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Modeling Sustainable Agricultural Residue Removal at the Subfield Scale

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ABSTRACT

This study developed a computational strategy that utilizes data inputs from multiple spatial scales to investigate how variability within individual fields can impact sustainable residue removal for bioenergy production. Sustainable use of agricultural residues for bioenergy production requires consideration of the important role that residues play in limiting soil erosion and maintaining soil C, health, and productivity. Increased availability of subfield-scale data sets such as grain yield data, high-fidelity digital elevation models, and soil characteristic data provides an opportunity to investigate the impacts of subfield-scale variability on sustainable agricultural residue removal. Using three representative fields in Iowa, this study contrasted the results of current NRCS conservation management planning analysis with subfield-scale analysis for rake-and-bale removal of agricultural residue. The results of the comparison show that the field-average assumptions used in NRCS conservation management planning may lead to unsustainable residue removal decisions for significant portions of some fields. This highlights the need for additional research on subfield-scale sustainable agricultural residue removal including the development of real-time variable removal technologies for agricultural residue.

The Energy Independence and Security Act of 2007 (H.R. 6, 110th Cong., 1st Sess.) requires annual U.S. biofuel production to increase to >136 billion L by 2022. Nearly 80 billion L of this production must come from non-cornstarch feedstock. Given a conversion rate of 330 L biofuel Mg^{-1} biomass feedstock (Aden et al., 2002; Phillips et al., 2011), meeting this target will require the development and utilization of >240 million Mg of biomass resources. In the near term, the largest potential source of this feedstock is agricultural residue, that is, material other than grain including stems, leaves, and chaff (Perlack et al., 2005). Sustainable removal of agricultural residue, however, is constrained by the role agricultural residue plays in maintaining soil health and productivity (Karlen et al., 2003; Johnson et al., 2006; Wilhelm et al., 2007).

Wilhelm et al. (2010) identified six environmental factors that potentially limit sustainable agricultural residue removal: soil organic C, wind and water erosion, plant nutrient balances, soil water and soil temperature dynamics, soil compaction, and off-site environmental impacts. A number of studies have considered subsets of these factors in an effort to determine the potential sustainable agricultural residue available for biofuel production (Nelson et al., 2004; Graham et al., 2007; Wilhelm et al., 2007; Gregg and Izaurralde, 2010; Muth and Bryden, 2012). The focus of these studies has been establishing the potential availability of agricultural residues across large geographic regions or establishing best management practices for guiding residue removal decisions. Currently, there are no computational methodologies or strategies for determining sustainable residue removal at the subfield scale.

We have developed a modeling strategy that integrates the individual models and databases required to evaluate the sustainable agricultural residue removal potential at a subfield scale based on specific crop yield, soil characteristics, and surface topography data. Sustainable agricultural residue removal from three typical Iowa fields was examined using both the current NRCS guidelines and the subfield modeling process and the results contrasted.

BACKGROUND

Past agricultural crop residue removal modeling efforts have focused on soil erosion from wind and water. Residue removal has been considered sustainable for removal rates where computed erosion losses are less than the tolerable soil loss limits established by the NRCS. Larson (1979) used the Universal Soil Loss Equation to perform the first major assessment of the sustainability of removing agricultural residues. The study examined soils and production systems in the Corn Belt, the Great Plains, and the U.S. Southeast. Residue removal was investigated under a range of tillage practices with respect to erosion constraints and potential nutrient replacement requirements. The broader issue of soil health and long-term productivity, specifically soil organic C levels, was not considered. The study used area-weighted averages for soil, climate, and crop yields across Major Land Resource Areas (MLRAs) (NRCS, 2006). The MLRAs investigated by Larson et al. (1979) were comprised of groups of approximately

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Abbreviations: DEM, digital elevation model; LiDAR, light detection and ranging; RUSLE2, Revised Universal Soil Loss Equation Version 2; SCI, Soil Conditioning Index; SSURGO, Soil Survey Geographic; WEPS, Wind Erosion Prediction System.

five to 20 counties. Soils were averaged to the MLRA level by extracting the primary erodibility factors for each soil from the available survey data and then using an area-weighted average to generate average erodibility factors for the MLRA.

The Revised Universal Soil Loss Equation (Renard et al., 1997) and Wind Erosion Equation (Fasching, 2006) were used by Nelson (2002) to estimate sustainable removal rates of corn (*Zea mays* L.) stover and wheat (*Triticum aestivum* L.) straw. This study expanded the analysis of Larson (1979) through the use of the Soil Survey Geographic (SSURGO) database (Soil Survey Staff, 2011), an open access national soil survey database provided by the NRCS. The methodology of Nelson (2002) considered water- and wind-induced erosion at the SSURGO soil map unit spatial scale for reduced-tillage and no-till management practices. The study was based on "county average, hectare-weighted fields." The approach developed county-level composite soil characteristics that were used to establish erodibility factors for the erosion equations. The analysis found that, in 1997, the midwestern and eastern United States could have sustainably supplied more than 58 million Mg of corn stover and wheat straw. Nelson et al. (2004) expanded this assessment with two additions: (i) the inclusion of five 1- and 2-yr crop rotations (e.g., corn–soybean [*Glycine max* (L.) Merr.]) and (ii) calculation of erosion at the SSURGO soil type spatial scale. At the soil type scale, residue retention requirements were established for each management scenario using county-average crop yields. Each soil was assessed using the representative slope from the SSURGO database. This study considered wind- and water-induced soil erosion constraints and found that if all hectares were in a corn–soybean rotation using reduced tillage practices; nearly 398 million Mg of agricultural residue could be sustainably removed annually from the 10 highest corn grain producing states in the United States. Graham et al. (2007) utilized the methodology of Nelson et al. (2004) to perform a nationwide corn stover availability assessment. The spatial scale of data and analysis assumptions were consistent with those of Nelson et al. (2004), but an additional constraint was added by restricting stover removal from unirrigated production in dry climates. This constraint was based on an assumption that for unirrigated production in dry climates, all stover was required on the soil surface to help maintain soil moisture levels. Including this additional constraint, Graham et al. (2007) found that sustainable national stover potential was nearly 106 million Mg annually.

The NRCS announced in 1998 that it was accelerating the development of a new erosion prediction model for implementation in its field offices by 2002 (National Sedimentation Laboratory, 2010). The new model was the Revised Universal Soil Loss Equation, Version 2 (RUSLE2) (NRCS, 2011). The RUSLE2 provided the ability to consider additional management and soil scenarios by adopting physics-based algorithms that detail the various environmental processes in place of the empirical-factor-based relationships used in the original RUSLE. Through the development of the RUSLE2, the NRCS conservation management planning process transitioned to process-based environmental modeling. In recent years, the NRCS has continued that transition to process-based analyses by adopting the Wind Erosion Prediction System (WEPS; http://www.weru.ksu.edu/nrcs/wepsnrcs.html) and the Soil Conditioning Index (SCI) (NRCS, 2012) models in conjunction with the RUSLE2 for conservation management planning. The NRCS field office implementation of the RUSLE2, WEPS, and SCI utilizes representative soil and slope, and field-average yield assumptions to analyze a management plan for a particular field (NRCS, 2008). The field-average yield assumptions may be replaced with hillslope or representative soil yields when that information is available to the field office technician. The choice for a representative soil and slope are based on selecting the "dominant critical" soil area. The NRCS field office technical note described the dominant critical soil area as having the following characteristics: (i) it is significantly large enough to effect a change in management, (ii) it is not an average of the field characteristics, (iii) it is not the worst case scenario, and (iv) if dominant in terms of area, it is not the flattest or least erosive soil in the field. There are two primary questions the models are used to answer. The first is whether soil loss due to erosion is greater than the tolerable soil loss limits (*T* value) set by the NRCS for each SSURGO database soil type. The second question is whether the SCI is >0, which qualitatively suggests that soil organic C levels will not be depleted for a given scenario.

As currently implemented, the tools require direct user interaction for each simulation scenario, thus limiting their application to a detailed scenario assessment. Scenario assessment is a time-consuming task in which data from one or more databases is formatted as input for one model, and then the output is combined with other data to become input for the other models. One way to address this concern is through an integrated modeling approach that takes advantage of the simulation capabilities of process-based environmental models and implements them within a modeling framework that facilitates hands-free model execution. This approach was used in a study by Muth and Bryden (2012) that investigated residue removal for the state of Iowa considering wind- and water-induced erosion and soil organic C as potential limiting factors. This study was performed using an integrated modeling toolkit that coupled the RUSLE2, WEPS, and SCI models with the SSURGO, CLIGEN (National Soil Erosion Research Laboratory, 2009), WINDGEN (Wagner et al., 1992), and NRCS crop management template (ftp://fargo.nserl.purdue.edu/pub/RUSLE2/Crop_Management_Templates/) databases. Figure 1 shows the framework for this integrated modeling toolkit. This assessment determined that under current crop rotations, grain yields, and tillage management practices, nearly 26.5 million Mg of agricultural residue could be sustainably removed in Iowa. The integrated modeling toolkit developed used political boundaries to specify the location and spatial scale for a particular assessment and then constructed the land management practices (i.e., crop rotation, tillage, and residue removal method) to be investigated. This assessment modeled sustainable agricultural residue removal at the SSURGO soil type spatial scale using representative slopes for each soil and used county-average crop yield and climate data.

None of the current modeling approaches supports analysis of the impact of subfield-scale variability on sustainable residue removal. The high-fidelity spatial data necessary to perform subfield-scale analyses are becoming increasingly available, however. The high-fidelity spatial data available for these analyses included crop yield data from combine harvesters and high-resolution digital elevation models (DEMs) describing surface topography.

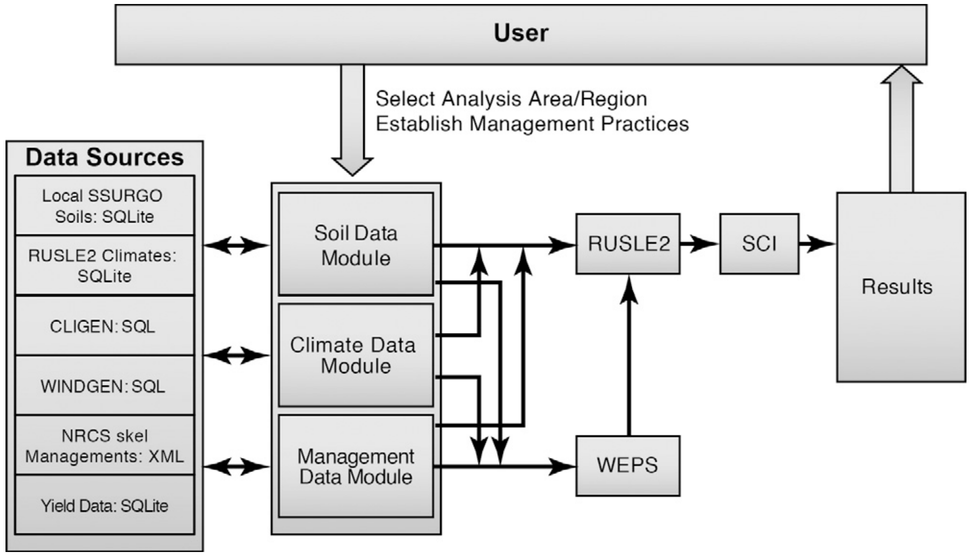

Fig. 1. Integrated residue removal modeling framework, using the Soil Survey Geographic (SSURGO) database, the Revised Universal Soil Loss Equation Version 2 (RUSLE2), the Cligen weather generator, the wind data generator WINDGEN, NRCS management database, SQLite software, the Wind Erosion Prediction System (WEPS), and the Soil Conditioning Index (SCI).

High-Fidelity Spatial Data

The emergence of GPS technologies and precision agriculture concepts in the 1990s resulted in a number of techniques and methodologies for acquiring and using high-fidelity spatial information in agricultural production systems (Stafford, 2000). One of the products of this revolution has been the commercial availability of harvester yield monitors. These data sets are acquired directly from harvester yield monitors in the form of ESRI shapefiles (Environmental Systems Research Institute, 2012). These data sets provide significant detail at the subfield scale. For example, a typical ESRI shapefile can contain >400 yield measurements ha^{-1}, and point-to-point yield across the field may vary by a factor of >10.

Surface slope impacts the spatial variability of several important agricultural productivity characteristics including soil water (Moore et al., 1988; Tomer et al., 1994; Western et al., 1999), agronomic variables (Moore et al., 1993; Bell et al., 1995; Odeh et al., 1994; Florinsky et al., 2002) and crop yields (Yang et al., 1998; Kravchenko and Bullock, 2000; Kaspar et al., 2003; Green and Erskine, 2004). High-fidelity surface topology is available in the form of DEMs. Several approaches to building DEMs have been developed for agricultural lands. These include the use of USGS-produced national data sets (Dosskey et al., 2005; Thompson et al., 2001) and more recently the use of light detection and ranging (LiDAR) through airborne laser scanning (Vitharana et al., 2008; McKinion et al., 2010). Several states, including Iowa, have worked toward LiDAR mapping of the entire state. In Iowa, this effort is moving forward through the GeoTREE LiDAR mapping project (GeoInformatics Training, Research, Education, and Extension Center, 2011). The LiDAR mapping is the highest fidelity surface slope data currently available and provides a more accurate representation of slope on agricultural land than the USGS-produced DEMs (USGS, 2010). Based on this, LiDAR data assembled through the GeoTREE project were utilized in this study.

Soil characteristics such as organic matter and sand fraction in the topsoil horizon have significant spatial variability and can impact crop yields and the availability of agricultural residue for removal. The SSURGO database provided by the NRCS is available through several web-based access points (Soil Survey Staff, 2011). Soil characteristic data in the SSURGO database are represented at approximately a 10- to 100-m scale.

THE INTEGRATED MODELING PROCESS AT THE SUBFIELD SCALE

Noting the variability of crop yields reported by precision harvesting, the variability of slope, and the variability of soil characteristics across individual fields, it is expected that there is also significant subfield variability in sustainable agricultural residue removal rates. We have developed an integrated model for subfield variability of sustainable agricultural residue removal. This model includes the current modeling tools (i.e., the RUSLE2, WEPS, and SCI), the existing data sources (i.e., SSURGO database soils, CLIGEN, WINDGEN, and NRCS crop management), and the available high-fidelity spatial information (i.e., LiDAR slope and crop yield monitor output). The basic modeling process remains the same as earlier investigations of sustainable agricultural residue removal. The difference is that instead of modeling based on average or representative values for crop yields, soil characteristics, and slope for a field, county, or larger area, the modeling inputs are based on the same spatial scale as the precision farming data available. There are three challenges for developing an integrated model for subfield variability of sustainable agricultural residue removal: the computational challenge of iteratively computing with 400 or more spatial points per hectare, the inclusion of geoprocessing tools, and the integration of data at different spatial scales. The starting place for our subfield model was the earlier integrated model developed by Muth and Bryden (2012). The model was built using the VE-Suite integration framework (McCorkle and Bryden, 2007), which enables extension and updating of the models, databases, and framework as needed without revision of the existing components.

Figure 2 shows the data flow within the subfield integrated model. As shown, the computational challenge of iteratively computing sustainable residue removal is handled by

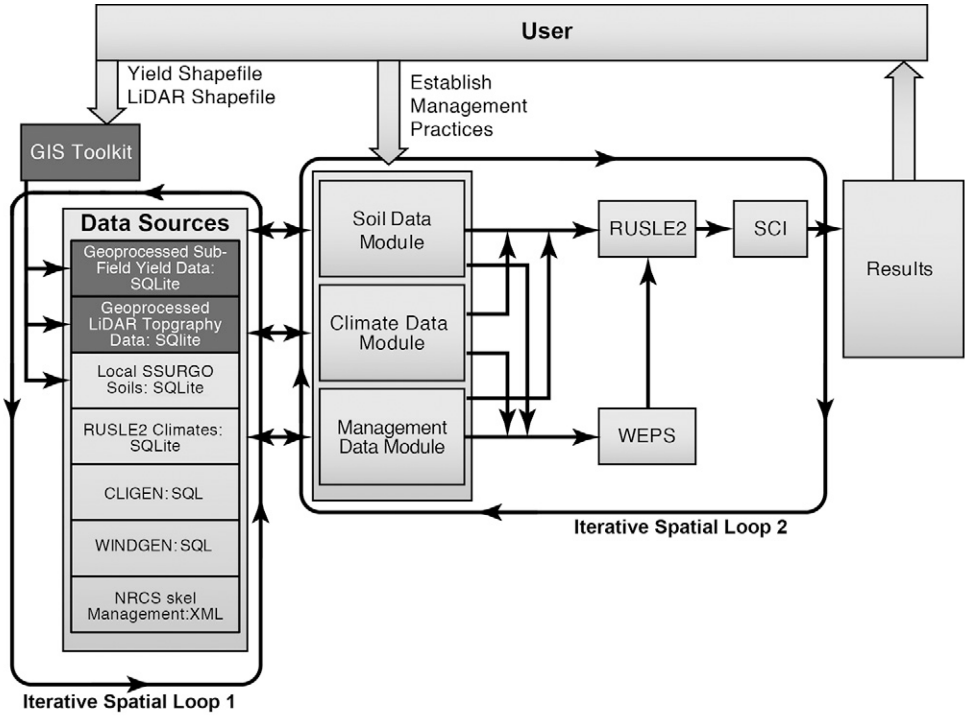

Fig. 2. The subfield-scale modeling process, using the Soil Survey Geographic (SSURGO) database, the Revised Universal Soil Loss Equation Version 2 (RUSLE2), the Cligen weather generator, the wind data generator WINDGEN, NRCS management database, SQLite software, the Wind Erosion Prediction System (WEPS), and the Soil Conditioning Index (SCI).

updating the scheduling algorithm. Two iterative loops are used. The first assembles databases with all needed information for each crop yield data point input as an ESRI shapefile (Environmental Systems Research Institute, 1998). Following completion of this task, the second loop uses the data and the RUSLE2, WEPS, and SCI models to simulate the environmental processes for each spatial location and management scenario of interest. For this study, about 1200 model executions per hectare (400 spatial elements, one management scenario, and three model executions [RUSLE2, WEPS, and SCI] per spatial element) were required. Upon completion of the scenario runs, the model results are provided to the user through an SQLite database that includes references to the original yield data point shapefile. The results are formatted for simple interaction through standard mapping and visualization tools. The database of results is also equipped with a set of queries that provide the user with the model results in numeric form.

The geoprocessing tool used in this project was ESRI ArcGIS 10, which was chosen because it has automated and commercially supported geoprocessing algorithms to perform the functions required for data processing in this study. An SQLite database structure is integrated into the model to provide management of the high-fidelity yield and topography data sets. The SQLite databases contain the necessary data for the soil, climate, and management data modules to assemble and organize the model input data. The computational scheduling algorithm packages the information and calls the models as needed. The resulting data are then accessible via an SQLite database.

Assembly of the needed data requires resolving information at different spatial scales among the various databases. The RUSLE2 has been developed with the base computation unit as a single overland flow path along a hillslope profile. For a particular field, a number of overland flow paths may exist. For conservation planning, a particular overland flow path is selected to represent a field, and a management practice is selected that controls erosion adequately for that flow-path profile. The conservation management planning application of the RUSLE2 requires selection of a representative soil, slope, slope length, and yield that are considered constant for the field. To use the RUSLE2 at the subfield scale, the assumption is made that the soil, slope, and yield characteristics at each spatial element provide the representative overland flow path for the field. In earlier studies, the representative values used were based on the primary factors of concern at a local scale. These factors were then used to create a representative area-weighted average applicable at a larger scale. In this study, those primary factors were used directly at a local scale and then aggregated. This is a reasonable approach but must be applied with care. Each spatial element does not exist as an independent entity but rather is influenced by its neighboring elements. Even so, significant insight can be gained by applying the RUSLE2, WEPS, and SCI on a spatial-element basis. A similar assumption was made for the WEPS model. The WEPS models a three-dimensional simulation region representing a field or small set of adjacent fields. Using WEPS for conservation planning also requires the selection of a representative soil, slope, and yield. The assumption made to use WEPS in the subfield-scale integrated model was that the soil, slope, and yield characteristics for a spatial element in question are representative for a field-scale simulation region. The SCI is modeled for each spatial element by using the SCI subfactors calculated by the RUSLE2 and WEPS using the assumptions as stated. The specific spatial details of each database are as follows:

1. Yield data are input directly as received from the harvester output. The crop yield data sets represent the base spatial discretization for the subfield-scale integrated model. Each yield

data point represents a spatial element at the meter scale. The ground speed of harvesting equipment, variability in surface slope, and yield variability have each been found to create errors in yield monitor measurements (Loghavi et al., 2008; Fulton et al., 2009; Sudduth and Drummond, 2007). Although tools have been investigated to help reduce these errors, there is no current commercial standard for dealing with potential errors. The yield monitor data for the fields investigated in this study were visually compared with characteristics of the fields, such as soil C and slope, that provide insight into potential productivity. Areas in the fields where the slope is higher and soil organic matter is lower correlated with areas of lower grain yield. Based on this, the high-fidelity yield data were used here as received from the harvester yield monitors.

2. The LiDAR DEM is intersected with the discretized spatial elements from the yield data. The LiDAR data are also at the meter scale. After intersection geoprocessing, each yield database record is appended with slope and slope length data. The GeoTREE LiDAR tool (GeoInformatics Training, Research, Education, and Extension Center, 2011) is used in the modeling process to provide the LiDAR data associated with the spatial extent of the high-fidelity yield data. Within the geoprocessing tool, the LiDAR data are used to create an elevation raster for the field(s) being investigated. A slope function in ArcGIS 10 Spatial Analyst is then used to generate a surface slope grid from the elevation raster. The slope function calculates the maximum rate of change between each elevation cell and its neighbors and assigns that value to each cell within the DEM raster. After the slope grid is built, the high-fidelity spatial elements are intersected with the grid.
3. The SSURGO database provides soil characteristic data at the 10- to 100-m scale. The SSURGO data are intersected with the discretized yield spatial elements and each yield element using ArcGIS 10. Each yield data point is associated with a SSURGO soil type and inherits the characteristics of that soil.
4. Climate data are provided to the integrated model at the county scale (kilometer scale) and are assumed constant across the spatial elements for an individual field. The centroid latitude and longitude for a given field are used to acquire climate data, and each yield spatial element uses the same climate data.
5. Management practice options are chosen by the user. Management data are field-scale characteristics and are taken as constant across the spatial elements. The NRCS crop management database provides the crop rotation, tillage practice, fertilizer application, and harvest practice management data.

Sustainability Criteria

Agricultural residue removal is defined as sustainable in this assessment using criteria consistent with NRCS field office assumptions. These criteria are that the combined wind and water erosion are less than or equal to the T value for each SSURGO soil map unit and that the SCI value is ≥ 0. Although these criteria are well established for conservation management planning, it should be clear that they do not compare the agronomic impact of residue removal with the impact of not removing residue. As a consequence, the erosion criteria may create situations where "sustainable" residue removal results in higher erosion losses than management practices that do not include residue removal. In the same way, "sustainable" residue removal will not decrease soil C; however, it is likely that soil C would be increased using management practices that do not remove residue. As in many agricultural and energy systems, sustainable residue removal involves tradeoffs between renewable energy production and environmental impact. By considering these tradeoffs at the subfield scale, a more informed and balanced decision can be made.

Model Validation

The initial integrated model coupling the RUSLE2, WEPS, and SCI was verified to provide the same conclusions as the NRCS field office versions of the models as described by Muth and Bryden (2012). In the case of subfield sustainability of agricultural residue removal, however, there are no computational or experimental results available for validation. Because of this, the code was validated in two ways. In the first, the high-fidelity spatial databases were populated with the same field-average data as used in the NRCS field office implementation. The code was then run and summarized at the subfield scale, demonstrating that the code properly called, formatted, computed, and assembled the data needed. In each case, the integrated subfield model provided the same conclusions as the standard model use cases. In the second way, the code was used to analyze three fields, and the results were examined to ensure that they could be explained. This is discussed further below.

RESULTS

Three representative fields in Iowa were chosen to examine the impact of subfield-scale variability on sustainable agricultural residue removal. Each of these fields was assessed using NRCS conservation management planning guidelines (NRCS, 2008) assuming the commercially available residue removal operations of rake and bale. The removal scenario was then evaluated for each field using the subfield-scale integrated model to investigate the sustainability of rake-and-bale removal at the subfield scale. The three fields examined were:

1. A 57-ha field located in Cerro Gordo County in north-central Iowa with significant diversity in soil properties, surface slope, and crop yield. This field has been in a continuous corn rotation, but is transitioning to a corn–soybean rotation. Tillage management practices for this field were modeled as reduced tillage.
2. A 19-ha field in Iowa County in east-central Iowa with uniform soil and surface slope but diverse crop yield. This field is managed in a continuous corn crop rotation and was modeled assuming reduced tillage practices.
3. A 77-ha field also in Iowa County with moderate soil diversity, surface slope, and crop yield. This field is managed in a continuous corn rotation and has been modeled assuming conventional tillage practices.

These fields were chosen because existing relationships with the growers managing these fields provided access to high-fidelity crop yield data sets, the location of the fields in Iowa ensured access to LiDAR surface topography data, and they provided a range of subfield-scale variability.

Conservation Management Planning Results

The NRCS conservation management planning guidelines (NRCS, 2008) were used to evaluate the residue removal potential for each of the three fields. Following NRCS practice, the representative soil for each field was selected by determining which SSURGO soil type best satisfied the dominant critical soil area criteria. Table 1 provides the list of soils that comprise each field and the dominant critical soil type selected as representative based on NRCS guidelines. The representative slope was taken directly from the SSURGO database for the selected soil type. The field-average crop yield was reported from the combine harvester yield monitor. The management practices were modeled as described above and are listed for each field in Table 1. Table 2 shows the results of this assessment. Removal rates are reported as average annual removals. For continuous corn rotations, residue removal takes place each year, but for corn–soybean rotations, residue removal happens only during corn growing seasons. The NRCS representation of the rake-and-bale residue removal operations considers the standing and flattened portions of the surface residue. The rake collects a portion of the flattened residue into a windrow and the bale operation collects a majority fraction of the windrow, thus effectively removing it from the field. As shown in Table 2, soil loss due to erosion for each field was less than the *T* value. For Field 1, the SCI was <0, which resulted in a determination that rake-and-bale residue removal would not be sustainable management in the field. For Fields 2 and 3, the SCI was >0. This led to the conclusion that rake-and-bale residue removal would be approved as sustainable by the NRCS.

Subfield Scale Data

To examine the impact of the subfield-scale variability of soil characteristics, surface topography, and grain yield on residue removal sustainability in each of these fields, the subfield integrated model used the same management practices and climate information as the NRCS management guidelines (NRCS, 2008). The yield, slope, and soil information were obtained from the high spatial fidelity crop yield, LiDAR, and SSURGO data as described above. The results of these analyses are shown in Fig. 3, 4, and 5 for Fields 1, 2, and 3, respectively.

Field 1

As shown in Table 1, seven different SSURGO database soil types comprise Field 1. The SSURGO data for the organic matter and sand fractions in the top horizon are shown in Fig. 3a and 3b. The dominant critical soil used for the NRCS conservation management planning guidelines for Field 1 was SSURGO Map Unit 83B Kenyon loam. This soil type comprises approximately 8 ha or 13% of the field. The soil with the largest area in the field is SSURGO Map Unit 84 Clyde silty clay loam, comprising 15 ha or 26% of the field. This soil does not satisfy the previously dominant critical soil area criteria as described above because it is the

Table 1. List of soils and primary assumptions for each field NRCS conservation management assessment.

Field	SSURGO soils (in order of area: high to low)	Dominant critical soil	Dominant critical slope	Field-average yield	Tillage	Crop rotation	Residue harvest operations
			%	Mg ha^{-1}			
1	84 Clyde silty clay loam, 0–2% slopes 198B Floyd loam, 1–4% slopes 173 Hoopeston fine sandy loam, 1–3% slopes 83B Kenyon loam, 2–5% slopes 407B Schley loam, 1–4% slopes 175B Dickinson fine sandy loam, 2–5% slopes 41B Sparta loamy fine sand, 2–5% slopes	83B Kenyon loam	4.0	10.85	reduced	corn–soybean	rake and bale
2	688 Koszta silt loam, 0–2% slopes 587 Chequest silty clay loam, 0–2% slopes	688 Koszta silt loam	1.0	12.60	reduced	continuous corn	rake and bale
3	587 Chequest silty clay loam, 0–2% slopes 687 Watkins silt loam, 0–2% slopes 88 Nevin silty clay loam, 0–2% slopes 7 Wiota silty clay loam, 0–2% slopes 133 Colo silty clay loam, 0–2% slopes 688 Koszta silt loam, 0–2% slopes 8B Judson silty clay loam, 2–5% slopes 422 Amana silt loam, 0–2% slopes 54 Zook silty clay loam, 0–2% slopes	587 Chequest silty clay loam	1.0	12.40	conventional	continuous corn	rake and bale

Table 2. Sustainability of rake-and-bale removal evaluated under NRCS conservation management planning guidelines.

Field	Residue removal rate	Water erosion	Wind erosion	Combined erosion	Soil *T* value	Soil Conditioning Index	Sustainable residue removal practice
	Mg ha^{-1}						
1	2.68	6.50	0.03	6.53	11.21	–0.15	no
2	6.46	2.13	0.01	2.14	11.21	0.33	yes
3	5.10	3.59	3.95	7.54	11.21	0.01	yes

lowest slope, least erosive, and highest organic matter soil in the field. The soil with the next largest area in the field is Map Unit 198B Floyd loam, which comprises about 13 ha or 20% of the field. This soil also has low surface slope values and high organic matter values compared with other soils in the field and subsequently was not selected as dominant critical. The SSURGO database slope for 83B Kenyon loam is 4.0% and was used as the representative slope for the field based on NRCS conservation management planning guidelines.

As shown in Fig. 3c, there is significant variability in the slope of this field. Figure 3d shows that the corn yields on this field for the 2010 growing season varied from <3 to >15 Mg ha^{-1}. The lower yield ranges seen in Fig. 3d can be generally associated with lower organic matter soils shown in Fig. 3a. A similar relationship exists between lower yields and higher sand fraction soils, shown visually in Fig. 3b. The visual correlation between lower yields in Fig. 3d and higher slope areas shown in Fig. 3c is also clear. These field characteristics can each limit the sustainable residue removal and in combination can have a compounding effect. The conservation management planning guidelines concluded that the annual average removal rate would be 2.68 Mg ha^{-1} and that this removal rate would be unsustainable. Although there is evidence that current high-yielding corn cultivars have a higher grain/residue ratio (Wilhelm et al., 2011), in this study it was assumed, consistent with NRCS guidelines, that the corn grain/residue ratio was 1:1. The NRCS-developed rake-and-bale operation collect approximately 52% of the residue. Applying these assumptions to the crop yields for the spatial elements in Field 1, the removal rate ranged from 0.0 to 3.92 Mg ha^{-1}. The result of this is shown in Fig. 3e, where rake-and-bale residue removal is a direct reflection of Fig. 3d, which shows grain yield.

Given the spatial variability in soils, slope, and yield, the key question is how much of this field would actually be managed sustainably under rake-and-bale removal. Figure 3f summarizes at a subfield scale where rake-and-bale removal would be sustainable in Field 1 and where one or more sustainability criteria would be violated. Specifically, Fig. 3f shows where (i) SCI values are <0, which simulates a decrease in soil C; (ii) combined wind and water erosion are greater than the T value for the

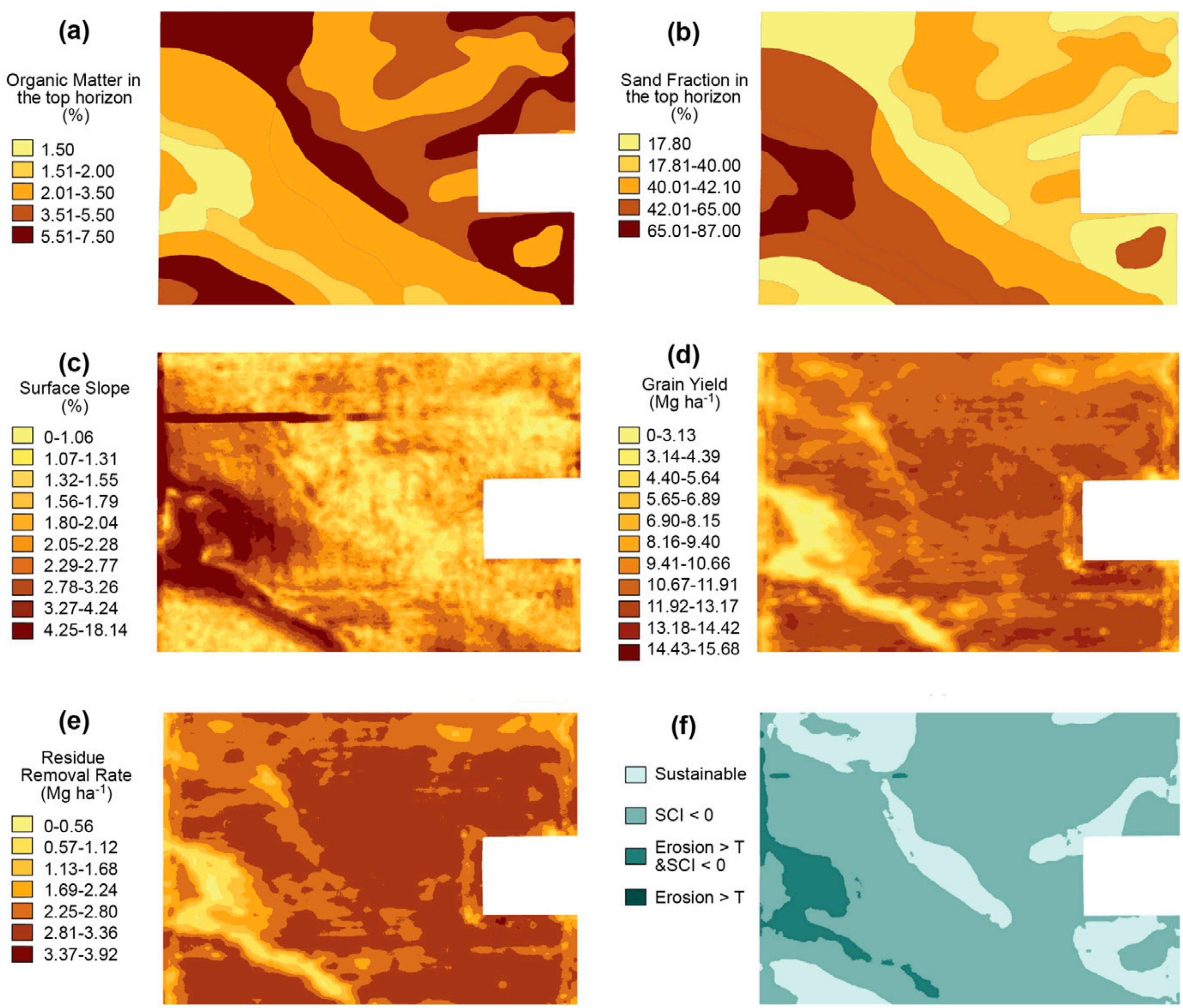

Fig. 3. Soil properties, crop yield, and residue removal results for Field 1, using the Soil Conditioning Index (SCI) and soil erosion tolerance (*T*) values.

soil; and (iii) the SCI is <0 and erosion is greater than the T value, thus simulating that both a soil loss and a soil organic C issue exist. As shown, the primary sustainability issue for rake-and-bale residue removal in this field is soil organic C. This is in agreement with the sustainability analysis performed using NRCS conservation planning guidelines. It is interesting to note, however, that 21% of Field 1 can be managed sustainably under rake-and-bale removal. Soil loss from wind and water erosion is only an issue in Field 1 in areas with surface slopes above approximately 3.5% and a soil sand fraction >40%. This is reasonable because water erosion becomes a problem with increasing slope, and wind erosion will typically be greater on soils with a higher sand fraction. In areas of the field where erosion is a problem, soil C is also an issue, and these areas align with lower grain yields.

The current NRCS practice finds that rake-and-bale residue removal operations are not sustainable for this field using the dominant critical soil area and slope and the field-average yield.

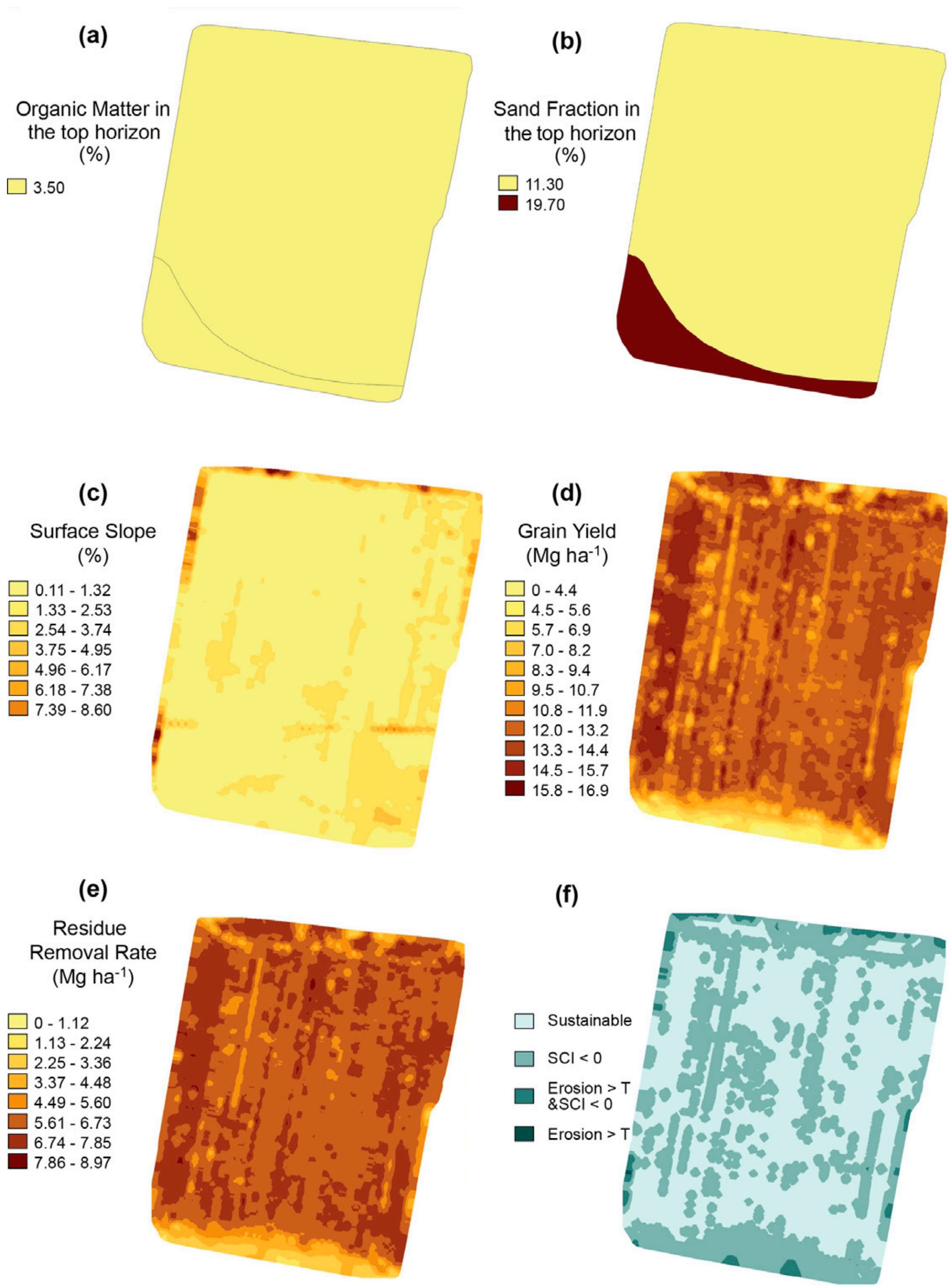

Fig. 4. Residue removal results, key soil properties, and crop yield for Field 2, using the Soil Conditioning Index (SCI) and soil erosion tolerance (*T*) values.

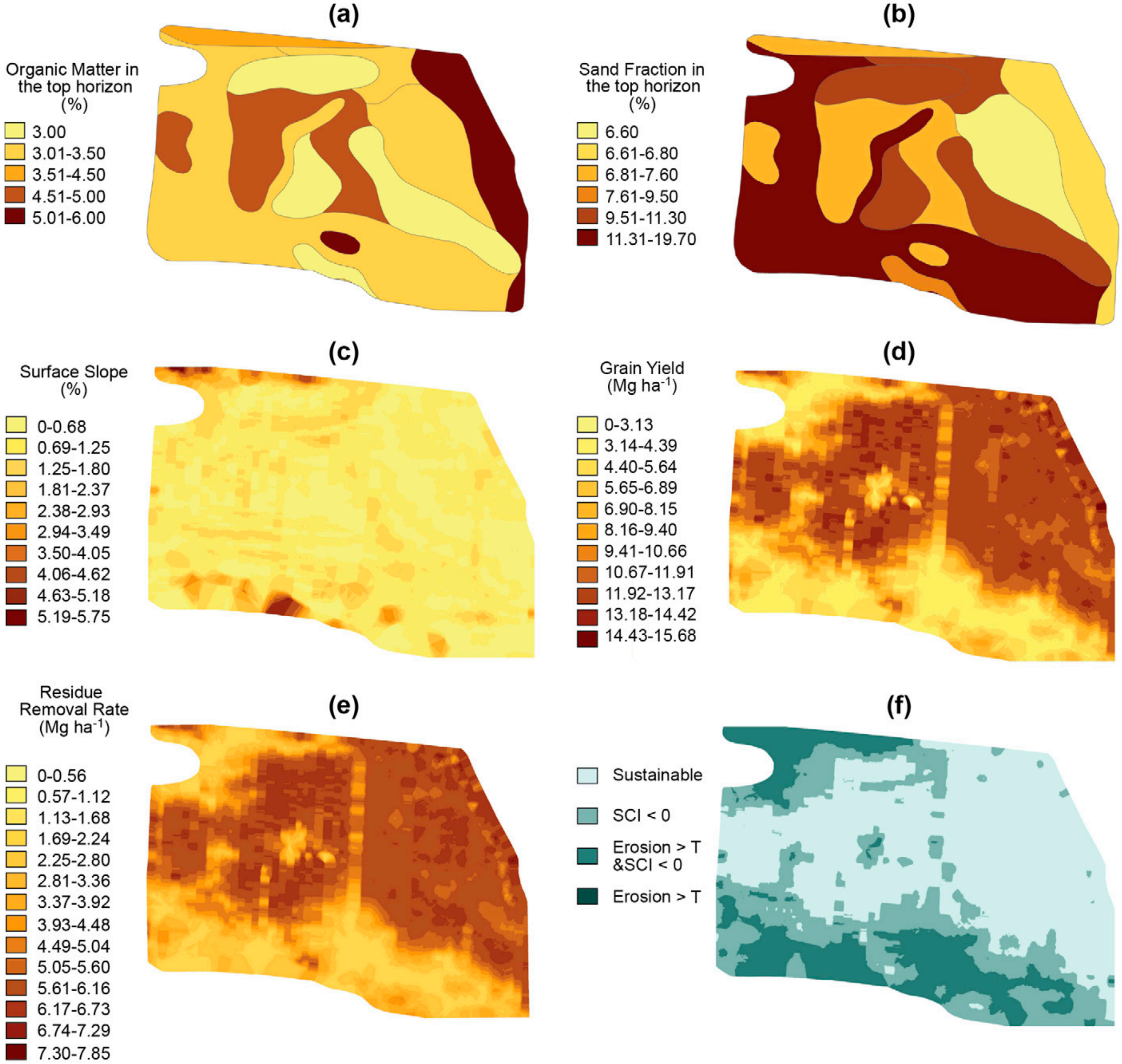

Fig. 5. Residue removal results, key soil properties, and crop yield for Field 3, using the Soil Conditioning Index (SCI) and soil erosion tolerance (*T*) values.

This is not surprising because the dominant critical soil area selection criteria for this field resulted in a representative soil with relatively high slope and moderate organic matter. The soil with the largest area for Field 1, SSURGO Map Unit 84 Clyde silty clay loam, has the most favorable characteristics for sustainable residue removal of all the soils comprising the field. This effect can be seen looking at Fig. 3a and 3f. The only areas of Field 1 where rake-and-bale removal is sustainable are those with high levels of soil organic matter. The lowest soil C, highest sand fraction, highest surface slope, and lowest grain yield are all found in the same parts of the field.

Field 2

Field 2 is comprised of two SSURGO soils, as listed in Table 1. Both soils have a representative organic matter of 3.5% (Fig. 4a) and a relatively low sand fraction of <20% (Fig. 4b). More than 90% of the area in this field has <2.5% slope (Fig. 4c). The 2010 corn grain yield data averaged 12.6 Mg ha^{-1} but ranged from <4 to nearly 17 Mg ha^{-1} (Fig. 4d). Figure 4e shows the residue removed across the field spatial elements using the NRCS assumptions for the grain/residue ratio (1:1) and rake-and-bale residue removal operations (approximately 52% removal rate). Figure 4f shows where rake-and-bale removal would be sustainable for Field 2 and where one or more sustainability criteria would be violated. The majority (89%) of Field 2 would be sustainably managed under rake-and-bale removal. As expected, the uniform soil and slope characteristics of Field 2 create a scenario where grain yields are relatively uniform across the field. There are few areas where erosion exceeds the tolerable limits, and these appear in areas with higher surface slope along the edges of the field. As a result, rake-and-bale removal is generally uniform and sustainable across Field 2.

The subfield analysis did find some soil C constraints on sustainability with rake-and-bale removal in pockets where grain yields are lower. As noted above, there are some questions about the accuracy of yield monitors at this scale, and these pockets may be an artifact of the yield monitors. In addition, residue left on the field will be generally spread out across larger areas, and soil organic C processes are continuous across larger areas than the small pockets seen in Fig. 4f. One solution to this may be aggregating soil C results to a larger reporting scale (e.g., averaging or other aggregation techniques) than the soil erosion results. Different environmental processes will probably require the use of data and models at different spatial scales to accurately simulate the effects of residue removal. This is a topic that needs further research and consideration.

Field 3

As shown in Table 1, nine SSURGO soils comprise Field 3. As shown in Fig. 5a and 5b, the organic matter of these soils ranges from 3 to 6%, and all of the soils have a relatively low sand fraction (<20%). Surface slopes in this field are generally <2.5%, with small regions near the field edge having slopes near 8% (Fig. 5c). The average corn grain yield in 2010 was 12.4 Mg ha^{-1}. Yields ranged from <3 to >15 Mg ha^{-1} (Fig. 5d). As noted above, Field 3 is managed under conventional tillage. Residue removal on conventionally tilled land has typically been considered not to be environmentally viable because of compounding negative soil erosion and soil C impacts caused by invasive tillage practices (Nelson, 2002; Nelson et al., 2004; Perlack et al., 2005). In spite of this assumption, the NRCS conservation management planning guidelines indicated that rake-and-bale removal for Field 3 would be sustainable. Figure 5e shows the residue removed across the field spatial elements using NRCS assumptions for the grain/residue ratio (1:1) and rake-and-bale residue removal operations (approximately 52% removal rate).

Figure 5f shows where rake-and-bale removal will be sustainable for Field 3 and where one or more sustainability criteria will be violated. Despite being managed under conventional tillage, subfield-scale analysis indicated that 62% of Field 3 would be sustainable with rake-and-bale removal. In contrast to Fields 1 and 2, erosion is a significant constraint for Field 3 (Fig. 5f). Considering that Field 3 has relatively low surface slope values, this is due to the use of conventional tillage practices.

Similarly to Field 1, it is surprising that current NRCS practice finds that rake-and-bale residue removal operations are sustainable. In contrast to Field 1, in Field 3 the difference in the models arises not because of the representative soil assumption, but rather because of the field-average yield assumption. The representative soil for Field 3 is SSURGO Map Unit 587 Chequest silty clay loam, which comprises nearly 37% of the field area. The spatial extent of the 587 Chequest silty clay loam in this field can be seen in Fig. 5b in those areas with the highest sand fraction. The field-average grain yield is 12.40 Mg ha^{-1}, and the NRCS guidelines using that yield indicate sustainable rake-and-bale operations. The subfield average yield for the areas of 587 Chequest silty clay loam in this field, however, is 8.4 Mg ha^{-1}. This mismatch between average grain yield and representative soil type results in nearly 40% of the field not meeting one or more sustainability criteria.

DISCUSSION AND CONCLUSIONS

Tables 3 and 4 summarize the results from comparing the NRCS conservation management planning guidelines and the subfield-scale analysis of sustainable agricultural residue removal for the fields investigated in this study. Each of the three fields raises different issues when the subfield-scale analysis is compared with the conservation management planning guidelines. As shown in Table 3, using NRCS conservation management planning guidelines in Field 1, rake-and-bale removal would provide an annual average 152 Mg of corn stover; however, none of this would be sustainably removed. In contrast, the subfield analysis of Field 1 showed that 23% of this potentially available residue would be removed sustainably, and Table 4 shows that 21% of the area in Field 1 would be managed sustainably. Field 1 presents a situation where current NRCS guidelines for selecting representative soil and slope characteristics protect the majority of the field from unsustainable practices, but the assumptions do leave residue in the field that could have been removed sustainably and may provide an opportunity to economically harvest biomass for bioenergy production.

Field 2 represents a situation where conservation management planning guidelines and the subfield analysis of sustainable agricultural residue removal generally agreed. Field 2 has much less variability in soil and slope. As shown in Table 3, the rake-and-bale operations would remove 119 Mg of residue. Subfield analysis indicated that 89% would be removed sustainably, and Table 4 shows that 83% of the 19 ha in Field 2 would be managed sustainably. The subfield analysis showed pockets where soil C would be an issue. Organic C dynamics in the soil, however, are understood to work over more continuous extents than these pockets. This raises questions about how to apply and report the subfield-scale model results for the SCI.

In Field 3, the assumption of a field-average grain yield is inconsistent with the subfield-scale data for significant portions of the field. As discussed above, the assumption in this analysis was that the grain/residue ratio for corn is 1:1. As a result,

Table 3. Available agricultural residue using rake-and-bale collection for each field.

Field	Total residue available if sustainability is not considered	Sustainable residue available based on NRCS guidelines	Sustainable residue available based on subfield analysis	Fraction of total residue available for sustainable removal based on subfield analysis
	Mg			%
1	152	0	35	23
2	119	119	106	89
3	387	387	279	72

Table 4. Field area that can be sustainably managed using rake-and-bale collection based on subfield analysis.

Field	Total field area	Area managed sustainably	Fraction of total area sustainably managed
	ha		%
1	57	12	21
2	19	16	83
3	77	48	62

although the NRCS guidelines indicate that rake-and-bale residue removal would be sustainable, the subfield analysis shown in Table 3 for Field 3 found that 72% of the 387 Mg of residue would be removed sustainably, and Table 4 shows that 62% of the 77 ha would be managed sustainably.

This study developed a computational strategy to model the impact of subfield-scale variability on sustainable agricultural residue removal. The computational strategy integrates data inputs from multiple spatial scales, geoprocessing tools to facilitate interaction with high-fidelity subfield-scale data, and models representing soil erosion from wind and water forces and soil organic matter. A computational scheduling algorithm is used to support integration of the multiple models, databases, and other information at the subfield scale. The model was then used to examine three representative fields in Iowa to examine the relationship between subfield variability and the current NRCS conservation management planning guidelines. For Field 1, the conservation management planning guidelines found that rake-and-bale removal of agricultural residue would be unsustainable. The subfield analysis showed that these assumptions protect the majority of the field from unsustainable practices but do understate the residue removal potential for significant portions of the field. In Field 2, the subfield analysis of the SCI was found to be sensitive to the high-fidelity yield data, thus resulting in small pockets in which the SCI was negative; however, soil organic C dynamics and the spread of agricultural residue occur at larger spatial scales. Based on this, a validated methodology for applying the SCI at the subfield scale needs to be developed. Field 3 was found to have significant areas in which the subfield analysis and the NRCS conservation management planning guidelines disagreed as to the sustainability of rake-and-bale residue removal.

These results point out key uncertainties with the integrated model. Specifically, there is uncertainty or error in the grain yield input data that may impact the results at specific points in the field. Similarly, the surface slope input data sets and slope length assumptions can have a significant impact on the results. Quantifying these errors is challenging and is a key aspect of our ongoing research efforts. As a starting place for understanding these errors, as discussed above, the use of the integrated model was validated using the NRCS online models for a given field, soil type, slope, and management practice. The results matched in all cases, so it is anticipated that results will be as accurate as current practice when applied at the field scale. When applied at the subfield scale, it is expected that the additional spatial information will provide a more accurate understanding of the impact of agricultural residues. More research is needed to quantify the error and to identify how subfield modeling can be used. In addition, research is needed to investigate the following issues and questions:

1. The current conservation management planning approach using representative soil, representative slope, and field-average yield may lead to unsustainable residue removal decisions or may understate the residue removal potential of a field. For Field 1, the NRCS guidelines found rake-and-bale removal to be unsustainable, whereas the subfield analysis found that >20% of the field could have residue removed sustainably using conventional rake-and-bale technologies. For Fields 2 and 3, the conservation management planning approach provided recommendations that rake-and-bale residue removal methods could be sustainably implemented. For Field 3, nearly 40% of the field would have unsustainable residue removal under conventional removal methods. Further research is needed to develop new planning algorithms that can utilize the increasing amounts of high-fidelity data that are becoming available.
2. Additional work needs to be done to establish how to apply the subfield-scale model results. As highlighted by the small pockets where soil C issues were identified in Field 2, the spatial scale of precision farming and the spatial scale of soil C dynamics are not directly comparable. Validated modeling algorithms need to be developed that address this issue.

In addition, the application of the subfield analysis of sustainable residue removal may provide motivation for the development of variable-rate residue removal technologies. In each of the fields examined, there are areas where residue is required for soil health functions and cannot be harvested using conventional residue removal systems. The subfield model developed in this work, however, could be used to quantify the potential benefits of variable-removal technologies and provide justification for the development and deployment of variable-rate residue removal technologies.

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REFERENCES

Aden, A., M. Ruth, K. Ibsen, J. Jechura, K. Neeves, J. Sheehan, et al. 2002. Lignocellulosic biomass to ethanol process design and economics utilizing co-current dilute acid prehydrolysis and enzymatic hydrolysis for corn stover. NREL/TP-510–32438. Natl. Renew. Energy Lab., Golden, CO.

Bell, J.C., C.A. Butler, and J.A. Thompson. 1995. Soil-terrain modeling for site-specific agricultural management. In: P.C. Robert et al., editors, Proceedings of the Site-Specific Management for Agricultural Systems 2nd International Conference, Minneapolis, MN. 27–30 Mar. 1995. ASA, CSSA, and SSSA, Madison, WI. p. 209–227.

Dosskey, M.G., D.E. Eisenhauer, and M.J. Helmers. 2005. Establishing conservation buffers using precision information. J. Soil Water Conserv. 60:349–354.

Environmental Systems Research Institute. 1998. ESRI shapefile technical description: An ESRI white paper. ESRI, Redlands, CA.

Fasching, R.A. 2006. Wind erosion equation: Management period method Microsoft Excel spreadsheet. Agron. Tech. Note MT-76 (Rev. 3). NRCS, Bozeman, MT.

Florinsky, I.V., R.G. Eilers, G.R. Manning, and L.G. Fuller. 2002. Prediction of soil properties by digital terrain modelling. Environ. Modell. Softw. 17:295–311. doi:10.1016/S1364-8152(01)00067-6

Fulton, J.P., C.J. Sobolik, S.A. Shearer, S.F. Higgins, and T.F. Burks. 2009. Grain yield monitor flow sensor accuracy for simulated varying field slopes. Appl. Eng. Agric. 25:15–21.

GeoInformatics Training, Research, Education, and Extension Center. 2011. Iowa LiDAR mapping project. Univ. of Northern Iowa, Cedar Falls. http://www.geotree.uni.edu/lidarProject.aspx (accessed 31 Dec. 2011).

Graham, R.L., R. Nelson, J. Sheehan, R.D. Perlack, and L.L. Wright. 2007. Current and potential U.S. corn stover supplies. Agron. J. 99:1–11. doi:10.2134/agronj2005.0222

Green, T.R., and R.H. Erskine. 2004. Measurement, scaling, and topographic analyses of spatial crop yield and soil water content. Hydrol. Processes 18:1447–1465. doi:10.1002/hyp.1422

Gregg, J.S., and R.C. Izaurralde. 2010. Effect of crop residue harvest on long-term crop yield, soil erosion and nutrient balance: Trade-offs for a sustainable bioenergy feedstock. Biofuels 1:69–83. doi:10.4155/bfs.09.8

Johnson, J.M.-F., D. Reicosky, R. Allmaras, D. Archer, and W. Wilhelm. 2006. A matter of balance: Conservation and renewable energy. J. Soil Water Conserv. 61:120A–125A.

Karlen, D.L., S.S. Andrews, B.J. Wienhold, and J.W. Doran. 2003. Soil quality: Humankind's foundation for survival. J. Soil Water Conserv. 58:171–179.

Kaspar, T.C., T.S. Colvin, D.B. Jaynes, D.L. Karlen, D.E. James, D.W. Meek, D. Pulido, and H. Butler. 2003. Relationship between six years of corn yields and terrain attributes. Precis. Agric. 4:87–101. doi:10.1023/A:1021867123125

Kravchenko, A.N., and D.G. Bullock. 2000. Correlation of corn and soybean grain yield with topography and soil properties. Agron. J. 92:75–83.

Larson, W.E. 1979. Crop residues: Energy production or erosion control? J. Soil Water Conserv. 34:74–76.

Loghavi, M., R. Ehsani, and R. Reeder. 2008. Development of a portable grain mass flow sensor test rig. Comput. Electron. Agric. 61:160–168. doi:10.1016/j.compag.2007.11.002

McCorkle, D.S., and K.M. Bryden. 2007. Using the semantic web to enable integration with virtual engineering tools to create extensible interfaces. Virtual Real. 11:253–260. doi:10.1007/s10055-007-0077-3

McKinion, J.M., J.L. Willers, and J.N. Jenkins. 2010. Spatial analyses to evaluate multi-crop yield stability for a field. Comput. Electron. Agric. 70:187–198. doi:10.1016/j.compag.2009.10.005

Moore, I.D., G.J. Burch, and D.H. Mackenzie. 1988. Topographic effects on the distribution of surface soil water and the location of ephemeral gullies. Trans. ASAE 31:1098–1107.

Moore, I.D., P.E. Gessler, G.A. Nielsen, and G.A. Peterson. 1993. Soil attribute prediction using terrain analysis. Soil Sci. Soc. Am. J. 57:443–452. doi:10.2136/sssaj1993.03615995005700020026x

Muth, D.J., and K.M. Bryden. 2012. An integrated model for assessment of sustainable agricultural residue removal limits for bioenergy systems. Environ. Modell. Softw. (in press).

National Sedimentation Laboratory. 2010. Revised Universal Soil Loss Equation 2: RUSLE2 development. Natl. Sediment. Lab., Oxford, MS. http://www.ars.usda.gov/Research/docs.htm?docid=6027 (verified 9 Jan. 2012).

National Soil Erosion Research Laboratory. 2009. Cligen overview. Natl. Soil Erosion Res. Lab., West Lafayette, IN. http://www.ars.usda.gov/Research/docs.htm?docid=18094 (accessed 15 June 2011).

Nelson, R.G. 2002. Resource assessment and removal analysis for corn stover and wheat straw in the eastern and midwestern United States: Rainfall and wind-induced soil erosion methodology. Biomass Bioenergy 22:349–363. doi:10.1016/S0961-9534(02)00006-5

Nelson, R.G., M. Walsh, J. Sheehan, and R. Graham. 2004. Methodology for estimating removable quantities of agricultural residues for bioenergy and bioproduct use. Appl. Biochem. Biotechnol. 113:13–26. doi:10.1385/ABAB:113:1-3:013

NRCS. 2006. Major Land Resource Area (MLRA): Land resource regions and major land resource areas of the United States, the Caribbean, and the Pacific Basin. Agric. Handbk. 296. U.S. Gov. Print. Office, Washington, DC.

NRCS. 2008. Choosing the planning area of a field by "dominant critical area." Iowa Tech. Note 29. NRCS, Des Moines, IA.

NRCS. 2011. Revised Universal Soil Loss Equation, Version 2 (RUSLE2). Official NRCS RUSLE2 program; official NRCS database. Natl. Soil Erosion Res. Lab., West Lafayette, IN. http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm (accessed 15 Jun. 2011).

NRCS. 2012. Using SCI to assess management effects on soil carbon. ftp://ftp-fc.sc.egov.usda.gov/SQI/web/Soil_Quality_SCI.ppt (verified 14 Jan. 2012). NRCS, Washington, DC.

Odeh, I.O.A., A.B. McBratney, and D.J. Chittleborough. 1994. Spatial prediction of soil properties from landform attributes derived from a digital elevation model. Geoderma 63:197–214. doi:10.1016/0016-7061(94)90063-9

Perlack, R.D., L.L. Wright, A.F. Turhollow, R.L. Graham, B.J. Stokes, and D.C. Erbach. 2005. Biomass as feedstock for a bioenergy and bioproducts industry: The technical feasibility of a billion-ton annual supply. DOE/GO-102005-2135, ORNL/TM-2005/66. Oak Ridge Natl. Lab., Oak Ridge, TN.

Phillips, S.D., J.K. Tarud, M.J. Biddy, and A. Dutta. 2011. Gasoline from wood via integrated gasification, synthesis, and methanol-to-gasoline technologies. Tech. Rep. NREL/TP-5100-47594. Natl. Renew. Energy Lab., Golden, CO.

Renard, K.G., G.R. Foster, G.A. Weesies, D.K. McCool, and D.C. Yoder, coordinators. 1997. Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). Agric. Handbk. 703. U.S. Gov. Print. Office, Washington, DC.

Soil Survey Staff. 2011c. Soil Survey Geographic (SSURGO) database. http://soils.usda.gov/survey/geography/ssurgo/(accessed 14 April 2011). NRCS, Washington, DC.

Stafford, J.V. 2000. Implementing precision agriculture in the 21st century. J. Agric. Eng. Res. 76:267–275. doi:10.1006/jaer.2000.0577

Sudduth, K.A., and S.T. Drummond. 2007. Yield Editor: Software for removing errors from crop yield maps. Agron. J. 99:1471–1482.

Thompson, J.A., J.C. Bell, and C.A. Butler. 2001. Digital elevation model resolution: Effects on terrain attribute calculation and quantitative soil-landscape modeling. Geoderma 100:67–89. doi:10.1016/S0016-7061(00)00081-1

Tomer, M.D., J.L. Anderson, and J.A. Lamb. 1994. Landscape analysis of soil and crop data using regression. In: P.C. Robert et al., editors, Site-Specific Management for Agricultural Systems: Proceedings of the 2nd International Conference, Minneapolis, MN. 27–30 Mar. 1994. ASA, CSSA, and SSSA, Madison, WI. p. 273–284.

USGS. 2010. Seamless data warehouse: National elevation data sets. http://seamless.usgs.gov (verified 31 Dec. 2011). USGS, Reston, VA.

Vitharana, U.W.A., M. Van Meirvenne, D. Simpson, L. Cockx, and J. De Baerdemaeker. 2008. Key soil and topographic properties to delineate potential management classes for precision agriculture in the European loess area. Geoderma 143:206–215. doi:10.1016/j.geoderma.2007.11.003

Wagner, L.E., J. Tartarko, and E.L. Skidmore. 1992. WIND-GEN: A statistical database and generator for wind data. Paper presented at: ASAE 1992 International Summer Meeting, Charlotte, NC. 21–24 Jun. 1992. ASAE, St. Joseph, MI. Pap. 922111.

Western, A.W., R.B. Grayson, G. Blöschl, G.R. Willgoose, and T.A. McMahon. 1999. Observed spatial organization of soil moisture and its relation to terrain indices. Water Resour. Res. 35:797–810. doi:10.1029/1998WR900065

Wilhelm, W.W., J.R. Hess, D.L. Karlen, J.M.F. Johnson, D.J. Muth, J.M. Baker, et al. 2010. Balancing limiting factors and economic drivers for sustainable midwestern agricultural residue feedstock supplies. Ind. Biotechnol. 6:271–287. doi:10.1089/ind.2010.6.271

Wilhelm, W.W., J.M.F. Johnson, D.L. Karlen, and D.T. Lightle. 2007. Corn stover to sustain soil organic carbon further constrains biomass supply. Agron. J. 99:1665–1667. doi:10.2134/agronj2007.0150

Wilhelm, W.W., J.M.F. Johnson, D.T. Lightle, D.L. Karlen, J.M. Novak, N.W. Barbour, et al. 2011. Vertical distribution of corn stover dry mass grown at several U.S. locations. BioEnergy Res. 4:11–21. doi:10.1007/s12155-010-9097-z

Yang, C., C.L. Peterson, G.J. Shropshire, and T. Otawa. 1998. Spatial variability of field topography and wheat yield in the Palouse region of the Pacific Northwest. Trans. ASAE 41:17–27.