

Broad-scale Assessment of Crop Residue Management
Using Multi-temporal Remote Sensing Imagery

Baojuan Zheng

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in
partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Geospatial and Environmental Analysis

James B. Campbell, Committee Chair
Kirsten M. de Beurs
John M. Galbraith
Randolph H. Wynne

November 9 2012
Blacksburg, VA

Keywords: conservation, agriculture, crop residue, tillage, remote sensing, multi-temporal,
Landsat

Copyright 2012, Baojuan Zheng

Broad-scale Assessment of Crop Residue Management Using Multi-temporal Remote Sensing Imagery

Baojuan Zheng

ABSTRACT

Tillage practices have changed dramatically during the past several decades as agricultural specialists have recognized the unfavorable environmental effects of mechanized tillage. Alternatively, conservation tillage management can mitigate adverse environmental impacts of tillage, such as soil and water degradation. Adoption of conservation tillage has continued to increase since its first introduction, which raises questions of when and where it is practiced. Spatial and temporal specifics of tillage practices form important dimensions for development of effective crop management practices and policies. Because Landsat has been and will continue to image the Earth globally, it provides opportunities for systematic mapping of crop residue cover (CRC) /tillage practices. Thus, the overall objective of this study is to develop methodologies to improve our ability to monitor crop management across different landscapes in a time-efficient and cost-effective manner using Landsat TM and ETM+ imagery, which is addressed in three separate studies. The first study found that previous efforts to estimate CRC along a continuum using Landsat-based tillage indices were unsuccessful because they neglected the key temporal changes in agricultural surfaces caused by tilling, planting, and crop emergence at the start of the growing season. The first study addressed this difficulty by extracting minimum values of multi-temporal NDTI (Normalized Difference Tillage Index) spectral profiles, designated here as the minNDTI method. The minNDTI improves crop residue estimation along a continuum ($R^2 = 0.87$) as well as tillage classification accuracy (overall accuracy > 90%). A second study evaluated effectiveness of the minNDTI approach for assessing CRC at multiple locations over several years, and compared minNDTI to hyperspectral tillage index (CAI), and the ASTER tillage index (SINDRI). The minNDTI is effective across four different locations (R^2 of 0.56 ~ 0.93). The third study, built upon the second study, addressed the Landsat ETM+ missing data issue, and devised methodologies for producing field-level tillage data at broad scales (multiple counties). In summary, this research demonstrates that the minNDTI technique is currently the best alternative for monitoring CRC and tillage practices from space, and provides a foundation for monitoring crop residue cover at broad spatial and temporal scales.

Acknowledgements

I am so blessed to have met so many wonderful, amazing, people during the past four years. Thank you all for being a part of my life as a graduate student at Virginia Tech (VT). Despite many stressful and exhausting moments, I very much enjoyed my research, teaching, and working (& hanging out) with VT faculties and fellow students. If you asked me how much I like graduate school, I would tell you that I like it a lot, because first, and most importantly, I am extremely lucky to have the best advisor in the world, who unconditionally inspires, supports, and cares about me so much. Jim is not only a mentor; he is also a friend who always brings the best out of me. Jim, thank you for everything you have done for me!

Secondly, I have three amazing committee members who are incredibly knowledgeable and helpful. Thank you all for your time and valuable contributions to my research! I would also like to thank Lin Li (IUPUI), Guy Serbin (InuTeq), Craig S. T. Daughtry (USDA), and Bill Carstensen (Geography Department Head) for their generous support of my research.

Thirdly, I have developed friendships that will last a lifetime. Thank you, both old and new friends, for sharing happiness and sadness. Thank you for always standing by my side.

Last but not least, I would like to thank my parents for their endless love! Thank you for supporting me in every decision I have made, although you don't know English and you don't know much about my research.

Baojuan

Table of Contents

ABSTRACT	ii
Acknowledgements	iii
Table of Contents	iv
List of Tables	vi
List of Figures	vii

Chapter 1 Introduction.....	1
1. Research Context and Justification	1
2. Dissertation Components, Attribution, and Research Objectives.....	3
References	5

Chapter 2 Remote Sensing of Crop Residue Cover Using Multi-temporal Landsat

Imagery	6
Abstract	7
1. Introduction.....	7
2. Remote Sensing Imagery for Crop Residue Detection	8
3. Study Area and Data	9
4. Methods.....	9
5. Results.....	10
6. Discussion	12
7. Conclusions.....	12
Acknowledgements.....	13
References	13

Chapter 3 Multi-temporal remote sensing of crop residue cover and tillage

practices: A validation of the minNDTI strategy in the United States	14
Abstract	15
1. Introduction.....	16
2. Remote Sensing Tillage	20
2.1 Tillage Indices	20
2.2 Confounding Issues	21
3. Materials and Methods.....	22

3.1	Study Sites	22
3.2	Crop Residue and Remotely Sensed Data	23
3.3	Tillage Indices and Methods.....	23
4.	Results and Discussion	25
4.1	Time-series NDTI.....	25
4.2	minNDTI	26
4.3	minNDTI, CAI, and SINDRI	30
5.	Summary and Conclusions	31
	References.....	33

Chapter 4 Broad-scale monitoring of tillage practices using sequential Landsat

imagery.....	50
Abstract	51
1. Introduction.....	52
2. Landsat 7 ETM+ Data Issue	54
3. Multiresolution Segmentation.....	56
4. Methods.....	57
4.1 Procedures of Gap-filling NDTI Layers	57
4.2 Gap-fill Validation	59
4.3 Tillage Map Generation	60
4.4 Tillage Map Validation	61
5. Results.....	62
5.1 Segmentation Maps.....	62
5.2 Gap-filled vs. Actual NDTI Values	63
5.3 County Tillage Maps.....	64
6. Discussion	65
7. Conclusions.....	69
Acknowledgement	70
References.....	71

Chapter 5 Conclusions..... 112

References.....	116
-----------------	-----

List of Tables

Table 1. Satellite-based tillage indices.....	8
Table 2. 2010 Indiana Crop Progress (Indiana Crop and Weather Report, 2010).....	10
Table 3. Error matrix for three residue cover classes using simple linear regression for test dataset.	11
Table 4. Error matrix for three residue cover classes using simple linear regression for all dataset.	12
Table 5. Error matrix for three residue cover classes using the percentage change method.	12
Table 6. Summary of Landsat 5 TM and 7 ETM+ scenes available for Central Indiana.	12
Table 3.1. Acquisition dates for field, Landsat, airborne hyperspectral, and ASTER data.	39
Table 3.2. Linear regressions of minNDTI and crop residue cover and overall classification accuracy for three categories of tillage intensity. Local models were calibrated and validated for each location. The regional model (Zheng et al. 2012) was used to predict crop residue cover and tillage intensity.	40
Table 3.3. Comparisons of minNDTI, CAI, and SINDRI for estimating crop residue cover and soil tillage categories.	41
Table 4.1. Comparison between remote sensing and CTIC tillage data at county level. .	76
Table 4.2. Tasseled cap image dates and characteristics of segmentation maps.	102
Table 4.3. Results of the gap-fill validation using the multi-scale object-based method.	103
Table 4.4. Overall classification accuracy for three tillage categories.	104

List of Figures

Figure 1. Pictures of agricultural fields: Before tillage (A), after tillage/planting with no or little vegetation (B&C), and crop emergence (D).	8
Figure 2. Locations of sampling sites in Central Indiana.	9
Figure 3. Comparison of time-series NDTI and NDVI values from the same pixel: non-conservation tillage (left); conservation tillage (right).	10
Figure 4. Comparison of time-series NDTI values with different levels of CRC. The magnitude of change in NDTI differs depending on the type of tillage practice – i.e., upon the amount of CRC left on the ground. In this instance, the tillage practice was applied around day 129 (May 9), as is highlighted in the graph. Daily precipitation data (NOAA Cooperative Station 126340, Noblesville 3 W) are also included.	10
Figure 5. Crop residue cover (CRC) as a function of minimum NDTI extracted from the time-series of Landsat images (calibration dataset: $n = 31$).	11
Figure 6. Measured vs. predicted crop residue cover (test dataset: $n = 32$).	11
Figure 7. Crop residue cover (CRC) as a function of minimum NDTI extracted from the time-series of Landsat images ($n = 63$).	11
Figure 8. The correlation between crop residue cover (CRC) and percentage change (PC) of NDTI ($n = 63$). Green dots: correctly classified as $CRC > 70\%$ ($PC < 40\%$); Blue dots: correctly classified as $30\% < CRC < 70\%$ ($40\% < PC < 70\%$); Orange dots: correctly classified as $CRC < 30\%$ ($PC > 70\%$); Red dots: misclassification.	12
Figure 3.1. Locations of the four validation sites discussed in this study and the Noblesville, IN site used by Zheng et al. (2012).	42
Figure 3.2. Kettles (prairie potholes) highlighted by white arrows in Ames, Iowa sites (A) and depressions in Fulton, Indiana site (B). Negative minNDTI values (white dots) were measured in the low-lying areas. Elevations of black dots (corresponding to positive minNDTI values) are about 1 meter higher than those of white dots (B). (Source: $42^{\circ}18'45.22''N$ & $93^{\circ}33'40.86''W$, April 14, 2008, USDA Farm Service Agency & 2012 DigitalGlobe (A); $41^{\circ}00'40''N$, $86^{\circ}18'50''W$, March 1, 2005, IndianaMap Framework Data (B), Google Earth , retrieved on January 8, 2012).....	43

Figure 3.3. NDTI and NDVI values of a sampling point with 59% crop residue cover (CRC) change over the time period of 2007 planting season in Centreville, MD. Highlighted areas indicate field acquisition dates (left) and the time (right) when NDTI drops abruptly to 0.028. The field data were collected too early to capture the correct tillage status which should be determined after day 136.	44
Figure 3.4. Time-series NDTI spectral profiles for each dataset with different levels of field-measured crop residue cover (CRC). minNDTI values were highlighted using solid symbols.	45
Figure 3.5. Crop residue cover (CRC) as a function of minNDTI for local calibration datasets.	46
Figure 3.6. Measured vs. predicted crop residue cover (CRC) for local test datasets.	47
Figure 3.7. Measured vs. predicted crop residue cover (CRC) for regional model.	48
Figure 3.8. Crop residue cover (CRC) as a function of minNDTI, CAI, and SINDRI. ...	49
Figure 4.1. Flow diagram of the multi-scale object based approach (*TC = first three layers of tasseled cap imagery).	105
Figure 4.2. Segmentation results for scales 10 and 15 with/without buffer. Segment boundaries (white) are overlaid on tasseled cap images in layer 1-2-3 color combination mode.	106
Figure 4.3. Sample NDTI layers for gap-filled validation: a) Landsat TM NDTI layer acquired on April 26, 2006 (location: upper-left corner of Champaign County in IL); b) NDTI layer with simulated data gap; c) gap-filled NDTI layer; white arrow points to areas with large predicted errors due to poorly defined field boundaries.	107
Figure 4.4. Flow diagram of the tillage map generation procedure.	108
Figure 4.5. NDTI SLC-off layers with overlaid segmentation maps (orange lines). Here the gap width is approximately ten pixels for IL site and nine pixels for MD site. Red circled regions show examples of small objects that are positioned completely within the gap.	109
Figure 4.6. Scatter plots of predicted and actual NDTI values. NDTI values were scaled by 10,000.	110
Figure 4.7. Tillage maps of Champaign County, IL (2006) and Marshall County, IA (2007). Non-conservation tillage practice dominated in Champaign County in 2006, but was rarely applied by farmers in Marshall County in 2007.	111

Chapter 1 Introduction

1. Research Context and Justification

Global population growth and increasing demands for food, goods, and energy create significant pressures on the environment (Kiers et al., 2008). Worldwide, the FAO (2011) estimates that approximately one billion people are undernourished, and events such as the severe and widespread drought conditions in the United States in 2012 illustrate the vulnerability of our current food security situation. We are facing incredible challenges to feed the world's population and to simultaneously maintain, and improve environmental conditions (Foley et al., 2011). Although we have successfully increased food production and reduced hunger, agricultural activities have also caused substantial environmental issues, such as CO₂ emission, soil degradation, biodiversity loss, and water degradation due to excessive nutrient leaching (Foley et al., 2011). Thus, sustainable agricultural management plays an important role in the world's food security and environmental conservation. Crop residue management, one of agriculture's most important conservation management in agriculture, has been deployed in many countries around the world to reduce soil erosion, labor input, and fuel consumption, and to enhance water use efficiency and soil fertility (Derpsch et al., 2010). Monitoring crop residue management could benefit crop production as well as environmental sustainability because it permits evaluation of management practices and assists designation of effective management plans and policies. Although ground observation of crop residue management is inefficient and expensive, remote sensing techniques permit systematic monitoring of the management effectively and efficiently over large areas.

The goal of this research is to improve our ability to monitor crop residue management using remote sensing techniques. The availability of large-scale crop residue management data allows analysis of coherent spatial patterns that could lead to a better understanding of the interactions among management, crop yields, and the environment. To forge sustainable solutions to meet the world's food security, monitoring agricultural activities is strongly demanded.

Monitoring crop residue management from space has encountered difficulties because there are no optical sensors designed to have specific spectral, spatial, and temporal resolutions for this task. We need to consider which spectral region is optimal to detect crop residues, in other words, to differentiate crop residues from other objects. We need to determine the appropriate spatial resolution. In this case, coarse spatial resolution remote sensing imagery, such as MODIS (Moderate Resolution Imaging Spectroradiometer), is not suitable for this task because of mixed-pixel problems arising from its coarse spatial resolution relative to most agricultural patterns. We also need to consider the availability of imagery for a specific region within a certain time period. Taking all these factors into account, Landsat TM (Thematic Mapper) & ETM+ (Enhanced Thematic Mapper) imagery offers the best potential for continuous crop residue monitoring over large areas. Landsat imagery provides a long-term synoptic view of the Earth at 30-meter spatial resolution. Because it is freely available to everybody, there are numerous studies on crop residue mapping using Landsat TM/ETM+ imagery. Although early studies were able to differentiate two broad tillage categories using logistic regression on a single Landsat image (Sullivan et al., 2008; Thoma et al., 2004; van Deventer et al., 1997), they failed to estimate crop residue cover along a continuum

(Daughtry et al., 2006). These studies focused on examining the correlation between the spectral data and crop residue cover, but neglected the temporal component – the timing of crop residue management relative to image acquisitions. This study, thus, aims to develop methodologies to enhance the capability of Landsat imagery in estimating crop residue cover, which could form a bridge to global monitoring of crop residue management. The ability to systematically acquire management data over broad regions, then, offers great opportunities to observe and study the spatial patterns and trends in the use of conservation tillage, and its impacts on food production and our environment.

2. Dissertation Components, Attribution, and Research Objectives

This dissertation is composed of three manuscript chapters prepared for submission to peer-reviewed academic journals. The three manuscripts present a progressive study of tillage mapping using multi-temporal Landsat imagery. The first manuscript (Chapter 2) develops a technique to improve mapping accuracy of crop residue cover and tillage categories using Landsat imagery. This manuscript with coauthors Dr. James B. Campbell (chair) and Dr. Kirsten M. de Beurs (committee member) was published in *Remote Sensing of Environment* in February 2012. The second manuscript (Chapter 3) tested the effectiveness of the technique at four different locations over several years, and compared the effectiveness of this technique to previous techniques that used Hyperion and ASTER remotely sensed data. This manuscript with coauthors Dr. James B. Campbell (chair), Dr. Guy Serbin (a GIS analyst at InuTeq LLC, Washington, DC), and Dr. Craig S.T. Daughtry (a research agronomist at USDA-ARS Hydrology and Remote Sensing Laboratory, Beltsville, MD) was accepted for publication in the *Journal of Soil and Water Conservation*. The third manuscript (Chapter 4), which

built upon the second manuscript, addressed Landsat 7 ETM+ SLC-off data issues and devised an object-based methodology to generate field-level tillage maps at a broader scale. This manuscript with coauthors Dr. James B. Campbell (chair), Dr. Yang Shao, and Dr. Randolph H. Wynne (committee member) was submitted to *ISRPS Journal of Photogrammetry and Remote Sensing*. Together, these three manuscripts present a progressive study of remote sensing of crop residue cover and tillage practices.

References

- Daughtry, C.S.T., 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 and Tillage Research* 91, 101-108.
- Derpsch, R., Friedrich, T., Kassam, A., Li, H., 2010. Current status of adoption of no-till farming in the world and some of its main benefits. *International Journal of Agricultural and Biological Engineering* 3, 1-23.
- FAO, 2011. The State of Food Insecurity in the World 2011: How does international price volatility affect domestic economies and food security. Food and Agriculture Organization of the United Nations, Rome.
- Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., Tilman, D., Zaks, D.P.M., 2011. Solutions for a cultivated planet. *Nature* 478, 337-342.
- Kiers, E.T., Leakey, R.R.B., Izac, A.-M., Heinemann, J.A., Rosenthal, E., Nathan, D., Jiggins, J., 2008. Agriculture at a Crossroads. *Science* 320, 320-321.
- Sullivan, D.G., Strickland, T.C., Masters, M.H., 2008. Satellite mapping of conservation tillage adoption in the Little River experimental watershed, Georgia. *Journal of Soil and Water Conservation* 63, 112-119.
- Thoma, D.P., Gupta, S.C., Bauer, M.E., 2004. Evaluation of optical remote sensing models for crop residue cover assessment. *Journal of Soil and Water Conservation* 59, 224-233.
- van Deventer, A.P., Ward, A.D., Gowda, P.H., Lyon, J.G., 1997. Using Thematic Mapper Data to Identify Contrasting Soil Plains and Tillage Practices. *Photogrammetric Engineering & Remote Sensing* 63, 87-93.

Chapter 2 Remote Sensing of Crop Residue Cover Using Multi-temporal Landsat Imagery

Baojuan Zheng ^a, James B. Campbell ^a, and Kirsten M. de Beurs ^{a,b}

^a Department of Geography, Virginia Tech, 115 Major Williams Hall, Blacksburg, VA 24061, USA

^b Department of Geography and Environmental Sustainability, The University of Oklahoma, 100 E. Boyd Street, Norman, OK, USA

Published in *Remote Sensing of Environment*, volume 117, February 2012, pages 177–183, available via <http://www.sciencedirect.com/science/article/pii/S0034425711003439>.

Elsevier grants authors publishing in Elsevier journals rights to include their published journal articles in a thesis or dissertation without needing to seek permission, as stated at <http://www.elsevier.com/wps/find/authorsview.authors/rights>.



Remote sensing of crop residue cover using multi-temporal Landsat imagery

Baojuan Zheng ^{a,*}, James B. Campbell ^a, Kirsten M. de Beurs ^{a,b}

^a Department of Geography, Virginia Tech, 115 Major Williams Hall, Blacksburg, VA 24061, USA

^b Department of Geography and Environmental Sustainability, The University of Oklahoma, 100 E. Boyd Street, Norman, OK, USA

ARTICLE INFO

Article history:

Received 5 August 2011

Received in revised form 26 September 2011

Accepted 29 September 2011

Available online 4 November 2011

Keywords:

Landsat

Remote sensing

Crop residue

Tillage

Normalized difference tillage index

Multi-temporal

ABSTRACT

Tillage practices, which have direct impacts on soil and water quality, have changed dramatically during the past several decades. Tillage information is one of the important inputs for environmental modeling, but the availability of this information is still limited spatially and temporally. Previous studies have encountered difficulties in defining reliable correlations between crop residue cover (CRC) and Landsat-based tillage indices because they neglected the significance of the timing of tillage implementation. This study explores relationships between temporal changes of agricultural surfaces and the normalized difference tillage index (NDTI) in Central Indiana. We found that minimum NDTI (minNDTI) values extracted from multi-temporal NDTI profiles reliably indicate the surface status when tillage or planting occurred. Simple linear regression reveals a coefficient of determination (R^2) of 0.89 between CRC and minNDTI for calibration. In addition, a percentage change (PC) method was tested for classifying CRC into three categories ($CRC < 30\%$; $30\% < CRC < 70\%$; $CRC > 70\%$). Both the minNDTI and PC methods resulted in overall classification accuracies of $> 90\%$, producer's accuracies of 83–100%, and user's accuracies of 75–100%. Our results indicated that both Landsat TM and ETM+ imagery are capable of mapping CRC, however, multi-temporal Landsat imagery is required. To establish a capability for crop residue mapping, designers of future remote sensing platforms should consider increasing temporal resolution.

© 2011 Elsevier Inc. All rights reserved.

1. Introduction

Agricultural best management practices, such as conservation tillage and cover crops, have been adopted widely in recent years. The benefits of conservation tillage are substantial, including improvement of soil and water quality, reduction of soil erosion, and maximization of agricultural water use efficiency (USDA-NRCS, 2001). Reliable and systematic site-specific conservation tillage data do not currently exist, but would form an important resource supporting the evaluation of the effectiveness of these practices.

Non-conservation tillage (intensive/conventional and reduced tillage) leaves less than 30% crop residue cover (CRC), while conservation tillage leaves more than 30% CRC (CTIC, 2010). Current CRC data are not surveyed systematically and vary from one location to another. The USDA Natural Resources Conservation Service (NRCS) collects CRC data visually using a line-transect method (Morrison et al., 1993). The Conservation Technology Information Center (CTIC) provides assessments of conservation tillage practices, but collects data using annual roadside surveys of crop residue levels, which is subjective. Its tillage data are available at county, state, and regional levels. The county-level data were recently aggregated to 8-digit Hydrologic Unit (HU) watersheds (Baker, 2011). The National Agricultural Statistics Service (NASS) data relies on survey respondents and is only available at state

and county level. These inventory data are either too coarse (i.e., they cannot provide field level detail, nor report within-field spatial variability), or are inconsistent, adding more uncertainties in the environmental modeling process. The spatial and temporal gaps in these inventory data restrict our ability to simulate the impact of crop management on water quality or carbon sequestration at broad scales (Jarecki et al., 2005; Saseendran et al., 2007). Thus, there is a strong need to develop methods to monitor agricultural practices over large areas, over time, using consistent methods. Multispectral remote sensing offers an opportunity to systematically obtain information describing crop residues efficiently and objectively over broad areas.

Early attempts to use remote sensing techniques for mapping CRC can be traced back to 1975 (Gausman et al., 1975). Since then, the potential of remote sensing of crop residue has been investigated both in the laboratory and in the field (Biard & Baret, 1997; Daughtry, 2001; Daughtry et al., 1995; Sullivan et al., 2007, 2006). Remote sensing tillage indices, such as the crop residue index multiband (CRIM) (Biard & Baret, 1997), the cellulose absorption index (CAI) (Daughtry, 2001), and crop residue cover index (Sullivan et al., 2006) are designed in the laboratory to amplify the differences in the spectral signals between crop residues and soils (Table 1). Most tillage indices are based on the cellulose and lignin absorption features near 2100 nm. Researchers have applied these tillage indices (Table 1) to airborne (Daughtry et al., 2005) and satellite remote sensing imagery (Daughtry et al., 2006; Gowda et al., 2003; Serbin et al., 2009a; Sullivan et al., 2008; Thoma et al., 2004; van Deventer et al., 1997).

* Corresponding author. Tel.: +1 646 750 7087.

E-mail address: baojuan5@vt.edu (B. Zheng).

Table 1
Satellite-based tillage indices.

Sensor	Tillage index	Formula	Description	Reference
Landsat	CRIM	SM/SR	SM: distance from point M to the soil line; SR: distance between soil and residue lines at point M	Biard & Baret, 1997
	Simple tillage index (STI)	$B5/B7$	B2: Landsat TM/ETM+ band 2; B4: TM/ETM+ band 4; B5: TM/ETM+ band 5; B7: TM/ETM+ band 7;	Van Deventer et al., 1997
	NDTI	$(B5 - B7)/(B5 + B7)$		
	Modified CRC	$(B5 - B2)/(B5 + B2)$		Sullivan et al. (2006)
	NDI5; NDI7	$(B4 - B5)/(B4 + B5);$ $(B4 - B7)/(B4 + B7)$		McNairn and Protz (1993)
Hyperion	CAI	$0.5(R_{2.0} + R_{2.2}) - R_{2.1}$	$R_{2.0}$ and $R_{2.2}$: the reflectance on the shoulders at 2021 nm and 2213 nm	Daughtry et al. (2006)
ASTER	LCA	$100(2 \times B6 - B5 - B8)$	B5, B6, B7, B8: ASTER shortwave infrared bands 5, 6, 7, and 8	Daughtry et al. (2005)
	SINDRI	$(B6 - B7)/(B6 + B7)$		Serbin et al. (2009a)

These previous methods neglect an important factor — the timing of tillage or planting, which can vary greatly from field to field within even small regions. Three different surface conditions can coexist in a single image during the planting season (Fig. 1): before tillage/planting (A), after tillage/planting with no or little vegetation (B&C), and crop emergence (D). Most fields are under condition A at the early planting season and in condition D at the end of the planting season. If there are agricultural fields tilled after an image was acquired, the previous methods would wrongfully designate these fields as no-till. If crops have emerged, the green vegetation is likely to confound the residue cover estimation (Daughtry et al., 2005). Therefore, the methods previously outlined (i.e., single image methods) could be problematic in predicting CRC and cannot be applied broadly. Watts et al. (2009) suggested that the use of higher temporal datasets might better capture surface disturbances in minimum tillage fields. Although Watts et al. (2011) produced better classification accuracy using a five-date Landsat model, a physical relationship between Landsat data and tillage categories was

not defined. Instead they generated classification models with the Random Forest classifier. The objective of this study is to reveal the important role of temporal changes in CRC mapping, and to present a simple and objective method to map CRC using multi-temporal Landsat imagery.

2. Remote sensing imagery for crop residue detection

Accurate mapping of CRC not only requires remotely sensed data with spectral and spatial detail, but also with high temporal resolution. Based on crop residue's unique absorption features near 2100 nm (Daughtry, 2001), past and current satellite remote sensing platforms capable of mapping CRC include Landsat 5 TM and 7 ETM+, EO-1 Hyperion, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and the Moderate Resolution Imaging Spectroradiometer (MODIS). Hyperion imagery, with a narrow swath width (7.5 km), has low temporal coverage because its sensor

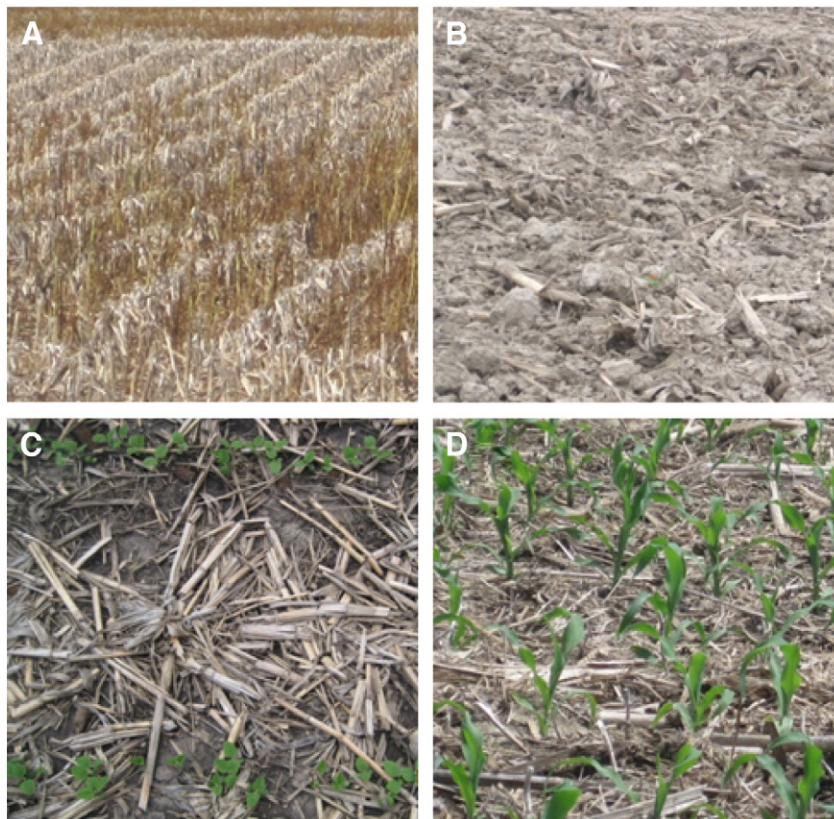


Fig. 1. Pictures of agricultural fields: before tillage (A), after tillage/planting with no or little vegetation (B&C), and crop emergence (D).

is only active when requested. ASTER's shortwave infrared (SWIR) detector failed in April 2008 (NASA, 2011). Thus, subsequently, ASTER imagery is not capable of CRC mapping. MODIS revisits the same area daily; however, MODIS data have coarse spatial resolution (500 m in SWIR bands), so may experience mixed pixel problems for many agricultural landscapes.

Landsat 5 TM and Landsat 7 ETM+ imagery currently provide the best available imagery for mapping CRC, not only because their short-wave infrared (SWIR) Band 7 (2080–2350 nm) is sensitive to crop residue, but also because they provide moderate spatial resolution (30 m) and an eight-day revisit rate using both Landsat 5 and 7.

3. Study area and data

3.1. Study site

This study was conducted in Central Indiana (Fig. 2), one of the most significant agro-ecoregions within the Eastern Corn Belt Plains of the United States. Locations of field data for this study are shown in Fig. 2.

Central Indiana is an extensive agricultural region with flat topography. This landscape is drained by long, shallow, streams occupying sinuous valleys. Agricultural lands often have drainage ditches and channelized streams to promote soil drainage in flat, poorly drained, areas. The principal crops are maize (*Zea mays*) and soybeans (*Glycine max*). Most of the soils of this region are Alfisols, Inceptisols, and Mollisols (Major Land Resource Area [MLRA] 111A). Soil erosion rates in this region are from 7.5 to 4.1 tons per acre from 1982 to 2007 (USDA-NRCS, 2007).

3.2. Field measurements

CRC was measured using a line transect method (Morrison et al., 1993) from May 13 to May 26 in 2010. We used a 50-foot (15.24 m) measuring tape which can be easily divided into 100 parts with 0.5-foot intervals shown as red markings. At each sampling site, the tape

was stretched diagonally across the rows (NRCS, 1992) and the number of markings intersecting crop residue was counted. Then we measured off diagonal and counted the number of markings intersecting crop residue again. Percent cover was calculated by the average of the two counted numbers of the markings. In addition, we used a Garmin eTrex GPS unit (positional accuracy of <15 m) to record the location of each measurement, acquired photographs, and made notes for each sampling site. We measured a total of 72 fields using the line transect method, among which 44 fields were planted with corn and 28 fields with soybean in 2009 with the confirmation of a cropland data layer (<http://www.nass.usda.gov/research/Cropland/SARS1a.htm>). We found that 17 of the 28 soybean fields displayed a mixture of corn and soybean residue.

3.3. Remotely sensed data

Five Landsat images (Path 21/Row 32) acquired on March 30 (ETM+ 7), April 15 (ETM+ 7), May 9 (TM 5), May 25 (TM 5), and June 10 (TM 5) in 2010 were atmospherically corrected to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al., 2006). Images acquired on May 9 and 25 are partially covered by clouds and cloud shadows. The Landsat 7 ETM+ images are scan line corrector (SLC)-off and have data gaps. Serbin et al. (2009b) compared several Landsat-based tillage indices and found that the Normalized Difference Tillage index (NDTI) was the best for separating crop residue and soil. Thus, we generated NDTI layers for each surface reflectance image and stacked the images into a time-series of NDTI image.

4. Methods

Multi-temporal Landsat imagery can capture agricultural changes during the spring planting season. Fig. 3 shows both the changes of Normalized Difference Vegetation Index (NDVI) and NDTI for our study region in Indiana between March 30 (day 89) and June 10 (day 161) in 2010. NDVI and NDTI are positively correlated with the

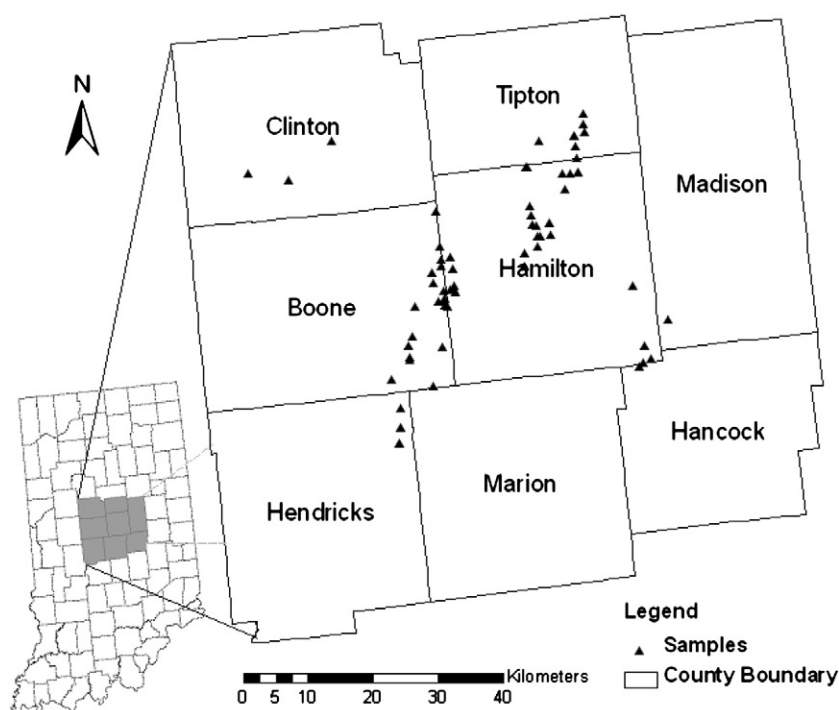


Fig. 2. Locations of sampling sites in Central Indiana.

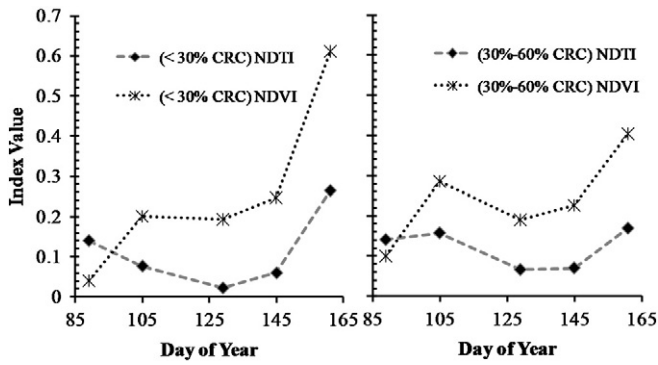


Fig. 3. Comparison of time-series NDTI and NDVI values from the same pixel: non-conservation tillage (left); conservation tillage (right).

green vegetation cover and CRC respectively. The decrease in NDTI values from day 89 to day 129 (Fig. 3) corresponds to the decrease of CRC due to residue weathering and tillage application on the field, while the rebound of NDTI values after day 129 is caused by growing vegetation. Thus, NDTI values are affected by greening vegetation. Fig. 4 shows how the NDTI values change through time from March 30 (day 89) to June 10 (day 161) in 2010 for three pixels with different levels of CRC. The abrupt change in NDTI value (the diamond dotted line) from day 105 (NDTI=0.10) to day 129 (NDTI=0.01) (Fig. 4) is due to significant decreases in the amount of CRC (<30%) caused by non-conservation tillage, while the change in NDTI value was less abrupt (e.g., changes from 0.14 to 0.09) when conservation tillage (>30% CRC) was applied to the fields. The increased NDTI value after day 129 (May 9) is caused by growing vegetation. For this specific example, the use of single images acquired on the days 105 or 145 would result in difficulties differentiating conservation from non-conservation tillage. A single image cannot provide reliable assessment of tillage practices because tillage or planting could happen anytime from April to early June in Central Indiana (Table 2), and in the absence of sequential imagery, analysts cannot determine the correct status of a field.

4.1. Minimum NDTI

Due to partial cloud cover in some Landsat images and data gaps in Landsat 7 ETM+ images, samples affected by clouds, cloud shadows,

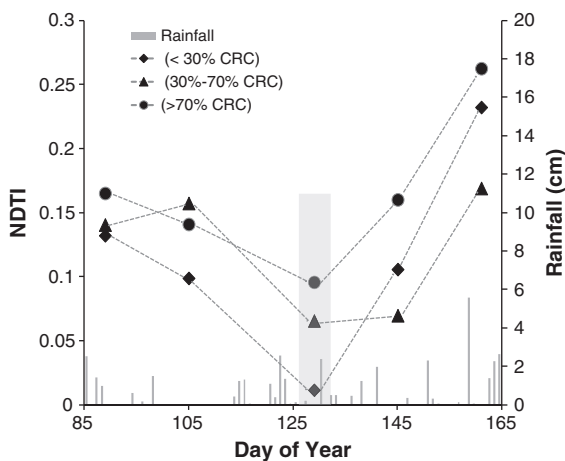


Fig. 4. Comparison of time-series NDTI values with different levels of CRC. The magnitude of change in NDTI differs depending on the type of tillage practice — i.e., upon the amount of CRC left on the ground. In this instance, the tillage practice was applied around day 129 (May 9), as is highlighted in the graph. Daily precipitation data (NOAA Cooperative Station 126340, Noblesville 3W) are also included.

Table 2

2010 Indiana crop progress (Indiana Crop and Weather Report, 2010).

Week ending	Corn (%)		Soybean (%)		Precip. ξ (cm)
	planted	Emerged	planted	Emerged	
April 11	1	NA*	NA	NA	3.3
April 18	17	NA	NA	NA	0
April 25	56	5	12	NA	1.3
May 2	71	26	23	NA	3.8
May 9	81	52	35	9	1.9
May 23	88	79	50	34	3.4
May 30	94	86	70	52	1.4
June 6	97	92	81	69	3.2
June 20	100	100	91	85	8.6

*NA: not available.

ξ Precip.: weekly total precipitation for Central Indiana.

and missing data were removed from analysis, resulting in 63 clean samples. The minimum NDTI (minNDTI) values, representing the closest status of the surface condition right after planting, were chosen from each spectral profile. We applied simple linear regression (SLR) to determine the relationship between minNDTI and field observed CRC. We first sorted our field observation samples by minNDTI values and divided them into calibration ($n=31$) and test ($n=32$) datasets by selecting every other sample to ensure representative subsamples. The regression equation from the calibration dataset was then applied to the test dataset. We divided CRC into three categories: CRC<30% (non-conservation tillage), 30%<CRC<70%, and CRC>70%. Conservation tillage was split into two categories (30%–70% and >70%) to identify fields that were likely managed with no-till (CRC>70%).

4.2. Percentage change method

In the next step, we applied a percentage change (PC) method to map CRC. We first selected the NDTI values before planting for each sample pixel (NDTI_B). NDTI_B was selected according to the following criteria: 1) it must be acquired before the minNDTI occurred; and 2) its value should be larger than 0.08 because some fields may have experienced several tillage operations at different times before planting. Note that the selection criteria for NDTI_B may be different for other regions.

The rationale for the PC method is to detect changes of the same pixel from time I (before tillage) to time II (after tillage/planting). The PC is calculated by

$$(\text{NDTI}_B - \text{minNDTI}) / \text{NDTI}_B \times 100\% \quad (1)$$

The magnitude of change in NDTI is different for different tillage types (Fig. 4). This method is unique in its ease of use, ability to minimize effects of soil variation, and to map tillage practices over broad regions. It requires less field validation effort, and can be applied retrospectively to archived imagery, as well as those acquired in the future.

5. Results

5.1. Minimum NDTI

We found a linear relationship between CRC and minNDTI with a coefficient of determination (R^2) of 0.89 and root mean square of error (RMSE) of 10.5% for the calibration data (Fig. 5). The R^2 between measured and predicted CRC is 0.85 and RMSE is 12.6% for the test dataset (Fig. 6). The slope is 1.05 when the intercept was forced to zero. The SLR results in an R^2 of 0.87 between CRC and minNDTI and RMSE of 11.5% using all 63 samples (Fig. 7).

Tables 3 and 4 show error matrixes for the three residue cover categories using SLR for the test dataset and the complete dataset

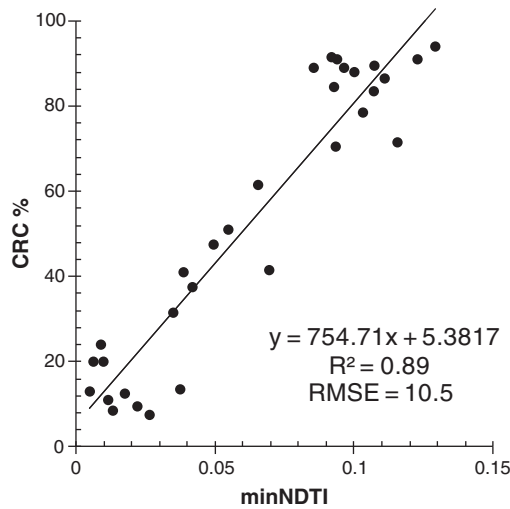


Fig. 5. Crop residue cover (CRC) as a function of minimum NDTI extracted from the time-series of Landsat images (calibration dataset: $n = 31$).

respectively. The overall accuracy is better than 90% and the Kappa coefficient (K) is 85% for both datasets. The K of 85% suggests that the classification accuracy is 85% better than chance alone. The user's accuracies are 72–100%, while the producer's accuracies are 83–100% for discriminating among three categories.

5.2. Percentage change method

The high correlation between PC values and the CRC ($R^2 = 0.80$) (Fig. 8) demonstrates the potential of this PC method for mapping CRC. Fig. 8 shows that the correct classification of classes with more than 70% CRC (green dots), more than 30% and less than 70% CRC (blue dots), and less than 30% CRC (yellow dots). Misclassification is shown in red dots. According to Fig. 8, we determined that the classification rules for this study area are as follows: pixels that reveal a PC less than 40% are assigned to class $CRC > 70\%$; pixels with a PC larger than 40% but smaller than 70% are classified as $30\% < CRC < 70\%$; and pixels with more than 70% change are assigned to non-conservation tillage ($CRC < 30\%$).

The error matrix using the PC method is shown in Table 5. Compared to Table 4, the PC method resulted in the same overall accuracy and K . However, the user's accuracy of the class, $30\% < CRC < 70\%$, is slightly lower than that of minNDTI. We evaluated the difference between the two classification accuracies using the minNDTI and PC methods using McNemar's test (Agresti, 1996; Foody, 2004) and

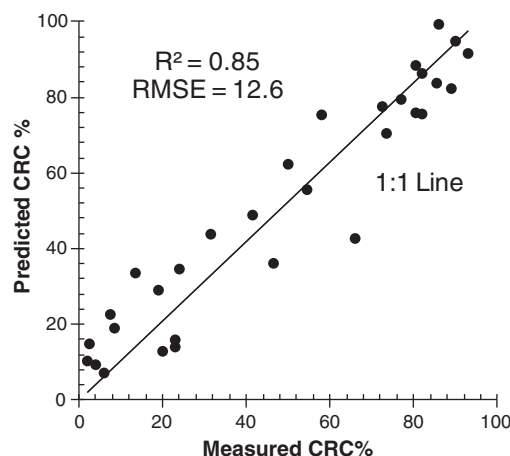


Fig. 6. Measured vs. predicted crop residue cover (test dataset: $n = 32$).

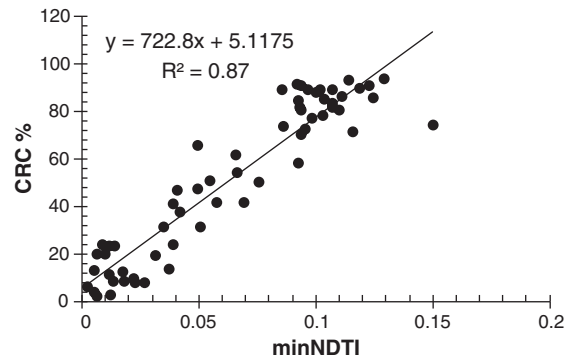


Fig. 7. Crop residue cover (CRC) as a function of minimum NDTI extracted from the time-series of Landsat images ($n = 63$).

found no significant difference between two classification results ($z = 0.38 < 1.96$).

6. Discussion

Both minNDTI and PC methods were able to classify CRC into three categories. minNDTI improves both continuous range mapping as well as categorical classification depending on user needs. Previous studies either classified CRC into two categories to achieve higher prediction accuracy (Gowda et al., 2001; Thoma et al., 2004), or found low correlations between tillage indices and CRC (Daughtry et al., 2006) using Landsat-based indices. The R^2 of 0.11 between CRC and NDTI reported by Daughtry et al. (2006) is probably because their Landsat image was acquired on June 12 when most crops had emerged and confounded the NDTI signal. Other studies (Daughtry et al., 2005; Serbin et al., 2009b) suggested exclusion of pixels with green vegetation from the analysis, especially for Landsat-based tillage indices. Hyperspectral tillage indices are more effective for mapping CRC than Landsat-based indices (Daughtry et al., 2005) because their narrow bands are more sensitive to crop residue and less sensitive to presence of green vegetation (Serbin et al., 2009b). Nevertheless, pixels with green vegetation should be masked out using NDVI or other vegetation indices as suggested by Daughtry et al. (2005). Variation in soil moisture content may have negative effect on mapping CRC (Daughtry & Hunt, 2008), but unfortunately, we don't have soil moisture data to examine the effect of soil moisture on our methods. No heavy rainfall happened immediately before our image dates (Fig. 4). Therefore, there is no indication here that soil moisture influences NDTI values.

Extracting minNDTI values from multi-temporal profiles can reduce unmapped areas because this method can eliminate effects of green vegetation and avoid consideration of areas that farmers have not tilled yet. Watts et al. (2011) discovered that tillage classification accuracy was better using all five available Landsat images instead of

Table 3

Error matrix for three residue cover classes using simple linear regression for test dataset.

Classification data	Reference data			Total	User accuracy
	CRC < 30%	30% < CRC < 70%	CRC > 70%		
CRC < 30%	10	0	0	10	100%
30% < CRC < 70%	2	6	0	8	75%
CRC > 70%	0	1	13	14	93%
Total	12	7	13	32	
Producer's accuracy	83%	86%	100%		

Overall accuracy: 91%; Kappa coefficient: 85%. Bold data are the number of pixels correctly assigned to each class.

Table 4

Error matrix for three residue cover classes using simple linear regression for all dataset.

Classification data	Reference data				
	CRC<30%	30%<CRC<70%	CRC>70%	Total	User accuracy
CRC<30%	19	0	0	19	100%
30%<CRC<70%	3	13	2	18	72%
CRC>70%	0	1	25	26	96%
Total	22	14	27	63	
Producer's accuracy	86%	93%	93%		

Overall accuracy: 90%; Kappa coefficient: 85%. Bold data are the number of pixels correctly assigned to each class.

using a single-date image, and demonstrated the importance of temporal frequency in tillage mapping.

Our methods are simple and can be easily adopted by others. The physical relationship is well explained by the SLR. Reflectance values at band 7 (2080–2350 nm) of TM/ETM+ images decrease as CRC increases because crop residues have absorption features near 2100 nm (Daughtry, 2001). Thus, the NDTI has a positive linear relationship with CRC. Other non-linear methods, such as Artificial Neural Networks (Sudheer et al., 2010), should also take into account temporal changes of agricultural surfaces when mapping tillage practices. Under similar soil moisture conditions, the PC method can mitigate soil color variation that could confound both single and multi-date approaches. The 40% break point of the PC method maximizes the classification accuracy for our study site. Logically, the break point should be 30%. The extra amount of change is probably due to residue weathering. Thus, one may adjust this value between 30 and 40% regionally. However, further investigation is needed to confirm the causes.

Currently, image availability is one of the most important factors that constrains our ability to map CRC broadly. Landsat provides global coverage at 30 meter spatial resolution. Multi-temporal Landsat imagery is required to map CRC because its tillage indices can be biased by any green vegetation (Serbin et al., 2009b). Multi-temporal methods for mapping CRC are subject to failure with insufficient temporal coverage of remotely sensed data. Watts et al. (2011) demonstrated the potential of STARFM-based synthetic dataset for mapping tillage practices, which is a potential solution for the lack of availability of cloud-free Landsat imagery. The planned version 2.0 of Web-enabled Landsat Data (WELD) (Roy et al., 2010) could be another source of gap-free Landsat 7 ETM+ data. Our study area includes

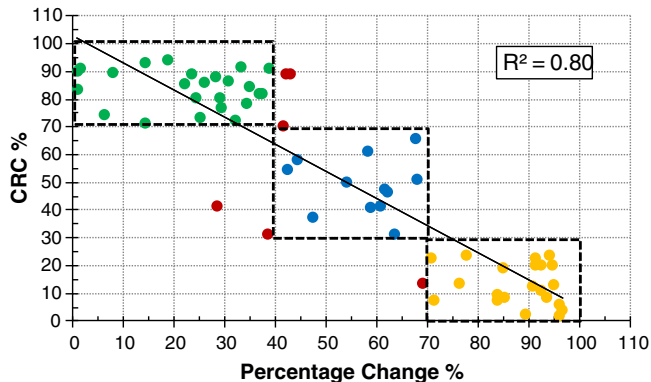


Fig. 8. The correlation between crop residue cover (CRC) and percentage change (PC) of NDTI ($n = 63$). Green dots: correctly classified as CRC > 70% (PC < 40%); blue dots: correctly classified as 30% < CRC < 70% (40% < PC < 70%); orange dots: correctly classified as CRC < 30% (PC > 70%); red dots: misclassification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5

Error matrix for three residue cover classes using the percentage change method.

Classification data	Reference data				
	CRC<30%	30%<CRC<70%	CRC>70%	Total	User accuracy
CRC<30%	21	0	0	21	100%
30%<CRC<70%	1	12	3	16	75%
CRC>70%	0	2	24	26	92%
Total	22	14	27	63	
Producer's accuracy	95%	86%	89%		

Overall accuracy: 90%; Kappa coefficient: 85%. Bold data are the number of pixels correctly assigned to each class.

ample Landsat 5 TM and 7 ETM+ scenes to support a temporal analysis for most of the years from 1999 to 2010 (Table 6). Table 6 illustrates the availability of Landsat data. Years with more than four Landsat scenes have a higher chance of success for mapping CRC accurately. Further studies are required to test the transferability of our method to new scenes.

7. Conclusions

Availability of practical and reliable methods for monitoring practice of tillage will reduce uncertainty in ecosystem models and permit identification of areas at risk for soil erosion and nutrient losses. Remote sensing is an efficient and cost-effective way to obtain information concerning CRC/tillage practices. Mapping tillage practices using single-date images could be problematic unless the area has very narrow window of planting dates. Watts et al. (2011) showed that incorporating high temporal datasets can improve mapping accuracy of conservation tillage. Our study supports the findings by Watts et al. (2011) that temporal resolution plays a significant role in mapping CRC/tillage practices accurately. Multi-temporal analyses (minNDTI and PC methods) are able to classify tillage categories and predict CRC along a continuum more accurately. Time-series of Landsat imagery have the potential to map CRC at broad scales and fill the temporal data gaps in the observation of tillage practices. The Landsat Data Continuity Mission (LDCM) will provide the opportunity for continuously mapping the Earth's continental surface. The Hyperspectral Infrared Imager (HyspIRI) mission will provide another opportunity for mapping crop residue with the global coverage and 60 meter spatial resolution. However, a 19-day revisit time of HyspIRI may not be short enough to provide two to three cloud-free images during planting season. Future remote sensing platforms should consider improvement of temporal resolution for crop residue detection.

Table 6

Summary of Landsat 5 TM and 7 ETM+ scenes available for Central Indiana.

Year	Image acquisition date	Total images [§]
2010	30-Mar*, 15-Apr*, 9-May, 25-May, 10-Jun	5
2009	4-Apr, 12-Apr*, 22-May, 23-Jun	4
2007	30-Mar, 15-Apr, 1-May, 2-Jun	4
2006	4-Apr*, 28-Apr, 6-May*, 22-May*, 30-May	5
2005	24-Mar, 9-Apr, 25-Apr, 11-May, 27-May	5
2004	14-Apr*, 8-May, 1-Jun*	3
2003	12-Apr*, 28-Apr*, 6-May, 22-May, 23-Jun	5
2002	25-Apr*, 3-May, 20-Jun	3
2001	21-Mar*, 14-Apr, 30-Apr, 8-May*, 9-Jun*, 17-Jun	6
2000	26-Mar, 27-Apr, 13-May, 29-May, 6-Jun*	5
1999	24-Mar, 25-Apr, 11-May, 27-May	4

*Images from Landsat 7 ETM+ archive.

[§]Total: total number of images; the average cloud cover of all the images is 7.43%.

Acknowledgements

This project was funded by the Graduate Research Development Program (GRDP) at Virginia Tech and Virginia Tech Geography Department's Sidman P. Poole Scholarship. The authors would like to thank the remote sensing team from IUPUI and Kai Wang for assisting data collection.

References

- Agresti, A. (1996). *An introduction to categorical data analysis*. New York, N.Y.: Wiley.
- Baker, N. T. (2011). Tillage practices in the Conterminous United States, 1989–2004-datasets aggregated by watershed. *United State Geological Survey Data Series*, 573. (pp. 13).
- Biard, F., & Baret, F. (1997). Crop residue estimation using multiband reflectance. *Remote Sensing of Environment*, 59, 530–536.
- CTIC (2010). *National survey of conservation tillage practices*. West Lafayette, IN: Conservation Technology Information Center Retrieved February, 2010, from <http://www.conservationinformation.org/pdf/TillageDefinitions.pdf>.
- Daughtry, C. S. T. (2001). Discriminating crop residues from soil by shortwave infrared reflectance. *Agronomy Journal*, 93, 125–131.
- Daughtry, C. S. T., Doraiswamy, P. C., Hunt, E. R., Jr., Stern, A. J., McMurtrey, J. E., III, & Prueger, J. H. (2006). Remote sensing of crop residue cover and soil tillage intensity. *Soil and Tillage Research*, 91, 101–108.
- Daughtry, C. S. T., & Hunt, E. R., Jr. (2008). Mitigating the effects of soil and residue water contents on remotely sensed estimates of crop residue cover. *Remote Sensing of Environment*, 112(4), 1647–1657.
- Daughtry, C. S. T., Hunt, E. R., Jr., Doraiswamy, P. C., & McMurtrey, J. E., III (2005). Remote sensing the spatial distribution of crop residues. *Agronomy Journal*, 97, 864–871.
- Daughtry, C. S. T., McMurtrey, J. E., III, Chappelle, E. W., Dulaney, W. P., Irons, J. R., & Satterwhite, M. B. (1995). Potential for discriminating crop residues from soil by reflectance and fluorescence. *Agronomy Journal*, 87, 165–171.
- Foody, G. M. (2004). Thematic map comparison: Evaluating the statistical significance of differences in classification accuracy. *Photogrammetric Engineering and Remote Sensing*, 70, 627–633.
- Gausman, H. W., Gerbermann, A. H., Wiegand, C. L., Leamer, R. W., Rodriguez, R. R., & Noriega, J. R. (1975). Reflectance differences between crop residues and bare soils. *Soil Science Society of America Journal*, 39, 752–755.
- Gowda, P. H., Dalzell, B. J., Mulla, D. J., & Kollman, F. (2001). Mapping tillage practices with landstat thematic mapper based logistic regression models. *Journal of Soil and Water Conservation*, 56, 91–96.
- Gowda, P. H., Mulla, D. J., & Dalzell, B. J. (2003). Examining the targeting of conservation tillage practices to steep vs. flat landscapes in the Minnesota River Basin. *Journal of Soil and Water Conservation*, 58, 53–57.
- Indiana Crop and Weather Report (2010). USDA National Agricultural Statistics Service. West Lafayette, 60. Retrieved September, 2011, from http://www.nass.usda.gov/Statistics_by_State/Indiana/Publications/Crop_Progress_&_Condition/2010/index10.asp.
- Jarecki, M. K., Lal, R., & James, R. (2005). Crop management effects on soil carbon sequestration on selected farmers' fields in northeastern Ohio. *Soil and Tillage Research*, 81, 265–276.
- Masek, J. G., Vermote, E. F., Saleous, N. E., Wolfe, R., Hall, F. G., Huemmrich, K. F., et al. (2006). A Landsat surface reflectance dataset for North America, 1990–2000. *IEEE Geoscience and Remote Sensing Letters*, 3, 68–72.
- McNairn, H., & Protz, R. (1993). Mapping corn residue cover on agricultural fields in Oxford County, Ontario, using Thematic Mapper. *Canadian Journal of Remote Sensing*, 19, 152–159.
- Morrison, J. E., Huang, C. -H., Lightle, D. T., & Daughtry, C. S. T. (1993). Residue measurement techniques. *Journal of Soil and Water Conservation*, 48, 478–483.
- NASA (2011). ASTER user advisory. Retrieved January, 2011, from <http://asterweb.jpl.nasa.gov/latest.asp>.
- NRCS (1992). Farming with crop residue brochure. Retrieved March 15, 2010, from <http://www.il.nrcs.usda.gov/news/publications/brochures/farmcrops/FarmCropRes-broc.html>.
- Roy, D. P., Ju, J., Kline, K., Scaramuzza, P. L., Kovalsky, V., Hansen, M., et al. (2010). Web-enabled Landsat Data (WELD): Landsat ETM+ composited mosaics of the conterminous United States. *Remote Sensing of Environment*, 114, 35–49.
- Saseendran, S. A., Ma, L., Malone, R., Heilman, P., Ahuja, L. R., Kanwar, R. S., et al. (2007). Simulating management effects on crop production, tile drainage, and water quality using RZWQM-DSSAT. *Geoderma*, 140, 297–309.
- Serbin, G., Daughtry, C. S. T., Hunt, E. R., Jr., Brown, D. J., & McCarty, G. W. (2009). Effect of soil spectral properties on remote sensing of crop residue cover. *Soil Science Society of America Journal*, 73, 1545–1558.
- Serbin, G., Hunt, E. R., Daughtry, C. S. T., McCarty, G., & Doraiswamy, P. (2009). An improved ASTER index for remote sensing of crop residue. *Remote Sensing*, 1, 971–991.
- Sudheer, K. P., Gowda, P., Chaubey, I., & Howell, T. (2010). Artificial neural network approach for mapping contrasting tillage practices. *Remote Sensing*, 2, 579–590.
- Sullivan, D. G., Shaw, J. N., Price, A., & van Santen, E. (2007). Spectral reflectance properties of winter cover crops in the Southeastern Coastal Plain. *Agronomy Journal*, 99, 1587–1596.
- Sullivan, D. G., Strickland, T. C., & Masters, M. H. (2008). Satellite mapping of conservation tillage adoption in the Little River experimental watershed, Georgia. *Journal of Soil and Water Conservation*, 63, 112–119.
- 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. *Agronomy Journal*, 98, 1236–1246.
- Thoma, D. P., Gupta, S. C., & Bauer, M. E. (2004). Evaluation of optical remote sensing models for crop residue cover assessment. *Journal of Soil and Water Conservation*, 59, 224–233.
- USDA-NRCS (2001). *A resources conservation act report*. Interim appraisal and analysis of conservation alternatives.
- USDA-NRCS (2007). 2007 National resources inventory. *Soil erosion on cropland* Retrieved April 10, 2011, from <http://www.nrcs.usda.gov/technical/NRI/2007/nri07erosion.html>.
- van Deventer, A. P., Ward, A. D., Gowda, P. H., & Lyon, J. G. (1997). Using Thematic Mapper data to identify contrasting soil plains and tillage practices. *Photogrammetric Engineering and Remote Sensing*, 63, 87–93.
- Watts, J. D., Lawrence, R. L., Miller, P. R., & Montagne, C. (2009). Monitoring of cropland practices for carbon sequestration purposes in north central Montana by Landsat remote sensing. *Remote Sensing of Environment*, 113, 1843–1852.
- 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 of Environment*, 115, 66–75.

**Chapter 3 Multi-temporal remote sensing of crop residue cover and tillage practices:
A validation of the minNDTI strategy in the United States**

Baojuan Zheng, James B. Campbell, Guy Serbin, and Craig S. T. Daughtry

Baojuan Zheng is a PhD Candidate, Department of Geography, and Geospatial and Environmental Analysis (GEA) program, Virginia Tech, Blacksburg, VA. James B. Campbell is Professor of Geography, Virginia Tech, Blacksburg, VA. Guy Serbin is a Remote Sensing and GIS Analyst at InuTeq LLC, Washington, DC. Craig S.T. Daughtry is a Research Agronomist at USDA-ARS Hydrology and Remote Sensing Laboratory, Beltsville, MD.

Accepted for publication in Journal of Soil and Water Conservation

Abstract

Accurate, site-specific tillage information forms an important dimension for development of effective agricultural management practices and policies. Landsat Thematic Mapper (TM) imagery provides the opportunity for systematic mapping of tillage practices via crop residue (plant litter/ senescent or non-photosynthetic vegetation) cover (CRC) estimation at broad scales because of its repetitive coverage of the Earth's land areas over several decades. This study evaluated the effectiveness of a multi-temporal approach using the minimum values of Normalized Difference Tillage Index (minNDTI) for assessing CRC at multiple locations over several years. Local models were generated for each dataset. In addition, we tested the feasibility of a regional model in mapping CRC. Results show that the minNDTI method was able to estimate CRC and a regional model is possible. We found that in addition to the known impact of emergent green vegetation, soil moisture and organic carbon can also confound the NDTI signal, thereby underestimating CRC for low-lying wet and dark areas. Accuracy of the minNDTI technique is comparable to the hyperspectral Cellulose Absorption Index (CAI) and the ASTER Shortwave Infrared Normalized Difference Residue Index (SINDRI) for tillage classification. This minNDTI technique is currently the best for monitoring CRC and tillage practices from space, opening the door for generating field-level tillage maps at broad spatial and temporal scales.

Key words: multi-temporal—Landsat—remote sensing—crop residue—tillage—minNDTI

1. Introduction

The rapid increase in human population and conversion of natural landscapes to agricultural production has significantly affected the Earth's environment (Brown et al. 2010). Although advances in plant genetics continue to fulfill the Green Revolution's promise of the 1960s to significantly increase food production for feeding growing populations and reducing starvation (Khush 2001), many of these improvements have been achieved at the cost of unfavorable impacts upon the landscape and its soil resources. Increased use of fertilizers and pesticides, coupled with intensive soil tillage practices, can cause serious public health and environmental problems, including soil erosion, nutrient loading into surface water, and disruptions to the local carbon balance (David 1996; Silgram and Shepherd 1999). Thus, sustainable land management also forms a foundation for the world's food security, environmental resources, and human health. To forge better agricultural management policies, monitoring impacts of different farming practices is a must (Sachs et al. 2010). An important parameter for assessment of agricultural impacts upon the landscape is that of crop residue management (CRM), which affects both the amount of soil disturbance and protective aboveground crop residue (plant litter/ non-photosynthetic or senescent vegetation) cover (Causarano et al. 2006).

Crop residues often completely cover the soil surface after harvest, but when the soil is tilled, residue cover decreases. Categories of soil tillage intensity are based on crop residue cover (CRC) after planting. *Intensive (conventional) tillage* leaves less than 15% CRC, while *conservation tillage* leaves at least 30% CRC on the soil surface. *No-till (or strip till) management* usually disturbs < 25% of row width (USDA-NRCS 2006a).

Conservation tillage practices and use of winter cover crops reduce soil losses, increase soil carbon sequestration, and partially mitigate the expected increases of atmospheric CO₂ (Kern and Johnson 1993; Lee et al. 1993; Phillips et al. 1993).

Although the effects of CRM differ spatially and temporally due to local conditions (Guérif et al. 2001), the lack of site-specific crop residue data constrains our ability to evaluate CRM practices over broad spatial extents (Foley et al. 2011; Sachs et al. 2010). Efforts to obtain crop residue data include roadside surveys by the Conservation Technology Information Center (CTIC), surveys of farmers by the National Agricultural Statistics Service (NASS), line-point transect methods by the USDA Natural Resources Conservation Service (NRCS), and remote sensing techniques (Daughtry et al. 2005; Gausman et al. 1975; Serbin et al. 2009a; Watts et al. 2011). Only remote sensing techniques have the potential to inventory CRC and thus soil tillage intensity in a systematic and cost-effective manner over large areas.

A distinguishing spectral reflectance characteristic of green vegetation is the step-like transition from low reflectance in the visible (400-700 nm) wavelengths to high reflectance in the near infrared (700-1200 nm) wavelengths (Gates et al. 1965). Crop residues lack this spectral feature and are spectrally similar throughout most of the 400-2500 nm wavelength region (Daughtry 2001). However, in the shortwave infrared (SWIR), an absorption feature near 2100 nm associated with cellulose is clearly evident in reflectance spectra of dry crop residues, but is absent in the spectra of soils (Daughtry 2001; Serbin et al. 2009b). Three indices utilizing narrow spectral bands were devised to detect crop residues. The Cellulose Absorption Index (CAI) was devised for hyperspectral sensors and targets the 2100 nm absorption feature (Daughtry 2001). Two

indices were devised for the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) SWIR sensor onboard the NASA Terra spacecraft: the Lignin-Cellulose Absorption (LCA) index (Daughtry et al. 2005), and the Shortwave Infrared Normalized Difference Residue Index (SINDRI) (Serbin et al. 2009a). Serbin et al. (2009a) found that of these two ASTER-based indices, SINDRI fared the best. Unfortunately, the utility of these two indices from existing satellite sensors (e.g., EO-1 Hyperion and Terra ASTER) that have these relatively narrow spectral bands for detecting cellulose absorption features are limited. The Hyperion sensor images narrow swaths (7.5 km), resulting in very limited spatial coverage, and suffers from detector line problems, generating a significant amount of noise and striping, and is now well-beyond its design lifetime (Beck 2003). SINDRI can no longer be acquired from the ASTER SWIR sensor due to detector failure (NASA/JPL 2009). In contrast, the Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) sensors provide the possibility of compiling tillage information for large regions over decadal intervals, including retrospective analysis when suitable coverage is available because it has systematic worldwide coverage since 1982. Furthermore, future TM-like sensors, e.g., the Landsat 8 Operational Land Imager (OLI) (USGS 2010) and the European Space Agency (ESA) Sentinel-2 (ESA 2011), will have similar spectral bands and are currently scheduled for launch in 2013, allowing for continuity of remote tillage assessment.

Research on utilizing Landsat TM and ETM+ sensors for CRC monitoring task has yielded mixed results. Some studies found low, or very low, correlations between Landsat-based tillage indices and CRC field data (Daughtry et al. 2006; Serbin et al. 2009a). Of these, the Normalized Difference Tillage Index (NDTI) (van Deventer et al.

1997) was found to be the most effective (Serbin et al 2009b, 2009c), but was not as effective as CAI, SINDRI, or LCA. In contrast, others concluded that these tillage indices were able to differentiate conventional and conservation tillage using logistic regression (Gowda et al. 2001; Sullivan et al. 2008; van Deventer et al. 1997). Zheng et al (2012) found that these mixed results were caused by inattention to the significance of the temporal dimensions of applications of tillage practices. By extracting the minimum values from time-series of spectral profiles of NDTI values; Zheng et al. (2012) showed an improved accuracy of CRC estimation as well as for tillage mapping. That is, tillage status is most effectively assessed by observing NDTI just before the effects of the emerging crop become evident on the TM imagery, when the differences between conventional and conservation tillage are most evident in the NDTI values. Observations made before implementation of tillage, or after crop emergence, will tend to conceal the correct tillage status of the field.

The ability to provide standardized tillage information can assist assessment of soil conservation, assessment of agricultural management strategies and policies, and reduction of ecosystem modeling uncertainties. Zheng et al. (2012) validated their technique with a single set of field data collected in 2010 for a site in Central Indiana; this study continues evaluation of the minNDTI strategy using four additional validation data sets collected over time in different regions of the United States. This paper addresses the following questions:

- 1) How does the minNDTI method perform when applied to a broader range of soils and landscapes (here designated as “local models”)?

- 2) How well does the Zheng et al. (2012) model transfer to other regions? (For convenience in designation, the Zheng et al. (2012) model is referred as a “regional model” in this paper although, strictly speaking, it is local in nature.)
- 3) Do local models perform better than the regional model?
- 4) How does minNDTI perform compared to the CAI and SINDRI indices?

Investigation of these questions will provide information about the performance of the minNDTI strategy in a wider range of soils and landscapes, will increase our understanding of the constraints and limitations for practical application of the technique, and will provide the basis for its application to survey broader areas of over intervals of several years.

2. Remote Sensing Tillage

2.1 Tillage Indices

Remote sensing spectral indices are designed to amplify useful information on specific targets based on unique absorption and reflectance features of the target. An optimal tillage index is sensitive to crop residue, and insensitive to soil background and green vegetation. This study investigated three tillage indices (i.e., CAI, SINDRI, and NDTI) from hyperspectral, ASTER, and Landsat sensors.

CAI uses three relatively narrow (10 nm) reflectance bands ~ one near 2100 nm (R_{2100}) and one on each shoulder at 2030 and 2210 nm (R_{2030} and R_{2210} , respectively) to estimate CRC (Daughtry 2001):

$$CAI = 100 \times [0.5 \times (R_{2030} + R_{2210}) - R_{2100}] \quad (1)$$

SINDRI utilizes SWIR bands 6 (2185 ~ 2225 nm) and 7 (2235 ~ 2285 nm), which occur along a shoulder of the cellulose absorption feature, to estimate CRC (Serbin et al. 2009a):

$$\text{SINDRI} = (\text{ASTER6} - \text{ASTER7})/(\text{ASTER6} + \text{ASTER7}) \quad (2)$$

NDTI utilizes Landsat TM/ETM+ bands 5 (1550 ~ 1750 nm) and 7 (2080 ~ 2350 nm) to detect the presence of CRC (van Deventer et al. 1997):

$$\text{NDTI} = (\text{TM5} - \text{TM7})/(\text{TM5} + \text{TM7}) \quad (3)$$

CAI, the hyperspectral tillage index, performs the best because its narrow hyperspectral spectral bands capture the cellulose absorption centered at 2100 nm (Serbin et al. 2009c). SINDRI, the best ASTER tillage index, is calculated using bands 6 and 7 where band 6 (2185 ~ 2225 nm) is located on the shoulder of the 2100 nm absorption region (Serbin et al. 2009a, 2009c). NDTI, which incorporates TM band 7 covering spectral region of 2080 to 2350 nm, is the optimal tillage index for Landsat sensors (Serbin et al. 2009c). All three tillage indices used in this paper are based upon use of those bands positioned close to the 2100 nm cellulose absorption.

2.2 Confounding Issues

Tillage index values could be influenced by local soils, presence of green vegetation, and age of residue. The residue absorption decreases as crop residue degrades (Daughtry et al. 2010; Serbin et al. 2009c), but residue weathering was not found to be a major confounding issue in CRC estimation using airborne and satellite imagery. Green vegetation, however, has been shown to have negative effects on CRC estimation (Daughtry et al. 2005; Serbin et al. 2009c; Zheng et al. 2012). Thus, previous research has recommended removal of pixels influenced by the presence of green vegetation as

assessed by use of the Normalized Difference Vegetation Index (NDVI). CAI, SINDRI, and NDTI showed, in sequence, increasing levels of sensitivity to green vegetation (Serbin et al. 2009a, 2009c) because the spectral bands of ASTER and Landsat imagery are wider, and therefore more sensitive to the effects of green vegetation. Variations in surface soil properties can also confound CRC estimation. Daughtry and Hunt (2008) and Serbin et al. (2009c) found that increases in soil water content decrease CAI values under laboratory conditions, and hence, cause underestimation of CRC. However, estimation of CRC was not significantly biased under wet conditions using CAI and SINDRI derived from airborne and satellite remote sensing imagery (Serbin et al. 2009a). CAI values of soils increase from negative to zero as organic carbon increases (Serbin et al. 2009b). Because the spectral resolutions of Landsat bands are coarser, soil water and organic carbon may have stronger impacts on NDTI. Effect of other soil properties can be obtained from Serbin et al. (2009b).

3. Materials and Methods

3.1 Study Sites

Field crop residue data were acquired for four sites located near Ames, Iowa; Pesotum, Illinois; Fulton, Indiana; and Centreville, Maryland (Serbin et al. 2009a) (figure 3.1). The first three sites are within Land Resource Region (LRR) M - Central Feed Grains and Livestock Region, while Centreville, MD falls in LRR T - Atlantic and Gulf Coast Lowland Forest and Crop Region (USDA-NRCS 2006b). Principal crops for all sites are corn (*Zea mays L.*) and soybeans (*Glycine max*), but the MD site also produces winter wheat. Corn/soybean rotations were common. Water erosion, wind erosion, and maintenance of soil organic matter and productivity of soils are the major resource

concerns. Thus, CRM, crop rotation, and cover crops are important conservation practices for these croplands. Land surfaces are mostly level to gently sloping for all sites. However, poorly drained post-glacial kettle (prairie pothole) depressions occur throughout the IA site (MLRA 103) (figure 3.2A) and the IN site (Major Land Resource Area [MLRA] 111C) (figure 3.2B). Serbin et al. (2009a) provided additional descriptions of these sites.

3.2 Crop Residue and Remotely Sensed Data

CRC was measured at two locations within corn and soybean fields using the line-point transect method (Morrison et al. 1993). Table 3.1 shows acquisition dates for field measurements, Landsat, airborne hyperspectral, and ASTER images. Airborne hyperspectral imagery was acquired by SpecTIR LLC (Sparks, NV, USA) for each location (Serbin et al. 2009a). Landsat images (both Landsat TM 5 and ETM 7+) were atmospherically corrected to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al. 2006) and geometrically corrected if positional errors were found. Clouds and cloud shadows were detected and masked as zero values using an object-based detection method (Zhu and Woodcock 2012) for those cloud contaminated Landsat images. All airborne and ASTER images were atmospherically and geometrically corrected (Serbin et al. 2009a).

3.3 Tillage Indices and Methods

CAI (equation 1), SINDRI (equation 2), and NDTI layers (equation 3) were generated from airborne hyperspectral, ASTER images, and Landsat images, respectively. SINDRI values were also calculated using airborne hyperspectral data

which were convolved over the equivalent ASTER band passes using relative spectral response functions when ASTER imagery were unavailable (Serbin et al. 2009a). Thirty-meter buffers were applied to the IA, IN, and IL imagery to extract mean spectral signatures of each sampling point, while 20 m buffers were used for MD imagery due to smaller field sizes. The minNDTI values for each sampling point were extracted from multi-temporal NDTI data (Zheng et al. 2012). Clouds and cloud shadows were excluded from analysis. Although the minNDTI technique has the ability to reduce or eliminate green vegetation effects, rare circumstances such as weeds growing rapidly in the fields before or after planting can occur and confound minNDTI values. Thus, pixels with $NDVI > 0.30$ (Daughtry et al. 2005) at the time of minNDTI were excluded from analysis. Further, we found that tillage status had changed for six MD samples. Field data were acquired in MD when no corn or soybeans were planted (Maryland Crop and Weather Report 2007). Furthermore, the temporal patterns of NDTI and NDVI also suggest that tillage was applied after field acquisition dates for those samples (figure 3.3). Tillage or planting occurred in this field several days before day 136 (May 16) and approximately one month after field data and airborne hyperspectral data acquisition, such that CRC was reduced because NDTI values decreased from 0.078 to 0.028. Because these field data were collected too early to represent the correct tillage status, they are not valid for application of the minNDTI model, and thus, were excluded from our analysis.

We developed local models for each location. Samples were sorted by minNDTI values, and divided into calibration and test datasets by selecting every other sample. Secondly, we applied the Zheng et al. (2012) relationship between minNDTI and CRC:

$$\text{CRC} = 754.7 \times \text{minNDTI} + 5.4 \quad (4)$$

to all four locations to test the effectiveness of applying a regional model in mapping CRC. Lastly, we evaluated minNDTI against CAI and SINDRI. The total number of samples for some datasets is further reduced because some samples fall on non-imaged areas. The performance of each model was evaluated using coefficient of determination (R^2), root-mean-square errors (RMSE), and classification accuracies. In addition, to facilitate use by a wider community of users, tillage status was classified into three classes: $\text{CRC} < 30\%$ (non-conservation tillage), $30\% < \text{CRC} < 70\%$ (conservation tillage), and $\text{CRC} > 70\%$ (conservation tillage – most likely no till). Classification accuracy was assessed using overall accuracy, kappa statistic ($\hat{k}$), and Z-statistic (Z-stat), the last of which is used to test the significance of the classifications (Congalton and Green 2008).

4. Results and Discussion

4.1 Time-series NDTI

The pattern of temporal NDTI spectral profiles varied depending on field surface status and image availability (figure 3.4). Most temporal spectral profiles show a decrease followed by an increase of NDTI values. The decrease in NDTI values not only relates to residue weathering and decreases of CRC due to tillage operations (Zheng et al. 2012), but also corresponds to removal of green vegetation if weeds are present in fields before planting. High NDTI values (> 0.20) of the first four observations in MD 2007 temporal spectral profile ($\text{CRC} = 53\%$ in figure 3.4) are due to the presence of green vegetation, while the first decrease from the third to the sixth observations are likely caused by weed removal. minNDTI values occurred on different image dates (figure 3.4) because the

timing of tillage and planting operations differ from field to field. The majority of the minNDTI values were observed between the first and last Landsat observations that were available to us (figure 3.4). However, because some fields were tilled or planted very early or very late in the planting season, when additional images were not available, minNDTI values of several samples were located at the first (e.g., IA 2007 CRC = 18% in figure 3.4) and last (e.g., IL 2006 CRC = 74% in figure 3.4) observations. Landsat image dates were marked in Table 3.1 if minNDTI of every field sample did not occur on that image. Markers on the first and last image dates indicated good temporal coverage for the purpose of tillage mapping. Despite the differences of time-series NDTI spectral profiles across multiple locations and over several years, the minNDTI technique detects the most correct tillage status.

4.2 minNDTI

Local calibration models show R^2 of 0.66 ~ 0.89 and RMSE of 7.8 ~ 13 (table 3.2). Figure 3.5 shows linear correlations between CRC and minNDTI. R^2 and RMSE range from 0.56 to 0.93, and from 8.4 to 15.1 respectively for local validation models (table 3.2). The slopes and intercepts of local validation models are not significantly different from one and zero respectively for IA and IN sites at the 5% significant level (table 3.2). Figure 3.6 presents the plots of measured CRC and predicted CRC. Overall accuracies for three tillage classes were 0.68 ~ 0.86, while $\hat{k}$ are 0.43 ~ 0.76. Z statistics show that all classifications are significantly better than chance alone at a 95% confidence level ($z = 3.37 \sim 6.69 > 1.96$) (table 3.2). The regional model (equation 4) yielded R^2 of 0.61 ~ 0.91, RMSE of 9.2 ~ 18.8, overall accuracies of 0.69 ~ 0.80, and $\hat{k}$ of 0.44 ~ 0.65 (table 3.2 & figure 3.7). All classifications were significant at a 95%

confidence level ($z = 3.96 \sim 10.99 > 1.96$), however, slopes and intercepts of regional models differ significantly from one and zero respectively at the 5% significant level. Both local and regional models perform best for the IA 2007 dataset, which has the lowest RMSE among the six validations (table 3.2, figures 3.6 & 3.7). Samples with high levels of CRC were mostly underestimated by the regional model in IL, while overestimation occurred for those samples with less than 30% CRC in MD (figure 3.7). The regional model tends to underestimate CRC for most samples of IA 2005, and partial samples of IN 2006 and 2007 datasets. RMSE is generally lower when models are developed locally (table 3.2). Local models result in better classification accuracies with the exception of IA and IN 2007 datasets.

Both the locally developed models and the regional model were effective in assessing tillage status and CRC levels, although specifics of the effectiveness of the two strategies differ. The minNDTI method was able to estimate and classify CRC into three categories for the six datasets. Locally developed models in general predicted CRC more accurately than the regional model. Significant tests for slope of one and intercept of zero suggest that locally tuned models are more robust than the regional model. However, in circumstances of unavailability of field data, the regional model would be able to meet the needs of tillage classifications. The regional model produced better classification accuracies for IA and IN 2007 datasets, due to correct classification of samples with negative minNDTI values (classified as non-conservation tillage) although the regional model underestimated their CRC. These negative minNDTI values were located in low lying areas which are often wetter and darker than other locations (figure 3.2). For the IA site, reported rains hampered spring fieldwork, delaying planting progress, and replanting

of corn and soybean due to flooded soils in 2005 (Iowa Crops and Weather 2005). Thus, we believe that most of the IA 2005 samples underestimated by the regional model were the result of abundant rainfall that increased moisture levels in the surface soil at the time that the image was acquired. Under such wet weather conditions, a local or soil moisture-calibrated model can improve accuracies in mapping CRC (figure 3.6 & table 3.2). The IN site was found to have higher SOC than the others (Serbin et al. 2009a). Samples with negative minNDTI are all poorly drained soils (Soil Survey Staff 2011). Therefore, these negative minNDTI values are likely due to wet and dark soils. Removal of negative values from the analysis for IN sites will improve prediction accuracy, as the other samples fall closely on the 1:1 line (figure 3.7). Results from the IN sites highlight the necessity to separate low-lying wet areas from relatively dry locations for CRC mapping. Application of a regional model for mapping CRC and tillage practices over large areas and over time is possible, but practitioners should be careful with ‘wet’ years and low-lying regions because they increase the risk of underestimation.

Starting and ending dates of a planting season vary across landscapes and over time. The key consideration for applying the minNDTI technique is to have sufficient numbers of Landsat observations to cover the entire planting season at intervals of approximately one or two weeks. For double-cropped or irrigated fields with multiple planting dates, additional sequences will be required for each planting date. An ideal NDTI temporal profile would depict a progressive decrease indicating application of tillage and planting, followed by an increase due to crop emergence (figure 3.3). The *USDA State Crop Progress & Condition Report* (www.nass.usda.gov/Publications/index.asp) can also assist in determination of a good

temporal NDTI profile. For example, according to Iowa 2007 *Crop and Weather Report*, only 8% of corn was planted by April 22, 14% by April 29 (due to heavy rainfall), 53% by May 6 (no emergence reported), 77% by May 13 (36% emerged), and 93% for the week ending on May 20. Therefore, the April 18 image covers the early planting season, the May 12 image was able to map CRC for at least 41% of corn fields which were planted but without crop emergence, the 20 May image was capable of mapping CRC for additional 16% of the corn fields, while the 13 June image covered the end of planting season. An additional image acquired around May 6 might have reduced mapping uncertainties for the 36% emergent corn fields, based on the above information. Weeds and replanting can complicate the NDTI temporal profile, but adequate satellite observations will help detecting these events. The use of NDVI can detect effects from green vegetation upon NDTI values. The tillage status of several samples in MD site changed after acquisition of the field validation data. Thus, for validation data, we suggest selecting fields with evidence of tillage or planting whenever possible. Kettles and small depressions within agricultural fields were found to have lower NDTI values than their surrounding areas due to their high SOC and tendency to accumulate water. An object-based (field-based) method calculating the average NDTI value of all pixels within a field can potentially minimize effects of variation due to elevation and soils, assuming farmers apply the same tillage practices to the entire field. Another option to avoid underestimation of CRC could be exclusion of poorly drained soils from analysis according to soil survey.

These findings highlight the following issues for the use of the minNDTI strategy:

(a) assure that the field observations are collected after planting, (b) screen field data to

detect points that may be influenced either by recent rain, or by low-lying terrain, that may retain moisture even when neighboring well-drained sites may be free of excessive moisture, and (c) verify that field sites are free of emergent vegetation that might contaminate minNDTI values.

4.3 minNDTI, CAI, and SINDRI

The higher R^2 and lower RMSE values suggest that CAI and SINDRI generally perform better than minNDTI (figure 3.8 & table 3.3). However, minNDTI performed slightly better than CAI for IL 2006 and MD 2007 datasets, and outperformed SINDRI for IA 2007 and MD 2007 dataset. SINDRI yielded R^2 of 0.55 and RMSE of 18.8 for MD 2007 dataset, which had the worst agreement between SINDRI and field-measured CRC. All three tillage indices produced significant classifications for every dataset ($z = 2.60 \sim 10.87 > 1.96$). minNDTI provided similar classification accuracies to the other two indices for most datasets except the Fulton, IN site where both CAI and SINDRI showed better classification accuracies.

minNDTI showed comparable results to CAI and SINDRI with the exception of study sites affected by soil moisture and SOC (i.e., IN 2006 & 2007). Note that SINDRI was derived from airborne hyperspectral data for IN and IL which had better data quality than the actual ASTER data. Therefore, it is possible that the higher data quality of airborne hyperspectral data was one of the reasons for a better result from SINDRI than minNDTI for IN and IL datasets, as ASTER data did not show significant improvement on CRC estimation for IA datasets. A low correlation between SINDRI and CRC for MD 2007 dataset was due to green vegetation (volunteer wheat and weeds were often common in this area in April). CRC was found to be overestimated by SINDRI for

samples affected by green vegetation. Thus, although SINDRI was less sensitive to green vegetation than NDTI, weeds and moderate crop cover were likely to cause inaccurate estimation of CRC, especially when images were acquired in the very late planting season. NDTI was also more sensitive to soil variation than CAI and SINDRI as shown in figure 3.8. The minNDTI technique can avoid most green vegetation effects, but not effects of surface soil variability. Nevertheless, the minNDTI strategy provides the best alternative for practical applications using existing sensor systems because of its low costs, and the availability of an open archive provides broad spatial and temporal coverage with suitable spatial detail.

5. Summary and Conclusions

The minNDTI technique was evaluated using data collected at multiple locations and different years. Regional mapping of CRC/ tillage is possible using the regional model of Zheng et al. (2012), but locally developed models were more accurate. We note that close attention should be devoted to areas that might have low-lying fields prone to flooding and has soils rich in organic matter, as they can confound results and reduce accuracy. USDA/NASS *Crop and Weather Reports* are useful for selecting appropriate Landsat observations by providing information about local field and weather conditions. The minNDTI technique is comparable to CAI and SINDRI in terms of tillage classification accuracies. Results from this study demonstrate the capability of this method for mapping CRC/tillage practices at broad scales. With availability of Landsat TM/ETM+ imagery since 1984, it is possible to trace the tillage history at site-specific detail, filling in spatial and temporal gaps of coverage of tillage data. Further, real-time series of tillage data can be used in agro-ecosystem models to evaluate impacts of CRM

practices on soil carbon, soil erosion, and nutrient losses, providing data resources to meet needs for improved environmental modeling highlighted by Shaffer and Ma (2001). Because field size is relatively large in the Midwestern United States, future studies can incorporate object-based (field-based) methods to fill data gaps in scan line corrector (SLC)-off Landsat 7 ETM+ products, and to fill missing data caused by small clouds and cloud shadows. The Advanced Land Imager (ALI) and historical ASTER imagery prior to the SWIR detector failure in May 2008 (NASA/JPL 2009) can be incorporated into the minNDTI technique when an adequate number of Landsat observations is lacking. The upcoming launches of Landsat 8 and the ESA Sentinel-2 constellation ensure that this method will be useful for future monitoring applications. The Sentinel-2 constellation is a particularly good candidate for CRC/ tillage mapping with this method because it will have a revisit time of < 5 days and will carry a shortwave infrared sensor with bands equivalent to Landsat 5 & 7 (ESA 2011). While the proposed Hyperspectral Infrared Imager (HyspIRI) (NASA/JPL 2012) would allow for the use of CAI, its 19-day revisit time might not be effective for tillage mapping considering cloud issues in conjunction with the narrow time window for tillage and planting operations (Zheng et al. 2012). As such, Landsat and Landsat-like sensors with spectral bands covering 1650 and 2100 nm provide the most cost and time efficient way for monitoring CRC and tillage practices via the minNDTI method.

References

- Beck, R. 2003. *EO-1 User Guide v. 2.3*. [cited March 9 2012]. Available from <http://eo1.usgs.gov/documents/EO1userguidev2pt320030715UC.pdf>.
- Brown, D.J., E.R. Hunt Jr, R.C. Izaurralde, K.H. Paustian, C.W. Rice, B.L. Schumaker, and T.O. West. 2010. Soil organic carbon change monitored over large areas. *Eos* 91 (47):441-442.
- Causarano, H.J., A.J. Franzluebbers, D.W. Reeves, and J.N. Shaw. 2006. Soil organic carbon sequestration in cotton production systems of the southeastern United States: A review. *Journal of Environmental Quality* 35 (4):1374-1383.
- Congalton, R.G., and K. Green. 2008. Assessing the accuracy of remotely sensed data: principle and practices. 2nd ed. ed. Boca Raton, FL: Levis Publishers.
- Daughtry, C.S.T. 2001. Discriminating Crop Residues from Soil by Shortwave Infrared Reflectance. *Agronomy Journal* 93 (1):125-131.
- Daughtry, C.S.T., E.R. Hunt Jr, P.C. Doraiswamy, and J.E. McMurtrey III. 2005. Remote Sensing the Spatial Distribution of Crop Residues. *Agronomy Journal* 97 (3):864-871.
- Daughtry, C.S.T., P.C. Doraiswamy, E.R. Hunt Jr, A.J. Stern, J.E. McMurtrey III, and J.H. Prueger. 2006. Remote sensing of crop residue cover and soil tillage intensity. *Soil and Tillage Research* 91 (1-2):101-108.
- Daughtry, C.S.T., and E.R. Hunt Jr. 2008. Mitigating the effects of soil and residue water contents on remotely sensed estimates of crop residue cover. *Remote Sensing of Environment* 112 (4):1647-1657.

- Daughtry, C.S.T., G. Serbin, J.B. Reeves III, P.C. Doraiswamy, and E.R. Hunt Jr. 2010. Spectral reflectance of wheat residue during decomposition and remotely sensed estimates of residue cover. *Remote Sensing* 2 (2):416-431.
- David, P. 1996. Green revolution agriculture and chemical hazards. *Science of The Total Environment* 188, Supplement (0):S86-S98.
- ESA. 2011. *ESA's Sentinel satellites*. [cited January 24 2012]. Available from http://www.esa.int/esaLP/SEMM4T4KXMF_LPgmes_0.html.
- Foley, J.A., N. Ramankutty, K.A. Brauman, E.S. Cassidy, J.S. Gerber, M. Johnston, N.D. Mueller, C. O'Connell, D.K. Ray, P.C. West, C. Balzer, E.M. Bennett, S.R. Carpenter, J. Hill, C. Monfreda, S. Polasky, J. Rockstrom, J. Sheehan, S. Siebert, D. Tilman, and D.P.M. Zaks. 2011. Solutions for a cultivated planet. *Nature* 478 (7369):337-342.
- Gates, D.M., H.J. Keegan, J.C. Schleter, and V.R. Weidner. 1965. Spectral Properties of Plants. *Applied Optics* 4 (1):11-20.
- Gausman, H.W., A.H. Gerbermann, C.L. Wiegand, R.W. Leamer, R.R. Rodriguez, and J.R. Noriega. 1975. Reflectance Differences Between Crop Residues and Bare Soils. *Soil Science Society of America Journal* 39 (4):752-755.
- Gowda, P.H., B.J. Dalzell, D.J. Mulla, and F. Kollman. 2001. Mapping tillage practices with landsat thematic mapper based logistic regression models. *Journal of Soil and Water Conservation* 56 (2):91-96.
- Guérif, J., G. Richard, C. Dürr, J.M. Machet, S. Recous, and J. Roger-Estrade. 2001. A review of tillage effects on crop residue management, seedbed conditions and seedling establishment. *Soil and Tillage Research* 61 (1-2):13-32.

- Iowa Crops and Weather 2005. USDA National Agricultural Statistics Service. Iowa Agricultural Statistics Service, Des Moines, IA.
- Kern, J.S., and M.G. Johnson. 1993. Conservation tillage impacts on national soil and atmospheric carbon levels. *Soil Science Society of American Journal* 57:200-210.
- Khush, G.S. 2001. Green revolution: the way forward. *Nature Review Genetics* 2 (10):815-822.
- Lee, J.J., D.L. Phillips, and R. Liu. 1993. The effect of trends in tillage practices on erosion and carbon content of soils in the US corn belt. *Water, Air, & Soil Pollution* 70 (1):389-401.
- Maryland Crop and Weather Report 2007. USDA Agricultural Statistics Service. Maryland Department of Agriculture, Annapolis, MD.
- Masek, J.G., E.F. Vermote, N.E. Saleous, R. Wolfe, F.G. Hall, K.F. Huemmrich, G. Feng, J. Kutler, and L. Teng-Kui. 2006. A Landsat surface reflectance dataset for North America, 1990-2000. *Geoscience and Remote Sensing Letters, IEEE* 3 (1):68-72.
- Morrison, J.E., C.-H. Huang, D.T. Lightle, and C.S.T. Daughtry. 1993. Residue measurement techniques. *Journal of Soil and Water Conservation* 48 (6):478-483.
- NASA/JPL. 2009. *ASTER User Advisory*. [cited Jan 30 2011]. Available from <http://asterweb.jpl.nasa.gov/latest.asp>.
- NASA/JPL. 2012. *HyspIRI Mission Study*. [cited January 24 2012]. Available from <http://hyspiri.jpl.nasa.gov/>.

- Phillips, D.L., P.D. Hardin, V.W. Benson, and J.V. Baglio. 1993. Nonpoint source pollution impacts of alternative agricultural management practices in Illinois: A simulation study. *Journal of Soil and Water Conservation* 48 (5):449-457.
- Sachs, J., R. Remans, S. Smukler, L. Winowiecki, S.J. Andelman, K.G. Cassman, D. Castle, R. DeFries, G. Denning, J. Fanzo, L.E. Jackson, R. Leemans, J. Lehmann, J. C. Milder, S. Naeem, G. Nziguheba, C.A. Palm, P.L. Pingali, J.P. Reganold, D.D. Richter, S.J. Scherr, J. Sircely, C. Sullivan, T.P. Tomich, and P.A. Sanchez. 2010. Monitoring the world's agriculture. *Nature* 466 (7306):558-560.
- Serbin, G., E.R. Hunt Jr, C.S.T Daughtry, G.W. McCarty, and P.C. Doraiswamy. 2009a. An Improved ASTER Index for Remote Sensing of Crop Residue. *Remote Sensing* 1 (4):971-991.
- Serbin, G., C.S.T. Daughtry, E.R. Hunt Jr, J.B. Reeves III, and D.J. Brown. 2009b. Effects of soil composition and mineralogy on remote sensing of crop residue cover. *Remote Sensing of Environment* 113 (1):224-238.
- Serbin, G., C.S.T. Daughtry, E.R. Hunt Jr, D.J. Brown, and G.W. McCarty. 2009c. Effect of Soil Spectral Properties on Remote Sensing of Crop Residue Cover. *Soil Science Society of America Journal* 73 (5):1545-1558.
- Shaffer, M., and M. Liwang. 2001. A Review of Carbon and Nitrogen Processes in Nine U.S. Soil Nitrogen Dynamics Models. In *Modeling Carbon and Nitrogen Dynamics for Soil Management*: CRC Press.
- Silgram, M., and M.A. Shepherd. 1999. The Effects of Cultivation on Soil Nitrogen Mineralization. In *Advances in Agronomy*, edited by L. S. Donald: Academic Press.

- Soil Survey Staff. 2011. Web Soil Survey. Natural Resources Conservation Service, United States Department of Agriculture. Available from <http://websoilsurvey.nrcs.usda.gov/>
- Sullivan, D.G., T.C. Strickland, and M.H. Masters. 2008. Satellite mapping of conservation tillage adoption in the Little River experimental watershed, Georgia. *Journal of Soil and Water Conservation* 63 (3):112-119.
- USDA-NRCS. 2006a. Tillage practice guide: A guide to USDA-NRCS practice standards 329 no-till/strip till/direct seed & 345 mulch till.
- USDA-NRCS. 2006b. Land Resource Regions and Major Land Resource Areas of the United States, the Caribbean, and Pacific Basin. [cited February 3 2012]. Available from <http://soils.usda.gov/survey/geography/mlra/>.
- USGS. 2010. *Landsat Data Continuity Mission*. [cited March 9 2012]. Available from <http://pubs.usgs.gov/fs/2007/3093/pdf/fs20073093.pdf>.
- van Deventer, A.P., A.D. Ward, P.H. Gowda, and J.G. Lyon. 1997. Using Thematic Mapper Data to Identify Contrasting Soil Plains and Tillage Practices. *Photogrammetric Engineering & Remote Sensing* 63 (1):87-93.
- Watts, J.D., S.L. Powell, R.L. Lawrence, and T. Hilker. 2011. Improved classification of conservation tillage adoption using high temporal and synthetic satellite imagery. *Remote Sensing of Environment* 115 (1):66-75.
- Zheng, B., J.B. Campbell, and K.M. de Beurs. 2012. Remote sensing of crop residue cover using multi-temporal Landsat imagery. *Remote Sensing of Environment* 117 (0):177-183.

Zhu, Z., and C.E. Woodcock. 2012. Object-based cloud and cloud shadow detection in Landsat imagery. *Remote Sensing of Environment* 118 (0):83-94.

Table 3.1. Acquisition dates for field, Landsat, airborne hyperspectral, and ASTER data.

Location	Ames, IA		Pesotum, IL	Fulton, IN		Centreville, MD
	2005	2007	2006	2006	2007	2007
Field	5/19 - 22	5/21 - 23	5/16, 18	5/20, 22, 23	5/21 - 24	4/11, 13
Landsat	4/03 [†] , 5/05, 5/22, 5/30, 6/06 [†]	4/18, 5/12, 5/20, 6/13 [†]	4/10, 4/18, 4/26, 5/04, 5/20, 5/28, 6/05, 6/13	4/19 [†] , 4/28, 5/06, 5/21, 5/29, 6/14	4/15 [†] , 4/22, 5/08, 5/24, 6/02, 6/09	4/21 [†] , 4/30 [†] , 5/07, 5/16, 5/23, 5/31, 6/17, 6/24 [†]
Airborne	NA*	5/27	6/08	5/29	6/06	4/10
ASTER	5/22	5/19	NA	NA	NA	NA

*NA: data not available.

[†]: no minimum NDTI value was found on the image, indicating tillage did not occur near the image date for the available samples.

Table 3.2. Linear regressions of minNDTI and crop residue cover and overall classification accuracy for three categories of tillage intensity. Local models were calibrated and validated for each location. The regional model (Zheng et al. 2012) was used to predict crop residue cover and tillage intensity.

Location			Ames, IA		Pesotum, IL	Fulton, IN		Centreville, MD
Year			2005	2007	2006	2006	2007	2007
Local	Calibration	R ²	0.69	0.84	0.89	0.66	0.76	0.89
		RMSE	10.1	8.1	8.8	13.0	12.3	8.5
		Samples	34	44	57	50	65	13
	Validation	R ²	0.59	0.78	0.83	0.56	0.72	0.93
		RMSE	11.0	8.4	10.3	15.1	14.3	10.2
		Slope	0.91*	0.92*	0.88	0.88*	1.03*	1.22
		Intercept	3.84*	3.38*	2.11*	4.91*	1.97*	8.59*
		Overall acc.	0.74	0.68	0.77	0.84	0.75	0.86
		$\hat{k}$	0.50	0.43	0.59	0.63	0.59	0.76
		Z-stat	3.37	3.37	6.33	5.60	6.40	5.17
		Samples	34	44	57	51	65	14
	Regional model [†]	R ²	0.64	0.81	0.86	0.61	0.74	0.91
		RMSE	16.5	9.2	10.2	18.8	17.7	12.5
		Slope	0.83	0.89	1.21	0.58	0.66	1.16
		Intercept	16.1	8	8.72	10.2	14.5	-15.39
		Overall acc.	0.69	0.75	0.72	0.80	0.80	0.74
		$\hat{k}$	0.44	0.56	0.52	0.53	0.65	0.60
		Z-stat	3.96	6.69	7.74	6.27	10.9	4.36
		Samples	68	88	114	101	130	27

* Slopes and intercepts are not significantly different than one and zero at the 5% significant level respectively.

† Regression equation from Zheng et al. (2012): $CRC = 754.7 \times \text{minNDTI} + 5.4$

Table 3.3. Comparisons of minNDTI, CAI, and SINDRI for estimating crop residue cover and soil tillage categories.

Location		Ames, IA		Pesotum, IL	Fulton, IN		Centreville, MD
Year		2005	2007	2006	2006	2007	2007
Samples		54	88	33	91	130	26
minNDTI	R ²	0.68	0.82	0.87	0.60	0.74	0.91
	RMSE	10.4	8.1	9.0	14.0	13.1	8.4
	Slope	655.7	671.8	935.4	431.3	501.6	871.2
	Intercept	19.7	12.0	2.3	13.8	18.1	8.5
	Overall acc.	0.78	0.75	0.64	0.82	0.75	0.85
	Kappa	0.59	0.56	0.46	0.56	0.59	0.75
	Z-stat	5.59	6.70	3.59	6.46	9.18	6.52
CAI	R ²	NA [*]	0.83	0.72	0.80	0.82	0.89
	RMSE	NA	7.7	13.2	9.8	10.8	9.3
	Slope	NA	23.8	15.2	27.1	27.3	19.4
	Intercept	NA	17.6	5.7	11.1	13.5	24.6
	Overall acc.	NA	0.68	0.58	0.92	0.79	0.69
	Kappa	NA	0.44	0.33	0.80	0.63	0.51
	Z-stat	NA	4.91	2.60	10.87	10.38	3.79
SINDRI	R ²	0.75	0.66	0.93 [†]	0.82 [†]	0.83 [†]	0.55 [†]
	RMSE	9.2	11.0	6.6	9.4	10.7	18.8
	Slope	2062.8	1650.0	2495.8	1741.4	1713.5	1081.8
	Intercept	18.2	27.3	10.6	-25.8	-38.1	64.9
	Overall acc.	0.74	0.67	0.70	0.85	0.78	0.69
	kappa	0.52	0.41	0.51	0.63	0.64	0.50
	Z-stat	4.66	4.50	4.35	7.77	10.74	3.80

* NA: not available

† ASTER bands were convolved from airborne hyperspectral data.



Figure 3.1. Locations of the four validation sites discussed in this study and the Nobelsville, IN site used by Zheng et al. (2012).

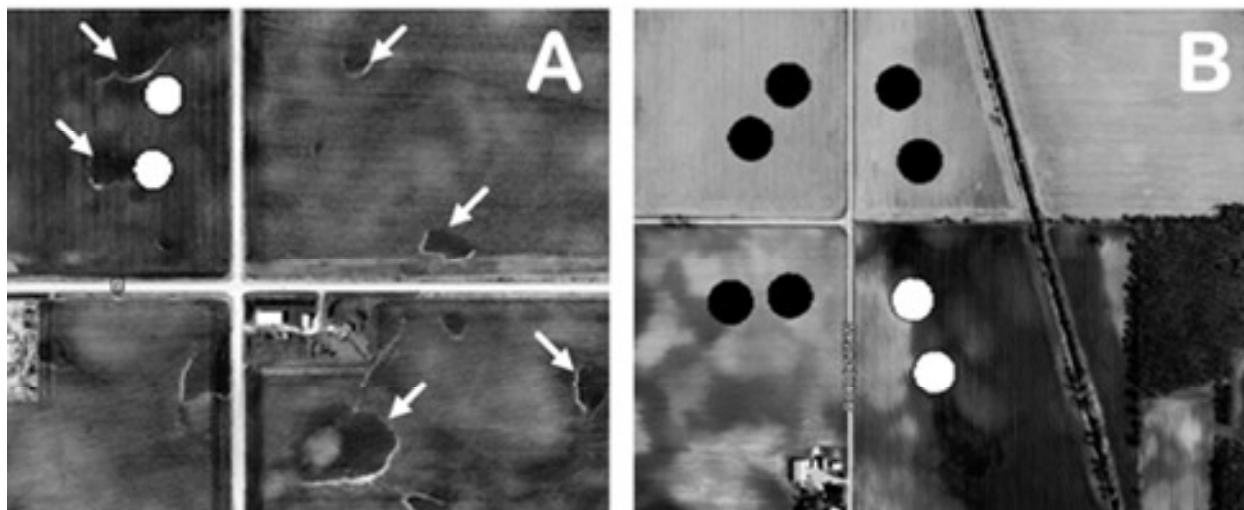


Figure 3.2. Kettles (prairie potholes) highlighted by white arrows in Ames, Iowa sites (A) and depressions in Fulton, Indiana site (B). Negative minNDTI values (white dots) were measured in the low-lying areas. Elevations of black dots (corresponding to positive minNDTI values) are about 1 meter higher than those of white dots (B). (Source: 42°18'45.22"N & 93°33'40.86"W, April 14, 2008, USDA Farm Service Agency & 2012 DigitalGlobe (A); 41°00'40"N, 86°18'50"W, March 1, 2005, IndianaMap Framework Data (B), **Google Earth**, retrieved on January 8, 2012).

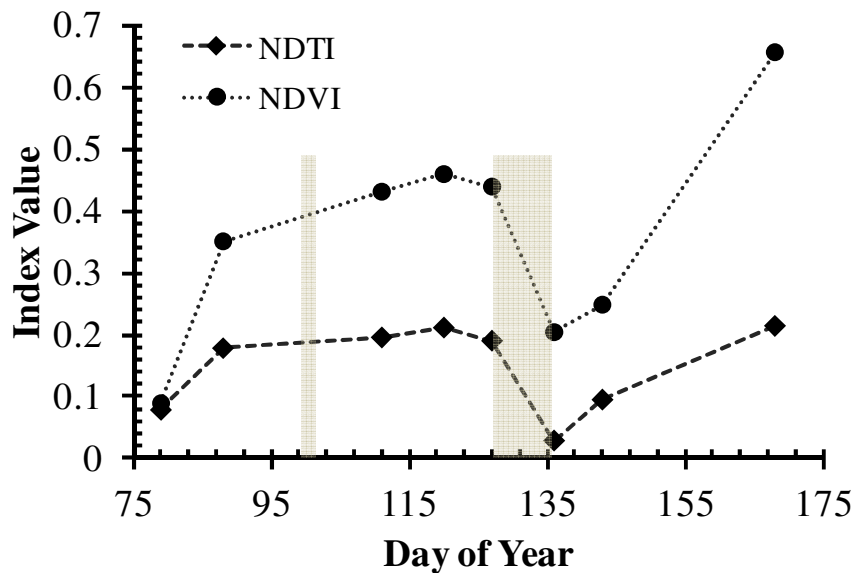


Figure 3.3. NDTI and NDVI values of a sampling point with 59% crop residue cover (CRC) change over the time period of 2007 planting season in Centreville, MD. Highlighted areas indicate field acquisition dates (left) and the time (right) when NDTI drops abruptly to 0.028. The field data were collected too early to capture the correct tillage status which should be determined after day 136.

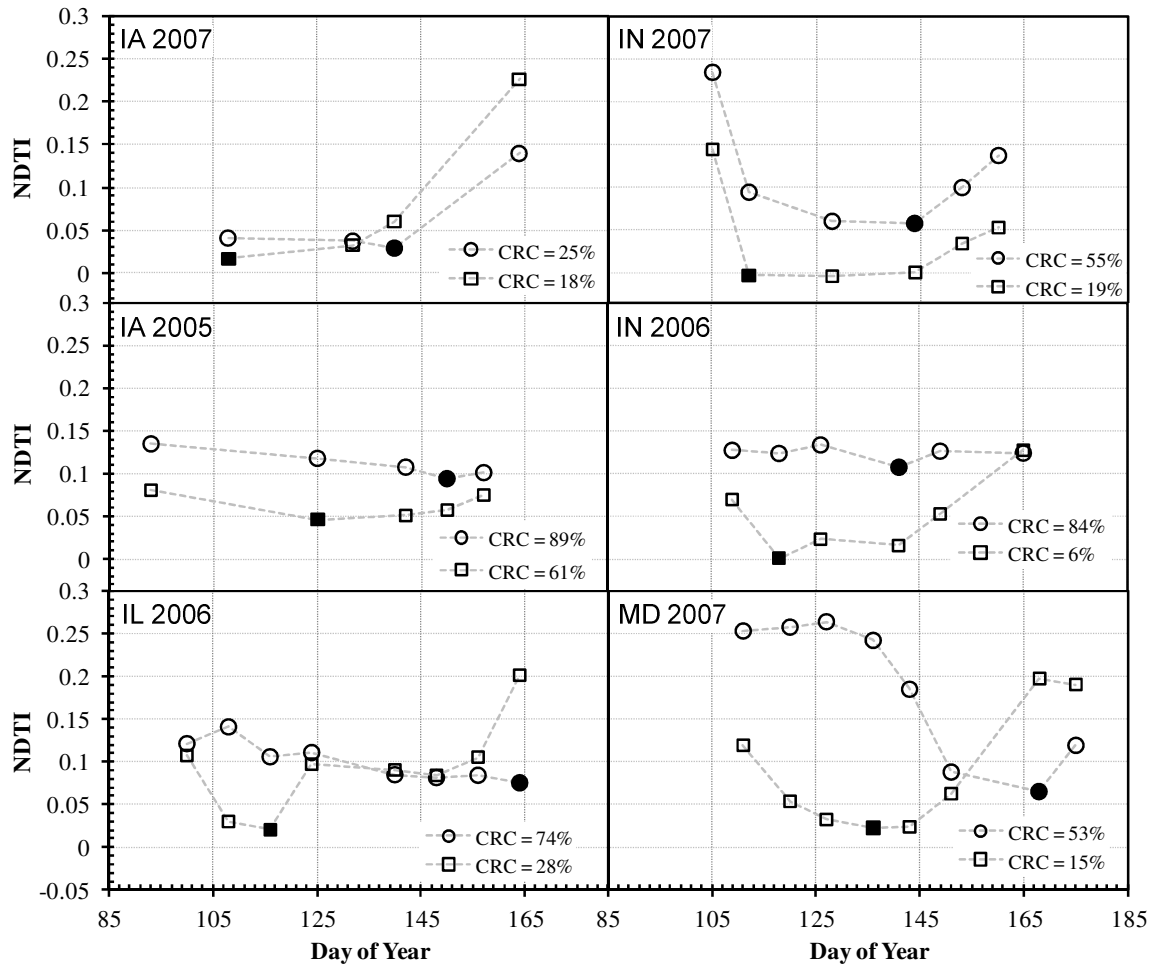


Figure 3.4. Time-series NDTI spectral profiles for each dataset with different levels of field-measured crop residue cover (CRC). minNDTI values were highlighted using solid symbols.

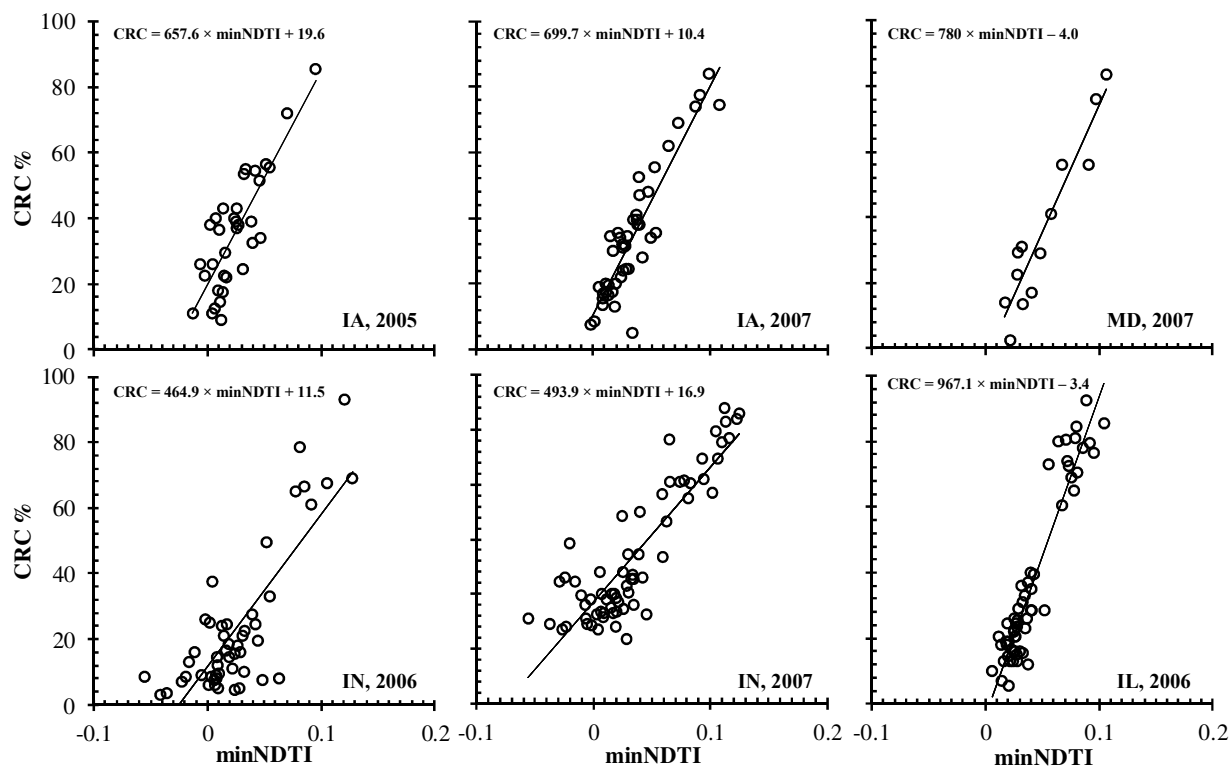


Figure 3.5. Crop residue cover (CRC) as a function of minNDTI for local calibration datasets.

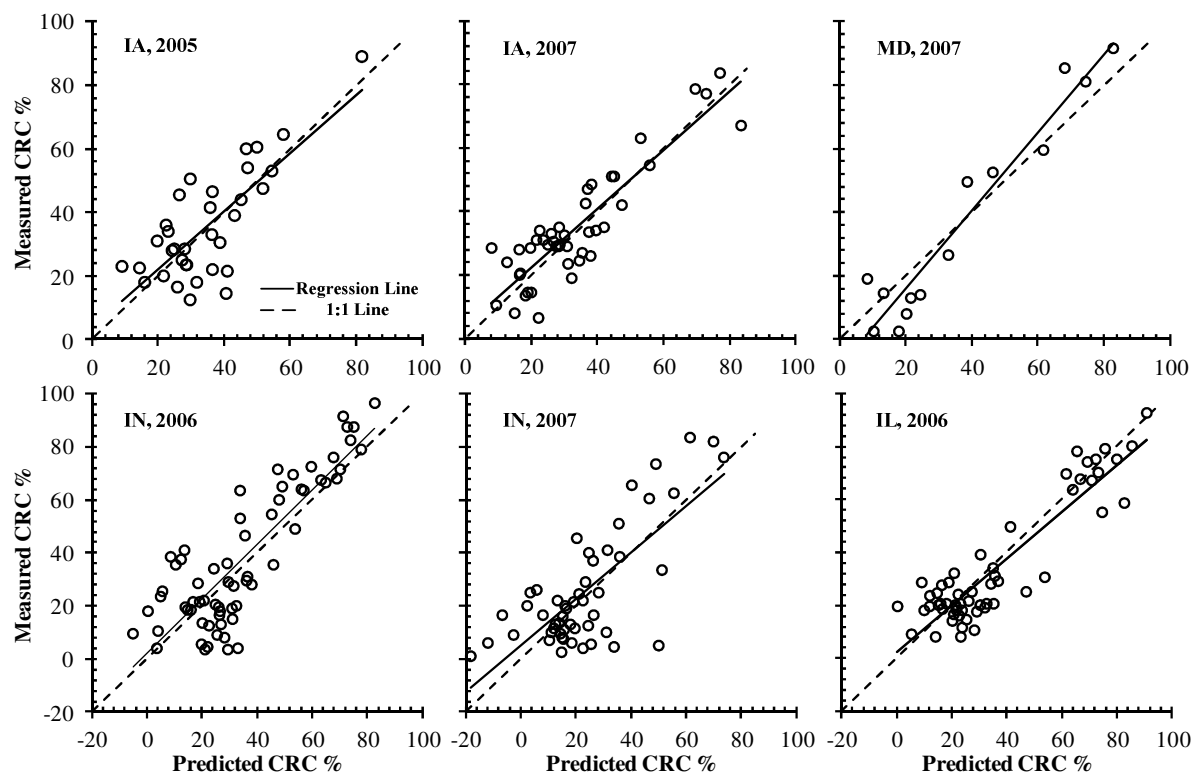


Figure 3.6. Measured vs. predicted crop residue cover (CRC) for local test datasets.

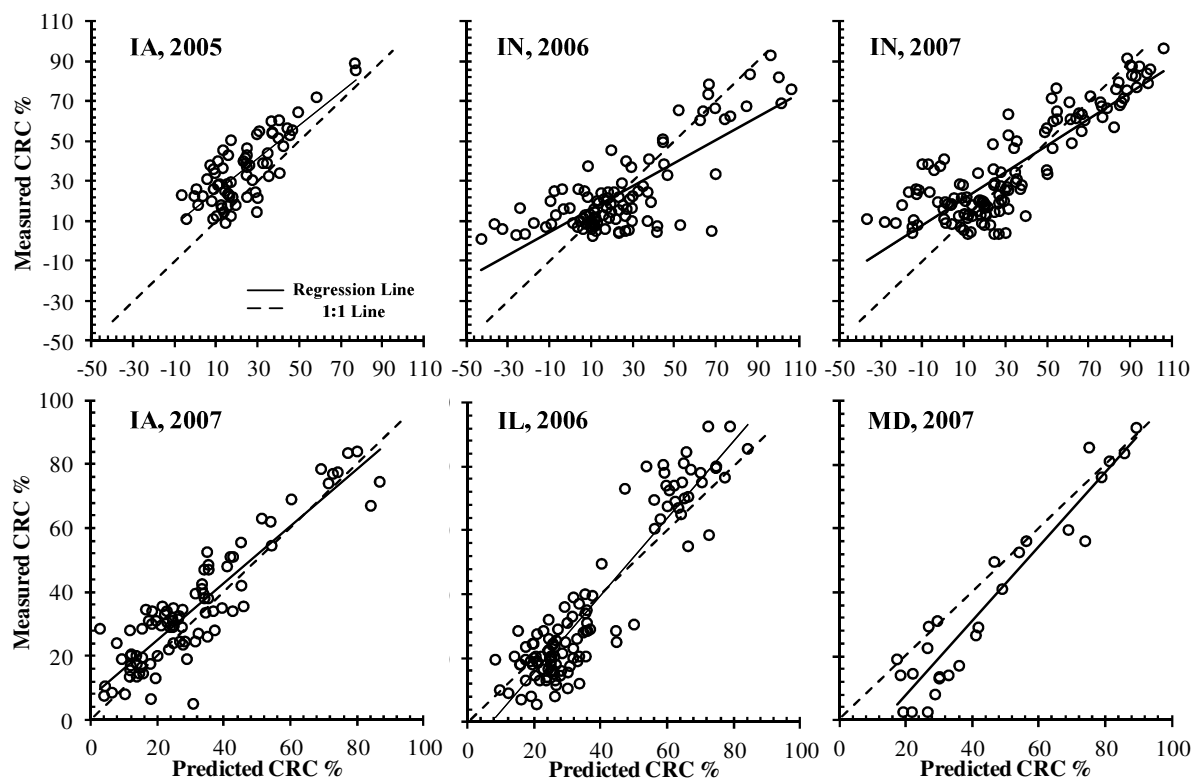


Figure 3.7. Measured vs. predicted crop residue cover (CRC) for regional model.

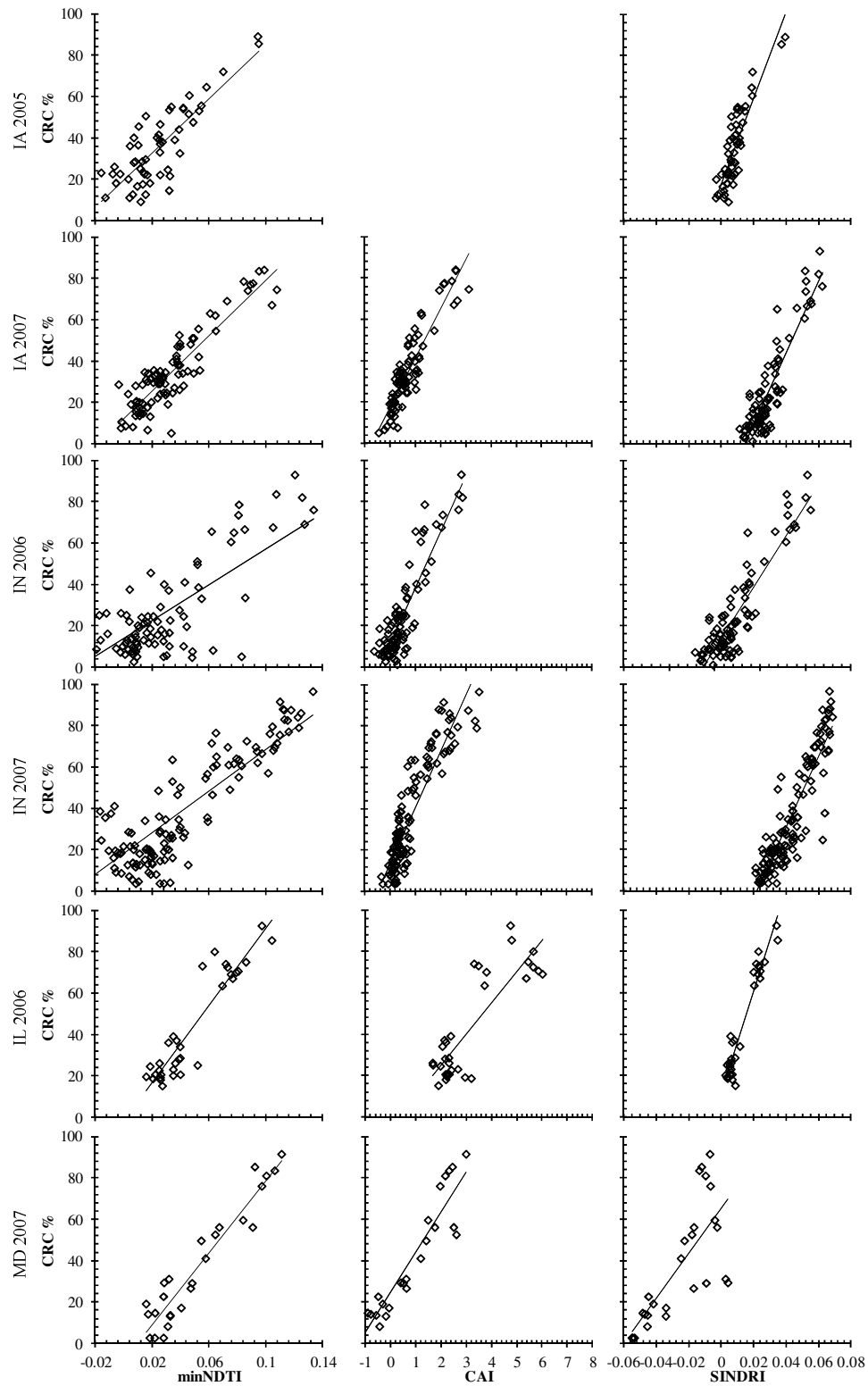


Figure 3.8. Crop residue cover (CRC) as a function of minNDTI, CAI, and SINDRI.

Chapter 4 Broad-scale monitoring of tillage practices using sequential Landsat imagery

Baojuan Zheng ^a, James B. Campbell ^a, Yang Shao ^a, and Randolph H. Wynne ^b

^a Department of Geography and Geospatial and Environmental Analysis (GEA) program,
Virginia Tech, 115 Major Williams Hall (Mail code: 0115), Blacksburg, VA 24061, USA

^b Department of Forest Resources and Environmental Conservation (Mail code: 0324),
Virginia Tech, 319 Cheatham Hall, VA 24061, USA

In Review: ISRPS Journal of Photogrammetry and Remote Sensing

Abstract

Crop residue management is an important soil management practice that can conserve soil and water resources. Monitoring how farmers manage their land in terms of tillage practices can assist development of best management strategies to optimize crop yields and environmental conservation. Remote sensing is a cost-effective and time-efficient tool for tillage monitoring. Previous studies have established the minNDTI technique at a pixel level for tillage mapping by extracting the minimum values from time-series Landsat NDTI (Normalized Difference Tillage Index) spectral profiles. The objective of this study is to evaluate the minNDTI technique and our proposed strategies for mapping tillage practices at the field level. We incorporated a multi-scale image segmentation approach to fill Landsat 7 scan line corrector (SLC)-off data gaps to facilitate site-specific and broad-scale mapping of tillage practices. The gap-filled Landsat 7 images were combined with Landsat 5 imagery to develop a multi-temporal image series for tillage mapping. We then applied object-based approaches and utilized the USDA cropland data layer to produce field-level tillage maps which were evaluated using Conservation Technology Information Center (CTIC) county-level tillage data. Our results show that the gap-filling procedure is effective for the purpose of tillage mapping. Overall classification accuracies of tillage maps range from 69% to 79%. Comparison between remotely sensed and CTIC tillage data suggests that we can monitor tillage practices systematically using remote sensing imagery. This study provides methods and guidelines for researchers and conservationists who are interested in obtaining field-level tillage information using Landsat imagery.

Keywords: Landsat; crop residue; tillage; multi-scale segmentation; SLC-off; gap filling

1. Introduction

Tillage prepares the soil for planting by mechanical disturbance of the soil surface. Tillage has been practiced since antiquity to aerate soil, mix crop residue into soil, suppress weeds, and, in mid-latitude climates, dry and warm the surface soil to advance spring planting. Widespread introduction of mechanized agricultural equipment in the early 20th century greatly increased uses of tillage and its impact upon soil quality. By the 1940s, agronomists recognized unfavorable impacts of conventional tillage practices, including soil compaction, soil erosion, and nutrient losses. Such concerns led to the introduction of alternative tillage practices, such as strip-till and mulch-till, which has been encouraged by governmental programs in the United States and elsewhere.

Interest in alternative tillage practices has led to efforts to monitor the adoption of conservation agriculture, and its impacts upon landscapes. However, accurate and systematic assessment of conservation tillage has been inhibited by weaknesses in data collection capabilities. Field data collection, self-reporting by farmers, agricultural censuses, and roadside surveys each have contributed to estimates, but fail to provide the scope, detail, and accuracy necessary to support practical applications of tillage data for environmental analysis (Sachs et al., 2010). Many of these difficulties can be addressed by applications of remote sensing, which offers the potential to quickly and inexpensively survey landscapes over large areas, at reasonable spatial detail.

Early attempts to use remote sensing techniques for mapping crop residue cover (CRC) date from 1975 (Gausman et al., 1975). Since then, numerous investigators have evaluated the potential of remote sensing for assessing crop residue both in the laboratory and in the field (Biard and Baret, 1997; Daughtry, 2001; Sullivan et al., 2007; Sullivan et

al., 2006). However, attempts to use remotely sensed imagery have also encountered practical difficulties. Satellite hyperspectral imagery with fine spectral detail can estimate crop residue cover accurately (Daughtry et al., 2006), but its limited spatial and temporal coverage constrains its broad-scale application.

Alternatively, Landsat imagery provides continuous global coverage of the earth. Thus, many studies have evaluated Landsat 5 Thematic Mapper (TM) and 7 Enhanced Thematic Mapper Plus (ETM+) for crop residue and tillage mapping (Daughtry et al., 2006; Sullivan et al., 2008; van Deventer et al., 1997; Watts et al., 2009). These studies led to development of several Landsat-based tillage indices (van Deventer et al., 1997), of which the Normalized Difference Tillage Index (NDTI) fared the best (Serbin et al., 2009a; Serbin et al., 2009b). The NDTI is calculated by dividing the difference between bands 5 and 7 by the sum of the two bands. Early applications of the NDTI encountered difficulties in estimating crop residue levels along a continuum using a single Landsat NDTI image (Daughtry et al., 2006; Gowda et al., 2001; Thoma et al., 2004), mainly because (1) the timing of tillage and planting varies greatly from field to field, resulting the presence of green vegetation (emergent crops) on some fields (Zheng et al., 2012); (2) Landsat's coarsely defined spectral bands cannot effectively detect crop residue in the presence of green vegetation (Daughtry et al., 2005). To minimize confounding effects of green vegetation on crop residue estimation, one solution is to incorporate multiple Landsat images which allow detection of freshly or recently tilled surface. Zheng et al. (2012) found that the minimum NDTI values extracted from time-series NDTI spectral profiles can reliably represent correct tillage status with adequate Landsat observations, and designate this technique as the minNDTI approach. The minNDTI approach

improved accuracy of crop residue estimation as well as classification accuracy of tillage practices (Zheng et al., 2012). Furthermore, Zheng et al. (in press) evaluated the effectiveness of this strategy at multiple locations over several years to demonstrate its capability for region-wide applications.

The minNDTI approach and the open availability of Landsat imagery together provide significant opportunities to map tillage practices at broad scales in a cost- and time-efficient manner. This approach is simple, but requires utilization of both Landsat 5 TM and Landsat 7 ETM+ imagery to provide the temporal sequences necessary to maximize mapping accuracy during the interval 2003-present (Zheng et al. in press). It is noteworthy for our discussion here to mention that tillage status must be assessed during a short interval within the early planting season, when the agricultural landscape is undergoing changes as farmers till and plant crops, and crops emerge (Zheng et al. 2012).

This paper continues the work of Zheng et al. (in press) to map tillage practices at the field level in the Midwestern United States using sequential Landsat imagery. First, in the following section, we address issues concerning the quality of Landsat data for tillage mapping, and then present and evaluate our methodologies to generate broad-scale, site-specific, tillage maps. This study will form the basis for large-scale tillage monitoring in the future.

2. Landsat 7 ETM+ Data Issue

In May 2003, the Landsat 7 ETM+ scan line corrector (SLC) failed, creating a pattern of stripes that cause approximately 22% of each Landsat 7 ETM+ scene to be lost (USGS, 2010). These missing data have prevented widespread use of Landsat 7 ETM+ in the remote sensing community. In our context, the missing data complicate

implementation of the minNDTI technique to generate tillage maps because they reduce the length and frequency of the time series required to assess tillage status. (Images acquired after the SLC failure are designated as “SLC-off images” in the rest of this paper.) Because gaps differ in location for each SLC-off image, the resulting minimum NDTI layer will have large gaps (pixel values of zero) when a time-series NDTI image consists of a composite of multiple SLC-off images. Thus, practical application of the minNDTI technique using TM and ETM+ imagery requires development of a strategy specifically designed to fill these missing data in the context of the minNDTI strategy.

Several methods have been proposed for filling gaps in SLC-off images: histogram matching (USGS, 2004), semi-physical fusion (Roy et al., 2008), multi-scale segmentation (Maxwell et al., 2007), geostatistical methods (Pringle et al., 2009; Zhang et al., 2007), a Neighborhood Similar Pixel Interpolator (NSPI) approach (Chen et al., 2011), and a hybrid of a geostatistical method and the NSPI (GNSPI) (Zhu et al., 2012). The histogram-matching method is simple, but does not work well if significant changes have occurred between input and SLC-off images, and if features are smaller than the local moving window size (USGS, 2004). The semi-physical fusion method that uses the Moderate-resolution Imaging Spectroradiometer (MODIS) to predict reflectance values of the missing pixels has a scale discrepancy problem because MODIS has much coarser spatial resolution than does Landsat imagery (Roy et al., 2008). The multi-scale segmentation approach is effective, although it tends to have lower predictive accuracies for narrow landscape features, such as roads and narrow streams (Maxwell et al., 2007). The geostatistical methods are computationally inefficient, and cannot predict well when ground-cover changes rapidly (Pringle et al., 2009). The NSPI and GNSPI were designed

to improve prediction accuracies for heterogeneous landscape pixels with reduced computing time (Chen et al., 2011; Zhu et al., 2012). With the exception of the multi-scale segmentation approach, each method requires one or several input images acquired close to the date of the SLC-off image to guide interpolation of missing pixels.

The multi-scale segmentation approach assumes that the pixels are spectrally similar within an object, and has the advantage of not requiring a cloud-free SLC-on image acquired close to the SLC-off image acquisition date (Maxwell et al., 2007). Thus, this method can be repetitively applied to the SLC-off images once field boundaries are correctly defined. We believe that the multi-scale segmentation approach is best suited for our application because of the following reasons: first, agricultural fields are generally large and uniform in shape in the Midwestern United States; second, CRC (i.e., the NDTI values) is relatively homogeneous within each agricultural field because farmers rarely apply two or more different tillage practices within a single agricultural field; third, segmentation maps are useful later in the map generation procedure. Because of the relatively homogeneous characteristics of fields in this application, we can simplify the multi-scale segmentation approach by making the reasonable assumption that pixels within an agricultural field are likely to have similar NDTI values.

3. Multiresolution Segmentation

Segmentation is a process of grouping pixels into objects according to spectral and spatial characteristics such that variability is maximized between objects and minimized within objects (Flanders et al., 2003; Haralick and Shapiro, 1985). The multiresolution segmentation algorithm is a bottom-up region-merging technique that

starts with one-pixel objects, which are then iteratively merged into larger patches using a pair-wise clustering process (Baatz and Schäpe, 2000; Benz et al., 2004).

Several elements need to be considered to optimize segmentation results for each application: input layers, scale, weighting between color and shape, and weighting between compactness and smoothness (Benz et al., 2004). One can use original image layers, or layers of a transformed image, as input layers according to each application. Image layers that can clearly define landscape features of interest are preferable. Here scale is an abstract term that controls the level of heterogeneity for the resulting image objects (Benz et al., 2004; Definiens, 2006). In general, a larger scale will result in larger objects and smaller total number of segments. Color and shape are used to control the homogeneity of the resulting objects (Benz et al., 2004; Definiens, 2006). The color criterion minimizes spectral variation of pixels within an object, while the shape criterion improves the shape of an object with respect to smoothness and compactness (Benz et al., 2004; Definiens, 2006). These weighting parameters can be adjusted to optimize segmentation results for each application.

4. Methods

4.1 Procedures of Gap-filling NDTI Layers

Our gap filling process is shown in Figure 4.1. The tasseled cap (TC) transformation was applied to cloud-free Landsat SLC-on imagery to reduce the dimensionality of the spectral data. The first three TC layers (brightness, greenness, and wetness), which explained more than 90% of spectral variance, were used as input layers for image segmentation. Segmentation maps were generated using the multiresolution segmentation algorithm implemented in Definiens Professional 5 software (Definiens

AG, Germany). We tested a range of scales and found that a scale of 10 is adequate to separate non-agricultural objects (including isolated farmhouses) from agricultural features (Figure 4.2) while minimizing over-segmentation. The weighting between color and shape was set to 0.9/0.1 because color plays a primary role in distinguishing different objects. The weighting between compactness and smoothness was set as default 0.5/0.5 because only minor changes were observed when we adjusted the weighting. Small objects that are completely within the data gaps could exist in scale 10 segmentation maps; hence, the missing pixels within these objects could not be filled. Some of these small objects are caused by within-object instead of between-object variation. Thus, scale 15 segmentation maps with larger segments were created to fill remaining unfilled pixels. Because missing data are assumed to have NDTI values similar to the observed NDTI values within each agricultural field, we can fill the missing data using the mean of the same-field valid pixels. We used the mean of a group of pixels instead of using nearest neighbor pixels to fill missing data because this approach can reduce the effect of soil variation and uncertainties caused by errors induced by the imaging system (such as bad pixels). In addition, the mean calculation is less computationally intensive than searching for nearest neighbor pixels.

SLC-off images were geometrically corrected if they did not line up with the segmentation map properly. Pixels located at field edges and end rows often have lower levels of crop residue than do the center pixels. Therefore, edge pixel values are less representative of the whole field. Furthermore, to address the potential of half-pixel misregistration between segmentation maps and SLC-off images, we applied buffers inside each object to exclude edge pixels from our analysis: 60-meter buffers for the scale

10 segmentation maps and 30-meter buffers for the scale 15 segmentation maps (Figure 4.2). We then applied a three-step gap filling procedure to fill the gaps (Figure 4.1). A 60-m buffer scale 10 segmentation (60-m S10) map was first applied to guide the interpolation. The 60-m buffer scale excluded small objects, such as roads and small buildings, from interpolation (Figure 4.2). Therefore, this segmentation map interpolates missing pixels for large objects, such as large agricultural fields. The scale 10 segmentation (S10) maps were then used to interpolate edge pixels of large segments and small landscape features. Lastly, the scale 15 segmentation maps with 30-m buffer (30-m S15) were used to fill the rest of unfilled pixels due to over-segmentation.

4.2 Gap-fill Validation

We evaluated the effectiveness of our gap-filling strategy by creating artificial SLC-off images from Landsat 5 TM images, then comparing our estimated values to the actual values from the Landsat 5 TM images. Landsat 5 TM NDTI layers of two distinct locations were selected to validate our gap-filling procedure. One was acquired on April 26, 2006 over Champaign (Figure 4.3a shows a NDTI image located in the upper-left corner of Champaign County) and Douglas Counties in IL; the other was acquired on March 29, 2007 over Queen Anne's, Talbot, and Caroline Counties in MD. Agricultural fields are uniform in shape (rectangular) in IL, while fields in MD are irregular in shape and smaller compared to the IL site. A scale of 10000 was applied to both NDTI layers, converting float into integer values, to reduce the size of the image files. We simulated SLC-off gaps within SLC-on images of the IL and MD areas using a mask generated by an SLC-off image (Figure 4.3b). Our gap-filling procedure was applied to these two simulated SLC-off NDTI layers. After the gaps were filled, we randomly sampled 5% of

the total number of filled pixels for each step. Then, predicted accuracy was evaluated using the square of the correlation coefficient (R^2) and mean absolute differences between predicted and actual images.

4.3 Tillage Map Generation

All SLC-off images were gap-filled using the above techniques. Figure 4.4 shows the procedures for producing tillage maps. We extracted minNDTI values from time-series NDTI imagery and applied local models (Table 4.1) developed by Zheng et al. (in press) to the minNDTI layers for each location to generate CRC maps. CRC maps were then classified into three tillage categories: non-conservation tillage (< 30% crop residue), conservation tillage (30% ~ 70%), and conservation tillage – no-till (70% ~ 100%). (Note that no-till is one type of conservation tillage. For convenience purposes, here, conservation tillage represents 30% to 70% crop residue level for the rest of this paper). This classification scheme was chosen to maintain consistency with the previous work by Zheng et al. (in press). Conventional and reduced tillage practices were combined as non-conservation tillage because it is difficult to differentiate them accurately using optical remote sensing imagery (Daughtry et al., 2006). We used the Cropland Data Layer (CDL) (USDA-NASS, 2006;2007) to locate corn and soybean fields and to incorporate other land cover/land use information (such as wheat, hay, and water bodies) into our tillage map products. We assigned class values of 301 to non-conservation tillage, 302 to conservation tillage, and 303 to no-till practices. Pixels with CRC larger than 100%, which often indicate that lands are green throughout the planting season (such as winter wheat or forest), are classified as a class value of 300. These class values were chosen because they are large enough to avoid replacing class values from

CDL data. Scale 10 segmentation maps were used to guide the cleanup process to produce field-level tillage maps (i.e., one tillage category for each segment). We used the segmentation map to generate field-level tillage data because CRC at pixel level could be over- or under-estimated due to soil background variations (Zheng et al., in press) and data noise. A majority filter was applied to assign the value that occurs most often of all pixels within each segment (Figure 4.4) as the output value. We then used CDLs to locate fields of corn (class value of 1) and soybeans (class value of 5), and assigned the tillage classes (class values of 300 to 303) for those fields. (Note that CDLs should be resampled into 30 m resolution if the spatial resolution is coarser than 30 m.)

4.4 Tillage Map Validation

To validate tillage maps, we conducted field-level and county-level comparisons. For the field-level comparison, we used the same crop residue data used in Zheng et al.'s (in press) study, measured using the line-point transect method (Morrison et al., 1993). Because there are two measurements at two different locations for each agricultural field, tillage status of each individual field was determined by averaging the two measurements. Classification accuracy was assessed using overall accuracy, kappa ($\hat{k}$), and Z-scores (Congalton and Green, 2008). Accuracy assessment was based on limited number of field observations instead of well-distributed random samples because of the lack of availability of ground observations of tillage status.

For the county-level comparisons, we compared our results to the county-level CTIC tillage data. Our tillage maps were clipped using county boundaries, and the percentage of each tillage category was calculated by dividing the number of pixels of each category by the total number of pixels in tillage categories. We selected counties for

comparison based on the availability of the CTIC tillage data and their proximity to the locations where Zheng et al. (in press) developed their local models. For conciseness, we refer the tillage data generated from remote sensing (RS) imagery as RS tillage data. To better understand the discrepancy between the RS and CTIC tillage data, we also sampled RS tillage data using the CTIC roadside survey sampling points (with GPS coordinates) provided by the Indiana Natural Resources Conservation Service (NRCS) in Indianapolis. According to the CTIC roadside transect survey procedures, field observers followed planned driving routes and stopped every half mile to two miles (depending on the number of cropland acres in each county) to observe tillage status on both sides of the roadway. Some counties also recorded the GPS coordinates of sampling locations. Because these points are superimposed on the driving routes, we shifted positions of these points up and down, or left and right, to fall within the field data observations on both sides of the routes, and thereby match to our RS assessments, and then summarized tillage statistics county-by-county. The comparison between the entire county sample and the subsample populations permits evaluation of expected differences between RS and CTIC tillage estimates.

5. Results

5.1 Segmentation Maps

The number of objects for scale 10 segmentation ranges from 27,825 to 71,715. The 60-m buffer excluded 29% to 55% of the total number of objects at scale 10 segmentation – the extent of decrease depends on the heterogeneity of the landscapes within each scene. In general, forests and waterways are more spectrally heterogeneous than cropland. Significant decreases in the number of objects after implementing a 60-m

buffer indicate large numbers of small objects in the scale 10 segmentation maps (Table 4.2). The number of objects at scale 15 with 30-m buffers is on average 51% less than that at scale 10. The average size of objects at scale 10 ranges from 4.3 to 14 ha (Table 4.2). The average size of farms ranges from 117 to 160 ha according to the 2007 Census of Agriculture County Profile (USDA-NASS, 2007). The average farm size of the MD site (Queen Anne's, Talbot, & Caroline) is smaller than the other study sites, although, the IN site has the smallest average size of objects. Small features, such as roads, narrow streams, and farm buildings, were well distinguished by segment boundaries (Figures 4.2 & 4.5).

Image acquisition dates of SLC-on images for each study region are shown in Table 4.2. We found that images acquired in the late planting season (i.e., in June for Northern United States) are optimal for defining individual field boundaries because of significant contrasts between agricultural fields and narrow features, such as riparian buffers and streams, and because of large variations in surface conditions between fields due to different timings of planting. If a cloud-free image is not available during this time, images acquired after harvest (i.e., September to November for Northern United States) are the second-best option for generating cropland segmentation maps. Images acquired in July or August are not good candidates for segmentation because two or more adjacent fields with similar greenness can be easily merged into a single patch. If a patch is formed from two adjacent fields that have different tillage conditions, interpolation using the mean NDTI of the combined patch will create large errors.

5.2 Gap-filled vs. Actual NDTI Values

Step 1 gap filling guided by 60-m S10 segmentation maps (Figure 4.1) yielded the highest R^2 values (> 0.78) between predicted and actual NDTI values and the lowest mean absolute differences for both IL and MD sites (Table 4.3 & Figure 4.6). Step 2 (S10) (see Section 4.1) resulted in slightly lower prediction accuracy ($R^2 > 0.69$) than step 1, while step 3 (30-m S15)'s prediction accuracy further decreases. Step 1 (60-m S10) filled 36.7% of total missing pixels for the IL site, and 13.5% for the MD site. Step 2 filled 61.8% of total missing pixels for the IL site, and 83.8% for the MD site. Steps 1 and 2 totally filled more than 97% of the missing pixels, with mean absolute differences of < 0.024 . Step 3 (30-m S15) filled less than 1% of the missing pixels, while one to two percent of missing pixels were still unfilled. Figure 4.3c shows a visual comparison of the actual NDTI image to the gap-filled NDTI image. Bright agricultural fields shown in figure 4.3 indicate high NDTI values, while dark fields correspond to low NDTI values. Large prediction errors could occur at locations with poorly defined field boundaries (Figure 4.3c).

5.3 County Tillage Maps

Overall accuracies for three tillage categories range from 69% to 79%, $\hat{k}$ from 0.43 to 0.57, and Z-scores from 3.07 to 5.67 (Table 4.4). Z-scores demonstrate that all classifications are significantly better than chance alone at a 95% confidence level ($z > 1.96$) (Table 4.4). For our sample of county tillage observations, tillage practices vary substantially from county to county (Table 4.1). Some counties have much higher percentages of non-conservation tillage practice than others. For example, 66% of corn and soybean fields were tilled using the non-conservation method for Champaign County, IL in 2006, in contrast, only 4% for Marshall County, IA in 2007 (Table 4.1 & Figure

4.7). More than 90% of the fields were reported to be under conservation tillage and no-till practice in Marshall County, IA in 2007 and no-till appears more frequently in fields positioned near streams (Figure 4.7).

For county-level comparison, the differences between RS and CTIC data range from 0 to 45% for all tillage categories (Table 4.1). RS tillage data of Champaign, Story, Polk, and Marshall Counties are, in general, consistent with the CTIC tillage data. The percentage of no-till agriculture is consistent with CTIC data for Jasper County, however, percentages of the other two tillage categories do not agree with CTIC data. For Fulton County, IN, the percentage of non-conservation tillage agrees with the CTIC data, but no-till category was consistently underestimated in both years using remote sensing imagery. Jasper County presents the biggest discrepancy between remotely sensed and CTIC data, followed by Douglas, Fulton, and Pulaski Counties. One to six percent difference was observed when we sampled the RS tillage data using CTIC road transect survey technique, suggesting that a 6% difference between RS and CTIC data could be considered as an expected difference due to application of alternative assessment strategies.

6. Discussion

Cloud-free images acquired in June are appropriate for generation of good segmentation maps, while images acquired in July or August often do not provide adequate separation of individual fields. Although soil variation can cause subfield segmentation, it does not, however, significantly affect the accuracy of gap-filled pixels. Agricultural field boundaries are consistently placed in these regions. A high-quality segmentation map can be used to fill missing NDTI values for any SLC-off image, but

users should assure that the segmentation map is still valid using local information about land use land cover change or using visual assessment if the time difference between the segmentation map and the SLC-off image is large. The time difference in Maxwell et al.'s (2007) application is approximately 10 years.

The scale 10 segmentation map (steps 1 and 2) filled the majority of missing pixels (>90%). Step 1 (60-m S10) resulted in the highest prediction accuracy with the highest R^2 and the lowest mean absolute difference, because the 60-m buffer excludes heterogeneous small landscapes and pixels at the edges of fields (including mixed pixels) from interpolation. Step 2 (S10) mainly interpolated edge pixels of large segments and small landscape features – it yielded slightly less accuracy than step 1. Step 3 (30-m S15) provided the lowest accuracy, and only filled small numbers of missing pixels. Thus, our simplified gap-filling procedure worked well for homogenous features. Step 3 can be omitted from the procedure if users believe that this additional step will not improve the image significantly. Although there are unfilled pixels after the gap-filling procedure, we do not suggest increasing the scale of segmentation map to fill those unfilled pixels because they are likely to be inaccurate. In addition, those unfilled pixels are likely to be non-agricultural lands, such as roads and farm houses, which can be filled during the tillage map generation procedure using CDL data.

Our simplified multi-scale segmentation gap-filling procedure can predict most of the missing NDTI data accurately. The advantages of the method are: (1) it does not require an additional image acquired close to the SLC-off image date to guide interpolation; (2) it can fill SLC-off images repetitively once the segmentation maps are generated; (3) it is easy to implement. This method assumes that agricultural fields are

large enough to encompass the entire width of the gap. If small agricultural fields are entirely located in the gap (although we found these to be rare for this application), there is no way that we can predict the NDTI values correctly for these pixels. This problem applies to other currently available gap-filling methods as well, unless we assume that spectral values remain the same from time A to time B. Our gap-filling procedure was designed specifically for tillage mapping application, and is not suitable for applications that require a high degree of prediction accuracy for each pixel.

Overall classification accuracies of county tillage maps are greater than 69%. The sample size for our accuracy assessment is small. However, these data are best available to us for this analysis. Table 4.1 shows the relationship between our tillage assessment and the CTIC surveys for the selected counties. The relationship is in high agreement for some counties. For example, the agreement is within 6% for non-conservation tillage for Champaign County, IL, and Fulton County, IN. Given that the two estimations are based upon different methods, they probably represent an upper limit for agreement for the two methods. For other counties, e.g., Jasper County, IA, and Douglas County, IL, the agreement is low. Disagreements of these magnitudes can be attributed to separate errors in the two assessment techniques. Zheng et al. (in press) have highlighted the significance of several soil and terrain conditions that can lead to errors in the minNDTI technique. Because Marshall and Jasper Counties of IA have similar soil and terrain characteristics (Soil Survey Staff, 2012), and because the two tillage estimations are in good agreement for Marshall County, we believe that soil variations are unlikely to be the source of disagreement for Jasper County. This conclusion also applies to Champaign and Douglas Counties in IL because they share similar soils. The CTIC tillage data are currently the

best available data for validating county tillage maps, however, the quality of the CTIC data may have varied over time, and from county to county, or state to state, because the roadside survey mainly relies on visual interpretation. We found that the CTIC sampling techniques have been effective in representing the tillage status of the larger population of fields within the counties in Indiana because subsampling results using the CTIC sampling points implied that $< \pm 6\%$ difference between RS and CTIC data. The sampling techniques here include the design of driving routes and sampling interval. Given the magnitude of the differences for Jasper and Douglas Counties, it seems likely that they are caused by errors introduced by human visual interpretation. In addition, the extremely low value (one percent) of conservation tillage reported by CTIC for Douglas County in 2006 seems likely to be a poor estimation.

Field observers' experience in visual estimation of CRC could vary from year to year and from county to county. "Windshield observations" (side-viewing angles) is one of the major contributions of poor accuracy of tillage classification (Daughtry et al., 2006). Human observers often have difficulty in differentiation of non-conservation and conservation tillage when CRC is near 30% (Thoma et al., 2004), and can easily misassign 60% CRC to no-till category. Variations in soil and sunlight conditions can also easily bias visual estimation. We note also that record-keeping practices vary over time, and from state to state, so opportunities for retrospective analysis of CTIC data for validation, although possible in some situations, are fragmented in space and time.

Given the overall classification accuracies of 69 to 79%, and the consistency between RS and the CTIC tillage data for some counties, we conclude that local models can be used to map tillage practices and our procedures to produce tillage maps are

effective. However, further studies are required to assess the impact of soil variation on CRC estimations, so that we can improve prediction accuracy and generalize this methodology to a broader region. Field-level tillage maps (Figure 4.7) show coherent spatial patterns of tillage applications. These spatial patterns might be related to soil and landscape characteristics or to indirect effects of government conservation programs which encourage farmers to adopt conservation and no-till practices. An important application of an operational remote-sensing-based tillage survey system would be to provide inventory data to report tillage data not only by county units, but also for drainage basins, terrain, and soil units. Our study focuses upon landscapes in the United States. However, its implications reach beyond the specific areas mentioned here because this issue has international scope (Derpsch et al., 2010).

7. Conclusions

This study examined the minNDTI technique on mapping tillage practices at field level. Our results indicate that it is possible to use local models (Zheng et al., in press) to generate field-level tillage data using Landsat time-series imagery. This study also provided a strategy to solve the Landsat SLC-off data issue for tillage assessment applications, and proposed procedures to facilitate field-level tillage mapping at large scales. We tested the simplified multi-scale segmentation gap-filling procedure for tillage mapping application; results show that this procedure meets our needs for this application. We then incorporated the segmentation maps and CDL data to produce field-level tillage maps using three tillage categories, evaluated classification accuracy of tillage maps, and compared our results to the CTIC county-level tillage data. Local variations in soils, terrain, and weather may prevent application of a generalized model to

a broad region over time (Zheng et al., in press). Future studies are needed to address difficulties in the transferability of empirical models developed using remotely sensed data from one region to another. A ground-based network that can provide CRC data for model calibration and accuracy assessment could be substituted for the CTIC roadside survey. Selection of calibration sites can be guided by knowledge of local soil and terrain variation. Field-level tillage maps permit evaluation of tillage spatial patterns and assist identification of areas subject to environmental issues, such as soil erosion and nutrient losses. As a result, we will be able to provide better assessment of tillage impacts on the environment and effective management strategies to conserve agricultural lands. We also strongly encourage Natural Resource Conservation Service (NRCS) office and scientists who have ground tillage observations test our methods, share data, and work together to push forward the tillage mapping effort.

Acknowledgement

The authors thank Drs. Kirsten de Beurs (The University of Oklahoma) and John M. Galbraith (Virginia Tech) for their valuable suggestions to this study. The authors would also like to thank Mr. Shannon Zezula (NRCS Indianapolis office in Indiana), Mr. Adam Stiegelmeier (NRCS Des Moines office in Iowa), Mr. Alan Gulso and Mr. Elliot Lagacy (NRCS Springfield office in Illinois) for their assistance in providing roadside survey route maps and sampling locations.

References

- Baatz, M., Schäpe, A., 2000. Multiresolution Segmentation: an optimization approach for high quality multi-scale image segmentation, in: Strobl, J. (Ed.), *Angewandte Geographische Informationsverarbeitung XII. Beiträge zum AGIT-Symposium Salzburg 2000*, Karlsruhe, Herbert Wichmann Verlag, pp. 12-23.
- Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing* 58, 239-258.
- Biard, F., Baret, F., 1997. Crop residue estimation using multiband reflectance. *Remote Sensing of Environment* 59, 530-536.
- Chen, J., Zhu, X., Vogelmann, J.E., Gao, F., Jin, S., 2011. A simple and effective method for filling gaps in Landsat ETM+ SLC-off images. *Remote Sensing of Environment* 115, 1053-1064.
- Congalton, R.G., Green, K., 2008. *Assessing the accuracy of remotely sensed data: principle and practices*, 2nd ed. Levis Publishers, Boca Raton, FL.
- Daughtry, C.S.T., 2001. Discriminating Crop Residues from Soil by Shortwave Infrared Reflectance. *Agronomy Journal* 93, 125-131.
- Daughtry, C.S.T., 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 and Tillage Research* 91, 101-108.

- Daughtry, C.S.T., Hunt Jr, E.R., Doraiswamy, P.C., McMurtrey III, J.E., 2005. Remote Sensing the Spatial Distribution of Crop Residues. *Agronomy Journal* 97, 864-871.
- Definiens, 2006. Definiens Professional 5 Reference Book. Definiens AG München, Germany.
- Derpsch, R., Friedrich, T., Kassam, A., Li, H., 2010. Current status of adoption of no-till farming in the world and some of its main benefits. *International Journal of Agricultural and Biological Engineering* 3, 1-23.
- Flanders, D., Hall-Beyer, M., Pereverzoff, J., 2003. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. *Canadian Journal of Remote Sensing* 29, 441–452.
- Gausman, H.W., Gerbermann, A.H., Wiegand, C.L., Leamer, R.W., Rodriguez, R.R., Noriega, J.R., 1975. Reflectance Differences Between Crop Residues and Bare Soils. *Soil Science Society of America Journal* 39, 752-755.
- Gowda, P.H., Dalzell, B.J., Mulla, D.J., Kollman, F., 2001. Mapping tillage practices with landstat thematic mapper based logistic regression models. *Journal of Soil and Water Conservation* 56, 91-96.
- Haralick, R.M., Shapiro, L.G., 1985. Image segmentation techniques. *Computer Vision, Graphics, and Image Processing* 29, 100-132.
- Maxwell, S.K., Schmidt, G.L., Storey, J.C., 2007. A multi-scale segmentation approach to filling gaps in Landsat ETM+ SLC-off images. *International Journal of Remote Sensing* 28, 5339-5356.

- Morrison, J.E., Huang, C.-H., Lightle, D.T., Daughtry, C.S.T., 1993. Residue measurement techniques. *Journal of Soil and Water Conservation* 48, 478-483.
- Pringle, M.J., Schmidt, M., Muir, J.S., 2009. Geostatistical interpolation of SLC-off Landsat ETM+ images. *ISPRS Journal of Photogrammetry and Remote Sensing* 64, 654-664.
- Roy, D.P., Ju, J., Lewis, P., Schaaf, C., Gao, F., Hansen, M., Lindquist, E., 2008. Multi-temporal MODIS–Landsat data fusion for relative radiometric normalization, gap filling, and prediction of Landsat data. *Remote Sensing of Environment* 112, 3112-3130.
- Sachs, J., Remans, R., Smukler, S., Winowiecki, L., Andelman, S.J., Cassman, K.G., Castle, D., DeFries, R., Denning, G., Fanzo, J., Jackson, L.E., Leemans, R., Lehmann, J., Milder, J.C., Naeem, S., Nziguheba, G., Palm, C.A., Pingali, P.L., Reganold, J.P., Richter, D.D., Scherr, S.J., Sircely, J., Sullivan, C., Tomich, T.P., Sanchez, P.A., 2010. Monitoring the world's agriculture. *Nature* 466, 558-560.
- Serbin, G., Daughtry, C.S.T., 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 of Environment* 113, 224-238.
- Serbin, G., Daughtry, C.S.T., Hunt Jr, E.R., Brown, D.J., McCarty, G.W., 2009b. Effect of Soil Spectral Properties on Remote Sensing of Crop Residue Cover. *Soil Science Society of America Journal* 73, 1545-1558.
- Soil Survey Staff, 2012. Soil Survey Staff. Web Soil Survey. Natural Resources Conservation Service, United States Department of Agriculture, <http://websoilsurvey.nrcs.usda.gov/> (Accessed January 27, 2012)

- Sullivan, D. G., Shaw, J. N., Price, A., Van, S., E, 2007. Spectral Reflectance Properties of Winter Cover Crops in the Southeastern Coastal Plain. American Society of Agronomy, Madison, WI, ETATS-UNIS.
- Sullivan, D.G., Strickland, T.C., Masters, M.H., 2008. Satellite mapping of conservation tillage adoption in the Little River experimental watershed, Georgia. *Journal of Soil and Water Conservation* 63, 112-119.
- 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. *Agronomy Journal* 98, 1236-1246.
- Thoma, D.P., Gupta, S.C., Bauer, M.E., 2004. Evaluation of optical remote sensing models for crop residue cover assessment. *Journal of Soil and Water Conservation* 59, 224-233.
- USDA-NASS, 2006;2007. Published crop-specific data layer [online], <http://nassgeodata.gmu.edu/CropScape/> (Accessed March 30, 2012)
- USDA-NASS, 2007. 2007 Census of Agriculture County Profile, http://www.agcensus.usda.gov/Publications/2007/Online_Highlights/County_Profiles/index.asp (Accessed March 30, 2012)
- USGS, 2004. Phase 2 gap-filled algorithm: SLC-off Gap-Filled Products Gap-Fill Algorithm Methodology.
- USGS, 2010. SLC-off products: background. http://landsat.usgs.gov/products_slc_offbackground.php (Accessed July 4, 2012)

- van Deventer, A.P., Ward, A.D., Gowda, P.H., Lyon, J.G., 1997. Using Thematic Mapper Data to Identify Contrasting Soil Plains and Tillage Practices. *Photogrammetric Engineering & Remote Sensing* 63, 87-93.
- Watts, J.D., Lawrence, R.L., Miller, P.R., Montagne, C., 2009. Monitoring of cropland practices for carbon sequestration purposes in north central Montana by Landsat remote sensing. *Remote Sensing of Environment* 113, 1843-1852.
- Zhang, C., Li, W., Travis, D., 2007. Gaps-fill of SLC-off Landsat ETM+ satellite image using a geostatistical approach. *International Journal of Remote Sensing* 28, 5103-5122.
- Zheng, B., Campbell, J.B., de Beurs, K.M., 2012. Remote sensing of crop residue cover using multi-temporal Landsat imagery. *Remote Sensing of Environment* 117, 177-183.
- Zheng, B., Campbell, J.B., Serbin, G., Daughtry, C.S.T., in press. Multi-temporal remote sensing of crop residue cover and tillage practices: A validation of the minNDTI strategy in the United States. *Journal of Soil and Water Conservation*.
- Zhu, X., Liu, D., Chen, J., 2012. A new geostatistical approach for filling gaps in Landsat ETM+ SLC-off images. *Remote Sensing of Environment* 124, 49-60.

Table 4.1. Comparison between remote sensing and CTIC tillage data at county level.

County	Local models ^a	CRC ^b %	RS ^c %	CTIC %	Difference between RS and CTIC %
Champaign, IL	CRC = 967.1 × minNDTI - 3.4	< 30	66	66	0
		30 - 70	26	17	9
		>70	8	17	9
Douglas, IL	(2006)	< 30	47	73	26
		30 - 70	44	1	43
		>70	9	26	17
Story, IA		< 30	44	49	5
		30 - 70	52	44	8
		>70	4	7	3
Polk, IA	CRC = 699.7 × minNDTI + 10.4	< 30	39	42	3
		30 - 70	49	45	4
		>70	12	14	2
Marshall, IA	(2007)	< 30	4	9	5
		30 - 70	62	44	18
		>70	34	46	12
Jasper, IA		< 30	5	46	41
		30 - 70	59	14	45
		>70	36	30	6
Fulton, IN	CRC = 464.9 × minNDTI + 11.5 (2006)	< 30	33	36	3
		30 - 70	59	25	34
		>70	8	39	31
Fulton, IN	CRC = 493.9 × minNDTI + 16.9	< 30	41	40	1
		30 - 70	48	22	26
		>70	11	38	27
Pulaski, IN	(2007)	< 30	42	24	18
		30 - 70	50	41	9
		>70	8	35	27

^a Local models from Zheng et al. (in press);

^b CRC: crop residue cover;

^c RS: tillage data developed from remote sensing imagery;

Table 4.2. Tasseled cap image dates and characteristics of segmentation maps.

Counties (State)	TC ^a image date	Average Size (ha)		Number of Objects		
		object ^b	farm ^c	Scale 10		Scale 15
				60-m buffer	No buffer	30-m buffer
Champaign & Douglas (IL)	2006/06/13	14	160	19721	27825	15978
Queen Anne's, Talbot, & Caroline (MD)	2007/06/17	6.3	117	20230	42035	19555
Story & Polk	2002/06/07	5.5	134	32522	71715	33118
Marshall & Jasper (IA)		6.0	145	30301	64270	30251
Fulton & Pulaski (IN)	2007/06/09	4.3	144	20043	57003	28770

^a TC: tasseled cap images.

^b average size of objects at scale 10 without buffer.

^c average size of farm size from 2007 Census of Agriculture data.

Table 4.3. Results of the gap-fill validation using the multi-scale object-based method.

Sites	Step	Percentage of missing pixels	R ²	Mean absolute differences ^a
IL	1	36.7	0.87	133
	2	61.8	0.78	243
	3	0.6	0.42	568
MD	1	13.5	0.78	201
	2	83.8	0.69	213
	3	0.9	0.34	382

^a NDTI values were scaled by 10,000.

Table 4.4. Overall classification accuracy for three tillage categories.

Counties	Champaign & Douglas, IL	Story, IA	Fulton, IN	
Year	2006	2007	2006	2007
Samples	49	41	52	68
Overall Accuracy	69%	71%	79%	72%
Kappa	0.46	0.43	0.57	0.51
Z-scores	4.42	3.07	5.09	5.67

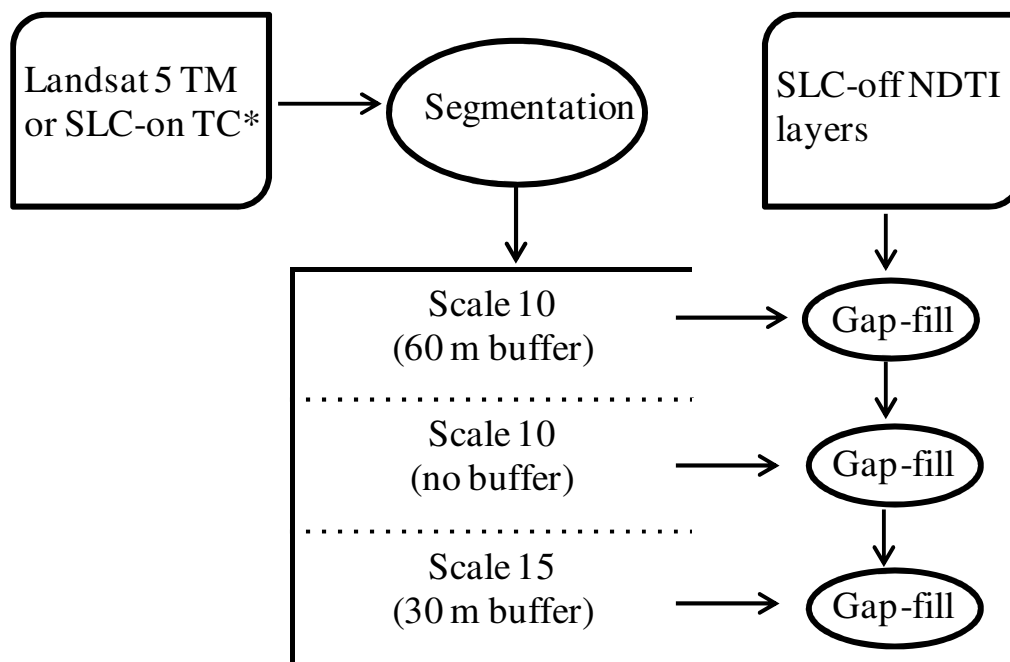
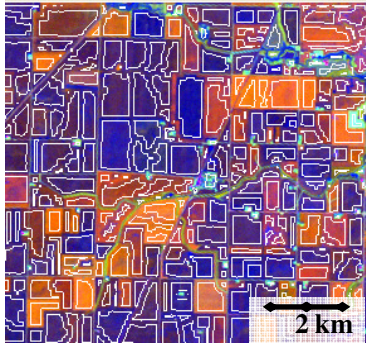
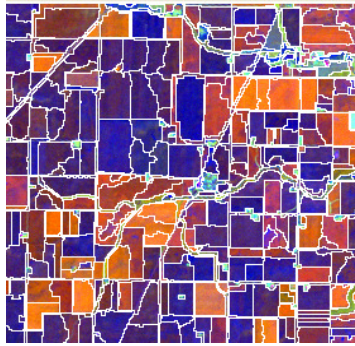


Figure 4.1. Flow diagram of the multi-scale object based approach (*TC = first three layers of tasseled cap imagery).

Scale 10 with 60 m buffer



Scale 10



Scale 15 with 30 m buffer

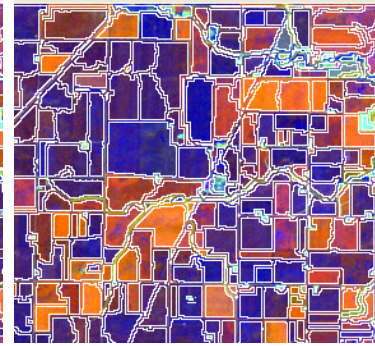


Figure 4.2. Segmentation results for scales 10 and 15 with/without buffer. Segment boundaries (white) are overlaid on tasseled cap images in layer 1-2-3 color combination mode.

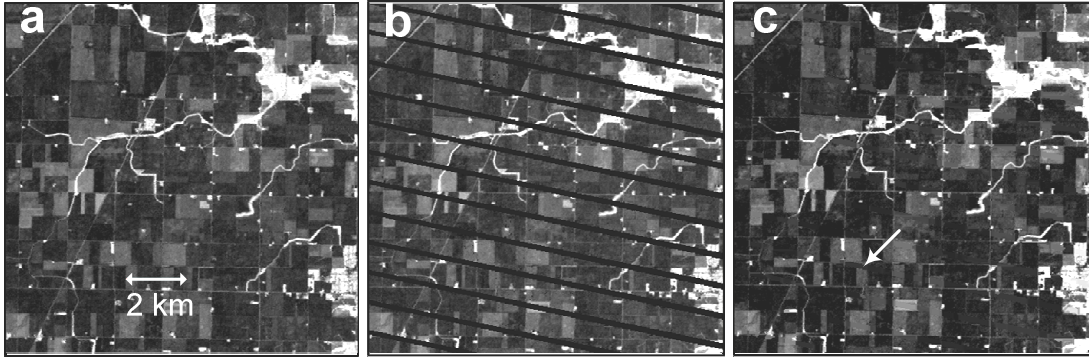


Figure 4.3. Sample NDTI layers for gap-filled validation: a) Landsat TM NDTI layer acquired on April 26, 2006 (location: upper-left corner of Champaign County in IL); b) NDTI layer with simulated data gap; c) gap-filled NDTI layer; white arrow points to areas with large predicted errors due to poorly defined field boundaries.

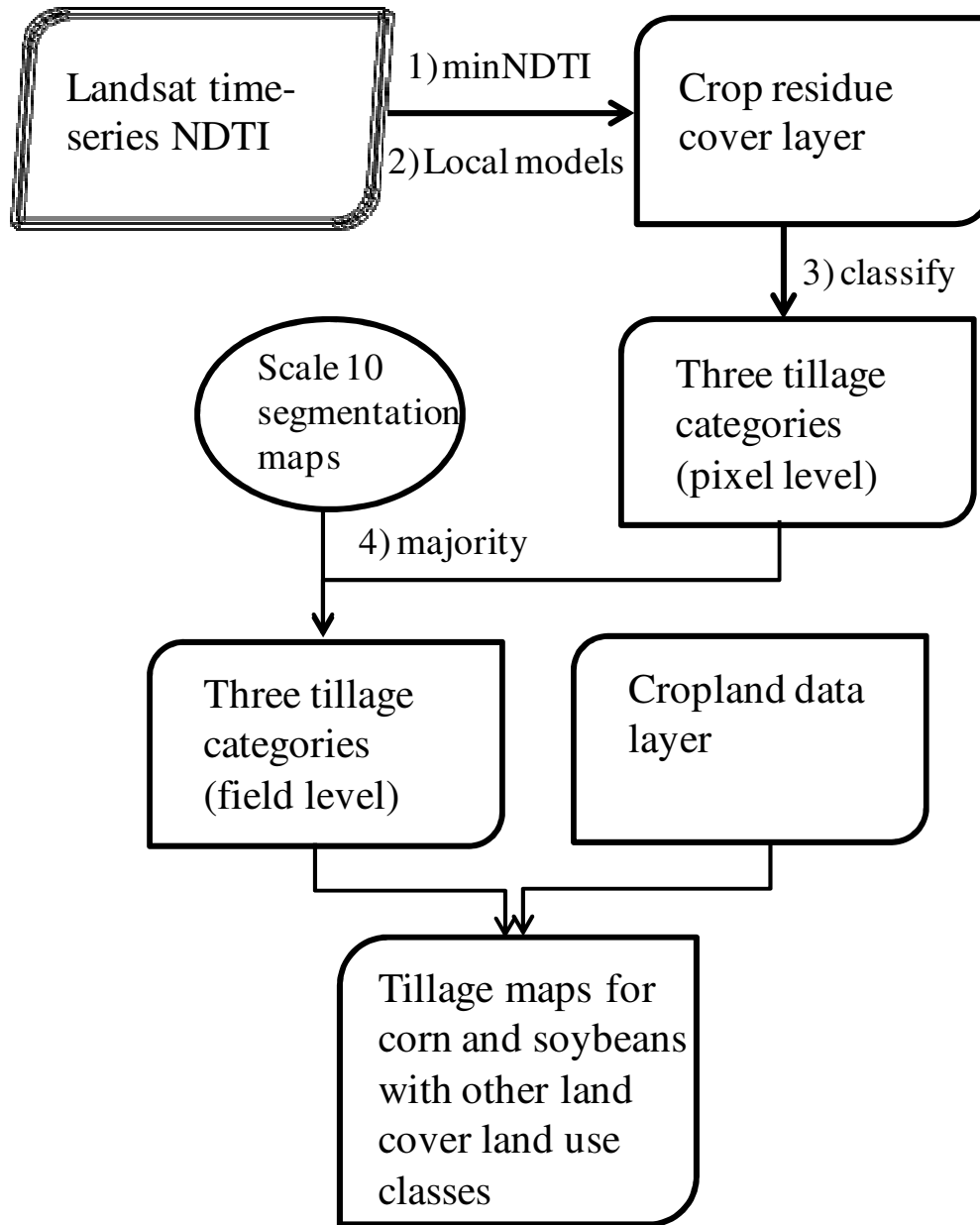


Figure 4.4. Flow diagram of the tillage map generation procedure.

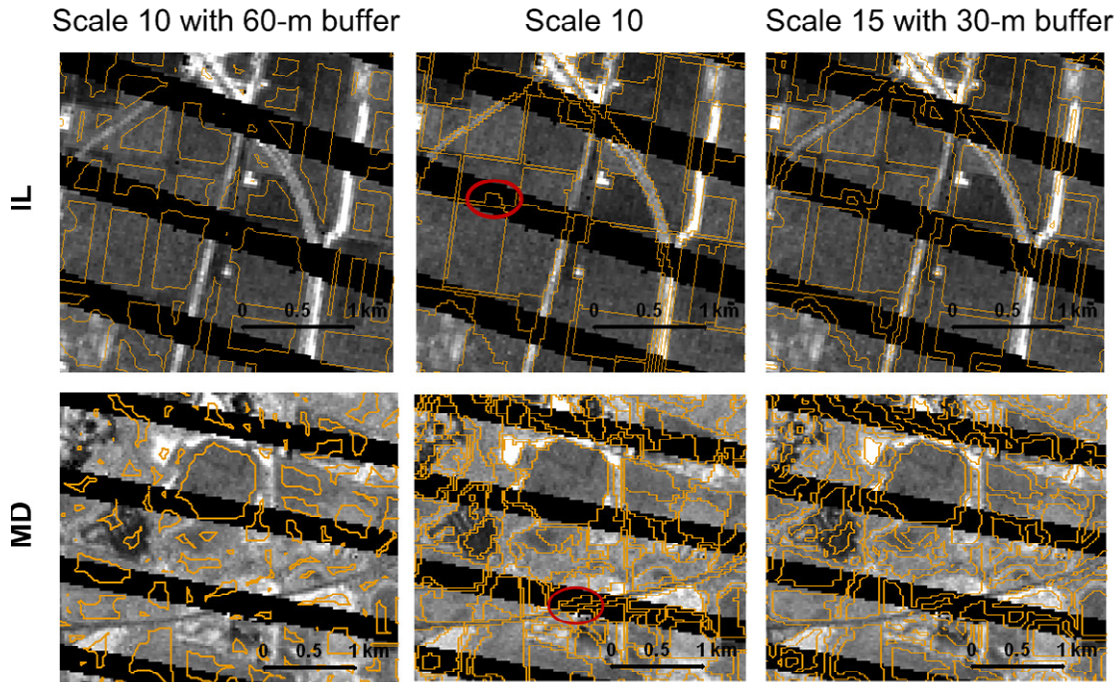


Figure 4.5. NDTI SLC-off layers with overlaid segmentation maps (orange lines). Here the gap width is approximately ten pixels for IL site and nine pixels for MD site. Red circled regions show examples of small objects that are positioned completely within the gap.

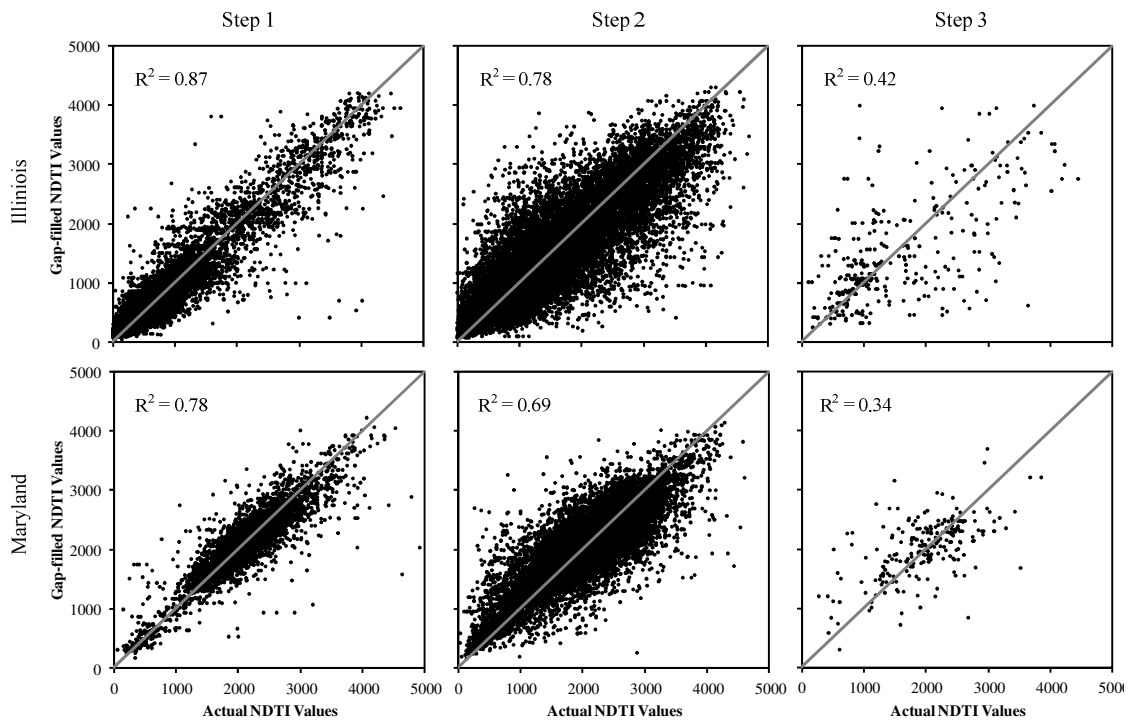


Figure 4.6. Scatter plots of predicted and actual NDTI values. NDTI values were scaled by 10,000.

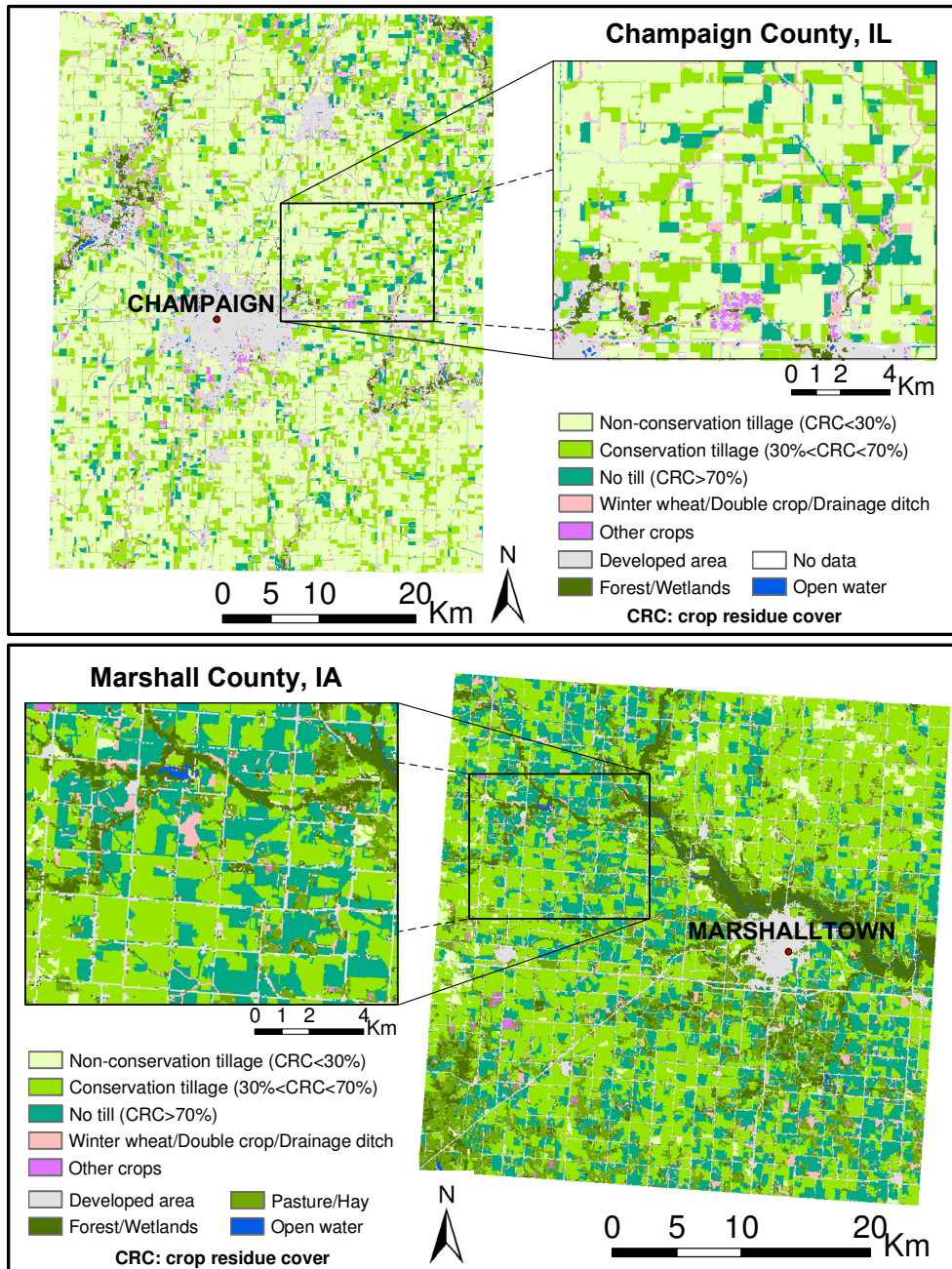


Figure 4.7. Tillage maps of Champaign County, IL (2006) and Marshall County, IA (2007). Non-conservation tillage practice dominated in Champaign County in 2006, but was rarely applied by farmers in Marshall County in 2007.

Chapter 5 Conclusions

Investigations of remote sensing of crop residue cover began in 1975 by Gausman et al. (1975). Two decades later, van Deventer et al. (1997) conducted the first study to test the capability of NDTI derived from Landsat TM imagery for differentiating conventional tillage from conservation tillage. NDTI was later found effective in classifying two broad tillage categories (Gowda et al. 2003; Sullivan et al. 2008; Thoma et al. 2004), but failed to predict crop residue cover along a continuum (Daughtry et al. 2006). In contrast, Hyperion and ASTER data, which have finer spectral resolution than Landsat data, have demonstrated better ability to predict crop residue cover (Daughtry et al. 2006; Serbin et al. 2009). Thus, results from previous studies led to a conclusion that the spectral bands of Landsat imagery are too coarse to detect crop residue. These studies, however, all used single images for tillage observations. While multitemporal NDVI analyses have been prevalent for more than two decades (Townshend et al. 1991), multitemporal NDTI analysis, one of the major contributions of this research, has only recently been introduced. The minNDTI methodology developed in this study significantly improves our ability to monitor site-specific applications of crop residue management at broad scales.

The first study (Chapter 2) presented a strategy that achieves improved mapping accuracy of crop residue cover (CRC)/tillage practices by incorporating sequential Landsat imagery into the analysis. The minNDTI values extracted from multi-temporal NDTI profiles minimize confounding effects of green vegetation (weeds or emerging crops), and reliably indicate the correct tillage status, if adequate numbers of satellite observations are available. The minNDTI was strongly correlated with CRC, with R^2 of

0.89. Both the minNDTI and PC methods were able to classify CRC into three tillage categories with overall classification accuracies of >90%, producer's accuracies of 83–100%, and user's accuracies of 75–100%. The results indicated that multi-temporal Landsat (both TM and ETM+) imagery is capable of mapping CRC. The strength of the minNDTI method is its ease of use and the well-defined physical relationship between NDTI and CRC.

The second study (Chapter 3) first tested the effectiveness of the minNDTI method in CRC estimation in four different locations. The minNDTI approach was able to estimate CRC with R^2 of 0.66 to 0.89 for local models. The less satisfactory performance of the minNDTI approach for some locations was attributed to confounding effects of soil variation. Thus, in addition to the known impacts of emergent green vegetation, soil moisture and organic carbon can also confound the NDTI signal, which tend to cause underestimation of CRC in low-lying wet and dark areas. This study also compared the minNDTI technique to hyperspectral Cellulose Absorption Index (CAI) and the ASTER Shortwave Infrared Normalized Difference Residue Index (SINDRI) for tillage classification. Accuracy of the minNDTI technique is comparable to those of the CAI and SINDRI. We also found that USDA/NASS *Crop and Weather Reports*, which provides local field and weather information, can be used to guide selection of appropriate Landsat observations. Results of this study demonstrated the potential of the minNDTI for mapping CRC/tillage practices at broad scales using sequential Landsat TM and ETM+ imagery.

While the first two studies developed and evaluated the minNDTI technique at the pixel level, the third study (Chapter 4) devised strategies to map tillage practices at the

field level and at broader scales. This study provided a strategy to solve the Landsat SLC-off data issue for tillage assessment applications, and proposed procedures to facilitate field-level tillage mapping at large scales. A simplified multi-scale segmentation gap-filling procedure was able to meet our needs for tillage application. Validation at field-level and county-level comparisons suggested that local models are capable of mapping tillage practices at the field level. However, local variations in soils, terrain, and weather may prevent application of a generalized model to a broad region over time. We observed coherent spatial patterns of tillage applications on the field-level tillage maps (Figure 4.7). These spatial patterns permit evaluation of the effects of crop residue management on different soil units, terrain, and drainage basins. Tillage data can also assist detection of “environmental hotspots” where improved conservation plans and policies may be warranted.

Monitoring crop residue management across different landscapes from space is not a simple task. Given the spatial variation of soil moisture and organic matter, further studies are needed to address the confounding issues of soil variation to improve tillage mapping accuracy. Currently, to cope with the difficulties in the transferability of empirical models, we suggest building a ground-based network that can provide CRC data for model calibration and accuracy assessment. The ground-based network, coupled with geospatial techniques, will form a more systematic, efficient, and environmental-friendly way to monitor crop residue management. Thus, it could be substituted for the CTIC roadside survey. Building an open-access database with crop residue data can accelerate the tillage mapping effort further.

The upcoming Landsat 8 Operational Land Imager (OLI) and ESA Sentinel-2 sensors will provide data for monitoring crop residue management in the future. The eight-day and five-day revisit times of Landsat 8 and Sentinel-2 ensure that the minNDTI method will be useful for future monitoring applications. The proposed Hyperspectral Infrared Imager (HyspIRI) mission will provide another opportunity for mapping crop residue using CAI. It images the Earth every 19 days with 60 meter spatial resolution, but its 19-day revisit time may not be short enough to take snapshots of agricultural surfaces within the narrow time window of tillage and planting operations, due to potential cloud coverage issues. Optical-radar data fusion might be able to improve our ability to accurately estimate CRC, as radar data have better capabilities to sense soil moisture and standing corn stalks. Integration of optical and radar data also permits analyses of how crop residue management has impacts on soil moisture.

This research, therefore, has proposed and validated, the minNDTI as a practical approach for site-specific, broad-scale monitoring of tillage status using multi-temporal, multispectral, satellite imagery. Although further research is required to document effects of terrain, soil organic matter, and soil moisture upon effectiveness of the minNDTI technique, it is clear that it forms an effective strategy both for retrospective analysis of agricultural landscapes, and for use with future satellite remote sensing systems.

References

- Daughtry, C.S.T., P.C. Doraiswamy, E.R. Hunt Jr, A.J. Stern, J.E. McMurtrey III, and J.H. Prueger. 2006. Remote sensing of crop residue cover and soil tillage intensity. *Soil and Tillage Research* 91 (1-2):101-108.
- Gausman, H.W., Gerbermann, A.H., Wiegand, C.L., Leamer, R.W., Rodriguez, R.R., & Noriega, J.R. (1975). Reflectance differences between crop residues and bare soils. *Soil Science Society of American Journal*, 39, 752-755
- Gowda, P.H., Mulla, D.J., & Dalzell, B.J. (2003). Examining the targeting of conservation tillage practices to steep vs. flat landscapes in the Minnesota River Basin. *Journal of Soil and Water Conservation*, 58, 53-57
- Serbin, G., Hunt Jr, E.R., Daughtry, C.S.T, McCarty, G., & Doraiswamy, P. (2009). An improved ASTER index for remote sensing of crop residue. *Remote Sensing*, 1, 971-991
- Sullivan, D.G., Strickland, T.C., & Masters, M.H. (2008). Satellite mapping of conservation tillage adoption in the Little River experimental watershed, Georgia. *Journal of Soil and Water Conservation*, 63, 112-119
- Thoma, D.P., Gupta, S.C., & Bauer, M.E. (2004). Evaluation of optical remote sensing models for crop residue cover assessment. *Journal of Soil and Water Conservation*, 59, 224-233

Townshend, J., Justice, C., Li, W., Gurney, C., & McManus, J. (1991). Global land cover classification by remote sensing: present capabilities and future possibilities. *Remote Sensing of Environment*, 35, 243-255.

van Deventer, A.P., Ward, A.D., Gowda, P.H., and Lyon, J.G. (1997). Using Thematic Mapper Data to Identify Contrasting Soil Plains and Tillage Practices. *Photogrammetric Engineering & Remote Sensing* 63 (1):87-93.