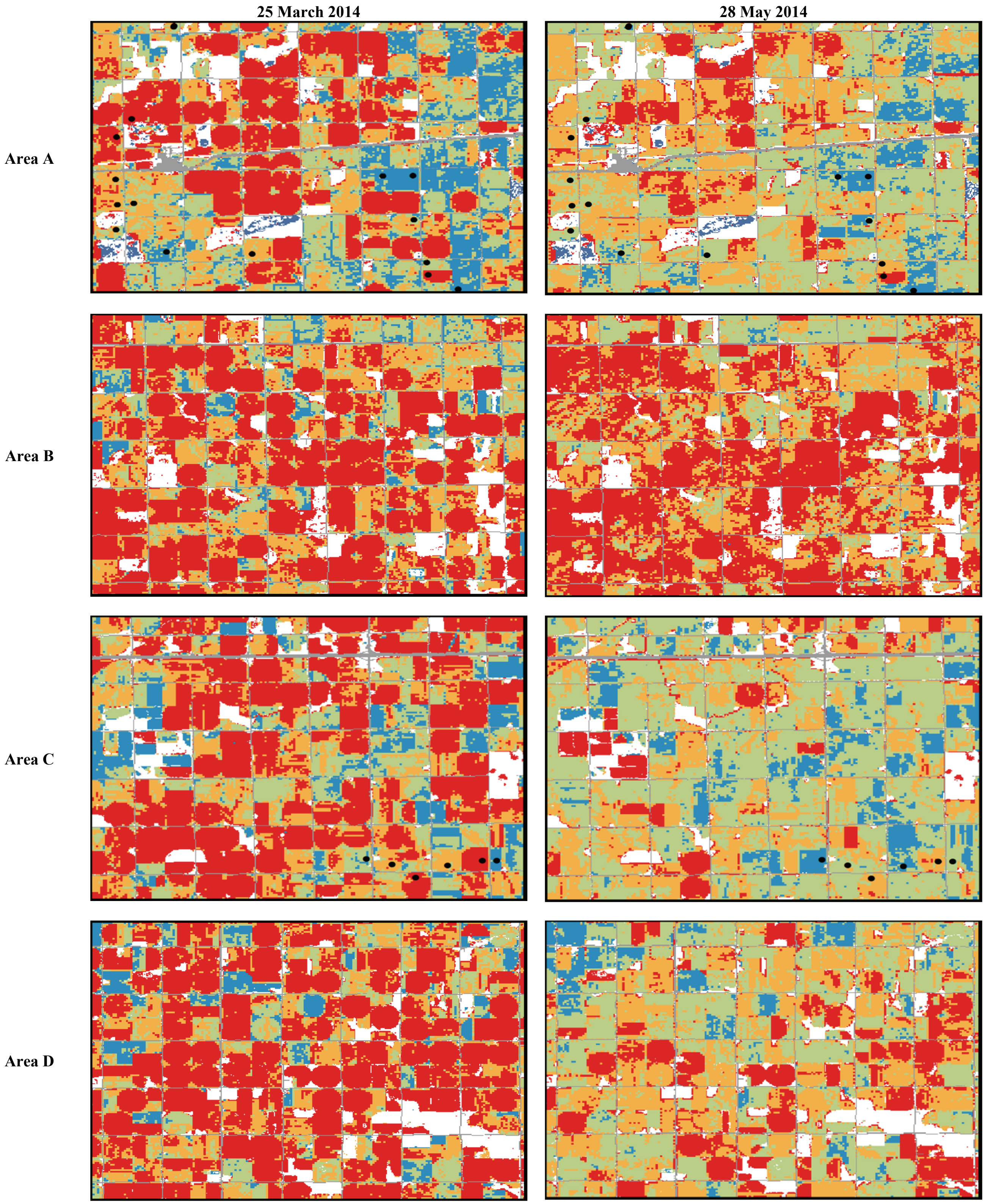


Figure 12. Distribution of CRC into four residue cover categories on 25 March 2014 and 28 May 2014 for areas A, B, C, and D in figure 11.

figure 12. Close analyses of these areas showed that the maximum change in CRC was observed in area C (Hamilton County, Neb.), where 85% of the area showed a reduction in CRC from the ≥70% category to less than 50% CRC, which might be a result of tillage operations across area C. The minimum disturbance in CRC was observed in area B (Clay County, Neb.), where most of the area was undisturbed and had high CRC even after planting. To further estimate the area in each CRC category for maize and soybean fields, the crop data layer for the 2013 growing season from NASS was overlaid on the developed tillage map for the 28 May 2014 image. Table 7 shows the percent area of maize and soybean cultivated in each CRC category across the study area and for each county.

In 2013, cropland areas across the study area planted to maize and soybeans were approximately 598,614 ha and 278,882 ha, respectively (USDA-NASS, 2013). On average, a total of 19% of the maize and soybean area (5% of maize fields and 14% of soybean fields) were observed under 30% residue cover (conventional tillage), and a total of 41% (26% of maize fields and 15% of soybean fields) of the total maize and soybean area had more than 70% CRC. Countywide analysis showed more soybean area having less than 30% CRC than maize, which was due to the fact that soybean produces less residue mass than maize, and there is only a small difference between the soil and soybean residue. This creates a challenge in distinguishing these surfaces from each other (Pacheco and McNairn, 2010; Biard and Baret, 1997), and even a small amount of tillage can result in a significant reduction in CRC. These results were based on the CRC calculations by minimum NDTI using Landsat imagery; however, research by Daughtry et al. (2006) and Serbin et al. (2009a, 2009b) indicated that more accurate results can be obtained using the CAI, LCA and SINDRI tillage indices with hyperspectral remote sensing data. For this study, these datasets were not available. Future research on the use of hyperspectral data for better identification of CRC at large scales is recommended. Furthermore, this study did not include the sensitivity of NDTI to surface soil and/or residue water content, since no large precipitation events occurred during the study. Thus, future research evaluating the sensitivity of different tillage indices to water content is suggested.

Table 7. Distribution of maize and soybean areas under three CRC categories for the study area and for eight Nebraska counties (Adams, Clay, Fillmore, Hamilton, Kearney, Saline, Seward, and York) within the study area on 28 May 2014.

Location and Crop		Total Area (ha)	Percentage of Area by CRC Category		
			<30%	30% to 70%	≥70%
Study area	Corn	598,614	5	69	26
	Soybean	278,882	14	71	15
Adams	Corn	77,473	3	66	30
	Soybean	31,320	13	74	14
Clay	Corn	77,725	4	66	30
	Soybean	29,725	11	68	21
Fillmore	Corn	80,879	1	71	28
	Soybean	41,226	8	79	13
Hamilton	Corn	85,619	7	79	14
	Soybean	28,389	25	70	5
Kearney	Corn	68,542	12	57	31
	Soybean	33,879	19	63	19
Saline	Corn	58,211	1	58	41
	Soybean	39,699	3	69	28
Seward	Corn	59,829	5	65	30
	Soybean	40,325	13	72	14
York	Corn	90,298	6	77	16
	Soybean	34,309	24	69	7

Summary and Conclusions

Accurate information on tillage practices and crop residue cover (CRC) can aid in the assessment and quantification of numerous benefits, including large-scale assessments of the impact of tillage practices on water resources and cropping system productivity analyses, policy decisions, etc. Developing accurate and robust methodologies to estimate the percent CRC and type of tillage practices implemented at large scales is still evolving, and currently there is no extremely accurate, robust, and scientifically valid method available to quantify and map CRC at a regional scale. In this research, multi-temporal Landsat-7 (ETM+) and Landsat-8 (OLI/TIRS) satellite data were used to evaluate the performance of tillage indices to map CRC for maize and soybean fields in south central Nebraska. To the best of our knowledge, this study was the first to use Landsat-8 satellite data to map the percent CRC at a regional scale. Four satellite images collected on 25 March, 18 April, 28 May, and 6 June 2014 were used in the analysis. Among all the indices, NDTI performed best for all image acquisition dates. The maximum accuracy with ground observations of percent CRC was observed for the 28 May 2014 images, with percent overall accuracy of 0.79 (κ = 0.78). Minimum NDTI was used to map the percent CRC, accounting for the planting date and other changes in CRC during the planting season. Total available data were divided into training (calibration) and testing (validation) subsets. The training dataset was used to develop the model, and the testing dataset was used to evaluate the performance of the training model. Linear regression the CRC model showed that NDTI performed well in differentiating the CRC for different tillage practices at large scales. The minimum NDTI method was then used to spatially map the CRC at a regional scale by considering the timing of planting and tillage implementation. Measured CRC was divided into training and testing datasets. A CRC model was developed using the training dataset between minimum NDTI and measured CRC with R^2 = 0.89 (RMSD = 10.63%).

The 3 × 3 classification matrix for three residue cover categories resulting from the testing dataset showed a high overall accuracy of 90% with κ = 0.89. Mapping of CRC showed that, on average, a total of 19% of maize and soybean area (5% of maize fields and 14% of soybean fields) were observed under 30% residue cover (conventional tillage), and 41% (26% of maize fields and 15% of soybean fields) of the total maize and soybean area had more than 70% CRC. This research and the procedures presented illustrate that multi-spectral Landsat images are capable of estimating and mapping CRC (error within 10.6%) on a regional scale and continual basis using locally developed tillage practice versus crop residue algorithms.

ACKNOWLEDGEMENTS

As a Principal Investigator, Dr. Suat Irmak expresses his appreciation to the funding agencies for providing support for this research. This research was partially supported by grants from the Nebraska Environmental Trust (NET) under Project Agreement No. 13-146, the Central Platte Natural Resources District (CPNRD) under Grant Agreement No. 38484, and the Nebraska Department of Natural Resources (NEDNR) under Project Agreement No. 477. This research is based on work that is supported by the USDA National Institute of Food and Agriculture (NIFA) Hatch Project under Project No. NEB-21-155.

REFERENCES

Al-Kaisi, M. M., & Hanna, M. (2009). Residue management and cultural practices. Extension Publication PM 1901a. Ames, Iowa: Iowa State University Extension.

Bannari, A., Haboudane, D., & Bonn, F. (2000). Interet du moyen infrarouge pour la cartographie des residus de cultures. *Canadian J. Remote Sensing, 26*(5), 384-393. http://dx.doi.org/10.1080/07038992.2000.10855270

Bannari, A., Pacheco, A., Staenz, K., McNairn, H., & Omari, K. (2006). Estimating and mapping crop residues cover on agricultural lands using hyperspectral and IKONOS data. *Remote Sensing Environ., 104*(4), 447-459. http://dx.doi.org/10.1016/j.rse.2006.05.018

Beyaert, R. P., Schott, J. W., & White, P. H. (2002). Tillage effects on corn production in a coarse-textured soil in southern Ontario. *J. Agron., 94*(4), 767-774. http://dx.doi.org/10.2134/agronj2002.7670

Biard, F., & Baret, F. (1997). Crop residue estimation using multiband reflectance. *Remote Sensing Environ., 59*(3), 530-536. http://dx.doi.org/10.1016/S0034-4257(96)00125-3

Carletta, J. (1996). Assessing agreement on classification tasks: The kappa statistic. *Computat. Linguistics, 22*(2), 1-6.

Chander, G., & Markham, B. L. (2003). Revised Landsat-5 TM radiometric calibration procedures and post-calibration dynamic ranges. *IEEE Trans. Geosci. Remote Sensing, 41*(11), 2674-2677.

Chander, G., Markham, B. L., & Barsi, J. A.(2007). Revised Landsat-5 thematic mapper radiometric calibration. *IEEE Geosci. Remote Sensing Letters, 4*(3), 490-494.

CTIC. (2004). National survey of conservation tillage practices. West Lafayette, Ind.: Conservation Technology Information Center. Retrieved from www.ctic.purdue.edu/CTIC/CRM.html.

Dalzell, B. J., Gowda, P. H., & Mulla, D. J. (2004). Modeling sediment and phosphorous losses in agricultural watershed to meet TMDLs. *JAWRA, 40*(2), 533-543. http://dx.doi.org/10.1111/j.1752-1688.2004.tb01048.x

Dam, R., Mehdi, B., Burgess, M., Madramootoo, C., Mehuys, G., & Callum, I. (2005). Soil bulk density and crop yield under eleven consecutive years of corn with different tillage and residue practices in a sandy loam soil in central Canada. *Soil Tillage Res., 84*(1), 41-53. http://dx.doi.org/10.1016/j.still.2004.08.006

Daughtry, C. S. (2001). Discriminating crop residues from soil by shortwave infrared reflectance. *J. Agron., 93*(1), 125-131. http://dx.doi.org/10.2134/agronj2001.931125x

Daughtry, C. S., Doraiswamy, P. C., Hunt Jr., E. R., Stern, A. J., McMurtrey III, J. E., & Prueger, J. H. (2006). Remote sensing of crop residue cover and soil tillage intensity. *Soil Tillage Res., 91*(1), 101-108. http://dx.doi.org/10.1016/j.still.2005.11.013

Daughtry, C. S., Hunt Jr., E. R., & McMurtrey III, J. E. (2004). Assessing crop residue cover using shortwave infrared reflectance. *Remote Sensing Environ., 90*(1), 126-134. http://dx.doi.org/10.1016/j.rse.2003.10.023

Daughtry, C. S., Hunt Jr., E. R., Doraiswamy, P. C., & McMurtrey III, J. E. (2005). Remote sensing the spatial distribution of crop residues. *J. Agron., 97*(3), 864-871. http://dx.doi.org/10.2134/agronj2003.0291

Daughtry, C. S., McMurtrey III, J. E., Chappelle, E. W., Hunter, W. J., & Steiner, J. L. (1996). Measuring crop residue cover using remote sensing techniques. *Theor. Appl. Climatol., 54*(1-2), 17-26. http://dx.doi.org/10.1007/BF00863555

Dick, W. A., & Van Doren, D. M. (1985). Continuous tillage and rotation combinations effects on corn, soybean, and oat yields. *J. Agron., 77*(3), 459-465. http://dx.doi.org/10.2134/agronj1985.00021962007700030023x

Edwards, J., Thurlow, D. L., & Eason, J. T. (1988). Influence of tillage and crop rotation on yields of corn, soybean, and wheat. *J. Agron., 80*(1), 76-80. http://dx.doi.org/10.2134/agronj1988.00021962008000010018x

Elder, J. A. (1969). Soils of Nebraska. Resource Report No. 2. Lincoln, Neb.: University of Nebraska Conservation and Survey.

Exelix. (2009). Case study: Mapping crop residue with Landsat data using ENVI from ArcGIS. Retrieved from http://exelis.http.internapcdn.net/exelis/pdfs/7-13_Residue_CaseStudy_LoRes.pdf

Galloza, M. S., Crawford, M. M., & Heathman, G. C. (2013). Crop residue modeling and mapping using Landsat, ALI, Hyperion, and airborne remote sensing data. *IEEE J. Selected Topics Appl. Earth Obs. Remote Sensing, 6*(2), 446-456. http://dx.doi.org/10.1109/JSTARS.2012.2222355

Gebhardt, M. R., Daniel, T. C., Schweizer, E. E., & Allmaras, R. R. (1985). Conservation tillage. *Science, 230*(4726), 625-630. http://dx.doi.org/10.1126/science.230.4726.625

Gowda, P. H., Howell, T., Evett, S., Chavez, J., & New, L. (2008). Remote sensing of contrasting tillage practices in the Texas Panhandle. *Intl. J. Remote Sensing, 29*(12), 3477-3487. http://dx.doi.org/10.1080/01431160701581810

Gregory, J. M. (1982). Soil cover prediction with various amounts and type of crop residue. *Trans. ASAE, 25*(5), 1333-1337. http://dx.doi.org/10.13031/2013.33723

Halvorson, A. D., Black, A. L., Krupinsky, J. M., & Merrill, S. D. (1999). Dryland winter wheat response to tillage and nitrogen within an annual cropping system. *J. Agron., 91*(4), 702-707. http://dx.doi.org/10.2134/agronj1999.914702x

Halvorson, A. D., Wienhold, B. J., & Black, A. L. (2002). Tillage, nitrogen, and cropping system effects on soil carbon sequestration. *SSSA J., 66*(3), 906-912. http://dx.doi.org/10.2136/sssaj2002.9060

Hussain, I., Olson, K. R., & Ebelhar, S. A. (1999). Impacts of tillage and no-till on production of maize and soybean on an eroded Illinois silt loam soil. *Soil Tillage Res., 52*(1), 37-49. http://dx.doi.org/10.1016/S0167-1987(99)00054-9

Irmak, S. (2010). Nebraska water and energy flux measurement, modeling, and research network (NEB-FLUX). *Trans. ASABE, 53*(4), 1097-1115. http://dx.doi.org/10.13031/2013.32600

Keteheson, J. W., & Stonehouse, D. P. (1983). Conservation tillage in Ontario. *J. Soil Water Cons., 38*(3), 253-254.

Lal, R., Kimble, J. M., Follett, R., & Stewart, B. A. (1998). *Management of Carbon Sequestration in Soil.* Boca Raton, Fla.: CRC Press.

Logan, T. J., & Adams, J. R. (1981). The effects of reduced tillage on phosphate transport from agricultural land. Lake Erie wastewater management study. Technical Report Series. Buffalo, N.Y.: U.S. Army Corp of Engineers.

McNairn, H., & Protz, R. (1993). Mapping corn residue cover on agricultural fields in Oxford County, Ontario, using thematic mapper. *Canadian J. Remote Sensing, 19*(2), 152-159.

http://dx.doi.org/10.1080/07038992.1993.10874543
Morrison, J. E., Huang, C., Lightle, D. T., & Daughtry, C. S. (1993). Residue measurement techniques. *J. Soil Water Cons., 48*(6), 478-483.
Nyakatawa, E. Z., Reddy, K. C., & Mays, D. A. (2000). Tillage, cover cropping, and poultry litter effects on cotton: II. Growth and yield parameters. *J. Agron., 92*(5), 1000-1007. http://dx.doi.org/10.2134/agronj2000.9251000x
Ogle, S. M., Swan, A., & Paustian, K. (2012). No-till management impacts on crop productivity, carbon input, and soil carbon sequestration. *Agric. Ecosyst. Environ., 149*, 37-49. http://dx.doi.org/10.1016/j.agee.2011.12.010
Pacheco, A., & McNairn, H. (2010). Evaluating multispectral remote sensing and spectral unmixing analysis for crop residue mapping. *Remote Sensing Environ., 114*(10), 2219-2228. http://dx.doi.org/10.1016/j.rse.2010.04.024
Qi, J., Marsett, R., Heilman, P., Bieden-bender, S., Moran, S., Goodrich, D., & Weltz, M. (2002). RANGES improves satellite-based information and land cover assessments in southwest U.S. *EOS, Trans. American Geophys. Union, 83*(51), 601-606. http://dx.doi.org/10.1029/2002EO000411
Ribeiro, M., Denardin, J., Bianchini, A., Ferreira, R., Flores, C., Kliemann, H., ..., Montoya, L. (2007). Comprehensive inventory and assessment of existing knowledge on sustainable agriculture in the Latin American platform of KASSA. Montpellier, France: CIRAD.
Serbin, G. D., Hunt Jr., E. R., McCarty, G. W., Doraiswamy, P. C., & Brown, D. J. (2008). Improved remotely sensed estimates of crop residue cover by incorporating soils information. In *Proc. Geosci. Remote Sensing Symp.* (pp. IV-267 to IV-270). Piscataway, N.J.: IEEE. http://dx.doi.org/10.1109/igarss.2008.4779709
Serbin, G., Daughtry, C. S., Hunt Jr., E. R., Reeves III, J. B., & Brown, D. J. (2009a). Effects of soil composition and mineralogy on remote sensing of crop residue cover. *Remote Sensing Environ., 113*(1), 224-238. http://dx.doi.org/10.1016/j.rse.2008.09.004
Serbin, G., Hunt Jr., E. R., Daughtry, C. S., McCarty, G. W., & Doraiswamy, P. C. (2009b). An improved ASTER index for remote sensing of crop residue. *Remote Sensing, 1*(4), 971-991. http://dx.doi.org/10.3390/rs1040971
Sim, J., & Wright, C. C. (2005). The kappa statistic in reliability studies: Use, interpretation, and sample size requirements. *Physical Therapy, 85*(3), 257-268.
Soane, B. D., Ball, B. C., Arvidsson, J., Basch, G., Moren, F., & Roger-Estrade, J. (2012). No-till in northern, western, and southwestern Europe: A review of problems and opportunities for crop production and the environment. *Soil Tillage Res., 118*, 66-87. http://dx.doi.org/10.1016/j.still.2011.10.015
South, S., Qi, J., & Lusch, D. P. (2004). Optimal classification methods for mapping agricultural tillage practices. *Remote Sensing Environ., 91*(1), 90-97. http://dx.doi.org/10.1016/j.rse.2004.03.001
Sudheer, K., Gowda, P., Chaubey, I., & Howell, T. (2010). Artificial neural network approach for mapping contrasting tillage practices. *Remote Sensing, 2*(2), 579-590. http://dx.doi.org/10.3390/rs2020579
Sullivan, D. G., Truman, C. C., Schomberg, H. H., Endale, D. M., & Franklin, D. H. (2007). Potential impact of conservation tillage on conserving water resources in Georgia. *J. Soil Water Cons., 62*(3), 145-152.
Sullivan, D. G., Truman, C. C., Schomberg, H. H., Endale, D. M., & Strickland, T. C. (2006). Evaluating techniques for determining tillage regime in the southeastern coastal plain and piedmont. *J. Agron., 98*(5), 1236-1246. http://dx.doi.org/10.2134/agronj2005.0294
Tarkalson, D. D., Hergert, G. W., & Cassman, K. G. (2006). Long-term effects of tillage on soil chemical properties and grain yields of a dryland winter wheat-sorghum/corn-fallow rotation in the Great Plains. *J. Agron., 98*(1), 26-33. http://dx.doi.org/10.2134/agronj2004.0240
USDA-NASS. (2013). Published crop-specific data layer. Washington, D.C.: USDA National Agricultural Statistics Service. Retrieved from http://nassgeodata.gmu.edu/CropScape/
USDA-NASS. (2014). Nebraska crop progress and condition. Washington, D.C.: USDA National Agricultural Statistics Service. Retrieved from www.nass.usda.gov/Statistics_by_State/Nebraska/Publications/Crop_Progress_&_Condition/
USGS. (2007). Earth Observing 1 (EO-1): Sensors - Hyperion. Sioux Falls, S.D.: USGS EROS Data Center. Retrieved from http://eo1.usgs.gov/sensors/hyperion
van Deventer, A., Ward, A., Gowd, P., & Lyon, J. (1997). Using thematic mapper data to identify contrasting soil plains and tillage practices. *Photogram. Eng. Remote Sensing, 63*(1), 87-93.
Watts, J. D., Powell, S. L., Lawrence, R. L., & Hilker, T. (2011). Improved classification of conservation tillage adoption using high temporal and synthetic satellite imagery. *Remote Sensing Environ., 115*(1), 66-75. http://dx.doi.org/10.1016/j.rse.2010.08.005
Zheng, B., Campbell, J. B., & de Beurs, K. M. (2012). Remote sensing of crop residue cover using multi-temporal Landsat imagery. *Remote Sensing Environ., 117*, 177-183. http://dx.doi.org/10.1016/j.rse.2011.09.016
Zheng, B., Campbell, J. B., Serbi, G., & Daughtry, C. S. (2013). Multitemporal remote sensing of crop residue cover and tillage practices: A validation of the minNDTI strategy in the U.S. *J. Soil Water Cons., 68*(2), 120-131. http://dx.doi.org/10.2489/jswc.68.2.120