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An investigation of sustainable agricultural residue availability for energy applications

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**An investigation of sustainable agricultural residue availability for
energy applications**

by

David J. Muth Jr.

A dissertation submitted to the graduate faculty in partial fulfillment of the requirements for

the degree of

DOCTOR OF PHILOSOPHY

Major: Mechanical Engineering

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Ames, Iowa

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CHAPTER 1. GENERAL INTRODUCTION

1.1 INTRODUCTION

The work presented in this dissertation was developed in response to calls from the cellulosic bioenergy research community requesting a comprehensive and robust decision support framework for guiding the sustainable removal of agricultural residues for bioenergy production. These calls came from across the bioenergy community including the US Department of Agriculture (USDA), the US Department of Energy (DOE), academia, and industry. The challenge is clear; commercial scale removal of agricultural residues is currently being implemented to supply biomass feedstock for multiple first-of-a-kind cellulosic biorefineries, but the tools required to ensure sustainable decisions were being made had not yet emerged. Wilhelm et al., 2010 presented a multi-institution perspective on the requirements for this decision support framework. These requirements include

1. The ability to evaluate multiple environmental factors that can potentially limit sustainable agricultural residue removal rates
2. Providing cellulosic biorefinery industry decision makers with the data and knowledge required to confidently make investments. This includes reliable resource estimates, perspective on sensitivity, and confidence in USDA conservation management planning certification for their contracted growers.
3. Providing biomass producers with the decision tools they need to sustainably manage their production operations. This includes a detailed understanding of what is going on within single management units and again includes certification through USDA's conservation management planning process.

The work presented in this dissertation represents the development of an integrated decision support framework which satisfies these requirements.

1.2 AGRICULTURAL RESIDUES AS BIOENERGY FEEDSTOCK

The DOE released a study in 2005 that identified scenarios with over 270 million metric tons of agricultural residue biomass (i.e., materials other than grain including stems, leaves, and chaff) available annually in the US (Perlack et al., 2005). Assuming a biomass to biofuel conversion rate of 330 liters per metric (Aden et al., 2002, Phillips et al., 2011), this resource base could produce over 89 billion liters of biofuels annually. Federal legislation through the Energy Independence and Security Act of 2007 calls for US biofuel production to increase above 136 billion liters annually by 2022. If this federal requirement is met, agricultural residues will play an essential role.

The challenge is that agricultural residue removal must be managed carefully to be sustainable. Residues play a number of critical roles within the agronomic system that must be considered when removal decisions are made (Karlen et al., 2003; Johnson et al., 2006; and Wilhelm et al., 2007). Specifically, there are six environmental factors that can limit sustainable agricultural residue removal—soil organic carbon, wind and water erosion, plant nutrient balances, soil water and temperature dynamics, soil compaction, and off-site environmental impacts (Wilhelm et al., 2010). There is a well-developed set of modeling, simulation, and database tools available to support investigation of these factors. The challenge is that these tools are disparate and focused on a specific environmental process for which they were developed. The question of sustainable agricultural residue removal requires the integration of these disparate tools to more comprehensively support decisions.

This work has built and implemented a model and data integration strategy to achieve the previously stated requirements for a sustainable agricultural residue removal decision support framework. The model and data integration strategy has been built on the following premises:

1. Models are required to support sustainable residue removal decisions because experimental approaches cannot feasibly describe the full range of system characteristics that must be explored.
2. The use of well-developed and validated models and databases provides significant advantages in terms of quickly achieving results that can provide confidence in residue removal decisions.
3. Capable tools supporting model and data integration for complex decision making have emerged within the engineering community and can be applied to the residue removal problem.

For executing the model and data integration strategy the first step was identifying the model and database tools that provide a sufficiently comprehensive analysis of the scenarios and also satisfy the decision making requirements stated above. With the appropriate modeling and database tools identified, the study was executed to deliver a product satisfying these requirements. The product of this work is an integrated residue removal analysis tool that is currently being used to support residue removal decisions and assessments for DOE, USDA Agricultural Research Service, USDA Farm Service Agency, USDA Natural Resources Conservation Service (NRCS), and multiple industry partners who harvest residues at a commercial scale.

1.3 DISSERTATION ORGANIZATION

This dissertation is comprised of four research papers included as Chapters 2 through 5. These papers are currently in the peer review process at several peer-reviewed journals. Chapter Two presents the development of the integrated multi-factor modeling strategy. It focuses on addressing the first requirement by selecting key models and databases and then computationally coupling the selected tools to support dynamic multi-factor assessments. Chapter 2 includes a review of existing model integration frameworks for engineering and environmental modeling applications and discusses the strengths and weaknesses of these frameworks for sustainable residue harvest. A detailed presentation of the management and distribution of data through the framework is provided. The integrated modeling and data flow through the decision framework is presented and then demonstrated with a case study evaluating residue removal potential in the state of Iowa.

Chapter 3 presents an application of the integrated modeling strategy to determine the sustainable agricultural residue that is available across the US. This analysis was performed to provide a more robust and comprehensive alternative to previous studies that faced a number of computational limitations. The previous efforts are reviewed and discussed. The analysis executed for Chapter 3 also satisfies the second requirement for residue removal decisions presented earlier. Data produced through this effort provides guidance for making decisions about residue removal that matches the scale and computations that will be performed by the NRCS to certify sustainability. This data includes nearly 100 million residue removal scenarios (each calculated at the 10–100m scale) that describe potential residue removal decisions across the entire United States. These scenarios are aggregated to provide a national assessment of sustainable agricultural residue removal potential.

Chapter 4 focuses on understanding sustainable removal at the field and sub-field scale. It discusses the challenges that sub-field scale variability in soil characteristics, surface topography, and yield create for determining sustainable residue removal rates. The model and data integration strategy is adapted and expanded to support higher fidelity spatial datasets required for sub-field scale analysis. The enhanced framework is applied to three standard production units to determine if existing residue removal equipment and approaches are capable of dealing with sub-field scale variability. The data and integrated modeling tool developed through this work satisfies the third requirement by providing biomass producers with the tools and information they need to make sustainable residue removal decisions at the field and sub-field scale.

Chapter 5 investigates the potential of variable rate residue removal as an approach for overcoming the challenges presented by sub-field scale variability in soil characteristics, surface topography, and grain yield. A conceptual single pass variable rate residue harvesting configuration was developed and evaluated. The conceptual configuration was compared to existing commercially available residue harvest systems, as well as research-based residue removal systems reported in the literature. The three fields investigated in Chapter 4 were evaluated with the sub-field scale integrated model simulating residue removal with the conceptual variable rate harvester. This analysis reports the impacts that the variable rate residue harvester has on sustainably accessible residue quantities, and provides insight on the performance requirements for the conceptual variable rate harvester within the representative fields where the analysis was performed.

The work presented through these four papers provides a number of key conclusions.

The application of an integrated modeling framework for multi-factor analysis of sustainable

residue removal can provide enhanced data and insight than previous assessments which focused on limited environmental factors and land management scenarios. Applying the framework for a spatially comprehensive analysis of residue removal potential across the US finds that there are over 150 million metric tons of residue that can be sustainably removed under current yield and land management scenarios. However, sub-field scale variability in soil characteristics, surface slope, and grain yield create challenges for existing residue removal equipment. There are several options for dealing with sub-field scale variability. One such option shown to have significant potential in this work is a variable rate residue harvester.

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**CHAPTER 2. AN INTEGRATED MODEL FOR ASSESSMENT OF
SUSTAINABLE AGRICULTURAL RESIDUE REMOVAL
LIMITS FOR BIOENERGY SYSTEMS**

A paper submitted to *Environmental Modelling and Software*

D. Muth, Jr.^{1,2} and K. M. Bryden¹

ABSTRACT

Agricultural residues have been identified as a significant potential resource for bioenergy production, but serious questions remain about the sustainability of harvesting residues. Agricultural residues play an important role in limiting soil erosion from wind and water and in maintaining soil organic carbon. Because of this, multiple factors must be considered when assessing sustainable residue harvest limits. Validated and accepted modeling tools for assessing these impacts include the Revised Universal Soil Loss Equation Version 2 (RUSLE2), the Wind Erosion Prediction System (WEPS), and the Soil Conditioning Index. Currently, these models do not work together as a single integrated model. Rather, use of these models requires manual interaction and data transfer. As a result, it is currently not feasible to use these computational tools to perform detailed sustainable agricultural residue availability assessments across large spatial domains or to consider a broad range of land management practices. This paper presents an integrated modeling strategy that couples existing datasets with the RUSLE2 water erosion, WEPS wind erosion, and Soil Conditioning Index soil carbon modeling tools to create a single integrated residue

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removal modeling system. This enables the exploration of the detailed sustainable residue harvest scenarios needed to establish sustainable residue availability. Using this computational tool, an assessment study of residue availability for the state of Iowa was performed. This study included all soil types in the state of Iowa, four representative crop rotations schemes, variable crop yields, three tillage management methods, and five residue removal methods. The key conclusions of this study are that under current management practices and crop yields nearly 26.5 million Mg of agricultural residue are sustainably accessible in the state of Iowa, and that through the adoption of no till practices residue removal could sustainably approach 40 million Mg. However, when considering the economics and logistics of residue harvest, yields below 2.25 Mg ha^{-1} are generally considered to not be viable for a commercial bioenergy system. Applying this constraint, the total agricultural residue resource available in Iowa under current management practices is 19 million Mg. This compares with previously published results showing residue availability from 22 million Mg to over 50 million Mg in Iowa.

2.1 INTRODUCTION

Global initiatives to develop renewable, low carbon energy sources have identified biomass feedstocks as a resource with significant potential (Bauen and Kaltschmitt, 2001). Biomass feedstocks provide a renewable pathway to support liquid transportation fuels and are also being investigated as a low net carbon feedstock for electricity generation. As in many countries, the United States has set national targets for bioenergy production through biofuel and biopower generation (Energy Independence and Security Act, 2007). Meeting

these goals requires development and utilization of biomass resources well beyond current production levels.

In 2005, a US Department of Energy (DOE) study identified that more than one billion tons of biomass may be available annually for energy production in the US (Perlack et al., 2005). Three hundred million tons of this biomass will come from agricultural residues (i.e., materials other than grain including stems, leaves, and chaff [Perlack et al., 2005]). However, sustainable use of agricultural residues for bioenergy production must take into consideration the critical role of agricultural residue in maintaining soil health and long-term productivity (Johnson et al., 2009; Johnson et al., 2006; Wilhelm et al., 2007; and Karlen et al., 2003). A recent review study identified six environmental factors that can limit sustainable agricultural residue removal—soil organic carbon, wind and water erosion, plant nutrient balances, soil water and temperature dynamics, soil compaction, and off-site environmental impacts (Wilhelm et al., 2010). These factors result from complex interactions between local soil characteristics, climate, and land management practices. Because of the breadth of soils, climate, and land management practices, it is not possible to determine the agricultural residue removal limits from experimental measurement or current practice at the level of detail and accuracy needed for policy decisions. Currently, there are no tools or models that perform this type of analysis (Wilhelm et al., 2010). Delivering this tool requires integrating the set of models that describe wind erosion, water erosion, and soil carbon together with an extensive set of databases that describe soil, climate, and soils management practices.

Agricultural residue availability analysis is further complicated by the need for aggregate assessments across entire states, regions, and the nation. Historically, due to the constraints imposed by manual input and interaction with models, large geographic assessments of

sustainable agricultural residue removal potential have relied on a reduced-scenario modeling approach that utilizes a limited number of representative agricultural production scenarios (Graham et al., 2007; Nelson, 2002; and Nelson et al., 2004). Using representative scenarios has several weaknesses. To accurately represent the wide variety of soil types, climates, and management practices, a large number of scenarios are needed, which requires significant computational time. Because of this, the reduced-scenario modeling approach cannot effectively represent the decision space. This approach significantly limits the ability of the decision maker to explore and understand unique or hypothetical management scenarios and provides little capability for performing robust sensitivity analysis. In addition, the manual process of developing a set of representative scenarios is not readily extensible. For example, adding a new model or a new database requires rebuilding the entire set of representative scenarios, which is time-consuming and costly.

This paper presents an integrated modeling strategy capable of characterizing the multiple limiting factors impacting sustainable agricultural residue removal within a single, extensible, interactive residue removal analysis system. To do this the integration framework must address three requirements:

1. *Seamless integration of existing models.* Well-developed, peer-reviewed models and databases that address individual aspects of this overall system exist today. These models are fully developed, validated, and peer-reviewed. The integration framework must be able to incorporate these models without change to their source code or validity.
2. *Plug-and-play interaction.* The core set of models has been developed independently from this framework and from each other. As a result, these models will continue to

be updated and revised independently from the integration framework. In addition, different scenarios will require different models and databases, and researchers may wish to compare the results of one set of models or databases with the results of another. Because of this, a “hard coded” approach is not appropriate and the integration framework must support interactive update and revision of the models and databases within the systems model.

3. *Intuitive, real-time interaction.* The integrated computational model will be used by a number of different groups and individuals, each with different skills and different analysis needs. The framework needs to be able to interactively support the disparate needs of each of these groups for varying models, assumptions, scenarios, and user interfaces.

The development of this integrated residue removal modeling system is described in this paper. The case study presented demonstrates the initial implementation of this modeling tool following the description of the development of the modeling system.

2.2 BACKGROUND

2.2.1 Sustainable Residue Removal Studies

In the past, the majority of efforts regarding the sustainability of agricultural crop residue removal were focused on limiting water and wind erosion to the tolerable soil loss limits established by the Natural Resources Conservation Service (NRCS) of the US Department of Agriculture (USDA). Little effort was focused on the impact of agricultural crop residue removal on broader soil tilth or productivity concerns. In 1979, Larson conducted one of the first large-scale studies focused on crop residue removal and its effect

on soil erosion using the Universal Soil Loss Equation. This study included the Corn Belt, the Great Plains, and the Southeast. The effect of tillage practices (i.e., conventional, conservation, and no-till) and residue management were investigated with respect to rainfall and wind erosion, runoff, and potential nutrient removal. This study found that for the management practices and crop yields at the time, nearly 49 million metric ton of residue was available annually throughout the Corn Belt. Soil carbon, tilth, and productivity maintenance were not considered.

As a result of limited interest in agricultural residues for energy production during the 1980s and 1990s, no additional large spatial scale assessments of residue availability were performed until more than two decades after Larsen's study. Nelson, 2002 used the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997) and Wind Erosion Equation (WEQ) (NRCS, 2011a) to expand on Larson's analysis to develop a methodology to estimate the sustainable removal rates of corn stover and wheat straw at the soil-type level. This methodology considered rainfall and wind-induced soil erosion as a function of reduced and no-till field management practices. In 2004, Nelson et al. used the same approach to assess five other major one- and two-year cropping rotations (e.g., corn-soybean). Neither of these studies addressed soil organic matter as a function of removal. Researchers have also used the Revised Universal Soil Loss Equation, Version 2 (RUSLE2) (NRCS, 2011b) and/or Wind Erosion Prediction System (WEPS) (USDA-ARS and NRCS, 2008) to address a number of erosion-based questions on crop residue removal (Karlen et al., 2003; Nelson, 2002).

Agricultural residue removal studies have also been performed using the DAYCENT (Adler et al., 2007), Environmental Policy Integrated Climate (EPIC) (Gregg and Izaurrealde, 2010), and Agricultural Policy/Environmental eXtender (APEX) (Powers et al., 2008)

models. These studies have focused on specific case study analyses without focusing on larger scale residue availability projections. Also, these analyses were focused on specific sustainability questions, such as greenhouse gas (GHG) impacts of residue removal, carbon sequestration impacts, and potential water quality impacts. Each of these models is reviewed below.

RUSLE2 simulates daily changes in field conditions based on soil aggregation, surface wetness, field management practices, and residue status, and is driven by daily weather parameters. Currently, these parameters are manually entered into RUSLE2 from various disparate databases. RUSLE2 is mainly used as a guide for conservation planning and accurately represents trends demonstrated in field data (McCool et al., 2004; Foster et al., 2003). It has been applied to applications involving cropland, pastureland, rangeland, and disturbed forestland (Ismail, 2008; Dabney et al., 2006; Foster et al., 2006; Schmitt, 2009). Several previous efforts have utilized RUSLE2 to simulate water erosion processes within broader analysis efforts ranging from watershed scale soil quality assessments (Karlen et al., 2008), to assessing risks at abandoned mining sites (Vaszita et al., 2009), and even socio-economic impacts of biophysical processes (Halim et al., 2007).

WEPS uses a Fortran 77 computational engine to implement a process-based daily time-step model that simulates soil erosion due to wind forces by direction and magnitude (Wagner and Tatarko, 2001). WEPS, like RUSLE2, simulates daily changes in field conditions, models a three-dimensional simulation region requiring a set of parameters describing climate, soil aggregation, surface wetness, field scale, field management practices (including crop rotation and growth) and residue status, and is driven by daily weather projections. WEPS has been evaluated for erosion predictions on cropland fields (Hagen,

2004) and has been used previously for case studies in corn stover harvest (Wilhelm et al., 2007).

RUSLE2 and WEPS each calculate components of an NRCS-developed metric for establishing management practice impacts on overall soil health. This metric is the Soil Conditioning Index (SCI). When coupled, the two models perform all of the calculations necessary for the integrated systems model to establish the SCI. The SCI provides qualitative predictions of the impact of cropping and tillage practices on soil organic carbon, which is an important factor in sustainable agricultural residue removal. The SCI has been used to support watershed scale soil quality assessments (Karlen et al., 2008), evaluate cropping systems in northern Colorado (Zobeck et al., 2008), and investigate southern high plains agroecosystems (Zobeck et al., 2007).

DAYCENT is a biogeochemistry ecosystem model that assesses soil GHG fluxes. It is a daily time step version of the CENTURY model (Parton et al., 1998). The DAYCENT model utilizes the ecosystem processes represented in CENTURY but also incorporates a land surface submodel to simulate plant production, nutrient cycling, and trace gas fluxes. DAYCENT has been used for a variety of applications including the assessment of soil N₂O and GHG fluxes for major US crops (Del Grosso et al., 2005), simulating global crop production (Stehfest et al., 2007), and simulating soil carbon in forest ecosystems (Pepper et al., 2005).

The EPIC model (<http://epicapex.brc.tamus.edu/>) was developed in the 1980s to estimate the impact of erosion on soil productivity. EPIC is a field-scale, daily time-step model. It simulates crop growth, carbon cycles, and erosion considering weather, soil characteristics, landscape, crop rotation, and management practices. EPIC has been used to explore

alternative nitrogen management practices (Rejesus et al., 1999), study the impact of high crop prices on environmental quality (Secchi and Babcock, 2007), and simulate potential switchgrass production in the US (Thomson et al., 2009).

The APEX model (<http://epicapex.brc.tamus.edu/>) has been developed as an extension to EPIC to simulate at the whole-farm and small-watershed scale. APEX has components that consider the routing of water, sediment, nutrients, and pesticides across the landscape. This includes components considering groundwater and reservoirs. These features allow the APEX model to simulate water quality impacts of land management practice changes. APEX has been used to investigate the impacts of alternative practices for livestock farms (Gassman et al., 2006), environmental benefits of dairy manure incorporation (Osei, et al., 2003), and simulate the potential effects of climate change on erosion and water quality (Williams et al., 1998).

Each of these modeling tools provides valuable simulation results for investigating factors that can potentially limit sustainable removal of agricultural residues. RUSLE2, WEPS, EPIC, and APEX each calculate soil erosion. SCI, DAYCENT, EPIC and APEX each simulate the impacts of management decisions on soil carbon cycles. Soil GHG fluxes are modeled within DAYCENT, EPIC, and APEX. For this modeling work, the RUSLE2, WEPS, and SCI models were chosen for three reasons: (1) each is currently part of the USDA conservation management planning process used to certify sustainable management practices, which makes the integrated model results directly relevant for bioenergy industry decision makers, (2) they take crop yields as model inputs, which facilitates investigation of impacts from spatial and temporal variability in crop yield, and (3) they have relatively short

model execution times (< 1 minute typically), which makes them viable within an integrated multi-model decision framework.

2.2.2 Model Integration Frameworks

The definitions of framework are varied and can refer to software libraries, software applications, structural components of a building, and everything in between. A general definition of framework is “a basic structure underlying a system, concept, or text” (Soanes and Stevenson, 2005). In this discussion, *framework* will refer to a software application that is the basic structure utilized to integrate, simulate, and understand complex systems. Padula and Gillian (2006) note that the main issues facing the development of software frameworks are

- Verification and validation of federated simulation environments
- Knowledge capture stemming from these large federated simulation environments
- Easy access to large simulations through graphical displays

One of Padula and Gillian’s key ideas is that many frameworks center on creating data repositories that tie information to the components they represent (Padula and Gillian, 2006). These repositories then enable the users of the frameworks to seamlessly query information on a per-component basis.

Considerable attention has focused on defining and evaluating integrated modeling frameworks specifically for environmental modeling applications (Lloyd et al., 2011; Argent et al., 2006; Schmitz et al., 2009; Rizzoli et al., 2008). The definition of *framework* used in this paper is consistent with the definition provided by Rizzoli et al. (2008): “a set of software libraries, classes, and components, which can be (re-)used to assemble and deliver an environmental decision support system (EDSS) or an integrated assessment tool (IAT) to

support modeling and processing of environmental knowledge and to enhance the re-usability and distribution of such knowledge.” Lloyd et al. (2011) further classified environmental modeling frameworks as “traditional vs. lightweight” and presented a methodology for measuring framework “invasiveness,” defined as the “degree to which model code is coupled to the underlying framework.”

In the model presented here, the goal is to create an integrated residue removal modeling tool that utilizes an integration framework to couple the RUSLE2, WEPS, and SCI models together with the databases needed. In addition to integrating a set of disparate models and databases, the integrated modeling framework chosen also needs to provide an extensible, easily understood user interface that enables the user to investigate opportunities for agricultural residue removal for energy use. Currently available open-source software frameworks addressing one or more aspects of this task include

- SCIRun for scientific visualization and computational steering (SCI, 2011)
- Dataflow visualization-oriented packages, such as OpenDX (2011), for visualization integration
- Common Component Architecture (CCA)-capable CCaffeine (Allan, 2005; Bernholdt et al., 2006), a general purpose component framework that uses wrappers to work with software source units
- Object Modeling System (OMS) (Lloyd et al., 2011; Ascough et al., 2005; David et al., 2002) facilitates component-oriented model development and provides an integrated development environment with GIS, visualization, statistical analysis, model calibration, and data retrieval tools.

- The Invisible Modeling Environment (TIME) (Rahman et al., 2003) utilizes a .NET platform to supports the development of new model components, utilization of multiple programming languages, testing of model components, and data handling.
- Open Modelling Interface (OpenMI) (Gregersen et al., 2007; Blind and Gregersen, 2005) provides a standardized time-step based interface to define, describe, and transfer data.
- VE-Suite (McCorkle and Bryden, 2007), which is a general purpose integration package that enables users to interact with coupled engineering models and simulations interactively

Examples of closed-source packages include

- Matlab's Simulink™ (MathWorks, 2011) for integrating third-party software such as LMS Virtual.Lab™ (LMS International, 2011) with Matlab™
- Execution Engine™ (formerly Fiper™) (Simulia, 2011) for distributed collaboration of design teams, which has been customized primarily for GE
- Aspen Plus™ (AspenTech, 2011) for chemical process plant simulation
- ModelCenter™ (Phoenix Integration, 2011) for integrating a wide range of third-party solvers (e.g., Excel™, user subroutines) with optimization and design space exploration
- Protrax™ (2011) for modeling large plants at a system level

Many of these packages tend to be targeted to specific applications (e.g., Aspen Plus for chemical process modeling) and do not address the need for a generalized framework that can be used to create integrated computational environments for the engineering of generic complex systems and processes. For example, SCIRun has computational steering capability

and visualization support but does not provide an extensible method for integrating generic simulation and modeling tools. ModelCenter™, Execution Engine™, Protrax™, and Matlab's Simulink™ all provide support for the integration of specific sets of tools or for high-level systems modeling capability. OMS, TIME, and OpenMI are focused on environmental model integration. OMS 3.0 provides a lightweight architecture using annotation for data transfer, but requires access to source code for the models being integrated. TIME requires utilization of .NET as the development environment, which presents limitations when considering cross-platform implementations. OpenMI is widely used in Europe for environmental model integration and provides a specification for linking components. Each of these packages fills a specific need and provides a desired set of tools for a specific clientele, but they do not include the capability for the inclusion of a generic set of models. VE-Suite provides a shared framework that integrates a generic set of models that can be accessed in real time (McCorkle and Bryden, 2007). Models can be included without access to the source code. In addition the longer term goal of this project is to integrate a broad set of engineering, economic, and environmental analyses. VE-Suite is not primarily focused on coupled environmental models, and OMS, TIME, and OpenMI have a larger literature base and existing bank of code for environmental model integration. However, VE-Suite enables users to incorporate component models and corresponding two-dimensional and three-dimensional graphical representations to create new plug-and-play framework components. By design, the framework components can be distributed across computational resources to make the most efficient use of resources. Based on the long term goals of this project, VE-Suite was selected as the integration framework for this project.

2.3 MODELS AND METHODOLOGY

2.3.1 RUSLE2

The RUSLE2 model used for the study was the RUSLE2 Object Modeling Environment (ROME) shared library version compiled from the core RUSLE2 code repository on 17 September 2010. RUSLE2 is a process-based daily time-step model that describes the effects of agricultural cropping practices on soil erosion by rainfall and overland water flow. It simulates erosion along an overland flow path by accounting for soil detachment and deposition processes using an algebraic formulation of mass conservation. RUSLE2 computes both temporal and spatially variable effects, such as the effect of soil and land management varying along a hill slope. RUSLE2 uses a set of databases concerned with soils, field management (e.g., tillage), climate, vegetation, and crop growth that are used at various times during the simulation period to make daily and/or annual soil loss calculations. The prediction of an average annual soil loss is a function of both erodibility and erosivity. Erodibility is related to the susceptibility (the inverse of resistance) of the soil to erosion and is affected by management. Erosivity is a measure of the forces actually applied to the soil by the erosive agents of raindrop impact, water drops falling from plant canopy, and surface runoff.

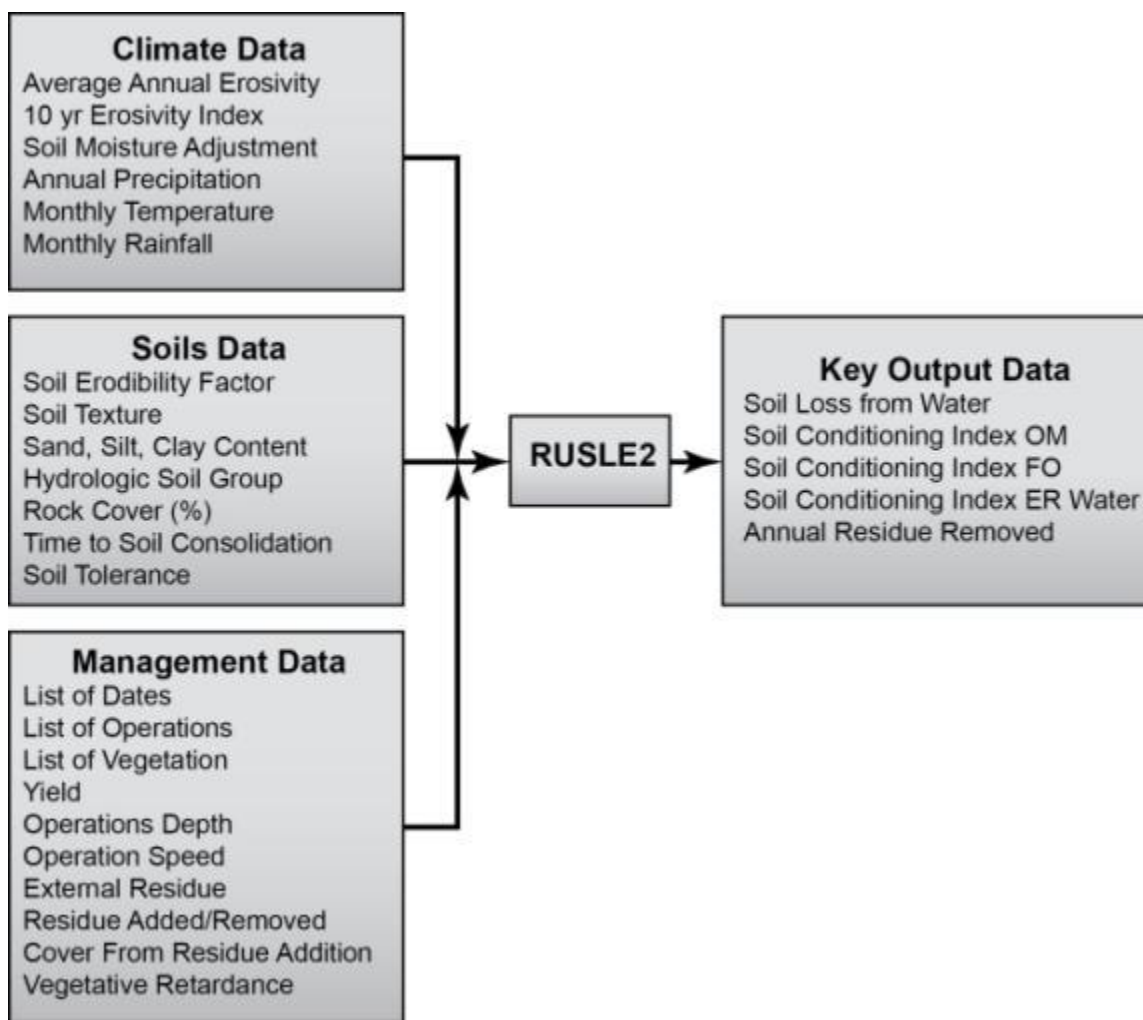


Figure 2.1. Information input and output for RUSLE2.

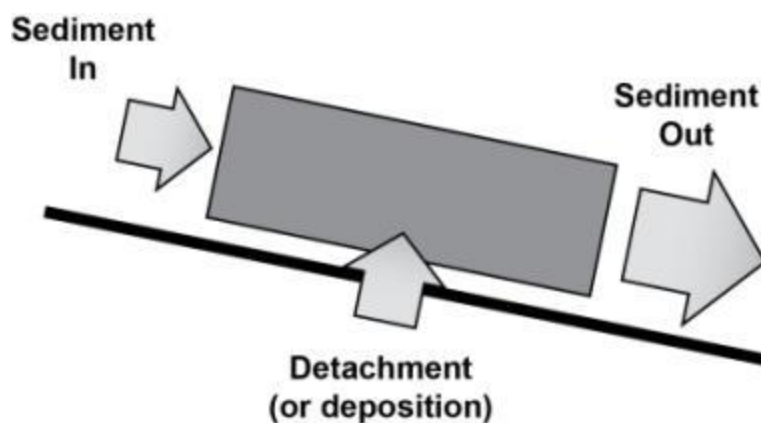


Figure 2.2. Conservation of mass principles in the RUSLE2 simulations.

Figure 2.1 shows the information flow into and out of the RUSLE2 model. RUSLE2 simulates soil loss using conservation of mass principles shown in Fig. 2.2. Each of the data elements in Fig. 2.1 is used within the model to establish the variables for the RUSLE2 soil loss simulation. The RUSLE2 equation for computing average annual soil loss for the i th day is presented in Eq. 2.1.

$$a_i = r_i k_i l_i S c_i p_i \quad (2.1)$$

where a_i is the average annual soil loss for day i , r_i is rainfall/runoff, S is the steepness of the slope, k_i is the soil erodibility, c_i is cover-management, l_i is slope length, and p_i is supporting practices. Equation 2.1 provides the daily soil loss, or total “Sediment Out” in Fig. 2.2, but Eq. 2.1 does not calculate the deposition component of the mass balance. Equation 2.2 represents the calculation for the deposition rate (i.e., mass per unit area). This equation represents simulation scenarios where the sediment load exceeds the transport capacity, which is determined through Eq. 2.3. With these parameters established, the steady state conservation of mass (Eq. 2.4) is used to establish net detachment and deposition. Eq. 2.5 is then used to aggregate the daily time steps determining the average annual soil loss.

$$D_p = \left(\frac{V_f}{q} \right) (T_c - g) \quad (2.2)$$

where V_f is the fall velocity of the sediment, q is the runoff rate, T_c is the transport capacity of the runoff, and g is the sediment load (i.e., mass per unit width).

$$T_c = K_T q s \quad (2.3)$$

where s is the sine of the slope angle and K_T is a transport coefficient calculated considering cover management parameters.

$$g_{out} = g_{in} + \Delta x D \quad (2.4)$$

where g_{out} is the sediment load leaving the lower end of a segment of the slope, g_{in} is the sediment load entering the upper end of a segment of the slope, Δx is the length of the sediment, and D is the net detachment or deposition within a segment.

$$A = \frac{\left(\sum_{i=1}^{365} a_i \right)}{m} \quad (2.5)$$

where A is the average annual soil loss, m is the number of years in the assessment, and a_i is as defined in Eq. 2.1.

Previous studies (Ismail, 2008; Karlen et al., 2008) implemented RUSLE2 within a manual data flow process where direct human interaction with the RUSLE2 user interface was required for each model run. Modeling systems requiring this level of interaction significantly limit the number and character of simulations that can be included in the analysis. Several researchers have worked to overcome these limitations by building conceptual model representations of RUSLE2 (Hai-yan et al., 2010) or custom recoding of the RUSLE2 equation set (Richard et al., 2007). These approaches of using conceptual models or recoding to utilize RUSLE2 allow for flexibility in the application of RUSLE2. The challenge is that recoding, or developing a simple conceptual model, does not leverage the significant investment that has already been made validating the version-controlled RUSLE2 core model. The most effective approach to take advantage of the extensive validation efforts is to integrate the model without changing code.

2.3.2 WEPS

The WEPS model used for this study is version 1.1, released August 30, 2010. There is overlap between the data required for the RUSLE2 and WEPS models, but the WEPS model requires significantly more data. This data is manually entered into WEPS from various

disparate databases. WEPS provides detailed data in annual and period erosion events, as well as saltation, creep, suspension, particulate matter less than 10 micrometers (PM-10) emissions, wind energy, and boundary loss (Fig. 2.3). Figure 2.4 shows the information flow into and out of the WEPS model. There is overlap between the data points required to execute the RUSLE2 and WEPS core equations, but the wind erosion processes require significantly more parameters.

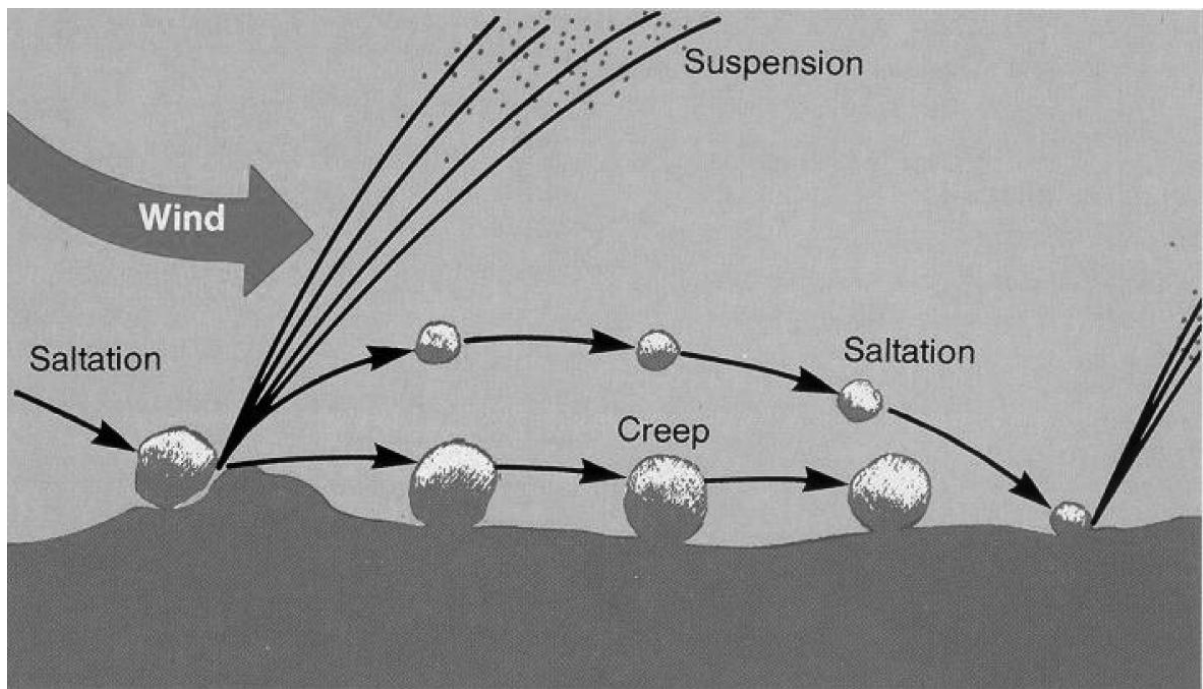


Figure 2.3. WEPS mathematically simulates the mechanisms for soil loss caused by wind using a process-based daily time-step simulation (Hagen et al., 1996).

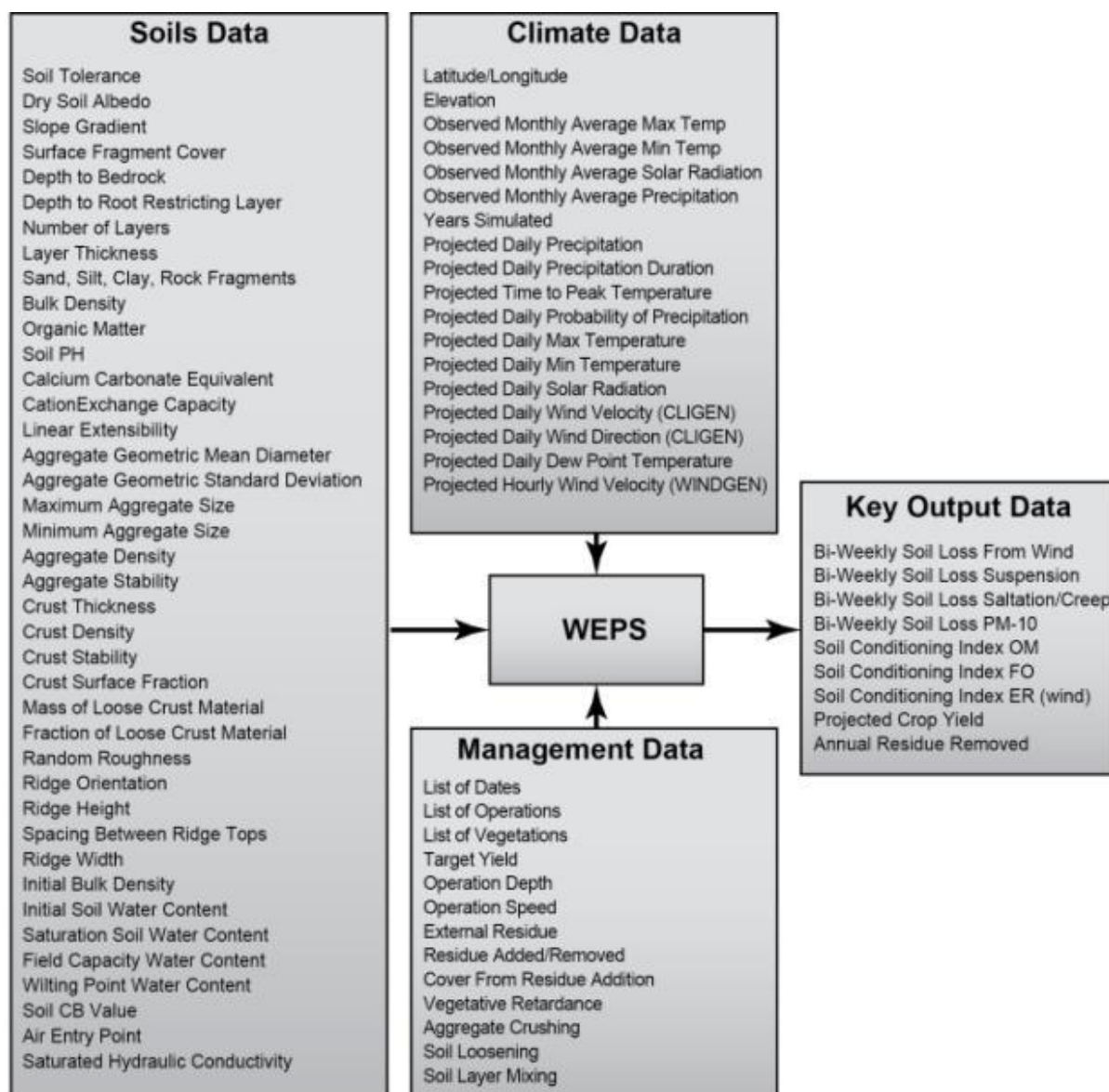


Figure 2.4. The WEPS model requires extensive soils, climate, and management data to perform wind erosion calculations. (PM-10 = particulate matter less than 10 micrometers, OM = Organic matter, FO = field operation, ER = erosion)

As shown in Fig. 2.5, WEPS utilizes a set of modular submodels to calculate wind erosion-induced soil losses. The submodels interact to characterize the conditions required for the soil loss equations within the erosion submodel. The erosion submodel executes mass conservation equations for each of the three size classes of eroding soil: (1) suspension (<0.1 mm), (2) saltation and creep (0.1 to 2.0 mm), and (3) PM-10 emissions (<0.01 mm). Each of

these conservation relationships utilize a series of parameters requiring detailed information about the simulation site. These parameters are fed into the model through a series of input files. The WEPS submodels parameterize and calculate the data points for the core soil loss calculations through the data inputs in Fig. 2.4.

Within WEPS, the erosion process is modeled as conservation of mass on a time-dependent basis using coupled partial differential equations resolving a computational control volume for the three previously mentioned size classes of eroding soil. Each of the conservation of mass equations requires a detailed characterization of the field site conditions including soil surface characteristics, soil hydrology, vegetative cover, weather events, and many others as seen in Fig. 2.4. The submodels in Fig. 2.5 utilize the data inputs from Fig. 2.4 to provide the detailed site characterization parameters to the conservation of mass equations within the erosion submodel. Equation 2.6 is the conservation equation for soil in the saltation and creep size class. This equation captures two sources of erodible material, emission (G_{en}) and abrasion (G_{an}), and two sinks for erodible material, surface trapping (G_{tp}) and suspension (G_{ss}).

$$\frac{\partial(\overline{CH})}{\partial t} = -\frac{\partial q_x}{\partial x} - \frac{\partial q_y}{\partial y} + G_{en} + G_{an} - G_{tp} - G_{ss} \quad (2.6)$$

where x and y equals the horizontal distances (m) in perpendicular directions parallel to the simulation region boundaries, t is time (s), C (kg/m^3) is the average concentration of saltating particles in the control volume of height H . The differential saltation discharge (saltation-sized particles leaving the control volume) terms q_x and q_y are the components of the saltation sized particles, q , leaving the control volume in the x and y directions (kg/ms). G_{en} , G_{an} , G_{tp} , G_{ss} are the net vertical soil fluxes from the emission of loose soil, the surface abrasion of

aggregates/crusts, the trapping of saltation, and the suspension of fine particles from the breakdown of saltation and creep, respectively ($\text{kg/m}^2\text{s}$). Through the convergence of the mass balance equations across the control volume, the soil loss is established and the relative changes in soil conditions are distributed to the other submodels in Fig. 2.5 for the next time step. The other conservation equations, for suspension and PM-10 size classes, work functionally the same as Eq. 2.6 within the control volume, but with size class specific source and sink terms.

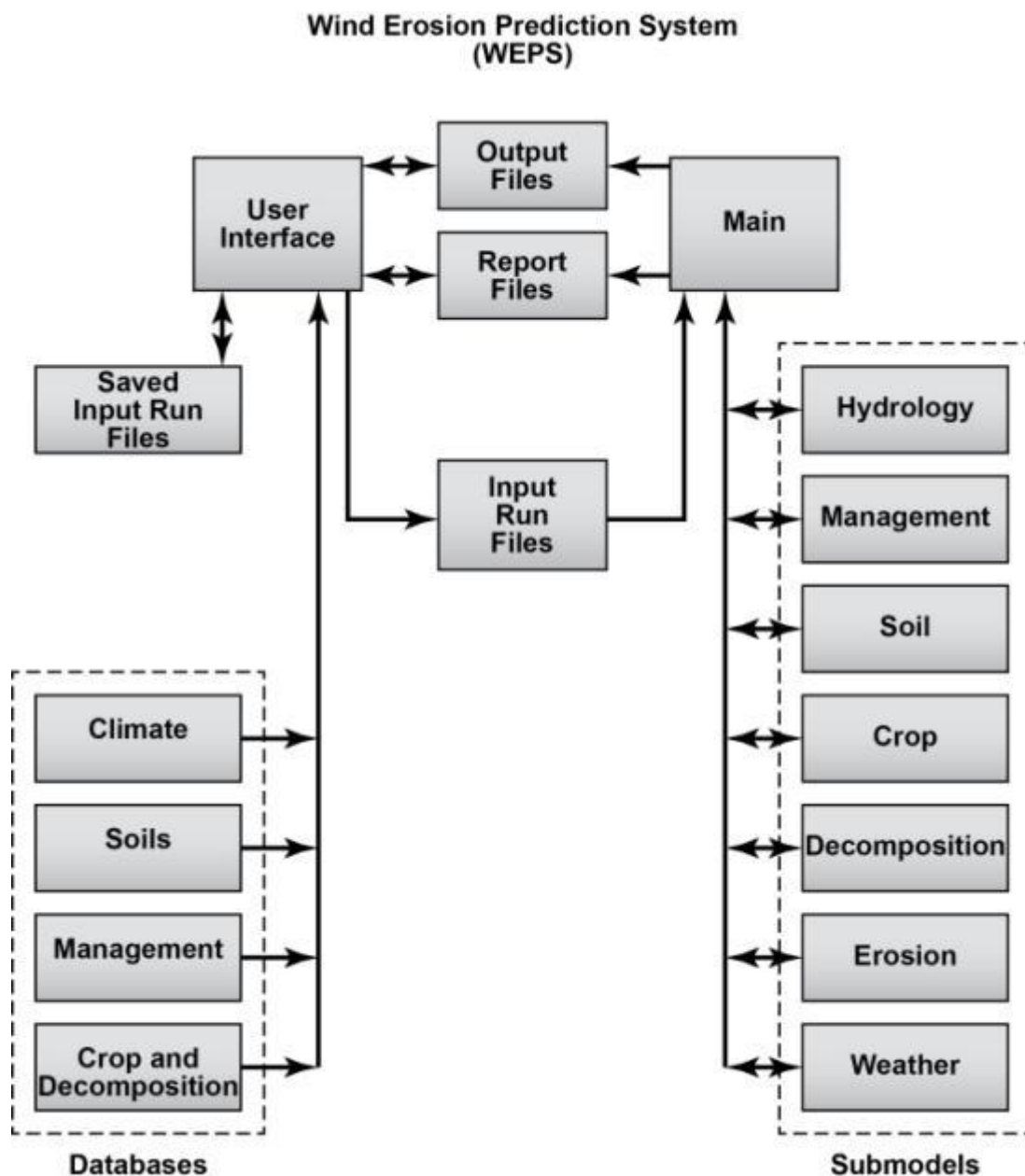


Figure 2.5. WEPS core models are built on a Fortran 77 infrastructure that implements a modular set of submodels to calculate losses due to wind erosion (Hagen et al., 1996).

2.3.3 Soil Conditioning Index

The SCI is comprised of three sub-factors: (1) the organic matter sub-factor (SCI OM); (2) the field operation sub-factor (SCI FO); and (3) the erosion sub-factor (SCI ER). The SCI

OM sub-factor models the amount of organic material returned to and removed from the soil. The SCI FO sub-factor takes into consideration the effects of field operations on organic matter decomposition and is calculated using the data describing the field operations in the RUSLE2 and WEPS database structures. The SCI ER sub-factor estimates whether erosion rates for a given site are degrading, steady-state, or aggrading. This is done by using empirical data for tolerable soil losses and comparing scenario results to set the ER sub-factor. The three sub-factors are used to calculate the SCI in Eq. 2.7 as follows:

$$SCI = (0.4 OM) + (0.4 FO) + (0.2 ER) \quad (2.7)$$

Through this calculation, the SCI provides a qualitative prediction of the impact of land management practices on the level of soil organic matter. An $SCI < 0.0$ predicts a decrease in soil organic matter, whereas an $SCI \geq 0.0$ predicts maintained or increased soil organic matter.

Utilizing the SCI to assess the soil organic carbon impacts of agricultural residue removal scenarios requires coupled analysis that includes both the WEPS and RUSLE2 models. The SCI FO component is a characteristic of the specific land management practices. The SCI OM component represents the interactions between soil characteristics, residue biomass decomposition, and climate conditions. The SCI ER component requires input from both RUSLE2 and WEPS to be comprehensive. In the integrated residue removal modeling tool described here, RUSLE2 models the SCI OM and SCI FO sub-factors as well as accounting for the water erosion component of the SCI ER sub-factor. The wind erosion component of the SCI ER sub-factor is calculated by WEPS. The SCI ER sub-factor is calculated by WEPS and then provided to RUSLE2 within the integrated model. With the data input from WEPS, RUSLE2 completes the SCI calculation.

2.3.4 Model Integration Framework

Three components of VE-Suite have been employed to support the development of the integrated environmental process modeling framework built for this analysis—VE-Open, VE-Conductor, and VE-CE. Considering the framework design classifications of traditional and lightweight provided by Lloyd et al. (2011), VE-Suite has characteristics of both classifications, but is more aligned with the lightweight framework classification. Specifically, framework components are bound dynamically at run time, are independent of the framework, prefer convention over configuration, and are integrated with a “small” programming interface (API). The characteristics of VE-Suite, which are more consistent with Lloyd et al.’s definition of a traditional framework, are dependencies on additional libraries and generalized data structures for framework data transfer. The invasiveness, as defined by Lloyd et al., within this integrated model is minimal. Model source code has not been changed for the tools integrated in this application. This is an important feature both in terms of the models being utilized and the decisions being supported by the integrated model. One characteristic important for model selection in this application is the direct connection to policy administration by NRCS. The models are continually under refinement and being improved, resulting in new releases. Through minimal invasiveness, new releases of the models can be implemented within the framework within hours. This creates a seamless connection between the decisions supported through this integrated model and the conservation management planning process within NRCS.

VE-Open is the interface specification and set of tools that facilitate the exchange of data between framework components. The VE-Open design builds on an open architecture approach to integrating information. VE-Open utilizes multiple integration formats by

specifying a schema for information to adhere to and leverage other schemas, such as COLLADA (Arnaud and Barnes, 2006), which has taken a useful approach to creating an extensible specification built on XML and XML Schema. The VE-Open interface specification is analogous to that of the Computer-Aided Process Engineering (CAPE)-Open specification used by chemical process simulation tools. VE-Open is also analogous to the Distributed Interactive Simulation (DIS) specification utilized in military applications to share war game simulation information across distributed computer resources with multiple clients (Distributed Interactive Simulation Committee of the IEEE Computer Society, 1998). Considering familiar tools within the environmental modeling community, VE-Open is similar to OpenMI (Gregersen et al., 2007; Blind and Gregersen, 2005) in that it provides a clear specification for framework component communication. There are two primary differences between VE-Open and OpenMI. First, VE-Open has been developed as a generalized interface for engineering applications, whereas OpenMI has been developed with a focus on integrated water management. This has resulted in more generalized data structures within VE-Open, including the support of advanced visualization. Second, OpenMI can require significant code changes to the framework components, whereas VE-Open has been designed to facilitate the use of executable versions of models. With certain modeling tools, this can be limiting in terms of complex two-way interactions, but for this framework it is a key feature to support the seamless exchange of model versions as described previously. The VE-Open model interface has a number of characteristics important in this application, including

- *Simplicity*. The functions that are implemented are general and can be adapted to a wide variety of simulation environments.

- *Generalization.* The interface removes the specificity of any discipline and provides generic structure for data types and software engine structure.
- *Enhanced data passing.* The interface provides for passing data beyond the level of simple scalars to downstream models.

VE-Conductor provides the graphical user interface (UI) component of the integrated framework. The UI is implemented with the following software design goals: (1) multi-platform support; (2) detachability; (3) location transparency; (4) extensibility; and (5) unified control. The UI is the controller that allows the engineer to interrogate the integrated modeling environment. The UI exists independently from the computational engine as a separate Common Object Request Broker Architecture component. This functionality allows the UI to be attached and detached from an active simulation on any compatible computer on the simulation network. For example, a user could build and start a simulation, detach from the computational engine or visualization engine, go to a different location, re-attach to the simulation, and regain monitoring and control functions.

VE-CE is the computational scheduler. It constructs, coordinates, schedules, and monitors simulation runs. It is capable of running a simulation containing a multitude of different types of models, each accepting and generating a myriad of data types. The computational scheduler is also able to analyze a simulation configuration, determine execution order, marshal system resources to create model instances, and coordinate the flow of data through the simulation framework. Tasks that require specific knowledge about a data type or model are relegated to either the detachable UI or to a specific model, thus keeping the computational engine highly generalized with a lightweight code.

2.3.5 The Integrated Residue Removal Modeling Tool

As discussed earlier, the challenge is to integrate a set of disparate models and databases to create an interactive assessment tool that enables a user to investigate opportunities for removing agricultural residue for energy use. Figure 2.6 shows the information flow within the integrated residue removal modeling system. In this design, the user specifies the area that will be assessed. This area can be as small as a single farm or as large as an entire country. The mechanisms for selecting the area currently include list box interfaces that provide all combinations of political boundaries (e.g., counties and states). The ability to input the specific set of soils that define a farm or group of farms is also provided.

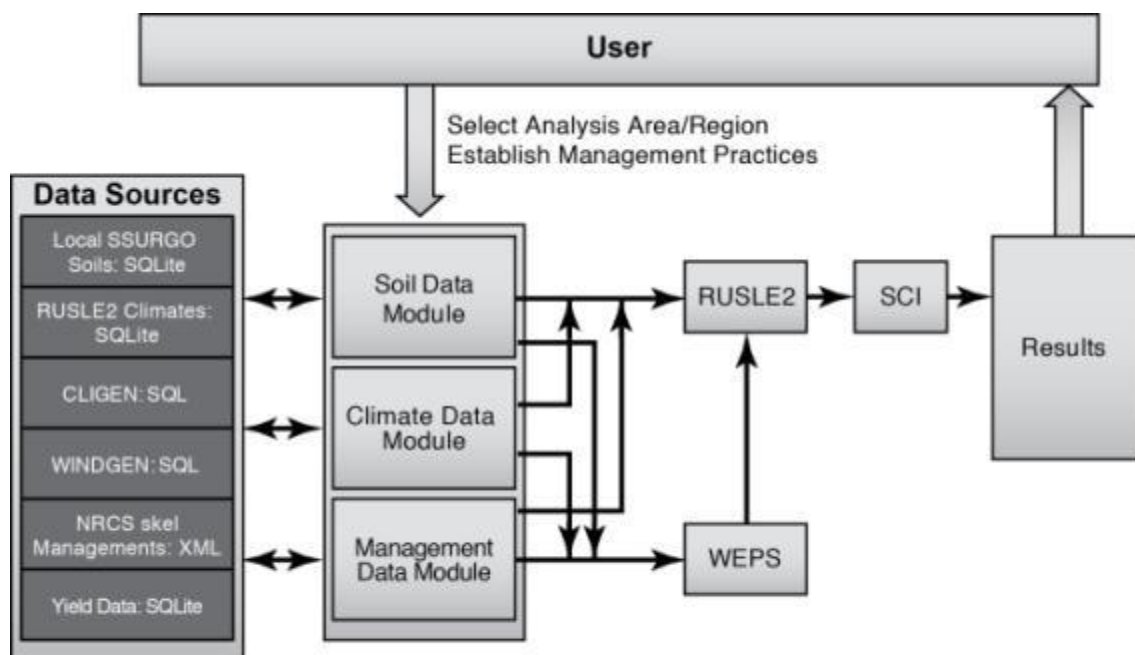


Figure 2.6. Representation of the data flows through the integrated residue removal systems model.

The climate data is dynamically acquired and assembled based upon the area(s) selected for an assessment. The user assembles the management practices by selecting from the

database of approximately 33,000 NRCS-developed management data points. Management practices can be selected and assembled at multiple levels. The user can pick a pre-built management practice that includes all of the data defining a scenario that represents the area of interest. The user can also assemble the management practices by selecting each specific tillage, crop, fertilizer, and harvest decision to create a custom land-management scenario. Table 2.1 lists the databases and models required for the integrated residue removal systems model.

Table 2.1. The key data sources and models used are identified with the method for public access to the data or model.

Data Input	Database	Access
Soil	SSURGO	NRCS NASIS Server (http://soils.usda.gov/technical/nasis/)
RUSLE2 Climate	RUSLE2 native.gdb format	http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm
WEPS Climate	CLIGEN	http://www.ars.usda.gov/Research/docs.htm?docid=18094
Wind	WINDGEN	http://www.weru.ksu.edu/
Land Management	NRCS native.gdb format	http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm
Crop Yields	NASS	http://www.nass.usda.gov/
Modeling Function	Model	Access
Water Erosion/SCI	RUSLE2	http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm
Wind Erosion/SCI	WEPS	http://www.weru.ksu.edu/weps/wepshome.html
Integration Framework	VE-Suite	http://www.vesuite.org

Because these databases are developed and maintained by different organizations, they are natively in different formats and provide different mechanisms for access and utilization. Each of these databases has been designed for utilization within executable programs distributed to NRCS field office computers. Because of this, they have been made publicly available for download and have not been designed for direct database access via webservice or other online mechanisms. These characteristics make the process of using these databases in this integrated systems model via web services slow and infeasible given the number of calls to the databases. To overcome this challenge, the databases were brought together and managed in an SQLite onsite data repository of less than 50 gigabytes. Although the choice of SQLite as a primary database tool for this model satisfies performance requirements, it should be noted there are potential downsides to this choice (e.g., the need for data duplication when distributing the model and the limitation that write commands can only be done one at a time). The use of SQLite databases allows optimized indexing and query development for fast communication within this application. The latency of these

communications is an important factor because there are more than 20 million database calls being executed for this study.

Three data modules—soils, climate, and management—receive the user instructions and interact with the databases to assemble and format the inputs for each model in the integrated system, as shown in Fig. 2.6. When the user specifies a scenario, each of the data modules processes the instructions and queries the databases required to build its assigned model inputs as follows:

- *Soils Data Module.* This module provides a fully automated pathway for soils data directly from the locally managed SQLite SSURGO database (Fig. 2.7) to reach the integrated models in their required input format. For RUSLE2, the soils data is assembled into the native model database format, which can be directly loaded and used via the model automated programming interface (API). In the case of WEPS, the soils data is output to specifically formatted files that are read when the model executes.

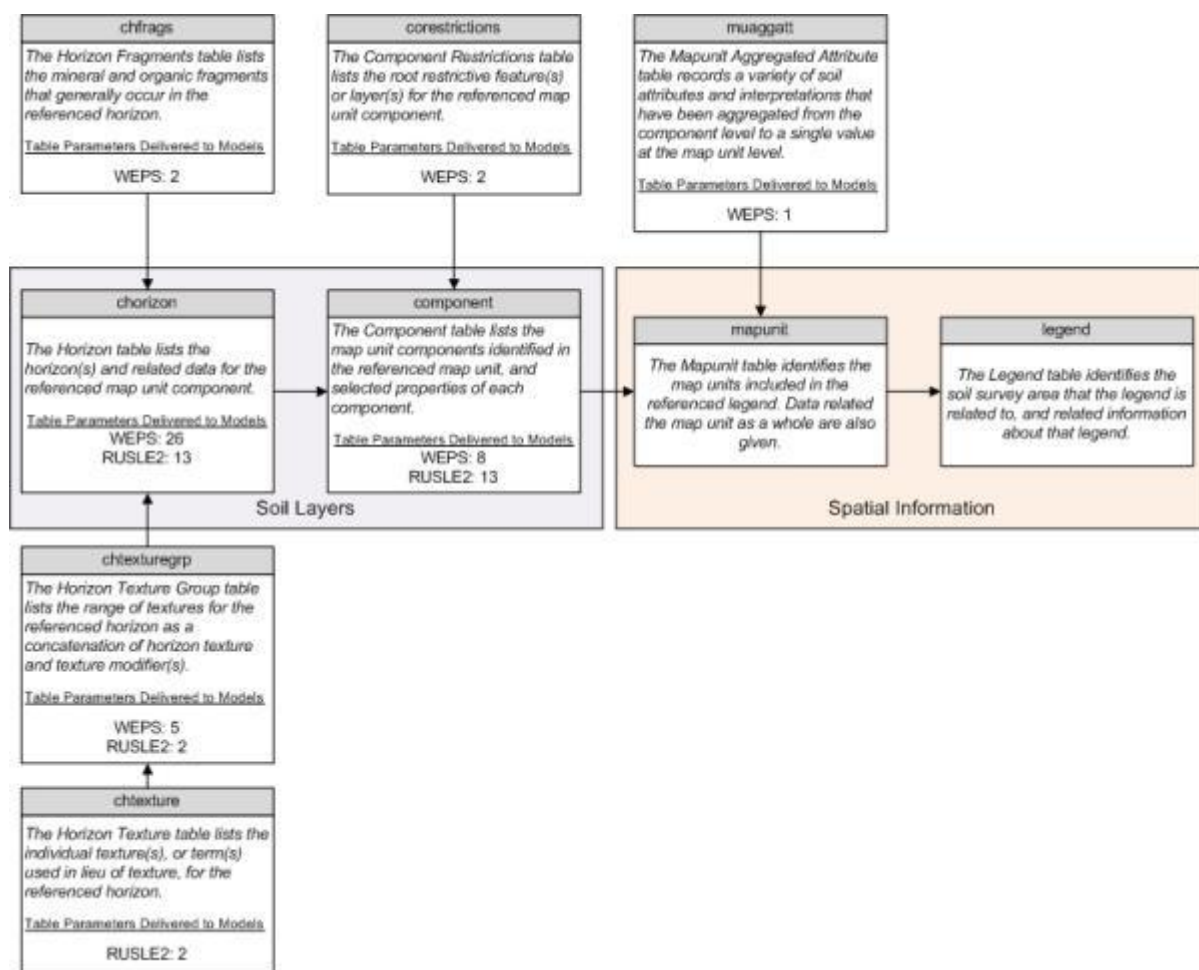


Figure 2.7. Schematic representation of the locally managed SQLite SSURGO database managed by the Soils Data Module.

- Climate Data Module.* Climate data for RUSLE2 is assembled into the model's native database format via its API. To support WEPS, the climate data module utilizes the climate generator models CLIGEN and WINDGEN as input data sources to generate weather files as shown in Fig. 2.8 (USDA-ARS, 2009; Wagner, 1992). CLIGEN and WINDGEN are stochastic weather generators that create daily weather events over specified time periods. CLIGEN generates daily values for precipitation, minimum and maximum temperatures, solar radiation, dewpoint, wind speed, and direction for a single geographical location based on historical measurements, whereas the

WINDGEN wind generator provides accurate hourly wind speed and direction that enables capturing hourly erosion events. *Management Data Module*. To facilitate plug-and-play interaction, the structure and organization of the module heavily leverages the USDA NRCS data schema for management scenarios. Leveraging this schema is advantageous for several reasons: (1) multiple NRCS models are utilized in the framework; (2) the schema is comprehensive and regularly updated; and (3) leveraging the NRCS methodology will enable the ongoing use of the work by practitioners in NRCS field offices across the country.

There are four primary interaction requirements for this modeling framework:

- (1) selecting the spatial area of interest;
- (2) establishing the land management practices;
- (3) selecting and connecting the models;
- and (4) displaying the results.

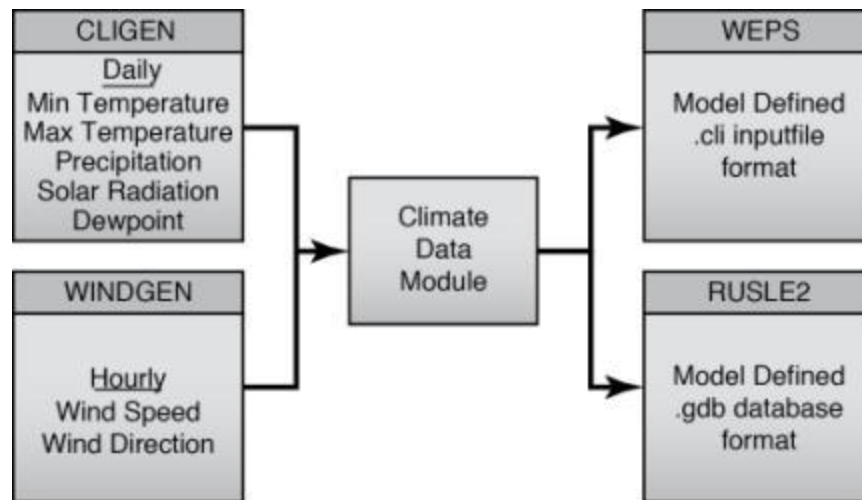


Figure 2.8. Block diagram of the climate module functionality.

2.3.5.1 Selecting the Spatial Extent for Analysis

The first function for the user is establishing the areas of interest for an assessment. The implementation of the framework used for this study requires selection of areas with political boundaries (e.g., counties, states, and countries). User interfaces are in place to select assessment areas ranging from a single county to multiple counties to states and to the conterminous US.

2.3.5.2 Establishing Land-management Practices

Input requirements for describing land management are extensive and variable across regions. The land management inputs generally fall into one of four categories: (1) cropping rotations; (2) tillage practices; (3) fertilizer applications; and (4) harvest practices. Management practice details are required at daily time steps for the models used. Depending on the scale of the assessment, the management practices can have different levels of detail and assumptions. Larger spatial assessments will utilize a set of management scenarios that encompass county or state averages. In the case of individual farms or fields, more precise management characteristics may be utilized.

User selection of management criteria is based on the existing management schemas that are available through the USDA NRCS, which has developed an XML-based data schema called the “skel” format that provides access to over thirty thousand management elements in an NRCS managed SQLite database. The skel format, described in greater detail later, is flexible in allowing the use of individual criteria (e.g., a specific piece of tillage equipment), or a complete management schema (e.g., all of the elements of a corn-soybean rotation in Boone County, IA).

2.3.5.3 Selection and Connection of Models

The framework design facilitates the use of multiple configurations of modeling tools. Making this design work requires the ability to create and interact with the network of models. VE-Suite's user interface, VE-Conductor, handles model and database network assembly. The user is given the available options for data and models, and is further given the ability to drag and drop the tools of choice onto the VE-Suite canvas. The connections between the tools on the VE-Suite canvas are then drawn with simple mouse clicks. The order of WEPS or RUSLE2 within the network can be seamlessly exchanged, with the SCI being the final model because of data input requirements from the other models. For the purpose of this study, the system has been configured as shown in Fig. 2.6. Connections on the VE-Suite canvas represent two-part sets for VE-CE: (1) the order of the computational elements on the canvas, and (2) the specific data elements to be exchanged. Calculation routines within the model and data wrappers check for issues associated with the current modeling network configuration, tell the user if there are any known problems with the current use of the modeling tools. This includes functions within the model wrappers that verify data formats and scales are correct for specific data elements. With the model network assembled, the user can then interact with each of the models, adjusting parameters as required for a specific assessment scenario. With the network built and the parameters set, the user initiates the simulation. The VE-Open interface (McCorkle and Bryden, 2007) facilitates the exchange of information across each of the models. The individual model wrappers include the data instructions and requirements for VE-Open to distribute the data. Upon connecting the models on the canvas as described, VE-Open is instantiated and the

data structures assembled for use. Feedback loops and two-way model communication can be specified with the connections on the canvas.

2.3.5.4 Display and Interact with Results

The requirements for interacting with the results are related to the spatial scale and fidelity of the assessment being performed. For the case of a specific field, delivering a single sustainable harvest rate is potentially the desired answer. In contrast, for precision removal of agricultural residue across a field, many thousands of data point results are needed. These results may be best delivered through a map. Typically, larger spatial assessments are aggregated to county-level results. Often it is preferred to receive these results in a database or tabular form, thereby facilitating use within a GIS package. Currently, the integrated residue removal modeling tool developed here provides populated databases that are formatted to load into external GIS tools for map generation.

The integrated systems model is built to work through the model scenarios as they are defined by the user input. For example, if the user is investigating a single farm they will have a set of soils and management practices (including crop yields) that couple with the local climate data to define the scenario. If the user is investigating a single average yield and actual management practices, then the integrated model will run that yield–management combination for each of the soils that comprise that farm. Modern harvesting equipment has the ability to collect in-field yield data at approximately 3–5 meter increments. In this case, a farm could potentially have thousands of yield–management–soil combinations for that single farm. When performing regional scale analyses, the number of soils that need to be investigated becomes large. The integrated systems model resolves the yield–management–soil combinations and iterates the integrated model set for each scenario as required.

After the user has assembled the scenario and the data modules have created the model inputs, the WEPS model is executed. Figure 2.9 shows the basic process flow for the functions performed by the framework interface for the WEPS model. Within the framework each WEPS model iteration, including the exchange of data, the construction of input files, the running of the model, and the acquisition of the model results, takes between five and ninety seconds, depending on the specific yield scenario for which the model is calibrated.



Figure 2.9. The WEPS model wrapper within the toolkit utilizes the data provided through the previously described models to perform all necessary functions setting up the WEPS model run scenario.

Upon completion of the WEPS model execution, RUSLE2 then runs and completes the analysis flow as shown in Fig. 2.10. The RUSLE2 API is extensible and facilitates the use of the model in this function. The data modules deliver the model inputs to RUSLE2 in its native database format. Through the API, the database is loaded, and the specific scenario-defining calls are then executed. Then the results from WEPS that are required to run the SCI calculations are delivered to RUSLE2 through the API. The model executes in approximately 1–2 seconds depending on the size of the input database loaded. When the model has successfully completed the run, the API is used to retrieve the results.

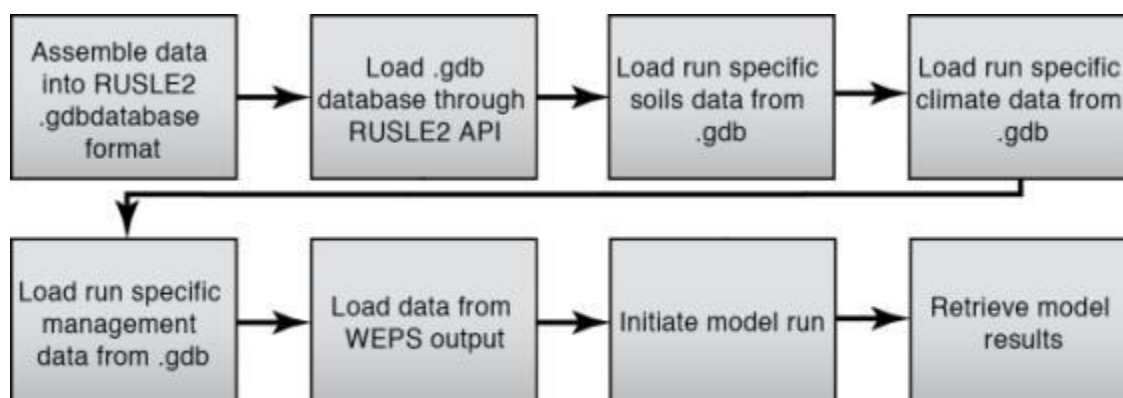


Figure 2.10. The basic functional flow of the RUSLE2 API wrapper is shown.

Using the SCI to assess the soil organic carbon impacts of various agricultural residue removal scenarios requires coupled analysis with both the WEPS and RUSLE2 models. The wind erosion component of the SCI ER sub-factor is calculated by WEPS. As shown in Fig. 2.6, upon completion of the WEPS model, the data required for SCI calculation is acquired from WEPS and passed into RUSLE2. In the modeling framework described here, RUSLE2 models the SCI OM and SCI FO sub-factors as well as accounting for the water erosion component of the SCI ER sub-factor. RUSLE2 then utilizes the WEPS SCI ER sub-factor input in the calculations and outputs the SCI result.

2.3.6 Integrated Model Application

The integrated residue removal model developed here was used to determine sustainable agricultural residue removal rates for the state of Iowa for several scenarios. The goals of this study were (1) to quantify residue availability under current production practices, (2) quantify the impacts of various tillage management strategies on residue availability, and (3) provide county level residue removal results that support environmentally and economically sustainable bioenergy production decisions. The study was performed through the following steps:

1. Define and assemble the analysis scenarios,
2. Execute the integrated systems model, and
3. Examine the impacts of tillage decisions.

The first step was determining the information required to define the cases being studied. These include establishing (1) the location and spatial extent of the study, (2) crop rotations, (3) tillage managements, (4) residue harvest methods, and (5) land management practices. Every scenario run of the integrated systems model requires that these characteristics be defined. Using the location and spatial extent; the local crop yields, soils data, and climate data are assembled from the coupled databases. As the integrated residue removal systems model executes this set of scenario runs, the data management modules are dynamically accessed to acquire and format the data needed for each of the models in the integrated residue removal systems model. The integrated residue removal systems model loops across this complete set of scenario runs pushing each model output to the results database. The integrated residue removal systems model then aggregates the county and state level results calculated for each of the scenario runs. With the county and state level results established, the user can then examine the results and draw overall conclusions. Each of these steps is described in greater detail below.

2.3.6.1 Define and Assemble the Analysis Scenarios

2.3.6.1.1 CROP ROTATIONS

Corn and winter wheat represent the two crops produced in Iowa that provide residues for bioenergy production. The rotations selected for this study were determined to be representative of Iowa's production systems through a five-year review (2006–2010) of USDA NASS production statistics (USDA-NASS, 2011). Corn and soybeans accounted for

greater than 90% of managed cropland in Iowa, and the standard crop rotations in the state of Iowa are assembled around the primary corn grain crop. Based on this, four standard crop rotations representing current practices in Iowa were selected. As shown in Table 2.2 these rotations produce corn, soybeans, and winter wheat.

Table 2.2. Crop rotation schema for the state of Iowa. Symbol reference notations are given to support later discussion.

Rotation	Year 1	Year 2	Year 3	Year 4	Symbol Notation	Reference
Continuous Corn	Corn	Corn	Corn	Corn	CC	Rot ₁
Corn/Soybean	Corn	Soybean	Corn	Soybean	CG-SB	Rot ₂
Corn/Corn/Soybean	Corn	Corn	Soybean	Corn	CG-CG-SB	Rot ₃
Corn/Soybean/Winter Wheat	Corn	Soybean	Winter Wheat	Corn	CG-SB-WW	Rot ₄

2.3.6.1.2 TILLAGE MANAGEMENT PRACTICES

As shown in Table 2.3, three tillage regimes were established for each of the four crop rotations used in this analysis—conventional tillage, reduced tillage, and no tillage. These three tillage regimes match the definitions provided by the Conservation Technology Information Center (2011). These three tillage regimes were selected for two primary reasons: (1) they cover the range from minimum to maximum soil disruption and (2) they represent how the majority of hectares are managed in Iowa. Table 2.3 lists the specific tillage operation associated with each crop under each of the tillage regimes. The NRCS maintained database of agricultural operations was used to establish key parameters defining the interaction between each tillage practice and the soil (NRCS, 2011b). Moldboard plowing of corn residue is the most invasive tillage modeled with depths up to 25.4 cm, 100% surface disturbance, and 99% residue burial ratios. Chisel plow operations on corn residue are

considered reduced tillage operations with depths up to 20.3 cm and residue burial ratios of 50–76%. Field cultivation operations are used in these modeled rotations to smooth the soil surface in the spring before planting. Field cultivation tills to depths up to 15.2 cm with a residue burial ratio of 20–40%.

Table 2.3. The tillage regimes are represented by specific equipment for each crop with the rotations.

	Conventional Tillage	Reduced Tillage	No Tillage
Corn Grain	Moldboard Plow, Field Cultivation	Chisel Plow, Field Cultivation	No Till
Soybeans	Field Cultivation	No Till	No Till
Winter Wheat	Field Cultivation	No Till	No Till

2.3.6.1.3 RESIDUE REMOVAL METHODS

Based on the need to investigate a range of removal rates, five standard residue removal methods were modeled for each crop rotation–tillage combination. Each of these harvest methods utilizes existing equipment and methods to remove agricultural residues from the field. Table 2.4 lists and describes each of these five removal rates. The decision to use existing equipment configurations rather than specifying hypothetical removal rates was based on the need to understand the orientation of the material left on the field. Often only the quantity of material left on the soil is considered when investigating sustainable residue removal limits. However, in many scenarios, the orientation of the remaining material is as or more important than the quantity. For example, water erosion is best controlled with residue covering as much of the soil surface as possible. Wind erosion, on the other hand, is best controlled by leaving taller standing stubble in the field to reduce the kinetic energy of the wind prior to interaction with the soil surface. By selecting existing harvest methods, the orientation of the material remaining on the field can be confirmed.

Table 2.4. Description and approximate residue removal rates for the five residue harvest methods used in this study.

Residue Harvest Level	Residue Collection Equipment and Process	Approximate Residue Collection Rate
No Residue Harvest	Combine harvester functions as normal.	0%
Harvest Grain and Cobs	Combine harvester internal mechanisms are set to break apart cobs and collect with the grain.	22%
Moderate Residue Harvest	Combine harvester residue chopper and spreader are disengaged leaving a windrow behind the machine. In a second pass a baler picks up the windrow making 3'x4'x8' square bales.	35%
Moderately High Residue Harvest	Combine harvester residue chopper and spreader are disengaged leaving a windrow behind the machine. A rake is used to collect additional surface residue into a single windrow. In a third pass a baler picks up the windrow making 3'x4'x8' square bales.	52%
High Residue Harvest	Combine harvester residue chopper and spreader are disengaged leaving a windrow behind the machine. A flail shredder is used to cut standing stubble and collect surface residue into a single windrow. In a third pass a baler picks up the windrow making 3'x4'x8' square bales.	83%

2.3.6.1.4 LAND MANAGEMENT PRACTICES

Complete land management practice descriptions were built for each crop rotation–tillage–removal method combination as described in Tables 2.2–2.4. These were conventional, reduced, and no tillage for each of the 5 residue removal methods resulting in 15 tillage-removal method scenarios that were investigated for each crop rotation. As described previously, four crop rotations were modeled resulting in a total of 60 land management practice scenarios. The timing of operations in each land management practice scenario was assumed to be the same for each county across the state. Table 2.5 shows the specific operations and their dates for each rotation for one of the fifteen tillage-removal

method scenarios, the reduced tillage–high residue harvest case. Each of the operations was selected from the NRCS standard agronomic management database. This database has nearly 33,000 crops, tillage practices, fertilization practices, planting methods, harvest practices, and other standard agronomic operations needed to define a management scenario. The parameters necessary to inform the environmental process model calculations are stored as a part of each of these database records. For example, the chisel plow tillage operation is represented with key parameters such as maximum and minimum tillage depth, surface area disturbance, residue burial ratios, surface roughness, and tillage intensity fractions. Vegetations such as corn are described with growth charts that represent key growth parameters including rootmass, canopy cover, and height, as well as descriptions of biomass to grain ratios, above ground biomass, and grain mass.

Table 2.5. For the four crop rotations identified in Table 2.2 each operation and its associated timing are identified for the reduced tillage–high residue harvest scenario.

Continuous Corn		Corn/Soybean		Corn/Corn/Soybean		Corn/Soybean/Winter Wheat	
11/1 Year 1	Chisel Plow	4/20 Year 1	Fertilizer Application	4/20 Year 1	Fertilizer Application	4/20 Year 1	Fertilizer Application
4/25 Year 2	Fertilizer Application	5/1 Year 1	Field Cultivation	5/1 Year 1	Field Cultivation	5/1 Year 1	Field Cultivation
5/1 Year 2	Field Cultivation	5/1 Year 1	Plant Corn	5/1 Year 1	Plant Corn	5/1 Year 1	Plant Corn
5/1 Year 2	Plant Corn	10/11 Year 1	Harvest Corn Grain	10/11 Year 1	Harvest Corn Grain	10/11 Year 1	Harvest Corn Grain
10/11 Year 2	Harvest Corn Grain	10/11 Year 1	Shred Standing Stubble	10/11 Year 1	Shred Standing Stubble	10/11 Year 1	Shred Standing Stubble
10/11 Year 2	Shred Standing Stubble	10/11 Year 1	Rake Residue	10/11 Year 1	Rake Residue	10/11 Year 1	Rake Residue
10/11 Year 2	Rake Residue	10/14 Year 1	Bale Residue	10/14 Year 1	Bale Residue	10/14 Year 1	Bale Residue
10/14 Year 2	Bale Residue	11/1 Year 1	Chisel Plow	11/1 Year 1	Chisel Plow	11/1 Year 1	Chisel Plow
		5/15 Year 2	Plant Soybeans	4/20 Year 2	Fertilizer Application	4/15 Year 2	Plant Soybeans
		10/1 Year 2	Harvest Soybeans	5/1 Year 2	Field Cultivation	9/1 Year 2	Harvest Soybeans
				5/1 Year 2	Plant Corn	9/15 Year 2	Plant Winter Wheat
				10/11 Year 2	Harvest Corn Grain	6/15 Year 3	Harvest Winter Wheat
				10/11 Year 2	Shred Standing Stubble	6/16 Year 3	Rake Residue
				10/11 Year 2	Rake Residue	6/17 Year 3	Bale Residue
				10/14 Year 2	Bale Residue		
				11/1 Year 2	Chisel Plow		
				5/15 Year 3	Plant Soybeans		
				10/1 Year 3	Harvest Soybeans		

2.3.6.1.5 CROP YIELDS

Grain yield for each crop is the input into the integrated systems model that describes productivity. Each of the models uses grain yield as the metric to determine residue production for the scenario runs. Each of the 60 crop rotation–tillage–removal method combinations was run for the nine grain yield scenarios shown in Table 2.6. The relationship between corn grain, soybean, and winter wheat was held fixed through these nine scenarios. This relationship was determined by developing a linear correlation from the five-year average yield statistics (Table 2.6) (2006–2010) provided by USDA NASS (USDA-NASS, 2011). Actual yields for each county were established using the same NASS production statistics five-year averages used to determine rotation distributions. The county level averages for corn grain yield are shown in Fig. 2.11.

Table 2.6. Assumed relationship between corn yield and soybean, winter wheat yields.

Crop	Primary Crop Grain Yield Scenarios Used in this Study (Mg ha⁻¹)								
Corn Grain	5.02	6.27	7.53	8.78	10.03	11.29	12.54	13.80	15.05
Soybeans	1.57	1.76	2.13	2.45	2.82	3.14	3.51	3.89	4.20
Winter Wheat	1.25	1.57	1.88	2.19	2.51	2.82	3.07	3.39	3.70

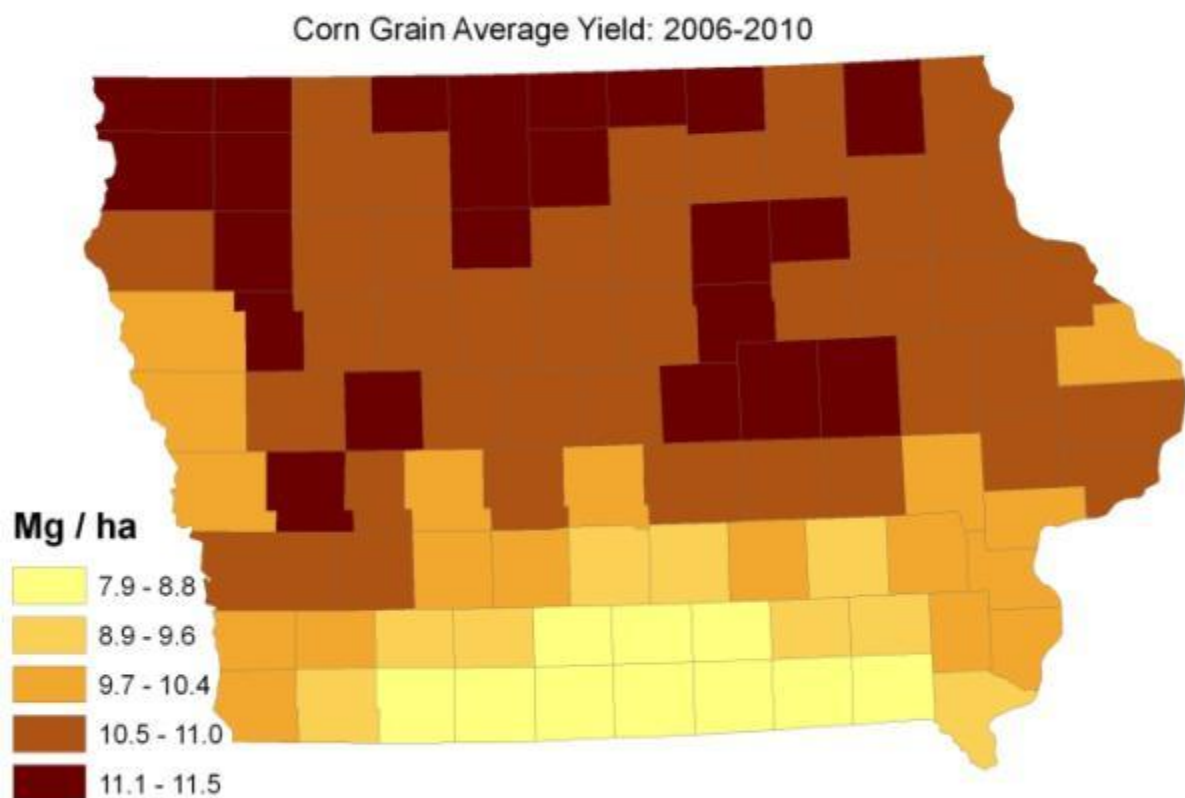


Figure 2.11. County level average corn grain yields.

2.3.6.2 Model Execution

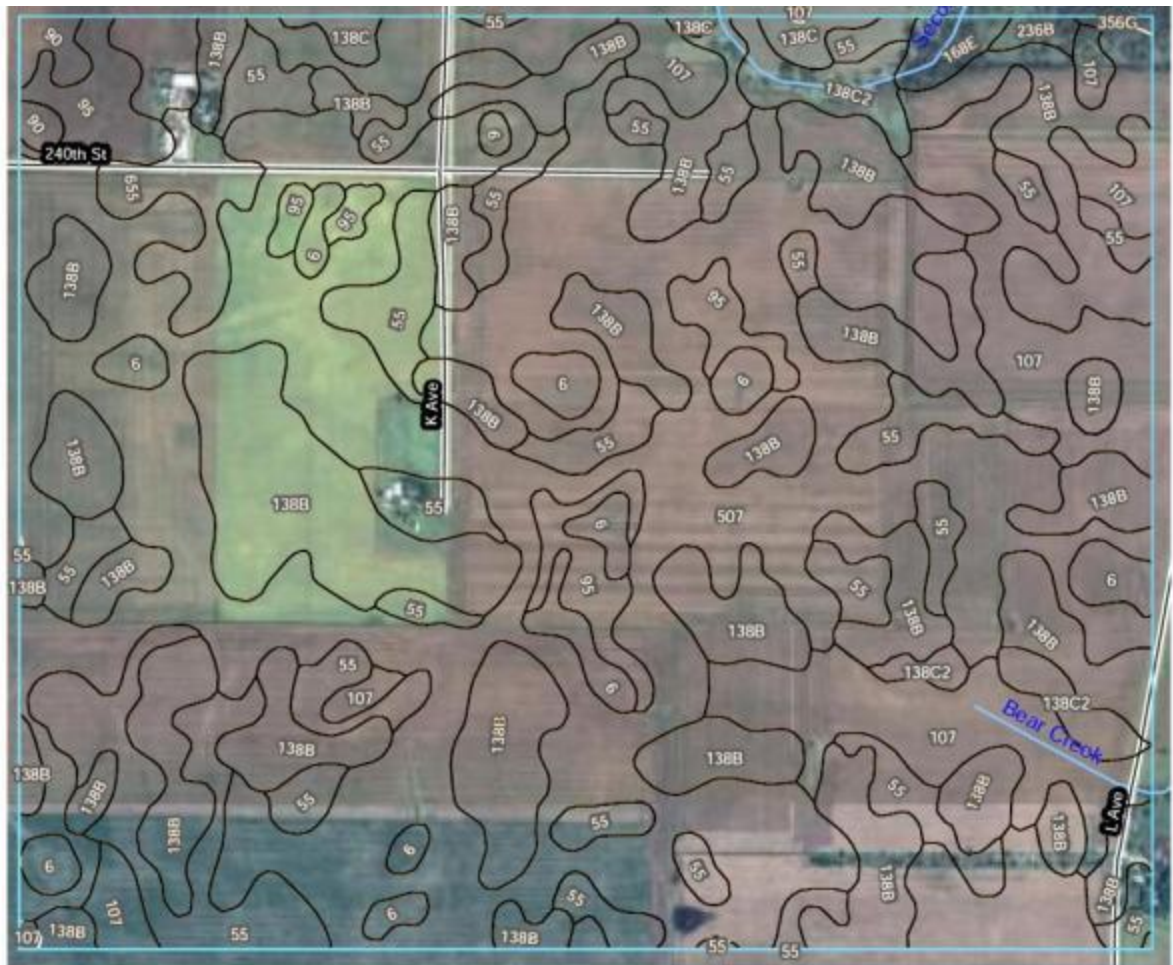
Section 3 presented the integrated residue removal modeling system and described the information flow through the modeling tools integrated for this study. As stated earlier, upon selecting the location and spatial extent of the analysis the soils and climate data are automatically acquired through the integrated databases. With the user inputs as described in Section 4.1 the model scenario runs are fully defined and can be executed.

2.3.6.2.1 SOILS DATA

Each crop rotation–tillage–removal method combination described previously was run for every soil in the state of Iowa from the NRCS SSURGO national soil survey database. Each soil in SSURGO is identified by a map unit symbol and the state of Iowa is comprised of over 10,000 soil map units. A map unit represents the base spatial unit for each of the model scenario runs. The crop rotation–tillage–removal method combinations create the unique scenario runs for each soil map unit. Figure 2.7 provides perspective on the level of detail provided by the integrated systems model. Each of the soil parameters shown are processed through the soil data module and then delivered to the models within the integrated framework. The SSURGO soil map unit served as the base spatial discretized unit for this analysis. Figure 2.12 gives perspective on the scale and layout of the SSURGO soil map units. As shown, each outlined region represents a specific map unit boundary. The legend below the figure provides a description of the map unit labels. The image is approximately two kilometers across from left to right, nearly 330 hectares in area, and is comprised of thirteen SSURGO soil map units.

Figure 2.12 represents a 330 hectare section of central Boone County, Iowa. The entire county is over 148,000 hectares, and is comprised of over 80 SSURGO soil map units. Approximately 70 of those SSURGO map units need to be considered in this analysis (water, landfills, etc. can be left out), then accounting for 4 crop rotations, 3 tillage practices, and 5 removal methods, detailed analysis of residue removal for Boone County requires 4200 scenario runs of the integrated systems model. In this study the 9 yield sets shown in Table 2.6 were run. This created a total of 37,800 scenario runs for Boone County. The state of Iowa, as mentioned previously, is comprised of over 10,000 soil map units. Accounting for

the crop rotation–tillage–removal method–yield combinations applied across the state, approximately 5.4 million scenario runs were required to investigate the sustainability of agricultural residue removal for energy use. Considering this requirement, it becomes clear that a fully integrated data management and modeling approach is essential for performing this type of study. Manual interaction with each a set of models is infeasible for generating this fidelity of results. Prior to the development of this integrated systems model, a user would have to manually perform each scenario run from each model user interface. Manually executing millions of scenario runs for each model is not practical, and further complicating this process is the necessary interaction with multiple disparate databases required to assemble each scenario run.



Boone County, Iowa (IA015)			
Map Unit Symbol	Map Unit Name	Hectares In Area of Interest	Percent of Area of Interest
6	Okoboji silty clay loam, 0 to 1 percent slopes	10.2	3.1%
55	Nicollet loam, 1 to 3 percent slopes	44.1	13.4%
90	Okoboji mucky silt loam, 0 to 1 percent slopes	1.8	0.5%
95	Harps loam, 0 to 2 percent slopes	10.2	3.1%
107	Webster silty clay loam, 0 to 2 percent slopes	28.0	8.5%
138B	Clarion loam, 2 to 5 percent slopes	93.8	28.4%
138C	Clarion loam, 5 to 9 percent slopes	2.1	0.6%
138C2	Clarion loam, 5 to 9 percent slopes, moderately eroded	5.9	1.8%
168E	Hayden loam, 14 to 18 percent slopes	1.7	0.5%
236B	Lester loam, 2 to 5 percent slopes	0.7	0.2%
356G	Hayden-Storden loams, 25 to 50 percent slopes	0.3	0.1%
507	Canisteo silty clay loam, 0 to 2 percent slopes	126.6	38.3%
655	Crippin loam, 1 to 3 percent slopes	4.7	1.4%
Totals for Area of Interest		330.3	100%

Figure 2.12. SSURGO map unit for a roughly 330 hectare area in central Boone County, IA (USDA-NRCS, 2011a).

2.3.6.2.2 *CLIMATE DATA*

The climate inputs for each residue removal systems model run in this study were established at the county level. RUSLE2 core climate databases, provided for each county by NRCS, were used for that model, and CLIGEN and WINDGEN files used for WEPS simulations were generated through the climate module for each of Iowa's 99 counties. Each SSURGO map unit in Iowa is within county boundaries allowing the set of climate inputs to be directly attributed.

2.3.6.2.3 *MODEL PERFORMANCE*

For each soil–crop rotation–tillage–removal method–yield combination, the integrated modeling framework distributes data and calculates the multi-factor scenario in approximately four seconds (wall-clock time), running a single thread of a standard multi-core processor desktop workstation. This time is increased for scenario runs where WEPS yield calibrations are required. The complete set of runs for this study was distributed on a 32-node computing cluster comprised of 3.0 GHz Intel Xeon Dual-Core rack-mounted machines running Microsoft Server 2003 Enterprise™. Each processor core was given a set of county scenarios to run. More than five million integrated residue removal modeling runs were performed in less than seven days total. Output databases were aggregated from the distributed compute nodes into the SQLite results database.

The WEPS model was run in standard NRCS field office mode. WEPS was run in calibration mode for each SSURGO map unit. Calibrations were set to run a minimum of ten and a maximum of fifty cycles, stopping when the modeled yield was within a defined range of the target yield. The RUSLE2 model was also run in standard NRCS field station mode.

2.3.6.2.4 *COUNTY AND STATE LEVEL RESULTS AGGREGATION*

With the model scenario runs complete and the results database populated, there were two steps required to establish county, and ultimately state level sustainable agricultural residue availability for the integrated systems model. These steps were (1) establishing the maximum sustainable removal rate for each soil–crop rotation–tillage combination for the crop yield in the county and (2) determining the area in each crop rotation (Table 2.2) for each county. The integrated systems model outputs results to an SQLite database, and the following steps were performed through an automated SQL query executed to that database.

The first step in establishing county level results was determining the highest sustainable removal rate for each soil–crop rotation–tillage combination in each county. The sustainability criteria were implemented as follows: (1) total soil erosion (wind + water) must be less than the soil T–value (T is the maximum rate of annual soil erosion allowed for each soil map unit as determined by NRCS); and (2) the combined SCI must be greater than or equal to zero. The highest of the five removal methods that meets these criteria was selected as the sustainable removal rate for each soil map unit and crop rotation–tillage combination. As discussed previously the county level crop yields in this study were acquired from a five-year average of NASS reported yields. The integrated model was run at approximately 1.25 Mg ha⁻¹ increments (Table 2.6), and a linear interpolation was used to scale the residue yield to the exact county yield. For example, if the five year average yield is 10.2 Mg ha⁻¹, only the 10.03 and 11.29 Mg ha⁻¹ yield scenario residue values were used to calculate the result.

The second step in establishing county level sustainable agricultural residue harvest rates was determining the number of hectares in each of the four crop rotations for each of the ninety-nine counties in the state. The NASS statistics that provided county level crop yields as described previously were used to get the hectares of each crop in each county. An

equation set relating the hectares of each crop to the hectares of the four crop rotations was built and put into matrix form. Two sets of equations were required to execute this step: one set of counties with winter wheat production, and one set for counties without winter wheat production. Given that only one of the four crop rotations included winter wheat, the first equation for counties with winter wheat sets all of that crops' hectares as the corn–soybean–winterwheat rotation as presented in Table 2.2. The equation also sets the matching number of corn and soybean hectares to that rotation, accounting for the crops that are in each year of the three-year rotation. The next step in the equation set for counties with winter wheat production is attributing the remaining soybean hectares across the corn–soybean and corn–corn–soybean rotations presented in Table 2.2. An assumption was made that 20% of the remaining soybean hectares would go to a corn–corn–soybean rotation, and 80% would be attributed to a corn–soybean rotation. The final equation in the set puts the remaining corn hectares in the continuous corn rotation as presented in Table 2.2. This equation set is represented in matrix form in Eq. 2.8. Within Eq. 2.8 CG represents corn grain, SB represents soybeans, and WW represents winter wheat.

$$\begin{bmatrix} \left(\frac{1 - \frac{WW_{area}}{CG_{area}}}{4} \right) & 0 & 0 \\ \left(\frac{1 - \frac{WW_{area}}{CG_{area}}}{4} \right) & \left(\frac{1 - \frac{WW_{area}}{SB_{area}}}{1.25} \right) & 0 \\ \left(\frac{1 - \frac{WW_{area}}{CG_{area}}}{2} \right) & \left(\frac{1 - \frac{WW_{area}}{SB_{area}}}{5} \right) & 0 \\ \frac{WW_{area}}{CG_{area}} & \frac{WW_{area}}{SB_{area}} & 1 \end{bmatrix} \begin{bmatrix} CG_{area} \\ SB_{area} \\ WW_{area} \end{bmatrix} = \begin{bmatrix} Rot_{1_{area}} \\ Rot_{2_{area}} \\ Rot_{3_{area}} \\ Rot_{4_{area}} \end{bmatrix} \quad (2.8)$$

The rotation designations match those listed in Table 2.2. The matrix representation facilitates fast and robust calculations from a database. Counties that do not have winter wheat production utilize an equation set which has the same assumption of 20% of soybean hectares being attributed to corn–corn–soybean rotations and 80% to corn–soybean rotations. Again the remaining corn hectares are attributed to the continuous corn rotation. Equation 2.9 is the matrix representation of the equation set for counties without winter wheat production.

$$\begin{bmatrix} \left(\frac{1 - \frac{0.2SB_{area}}{2.0CG_{area}}}{2} \right) \\ \left(\frac{1 - \frac{0.2SB_{area}}{2.0CG_{area}}}{2} \right) \\ \left(\frac{0.2SB_{area}}{2.0CG_{area}} \right) \end{bmatrix} \begin{bmatrix} 0 \\ 0.8 \\ 0.2 \end{bmatrix} \begin{bmatrix} CG_{area} \\ SB_{area} \end{bmatrix} = \begin{bmatrix} Rot_{1_{area}} \\ Rot_{2_{area}} \\ Rot_{3_{area}} \end{bmatrix} \quad (2.9)$$

An example application of this methodology is shown in Eq. 2.10, which calculates the rotation areas (ha) for Lee County in southeast Iowa for the 2008 crop year. Lee County has winter wheat production per the NASS statistics, so Eq. 2.8 is used.

$$\begin{bmatrix} 0.238 & 0 & 0 \\ 0.238 & 0.850 & 0 \\ 0.476 & 0.094 & 0 \\ 0.048 & 0.055 & 1 \end{bmatrix} \begin{bmatrix} 29,542 \\ 25,617 \\ 1,416 \end{bmatrix} = \begin{bmatrix} Rot_{1_{area}} \\ Rot_{2_{area}} \\ Rot_{3_{area}} \\ Rot_{4_{area}} \end{bmatrix} \quad (2.10)$$

From Eq. 2.10, the 2008 hectares harvested were 29,542; 25,617; and 1,416 respectively for corn grain, soybeans, and winter wheat. The results are provided in Table 2.7.

Table 2.7. Rotation area (ha) for Lee County, IA using 2008 production statistics.

Continuous Corn Rotation	7,031
Corn/Soybean Rotation	28,812
Corn/Corn/Soybean Rotation	16,483
Corn/Soybean/Winter Wheat Rotation	4,249

Figure 2.13 represents the structure assembled for these steps to be executed within the integrated residue removal systems model results database. The results database is comprised of three components, a soils data component that connects map units to information within SSURGO, a management data component that stores the crop rotation–tillage–removal rate combinations used in the study, and the results data component which is populated with the outputs from the integrated residue removal model scenario runs. These components are all managed in local SQLite databases, and the aggregation methodology was implemented through an SQL query. The first step of determining the maximum sustainable residue removal method finds each unique soil–crop rotation–tillage combination and performs the sustainability test as described previously, identifying the maximum of the five removal methods that meet the criteria. With this step performed the query moves to calculating the county level results. The SSURGO soils database is queried to acquire the area that each soil map unit represents for a specific county. A summation of the area of all soils in a county is performed, and the percentage of area attributed to each soil in the county is calculated. This distribution of soils identified for a county is assumed to be the same for all crop rotations. The hectares of each crop rotation in a county are then calculated as described above. At this point each soil–crop rotation–tillage combination has a sustainable removal rate identified, and each soil–crop rotation has the area they account for in a county identified. The query now aggregates the results with the selection of the tillage scenario of interest. The query performs these steps and calculations on the over five million records in approximately thirty seconds on a standard desktop workstation.

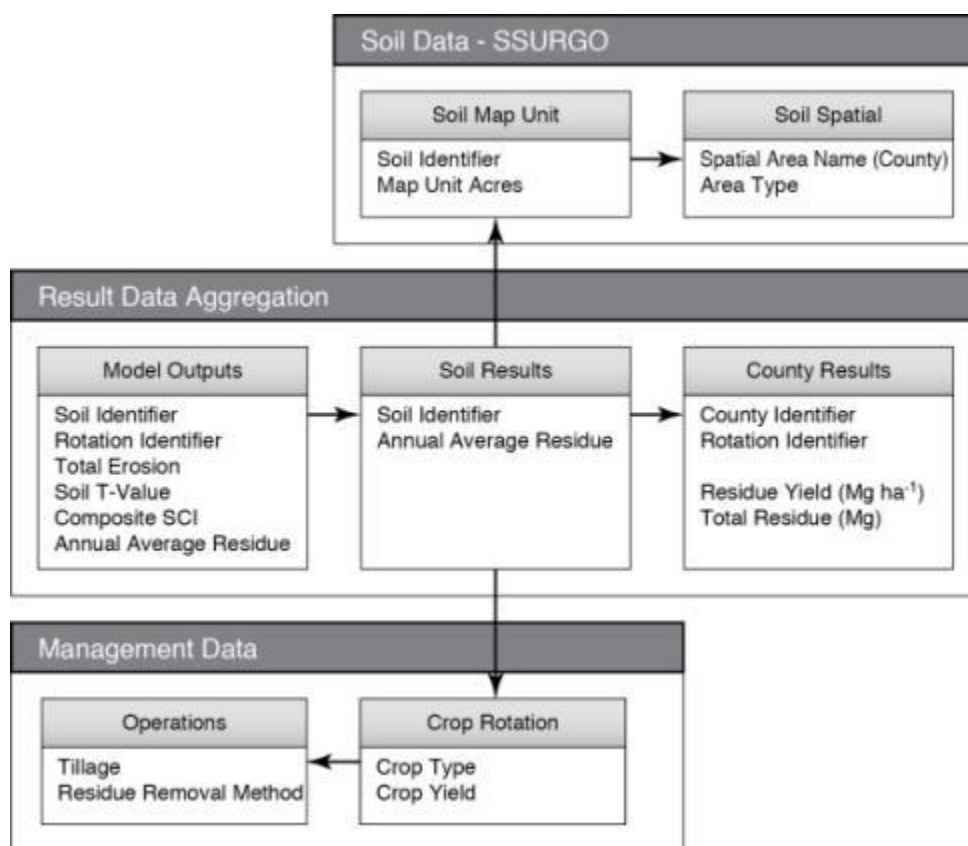


Figure 2.13. The “by soil type” results were written to an SQLite database and the pictured query structure was developed to process the results for scenarios of interest.

2.4 RESULTS AND DISCUSSION

2.4.1 Determining the Impacts of Tillage Management Decisions

Figure 2.14 provides the county level results for the state of Iowa comparing the three tillage regimes run for this study, as well as projecting the sustainably available residue based on current tillage practices. Current tillage practices were acquired from survey data from the University of Purdue’s Conservation Technology Information Center (CTIC, 2011). The average tillage practices for the state were assumed for each county. Table 2.8 shows how much agricultural residue can be sustainably removed in the state of Iowa, as well as average yields under the different scenarios in Mg ha^{-1} . The state average yield, AY , from Eq. 2.11

shown in column 1 of Table 2.8 represents a simple average of the sustainable yield for each county across the state, where AY_i is the average yield for each county.

$$AY = \frac{\sum_{i=1}^{99} AY_i}{99} \quad (2.11)$$

The mass weighted average, AY_{MW} from Eq. 2.12 shown in column 2 of Table 2.8 considers not just the county average yields, but also the total mass produced in each county. In Eq. 2.12 the statewide mass weighted average yield is AY_{MW} , TM_i is the total mass produced for each county, and TM_s is the total mass produced in the state.

$$AY_{MW} = \frac{\sum_{i=1}^{99} \left(\frac{AY_i \times TM_i}{TM_s} \right)}{99} \quad (2.12)$$

Under conventional tillage practices, which are disruptive and invasive to the soil, the majority of counties (75 out of 99) in the state sustainably provide less than 2.25 Mg ha⁻¹ of residue. Previous analyses have quantified operational cost sensitivity to residue yield (Hess et al, 2009a, Hess et al., 2009b), and the results suggest that 2.25 Mg ha⁻¹ is a minimum threshold residue removal rate required to support harvest and collection operations from an economic and logistics perspective. Using reduced tillage practices, 59 of Iowa's 99 counties can sustainably provide average residue removal rates above the 2.25 Mg ha⁻¹ threshold. Through the implementation of no tillage practices, all but 10 of the 99 counties average a sustainable residue yield above the 2.25 Mg ha⁻¹ threshold.

The results in Fig. 2.14 representing current tillage practices show that 55 of the 99 counties in the state of Iowa are above the 2.25 Mg ha⁻¹ threshold. As shown in Table 2.8, the results for the current tillage practices and five-year average grain yields show that more than

26 million Mg of residue is sustainably available currently in the state of Iowa. The USDA NASS county level grain yields are reported as a county average with no distinction between tillage management practices. The assumption is subsequently made in using this data that grain yield is the same across all tillage regimes. The average yield per harvested Mg of residue is nearly 3.31 Mg ha^{-1} . The current total removal potential equates to 27% of the residue produced.

The final column of Table 2.8 provides the impact of considering the 2.25 Mg ha^{-1} yield threshold. In this data the mass of residue produced in counties that have an average yield of less than 2.25 Mg ha^{-1} is discounted. Applying this discount factor has the greatest impact on the conventional tillage scenario. These results clearly demonstrate the impact of reducing tillage on the availability of agricultural residues for bioenergy production.

The 26.5 Tg of residue (nearly all of which is corn stover) sustainably available under current management practices is higher than the 13.7 Tg of corn stover identified in Iowa by Graham et al., 2007. There are three primary reasons for this difference. Graham et al. (2007) placed collection constraints on stover removal based on the equipment being modeled which are not present in the sustainability study presented here. Another difference is that the Graham et al. study represents data from significantly increasing corn production in terms of area (4.86 million ha in 2000, and 5.38 million in 2009) and yield (9.0 Mg ha^{-1} in 2000, and 11.4 Mg ha^{-1} in 2009). The third reason for this difference is the computational extent of the studies. The framework approach used in this study has utilized the latest models and provided an integrated model capable of dynamic investigation of significantly more soil and land management scenarios.

This study shows that as no tillage practices are adopted, the potential agricultural residue production across the state becomes nearly 40 million Mg annually, or about 40% of the total residue produced. The cellulosic biorefinery facility design presented by Aden et al. (2002) assumes a plant size of 2,000 metric tons per day and an ethanol conversion rate of approximately 320 liters per Mg of corn stover. The results from this study suggest that current sustainable agricultural residue available in the state of Iowa could support 38 biorefineries producing over 8.5 billion liters of cellulosic ethanol. With further adoption of no tillage practices, sustainable residue harvest could support as many as 56 biorefineries producing over 13.2 billion liters of cellulosic ethanol. Furthermore, these results show that there is a significant spatial variation of production potential across the state, as well as sensitivity to tillage practices. Variability in productive potential represents a risk across the biofuel supply chain and is a key consideration for decision makers.

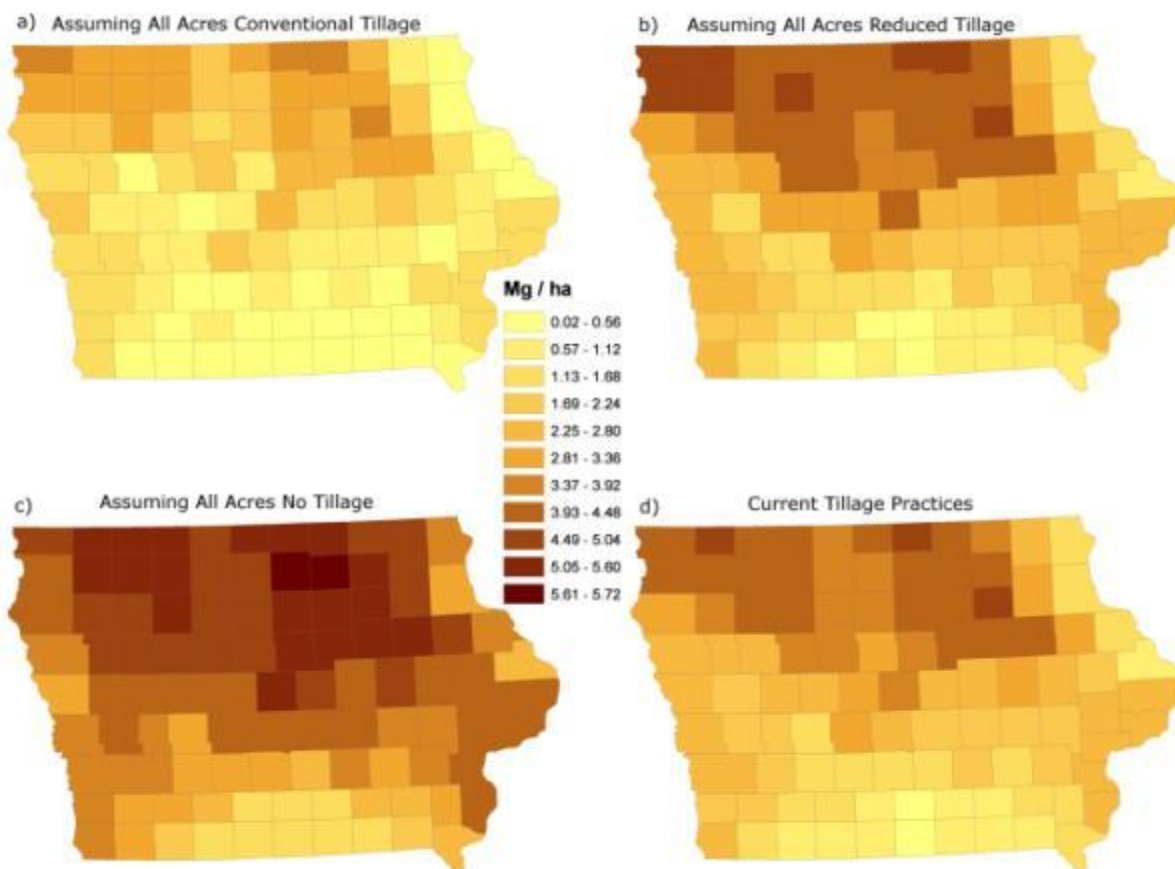


Figure 2.14. County level residue yield for each of the three tillage management approaches, and the current tillage practices scenario are presented.

Table 2.8. State total results for the three tillage scenarios and current tillage practices.

	State Average Residue Yield (Mg/ha)	Mass Weighted Average Residue Yield (Mg/ha)	Total Residue (Tg)	Sustainably Harvestable as Percentage of Total Residue Produced	Total Residue Available Above 2.25 Mg/ha Residue Yield Threshold (Tg)
Conventional Tillage	1.45	2.27	15.1	15%	4.2
Reduced Tillage	2.66	3.48	27.4	28%	22.5
No Tillage	3.98	4.48	39.1	40%	32.6
Actual Tillage	2.59	3.31	26.5	27%	19.0

Comparing the tillage scenarios in Fig. 2.14 provides several conclusions. Counties in the northwest and north central parts of the state show less sensitivity to tillage. Figure 2.15 shows a county level relative tillage impact factor, which was calculated by comparing the sustainably available residue for each county under conventional tillage as a percentage of the residue available under no tillage practices. Equation 2.13 presents this calculation with TS_i as the tillage sensitivity factor for county i , $AY_{i_{CT}}$ representing the average residue yield for county i under conventional tillage, and $AY_{i_{NT}}$ representing the average residue yield for county i under no tillage.

$$TS_i = \left(\frac{AY_{i_{CT}}}{AY_{i_{NT}}} \right) \quad (2.13)$$

The central and south central parts of the state show much greater sensitivity to tillage. It is useful to note the inverse relationship between corn grain yield (Fig. 2.11) and tillage sensitivity (Fig. 2.15). The counties in the state that have consistently high yields show less sensitivity to tillage. This is important from two perspectives. The first is that as genetic and agronomic advances continue to push grain yields higher in lower yielding counties, the sensitivity to tillage in those counties could potentially decrease. The second is that more intense tillage is often required with higher grain yields due to the large quantity of residue left on the field. The consequence is that removing residue at sustainable levels has the potential to allow land managers to do less tillage. The data in Fig. 2.15 in conjunction with the final column of Table 2.8 provides critical information for bioenergy producers considering the use of agricultural residues under current management practices. Much of the state has the ability to provide significant quantities of this resource, but may require

management changes to sustainably and economically collect large quantities of this resource. The northwest and north central parts of the state, which are less sensitive to tillage, will rely less on management changes to facilitate large scale residue harvest.

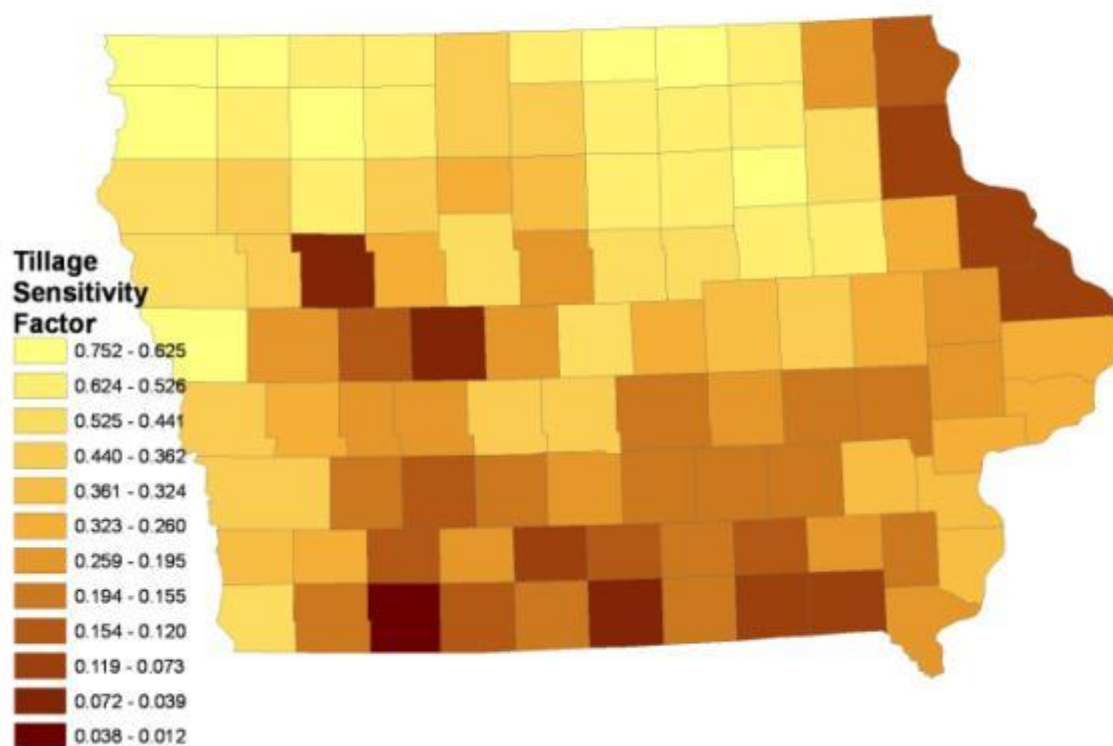


Figure 2.15. Identifying if residue removal in a particular area is sensitive to tillage is important because that area may require management changes from current practices to establish sustainable residue harvest. Lower sensitivity to tillage is desirable in this scenario.

2.4.2 Integrated Model Verification and Sensitivity

The models used in this study were integrated with the explicit requirement that source code could not be altered through the integrated process. This is important for preserving the extensive investment into model development and validation for each of the models. A set of

verification runs was assembled and performed to ensure that the results from the integrated model resulted in the same conclusions as utilizing the NRCS field office versions. Table 2.9 shows the results of this comparison from an Adair County example. Two soils with differing characteristics in terms of slope and organic matter were selected. The integrated and NRCS field office version of the models were compared for a reduced tillage, a corn-soybean rotation, and removal rate considering two different yield levels for each of the soils. In all cases the results from the integrated and NRCS field office versions of the models provided the same conclusions about the sustainability of the particular residue removal scenario. Slight differences in the specific erosion values for RUSLE2 can be attributed to significant digit rounding differences between the NRCS and integrated versions of the model. The results extracted from the RUSLE2 API have up to ten significant digits for each value, whereas the results presented through the graphical interface of the model are given with two or three significant digits in most cases. Differences in the results for WEPS can be attributed to the ongoing development in preparation for a new version release to NRCS field offices. The version coupled in the integrated model represents an updated revision of the code as compared to the current NRCS field office version. The ability to quickly exchange model versions is an important feature of the integrated framework used in this study. During development and execution of the model, important changes to the WEPS code were made that created better results. For this study, we were able to quickly couple to the latest version in the software repository.

A set of 10 geographically dispersed comparisons were performed to compare the results from the integrated model and NRCS field office versions. Table 2.9 presents a subset of these comparisons. Specifically, Table 2.9 shows two unique soils from Adair County, Iowa.

The “876B Ladoga silt loam, benches, 2 to 5 percent slopes” represents a higher organic matter and moderate slope soil, while the “175C2 Dickinson fine sandy loam, 5 to 9 percent slopes, moderately eroded” represents a lower organic matter and high slope soil. The 876B soil results are presented for a corn-soybean rotation assuming reduced tillage management practices and are given for all five residue removal rates. Two different crop yield scenarios are shown for 876B in Table 2.9 also. The 876B soil shows little susceptibility to wind erosion with the exception of the highest residue removal rate, which cuts down the standing corn stubble that serves as a wind break. This soil also shows a reasonably high water erosion rate, which progressively increases as the residue removal rate increases. This is an expected result because the surface cover provided by the residue to protect the soil is less with higher removal rates. In all cases the decision about whether the removal rate is sustainable is the same using the integrated model or the NRCS models. The RUSLE2 results are within a 0.4 Mg ha⁻¹ difference, which is approximately 3.5% of the tolerable soil loss limit for this soil. The WEPS results are within a 0.16 Mg ha⁻¹ difference, which is less than 1.5% of the tolerable soil loss difference. The qualitative SCI results all provide the same conclusion for the sustainability of the practice. Looking at the higher slope, lower organic matter soil 175C2, shown in the bottom portions of Table 2.9, the results between the integrated model and field office versions will lead to the same decisions about sustainability of the management practices. This soil has a higher sand fraction in the top soil layer, which results in higher wind erosion rates. The results of the investigation for this soil show that row cropping practices on this field have to be handled with caution, and residue removal will almost certainly result in negative impacts on the future productive capacity of the soil. For the 175C2 soil, the wind erosion rates under the high residue harvest (HRH) cases are more

than double the tolerable soil loss rate for the soil. These cases present the largest difference between the integrated model and NRCS field office versions, showing a nearly 8% difference.

The results in Table 2.9 present two different soils, two different crop rotations, and two different grain yield scenarios, and in all cases the integrated model leads to the same decisions as the NRCS field office versions of the models. In the test case scenarios, in addition to those presented in Table 2.9, the sustainable residue removal conclusions were the same between the NRCS field office and integrated models.

Table 2.9. Results comparing the integrated model outputs with the NRCS field office versions for two soils with different characteristics and two different yield scenarios.

Soil: 876B Ladoga silt loam, benches, 2 to 5 percent slopes													
Corn-Soybean Rotation: Reduced Tillage Practices													
Corn Yield: 10.03 Mg ha ⁻¹							Corn Yield: 7.53 Mg ha ⁻¹						
Soybean Yield: 2.82 Mg ha ⁻¹							Soybean Yield: 1.88 Mg ha ⁻¹						
Model Outputs (Erosion Rates in Mg ha ⁻¹)							Model Outputs (Erosion Rates in Mg ha ⁻¹)						
Rem. Rate	WEPS Integrated	WEPS NRCS	RUSLE2 Integrated	RUSLE 2 NRCS	SCI Integrated	SCI NRCS	Rem. Rate	WEPS Integrated	WEPS NRCS	RUSLE2 Integrated	RUSLE 2 NRCS	SCI Integrated	SCI NRCS
NRH	0.00	0.00	8.80	8.70	0.20	0.19	NRH	0.00	0.00	11.30	11.70	-0.01	-0.01
HCG	0.00	0.00	9.60	9.40	0.05	0.08	HCG	0.00	0.00	12.30	12.60	-0.11	-0.12
MRH	0.00	0.00	10.20	10.10	0.03	0.03	MRH	0.00	0.00	13.00	13.20	-0.16	-0.17
MHH	0.00	0.00	11.30	11.00	-0.08	-0.04	MH II	0.00	0.00	14.00	14.30	-0.23	-0.23
HRH	2.31	2.47	14.60	14.30	-0.34	-0.34	HRH	3.41	3.52	17.70	17.90	-0.55	-0.57

Soil: 175C2 Dickinson fine sandy loam, 5 to 9 percent slopes, moderately eroded													
Continuous Corn Rotation: Reduced Tillage Practices													
Corn Yield: 10.03 Mg ha ⁻¹							Corn Yield: 7.53 Mg ha ⁻¹						
Model Outputs (Erosion Rates in Mg ha ⁻¹)							Model Outputs (Erosion Rates in Mg ha ⁻¹)						
Rem. Rate	WEPS Integrated	WEPS NRCS	RUSLE2 Integrated	RUSLE 2 NRCS	SCI Integrated	SCI NRCS	Rem. Rate	WEPS Integrated	WEPS NRCS	RUSLE2 Integrated	RUSLE 2 NRCS	SCI Integrated	SCI NRCS
NRH	0.00	0.00	5.90	5.80	0.43	0.43	NRH	0.00	0.04	8.20	8.30	0.16	0.17
HCG	0.22	0.13	8.20	7.80	0.17	0.16	HCG	0.93	0.38	11.00	11.20	-0.11	-0.09
MRH	0.69	0.47	9.50	9.20	0.08	0.04	MRH	1.86	1.14	12.50	12.80	-0.25	-0.22
MHH	1.14	1.01	11.70	11.40	-0.17	-0.14	MH II	3.04	2.71	15.30	15.50	-0.45	-0.43
HRH	24.88	23.04	20.20	20.20	-1.43	-1.40	HRH	31.32	31.76	24.70	24.70	-1.76	-1.90

2.4.3 Framework Evaluation

The integrated modeling approach developed here provides a more comprehensive understanding of the residue removal issues than previous single model evaluations. The current integrated model is extensible for investigating residue removal scenarios for land management practices, soil conditions, and climatic conditions across the nation. The model

integration framework has met the requirements specified previously for the integration framework. First, seamless integration of existing models was satisfied for the RUSLE2, WEPS, and SCI models integrated for this study. The tools could then be used within the system in the same way they were utilized as standalone executables. Second, plug-and-play interaction is available with these tools. The system can function with any combination of the three models in the simulation. The most important plug-and-play function supported by the framework is the nearly seamless exchange of model versions. The tools used in the framework are continually being improved and refined, and their results are used to administer policy. For this integrated model to be an effective decision making tool, it needs to quickly and effectively make use of new model releases. Third, intuitive, real-time interaction is supported for each model.

There are two components to integrating new models into the framework: (1) ensuring the representation of the input data is correct for the new model in the system, and (2) ensuring the framework scheduling algorithms are managing the necessary data exchanges and model interactions. Considering these two things, the specific level of effort for new model integration will be model dependent. The computational engine and data management tools currently in place will typically facilitate initial integration in a matter of weeks.

The ability to integrate the selected models without changes to model source code accelerated the development of this integrated model. The tasks of selecting the models and assembling the data and information sources for the study required significantly more effort than model integration tasks. This can be attributed to the use of the VE-Suite integration framework.

2.5 CONCLUSIONS

Determining sustainable removal methods for agricultural residues requires assessing multiple agronomic and environmental factors simultaneously. This paper has presented an integrated residue removal analysis tool that supports the investigation of sustainable residue removal relative to water erosion, wind erosion, and soil organic matter constraints. The residue removal analysis tool has been built with the VE-Suite model integration toolkit. The WEPS, RUSLE2, and SCI models have been coupled in the residue removal analysis tool. The modeling tool includes a robust and generic set of data interfaces supporting interaction with the wide variety of data sources required for these assessments. These data interfaces are managed through three data modules (climate, soils, and management), which facilitate the interaction with raw data sources and the formatting of data for input into the disparate models.

The integrated analysis approach developed here has enabled a more comprehensive assessment of sustainable agricultural residue removal than has been performed previously. The complex interactions between soils and land management practices creates the need for dynamic integrated modeling of the processes that potentially limit access to residues, and requires extensive model scenario runs to effectively capture the land management scenarios. The soil–crop rotation–tillage–removal rate combinations in this study total to nearly 5.4 million integrated model scenario runs. This level of fidelity of analysis is infeasible without using an integrated modeling framework.

The residue removal analysis tool developed was used to assess the currently sustainably accessible agricultural residue in the state of Iowa. This assessment included an investigation of the impact of tillage management practices on residue availability. The results of the

assessment show significantly increased residue harvest potential for reduced and no tillage management practices. The results also demonstrate that nearly 26.5 million Mg of residue is sustainably accessible under currently management practices, enough to produce over 8.5 billion liters of cellulosic ethanol. The fidelity of results generated for this analysis also enable investigation of residue availability under economic and logistics constraints, i.e. the impact of the recognized lower threshold of 2.25 Mg ha⁻¹ average yield for economic and logistic residue removal. This type of data and assessment is critical for supporting the development of a bioenergy industry that uses agricultural residues as a biomass resource while assuring that our land management practices maintain our soil resources.

The integrated model approach to exploring the sustainability of agricultural residue removal creates opportunities for exploring additional limiting factors and potential impacts of residue removal. For example, additional models such as DAYCENT and EPIC can be plugged into the system to simulate the nitrous oxide gas flux impacts of residue removal. With the existing integration framework in place, adding these additional models will require two things: (1) preparing the data modules to format the input data correctly for the additional models, and (2) developing the software wrappers that can execute the additional models when instructed by the computational engines. For models with API's, these tasks are straight-forward with the existing framework. Models that don't have API's can be more challenging to integrate.

There are limitations to the current study. Higher fidelity land management practice data is becoming available via the USDA Cropland Data Layer mapping project. Utilizing this data in the future will provide better cropping rotation data. Moreover, research is emerging that shows that as crop yields get higher, the harvest index (ratio of grain to plant biomass)

gets larger also. This would mean that less biomass is available at higher yields.

Consideration of this harvest index change has not been considered here. The integrated modeling framework also needs to be extended to include quantitative soil carbon assessments, as well as GHG cycles and water quality. As discussed previously, there are available models that can capture these characteristics.

Further research is needed to extend this analysis to both smaller and larger scales. In-field variability of grain crop yield and soil characteristics can be significant, and sub-field is the scale where residue harvest decisions will be made. In addition this integrated residue removal modeling system needs to be extended to high spatial fidelity yield data. This will enable investigation of the impact this in-field variability has on sustainable residue availability. Another potential application of this type of integrated modeling tool is to explore the capability of current residue harvesting technologies, as well as the need for new residue harvest equipment. Another important question is what are the potential impacts of climate change on sustainable residue removal rates. This question is being investigated as part of the next steps for this integrated model. The framework developed here can potentially accept a climate change dataset as the climate data input with the Climate Data Module being adapted to format the climate change dataset for each model input.

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CHAPTER 3. SUSTAINABLE AGRICULTURAL RESIDUE REMOVAL FOR BIOENERGY: A SPATIALLY COMPREHENSIVE NATIONAL ASSESSMENT

A paper submitted to *Applied Energy*

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ABSTRACT

This study provides a spatially comprehensive assessment of sustainable agricultural residue removal potential across the US is needed to support development and investment decisions for an emerging bioenergy industry. Earlier assessments determining the quantity of agricultural residue that could be sustainably removed for bioenergy production at the regional and national scale faced a number of computational limitations. These limitations included the number of environmental factors, the number of land management scenarios, and the spatial fidelity and spatial extent of the assessment. This study utilizes an integrated multi-factor environmental process modeling and high fidelity land use datasets to perform a spatially comprehensive assessment composed of over ten thousand land management scenarios of the sustainably removable agricultural residues across the conterminous US. Soil type represents the base spatial unit for this study and is modeled using a national soil survey database at the 10–100 m scale. Current crop rotation practices are identified by processing land cover data available from the USDA National Agricultural Statistics Service Cropland Data Layer database. Land management and residue removal scenarios are identified for each unique crop rotation and crop management zone. Estimates of county average and state totals

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of sustainably available agricultural residues are provided. The results of the assessment show that in 2011 over 150 million metric tons of agricultural residues could be sustainably removed across the US. Projecting crop yields and land management practices out to 2030, the assessment determines that over 207 million metric ton of agricultural residue can be sustainably removed for bioenergy production at that time.

3.1 INTRODUCTION

The US federal government has established goals for biofuel production through the Energy Independence and Security Act, 2007. The law specifically calls for US biofuel production to increase above 136 billion liters annually by 2022, with approximately 56 billion liters coming from non-cornstarch feedstocks. Assuming a conversion rate of 330 liters of biofuel per metric ton for cellulosic feedstock (Aden et al., 2002, Phillips et al., 2011), meeting this target will require at least 240 million metric tons of biomass resources. A number of research efforts have examined cellulosic bioenergy feedstocks such as switchgrass, miscanthus, energycane, energy sorghum, willow, hybrid poplar, forest residues, and agricultural residues and conversion technologies that can utilize these feedstocks (Jin et al., 2010; Li et al., 2010; Heo et al., 2010; Szijártó et al., 2011). Of these feedstocks, the resource with the greatest near term potential (1–5 years) for achieving national targets is agricultural residues (DOE, 2012).

Identifying a sustainable and reliable agricultural residue resource base has been a significant challenge for the emerging cellulosic biofuels industry (Wilhelm et al., 2010). Agricultural residue removal must be managed carefully to be sustainable, and spatial and temporal variability (soil, climate, and management practices) impact the reliability of the supply. Residues play a number of critical roles within an agronomic system including direct

and indirect impacts on soil physical, chemical, and biological processes (Karlen et al., 2003; Johnson et al., 2006; and Wilhelm et al., 2007, Wilhelm et al., 2011). Excessive residue removal can degrade the long term productive capacity of soil resources (Sheehan et al., 2004, Mann et al., 2002). The large capital investments required for cellulosic biorefineries (>\$100M) require a reliable knowledge of the agricultural residue resource base locally available for a facility. The challenge is that the assessments need to provide regional and national scale perspectives, but also need to capture local spatial (10-100 m) and temporal impacts on residue removal potential. Furthermore, the assessments need to provide analysis that leads to residue removal rates that will be certified as sustainable by the Natural Resource Conservation Service (NRCS) of the US Department of Agriculture (USDA) conservation management planning process.

To address this need for a robust national assessment of sustainably available agricultural residues built upon local soil, climate, and land management data this study utilizes an integrated modeling strategy to perform a multi-factor assessment of sustainably available agricultural residue across the US. The integrated assessment utilizes the models and data currently used by NRCS to administer agricultural land management policy. The approach integrates the environmental process models and associated databases required to dynamically calculate the impact of residue removal decisions. These calculations are performed at the Soil Survey Geographic (SSURGO) Database (NRCS, 2011a) soil type scale (10-100 m) and aggregated to county level projections using the USDA Cropland Data Layer data (USDA, 2012) (56 m grid). The data produced through the study is consistent with the guidance of sustainable agricultural land management practices as administered by the farm bill and USDA. Based on this, the results of the integrated assessment performed

here are data and analyses that can support cellulosic biorefinery decisions utilizing agricultural residues as the primary sources.

3.2 BACKGROUND

One of the key challenges associated with identifying potential of agricultural residues is accounting for the many important roles that residues play in the agronomic system. Wilhelm et al., 2010 performed an extensive review of sustainability indicators for agricultural residue removal. The result of this review was the identification of six environmental factors that potentially limit agricultural residue removal—soil erosion from wind and water, soil organic carbon, plant nutrient balances, soil water and temperature dynamics, soil compaction, and off-site environmental impacts. Wilhelm et al. also noted that their review determined that no model or methods were available that could comprehensively consider the range of factors that potentially limit agricultural residue removal.

Several previous efforts have considered a subset of Wilhelm's six limiting factors in projecting regional or national sustainable residue availability. The first large spatial scale of agricultural residue availability was published by Larson (1979). He estimated that approximately 49 million metric tons of crop residues could be sustainably harvested at that time in the Corn Belt, Great Plains, and Southeast regions of the US. The focus of this study was limiting erosion below tolerable soil loss limits and the calculations were performed utilizing the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978). The study investigated the effect of tillage practices on residue removal potential and considered nutrient removal impacts. Using USLE at that time required significant spatial aggregation of soil characteristics, land management practices, and crop yields to reduce the number of calculations. Because of this requirement this study provided regional scale projections of

residue availability, but could not provide the local sustainable removal projections needed by bioenergy industry decision makers. In addition, Larson's study did not consider the relationship between residue removal and soil organic carbon.

As a result of low oil prices and generally decreased interest in bioenergy development in the US, the next large scale assessment of agricultural residue availability was presented by Nelson in 2002. This was the first of a series of assessments focused on residue removal within the context of retention requirements. The approach for these assessments was to assemble a limited set of representative crops, rotations, and field management scenarios; apply them to land capability class 1–4 soils; and then utilize the Revised Universal Soil Loss Equation (RUSLE) and the Wind Erosion Equation (WEQ) to generate residue retention requirements to limit rainfall and wind erosion below tolerable loss limits. The yield needed at time of harvest was then correlated to an average county-level yield to determine the possible quantity of available residue at the county scale. The methodology in Nelson, 2002 was employed for 37 states from the Great Plains to the East Coast for the period of 1995 to 1997 and determined that over 50 million metric tons of corn stover and wheat straw were potentially available annually for removal over this span. Soil organic carbon was not considered in this study.

The ability to determine residue availability at the county scale provided a significant step forward in generating data that could support bioenergy industry decisions. However, this study was computationally limited in the number of scenarios that could be investigated and was not able to consider the variability in soil characteristics and management practices that are typically found within a single county. These local (10-100 meters) considerations

are important for certifying sustainable removal practices within NRCS conservation management planning guidelines, and thus ensuring reliable biomass supplies for biorefiners.

The methodology developed by Nelson, 2002 was applied to a life cycle assessment of corn stover to produce ethanol by Sheehan et al., 2004. This study focused on providing a stover-to-ethanol system level analysis including collection, transport, and conversion for the state of Iowa. The Nelson, 2002 methodology was extended by including the CENTURY agro-ecosystem model (Parton et al. 1988, 2001) to quantitatively assess soil carbon impacts of residue removal. The scale of the calculations was county level, consistent with the Nelson, 2002 methodology. The study made the significant assumptions that all land would shift to a continuous corn crop rotation and no-till management practices. These assumptions, along with the implementation at county scale, were due to the computational limitations on the number of scenarios that could be investigated with the analysis tools being used. Residue removal was established using the Nelson, 2002 erosion methodology and the 0, 5, 10, 15, 20, and 90 year soil carbon values at the county level removal rates was calculated. The Sheehan et al., 2004 study found that for the scenarios investigated soil organic matter is maintained at removal rates determined by limiting erosion below tolerable limits. This study provided a life cycle perspective on producing ethanol using corn stover in Iowa. However the coarse spatial fidelity and limited production scenarios investigated do not provide sufficient detail for cellulosic bioenergy industry decision makers.

In 2004 Nelson et al. introduced an updated methodology that calculated residue retention requirements at the SSURGO soil type scale (10-100 meters). The updated methodology was applied to the top 10 corn producing states in the US based on total production from 1997–2001. SSURGO soils with land capability classes from 1–8 (NRCS,

2012) were investigated. The RUSLE and WEQ computational approach from the Nelson, 2002 study was applied at the soil type scale rather than using county level aggregation. The updated methodology investigated a broader set of crop rotations and tillage scenarios. For each soil type–crop rotation–tillage combination the residue retention requirement for limiting water and wind erosion losses to below tolerable limits was identified. Following this additional residue above the retention requirement was identified as available for removal based on actual crop yields. Soil organic carbon and general soil tilth were not considered. This study concluded that 30.2 million dry metric tons of corn stover and 13.4 million dry metric tons of wheat straw were available for removal annually across the 10 states investigated over the five year span from 1997–2001. The Nelson et al., 2004 methodology advanced sustainable residue availability analysis by investigating scenarios at the SSURGO soil map unit scale. Calculations at the soil map unit scale provide useful insight for residue removal decisions in individual fields and can be directly applicable within the NRCS conservation management planning process. However, the study investigated a limited set of environmental factors, land management scenarios, and areas in the US.

The Nelson, 2004 methodology was implemented by Perlack et al., 2005 in a broader economic analysis framework for a study outlining the path to a billion-ton annual biomass supply in the US. The methodology was applied across the US for a limited set of crop rotation and tillage scenarios. The approach considered only erosion constraints. The result of this study was that nearly 176 million metric tons of agricultural residues were available annually. The study projected that within 35–40 years over 400 million metric tons of agricultural residue could potentially be available annually under specific tillage and yield

increase assumptions. The results of the Perlack et al., 2005 study were challenged within the soil science and agronomy communities as being aggressive in the projections by not considering a broader set of limiting factors, specifically soil organic carbon (Wilhelm et al., 2007; Wilhelm et al., 2010). Despite these objections, by establishing a roadmap to biomass resource production at levels that could support large scale cellulosic biofuels production the Perlack et al. (2005) provided a key dataset for an emerging biorefining industry.

A study by Graham et al., 2007 examined corn stover availability and built upon the Nelson, 2004 methodology by disqualifying non-irrigated corn production in arid climates on the basis that stover would be required on the soil surface to conserve soil moisture. Considering soil erosion and the assumed soil moisture constraint, this study estimated that 58.3 million metric tons of stover could be sustainably removed. The study noted the importance of considering soil organic carbon but given the computational limitations of the available tools Graham et al., stated that “in its current form with manual input, the Soil Conditioning Index is not practical to run for the thousands of corn production situations that occur in the USA.”

Gregg and Izaurrealde (2010) designed a factorial modeling study to investigate soil erosion, crop yield, soil carbon, and nitrogen balance impacts of residue harvest. The Erosion Productivity Impact Calculator/Interactive Environment Policy Integrated Climate (EPIC) model (Williams, 1995) was employed for this study. This analysis addressed the computational limitations of the existing modeling tools in a similar way to the studies discussed previously, by selecting a subset of representative scenarios to determine a broadly applicable sustainable removal rate. Gregg and Izaurrealde, 2010 investigated a greater number of limiting factors than previous studies, but were only able to look at four crop

rotations in sixteen counties across the entire country. The conclusions of Gregg and Izaurrealde, 2010 were that a 30% residue removal assumption will typically be sustainable and for flat, highly productive land removal rates could be higher. This provided useful perspective on a broad set of factors potentially limiting agricultural residue removal, and provided the research community an analysis toolset differing from previous studies. However, the results from this study were of limited value to cellulosic bioenergy decision makers in terms of identifying a spatial explicit sustainable and reliable resource base, and in providing confidence to growers that USDA NRCS conservation management planning certification would be attained.

Muth and Bryden (2011) developed an integrated modeling approach that addressed a number of the challenges from previous studies. A model and data integration framework was built to allow investigation of the full range of soil characteristics, climate conditions, crop rotations, and land management practices. This approach enabled large numbers of scenarios to be investigated computationally, thus allowing analyses across a full range of spatial scales from field scale to a national assessment. Integrating USDA NRCS models and data to calculate soil erosion from wind and water, and soil organic carbon impacts of residue removal decisions, this study evaluated potential residue removal scenarios across the state of Iowa. The study was performed with SSURGO soil map units as the base spatial units and included representative crop rotations, tillage management practices, and crop yields at the county level for the state of Iowa. Five commercially available residue removal configurations were modeled providing a range of potential removal rates. Over five million scenarios were calculated in the study representing residue removal in the state of Iowa. The conclusion was that for yield and management practices at the time that the state could

sustainably provide nearly 26.5 million metric tons of residue sustainably. The data produced from this study provides guidance for cellulosic bioenergy industry decision makers in Iowa because it represents the conservation management planning process used to administer farm bill programs.

3.3 METHODS

The integrated modeling approach developed by Muth and Bryden, 2011 is used for this study. The key limiting factors are modeled as discussed by Muth and Bryden, 2011. Soil compaction effects are not included in this study. The assumption used in this analysis is that best management practices would be implemented for the specific residue removal scenarios. This implies that operational decisions will be made to avoid detrimental soil compaction. The potential nutrient replacement requirements from residue removal decisions are considered in this analysis. The assumption is made that the required nutrients can be replaced through existing operations, but will come at additional costs. This study does not directly consider off-site environmental impacts.

This paper presents an assessment of sustainably removable agricultural residue across the conterminous US for bioenergy production. Soil erosion from wind and water, and soil organic carbon sustainability factors were considered in the assessment through the implementation of the integrated multi-model computation framework presented in Muth and Bryden, 2011. The assessment includes two yield scenarios, 2011 projected yields, and 2030 projected yields. The integrated model is built around the computational methodologies used for USDA NRCS conservation management planning, the mechanism used by USDA to ensure sustainable agricultural land management. There are several advantages for utilizing this approach. The models and datasets, presented in Table 3.1, are well defined, tested, and

validated. The validated models are used directly without alteration. This enables leveraging of substantial previous investment toward development and validation of the modeling tools. Another key advantage of adopting this approach is that the data produced in the analysis can be used to make residue removal decisions with confidence that the removal rates will be deemed sustainable by USDA.

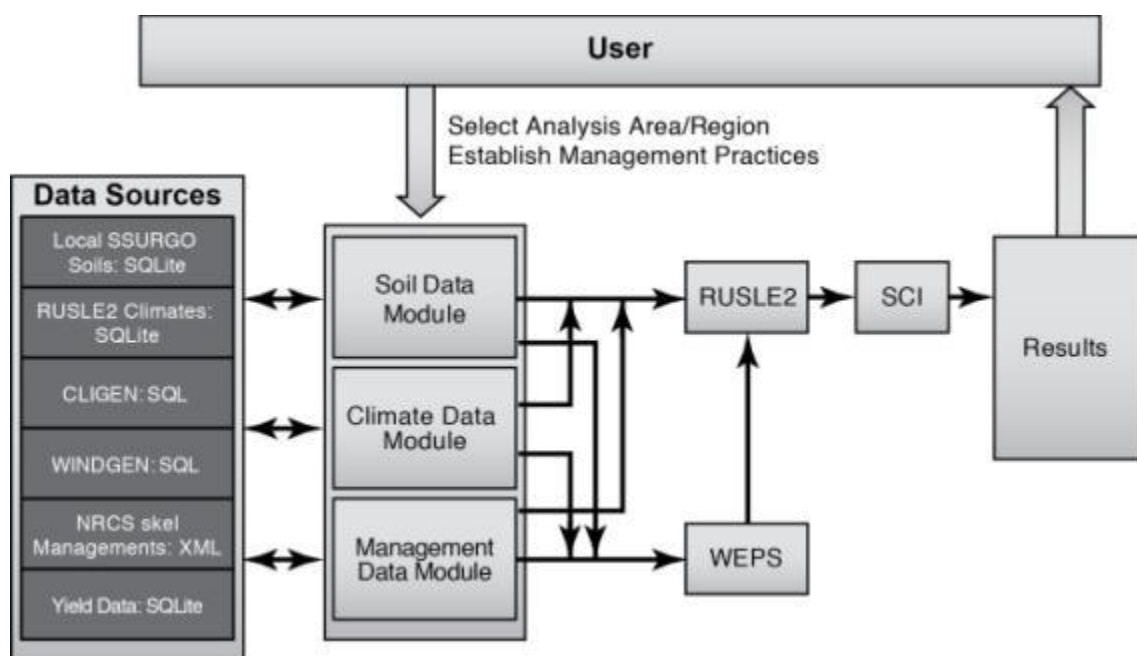


Figure 3.1. Integrated model utilized for this assessment. (Muth and Bryden, 2011)

The models used in the integrated model are the Revised Universal Soil Loss Equation 2 (RUSLE2) (NRCS, 2011c), the Wind Erosion Prediction System (WEPS) (NRCS, 2011d), and the Soil Conditioning Index (SCI) (NRCS, 2011e). RUSLE2 simulates daily changes in conditions including soil water and temperature dynamics to quantify the impacts of water erosion processes. It has been applied to a wide range of land management scenarios including cropland, pastureland, rangeland, and disturbed forestland (Ismail, 2008; Dabney et al., 2006; Foster et al., 2006; Schmitt, 2009). WEPS is a process-based daily time-step model

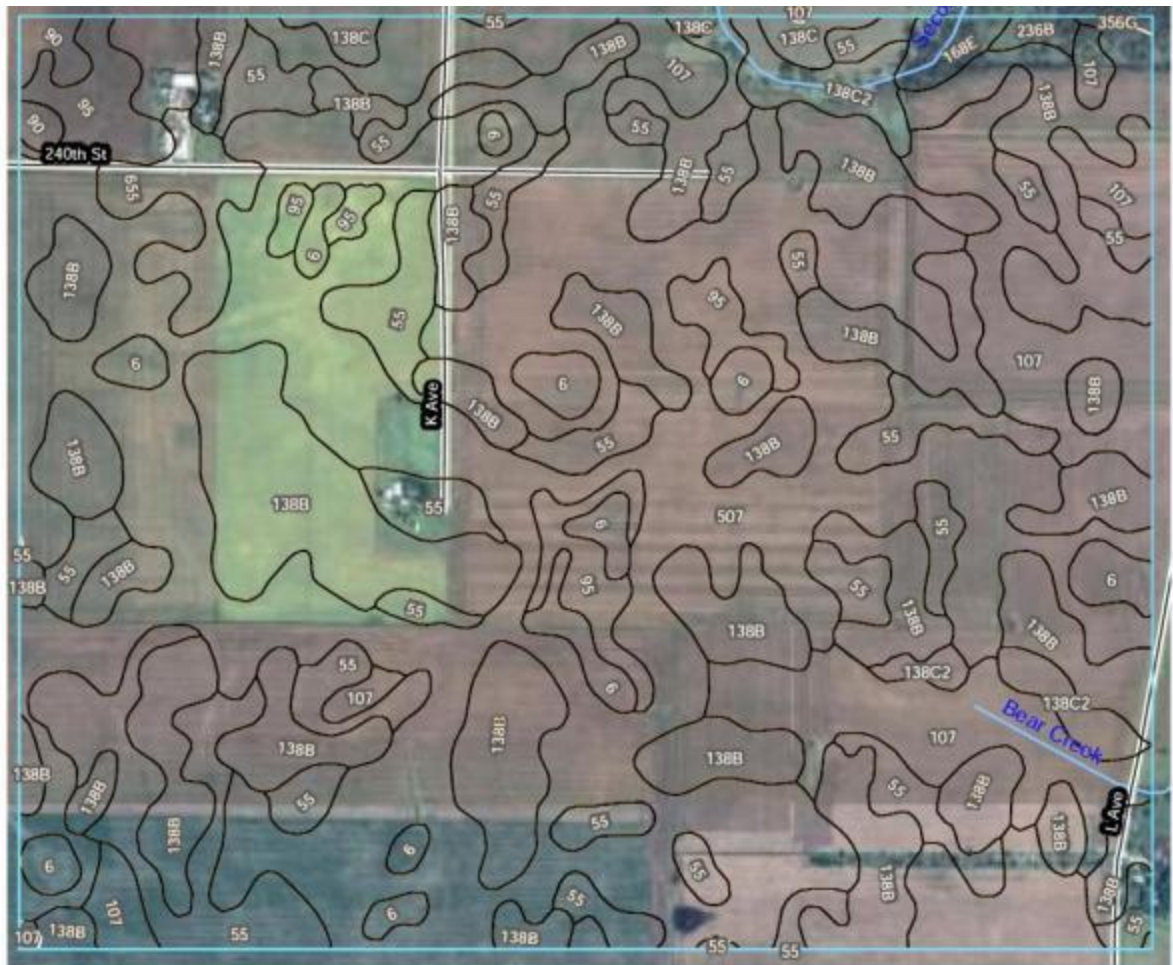
that simulates how field conditions including soil water and temperature interact with wind forces including direction and magnitude. WEPS models a three-dimensional region to resolve mass balance equations and project wind erosion impacts. WEPS has been used for cropland scenarios (Hagen, 2004), including previous studies for evaluating the impacts of corn stover removal (Wilhelm et al., 2007). The SCI utilizes parameters contributed by RUSLE2 and WEPS to provide qualitative prediction of the impact of land management practices on soil organic carbon. The SCI has been used for a broad range of soil quality assessments (Karlen et al., 2008, Zobeck et al., 2008, Zobeck et al., 2007). The integrated model in Fig 3.1 is executed for all scenarios where residue producing crops are grown in the conterminous US. The following sections describe these scenarios.

Table 3.1. The key data sources and models used are identified with the method for public access to the data or model.

Data Input	Database	Access
Soil	SSURGO	NRCS NASIS Server (http://soils.usda.gov/technical/nasis/)
RUSLE2 Climate	RUSLE2 native.gdb format	http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm
WEPS Climate	CLIGEN	http://www.ars.usda.gov/Research/docs.htm?docid=18094
Wind	WINDGEN	http://www.weru.ksu.edu/
Land Management	NRCS native.gdb format	http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm
Crop Yields	NASS	http://www.nass.usda.gov/
Modeling Function	Model	Access
Water Erosion/SCI	RUSLE2	http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm
Wind Erosion/SCI	WEPS	http://www.weru.ksu.edu/weps/wepshome.html
Integration Framework	VE-Suite	http://www.vesuite.org

3.3.1 Soil Data

The SSURGO soil survey database provides the soil data used in the assessment. The SSURGO soil map units represent the base spatial elements for this assessment. SSURGO soil map units typically represent spatial discretization in the 10–100 m scale. Figure 3.2 represents SSURGO map unit spatial data from a 330 ha area in the central Boone County, Iowa. The SSURGO data used in this study represents a snapshot from the USDA NASS server from April 8th, 2011. The SSURGO snapshot is used in a locally managed SQLite database. This choice was made because network or server interruptions would have represented a significant challenge considering the total number of queries required (nearly 600,000). Muth and Bryden, 2011 describe in detail the data flow from the SSURGO database into the integrated model. This includes description of the specific queries, data tables, and soil characteristics used for each individual model.



Boone County, Iowa (IA015)			
Map Unit Symbol	Map Unit Name	Hectares In Area of Interest	Percent of Area of Interest
6	Okoboji silty clay loam, 0 to 1 percent slopes	10.2	3.1%
55	Nicollet loam, 1 to 3 percent slopes	44.1	13.4%
90	Okoboji mucky silt loam, 0 to 1 percent slopes	1.8	0.5%
95	Harps loam, 0 to 2 percent slopes	10.2	3.1%
107	Webster silty clay loam, 0 to 2 percent slopes	28.0	8.5%
138B	Clarion loam, 2 to 5 percent slopes	93.8	28.4%
138C	Clarion loam, 5 to 9 percent slopes	2.1	0.6%
138C2	Clarion loam, 5 to 9 percent slopes, moderately eroded	5.9	1.8%
168E	Hayden loam, 14 to 18 percent slopes	1.7	0.5%
236B	Lester loam, 2 to 5 percent slopes	0.7	0.2%
356G	Hayden-Storden loams, 25 to 50 percent slopes	0.3	0.1%
507	Canisteo silty clay loam, 0 to 2 percent slopes	126.6	38.3%
655	Crippin loam, 1 to 3 percent slopes	4.7	1.4%
Totals for Area of Interest		330.3	100%

Figure 3.2. SSURGO map units in an approximately 330 hectare area in Boone County, IA . The width and height of the figure are slightly greater than 1.8 km (USDA, 2011b).

The SSURGO soil database includes soils covering agricultural and non-agricultural land. Land capability classes ratings range from 1–8. The soils considered in this study have SSURGO land capability class ratings of 1–4, that represent the classes considered capable for agricultural production. In addition, SSURGO soils with less than 405 ha in each county were not considered. Within the area in Fig. 3.2 four of the thirteen soils account for nearly 90% of the area. This relationship is common for entire counties. The choice to only consider soils that represent areas greater than 405 ha within a county reduces computational time required for this national scale study by over 70%, but still accurately represents more than 90% of the agricultural lands.

3.3.2 Climate Data

Three data sources are used to provide the required climate data for this assessment; NRCS managed RUSLE2 climate databases, the CLIGEN daily climate generator, and the WINDGEN daily wind speed and direction generator. The integrated model identifies the county location of the SSURGO map unit for a model scenario and loads the required RUSLE2 climate data from the NRCS assembled dataset. The WEPS model requires input from two climate generator models CLIGEN and WINDGEN. Both generators are stochastic models utilizing historic data and provide daily weather inventories for specified time periods. CLIGEN generates precipitation, minimum and maximum temperatures, solar radiation, dewpoint, wind speed, wind direction as daily inventories for a specific geographic location. WINDGEN generates hourly wind speed and direction inventories that provide the WEPS model with wind event intensity data required to calculate erosion. The CLIGEN and WINDGEN generators used for this study are given the location of the model scenario at the

county level based on the SSURGO soil map unit location. The generators are used to create 75 year datasets to drive the model scenario

3.3.3 Establishing Crop Rotations

A new methodology for determining representative crop rotation scenarios and establishing the county level distribution of crop rotations is used in this study. In the past establishing representative crop rotations for large scale assessments has been challenging because of the computational limitation of the number of crop rotation scenarios that could be examined and the spatial distribution of crop rotations has not been readily available. The integrated model approach used for this study addresses the first challenge by facilitating the investigation of significantly more crop rotation scenarios than previous approaches. The second challenge has been addressed by the use of the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) information (USDA 2011). The CDL provides spatially explicit descriptions of where different crops are grown by executing a “census by satellite” (USDA NASS, 2011) that delivers in-season, spatially explicit remote sensing estimates of acreages in a range of crop and land-use categories. Prior to 2009 the CDL data was delivered at 56 m resolution with incomplete coverage of the conterminous states. In 2009 and 2010 coverage for all lower 48 states was delivered at 30 m resolution. Figure 3.3 represents the 30 m resolution data produced for Iowa in 2009 with a closer look provided for Pocahontas County in NW Iowa. The closer look at Pocahontas County shows the fidelity of the CDL data and provides perspective on which crops were grown on individual land management units, or fields.

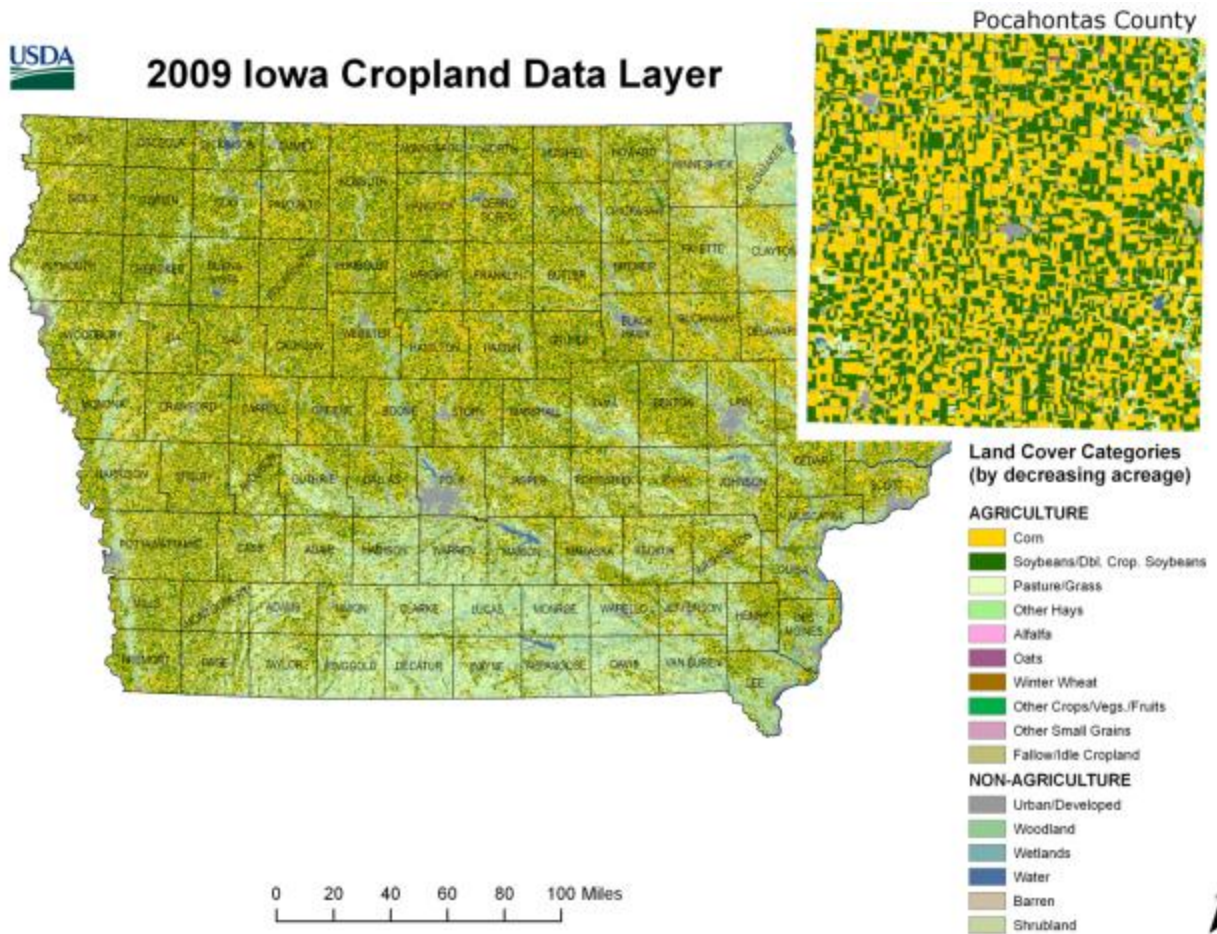


Figure 3.3. CDL data representing land use in Iowa and Pocahontas County for 2009.

The methodology developed for this assessment utilizes the CDL product to establish three-year crop rotations by overlaying the CDL for each state for 2008, 2009, and 2010. The 2008 CDL was not published for six states: California, Florida, Idaho, Montana, Oregon, and Washington. For these six states the approach was applied to establish two-year crop rotations. It should also be noted that the 2008 CDL was delivered at 56 m resolution, so the 2009 and 2010 CDL's were scaled from 30 m to 56 m to perform the data layer intersection.

Data for all three years was spatially joined and intersected for every county in the conterminous US. The land cover category in each year for each 56 m grid cell was written to

a database. All “like” grid cells were then aggregated. The next step in processing the CDL was selecting the crop rotations of interest for this assessment. Those areas that do not include at least one year of a residue producing crop were removed. The crops assumed to produce removable residue are: barley, corn, rice, sorghum, durum wheat, spring wheat, and winter wheat. All wheat crop are reported together in this analysis. It was found that 13.9% of the land across the US had a residue producing crop for at least one year from 2008–2010.

The next step was to remove those areas that had land cover category shifts between agricultural and non-agricultural uses. Using the example in Fig 3.4, if any of the years in a rotation included one of the following land cover categories it was removed from the dataset: urban/developed, woodland, wetlands, water, barren, shrubland. This is reasonable because shifts from agricultural categories to non-agricultural categories will typically represent a long term move that makes that land unavailable for residue removal; and land that is shifting from non-agricultural uses to agricultural uses will typically experience a number of agronomic challenges making the transition and residue removal practices are not likely to be adopted. In addition those areas that have transitions between agricultural and non-agricultural land uses often represent error in the spatial processing.

The multi-year data generated is then mapped to the set of crop rotations to be modeled in the assessment. For example Corn-Soybean-Corn grid cells and Soybean-Corn-Soybean grid cells are both mapped to a Corn-Soybean rotation for the model scenarios and Corn-Corn-Soybean grid cells and Soybean-Corn-Corn grid cells are both mapped to Corn-Corn-Soybeans for the model scenarios.

3.3.4 Land Management Scenarios

Defining a complete land management scenario requires comprehensive descriptions of all interaction with the land including the crop(s) grown, fertilizer treatments, tillage managements, and crop yields. For this study the land management scenarios use crop rotation and geographic location to establish crop planting timing and equipment, tillage timing and equipment, grain harvest timing and equipment, and residue removal timing. The approach used to define the timing and order of field operations is based on NRCS crop management zones (CMZ) (NRCS, 2011e) (Fig. 3.4). NRCS has established the 72 CMZs as regions where the field operations and their associated timing are generally consistent. Furthermore NRCS has built an extensive database of management operations and scenarios using the CMZ methodology.

Building land management scenarios for a CMZ requires establishing the complete list of crop rotations for each county that falls within the CMZ. With all of the unique crop rotations identified for each CMZ the land management scenarios including operational timing, tillage, and removal rate scenarios are built. Two criteria were applied to limit the number of management scenarios for each CMZ. First the rotations in a CMZ were ordered from largest area to smallest area. Then moving down on the list the rotations needed to include 90% of the area in the CMZ are selected, and all others beyond that cut off point were discarded. The second eliminated any rotation that did not comprise at least 405 ha in the CMZ. These assumptions significantly reduced the number of computations required while still providing an accurate representation of the land management practices for 90% of the area. Table 3.2 lists the number of crop rotations for each CMZ.

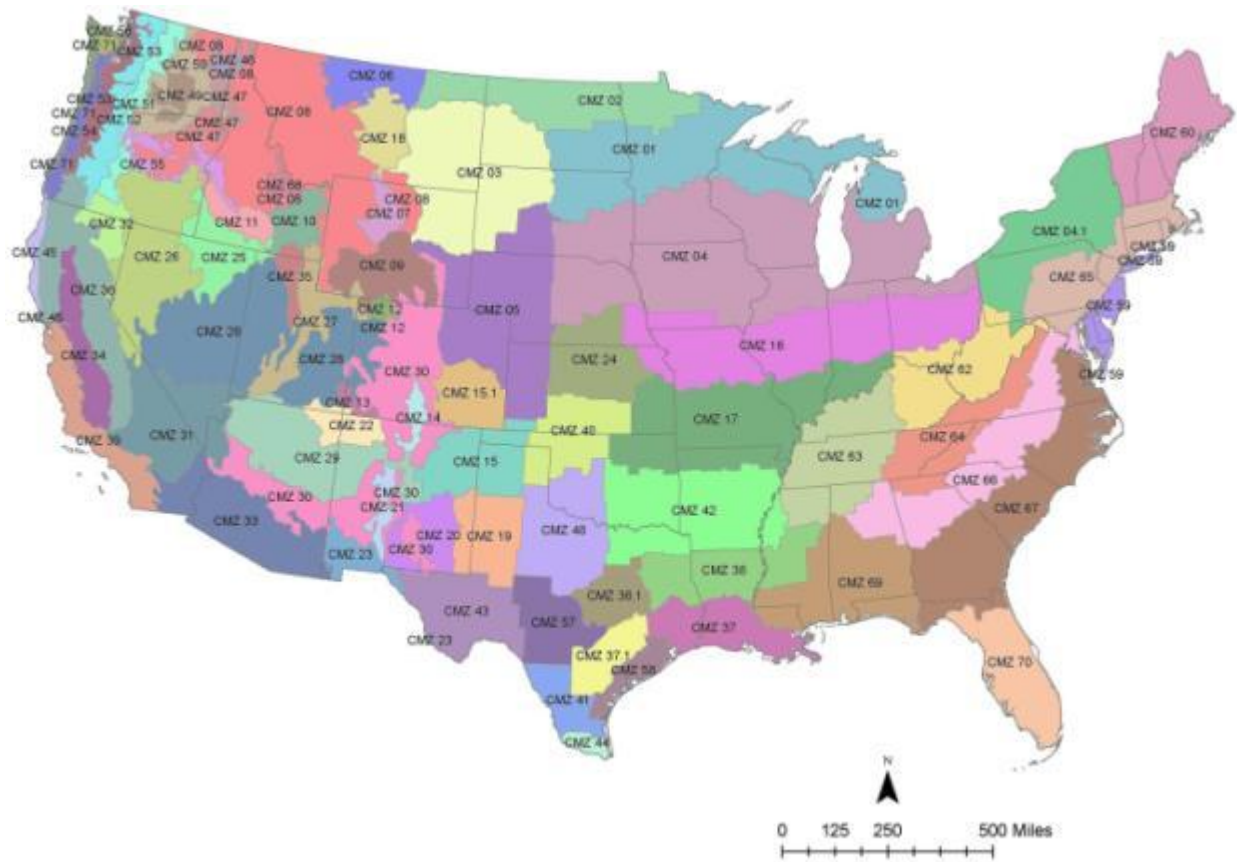


Figure 3.4. NRCS designated crop management zones (DOE, 2012)

Table 3.2. Number of crop rotations required for each CMZ to account for 90% of the CMZ area.

CMZ	No. Rots.	CMZ	No. Rots.	CMZ	No. Rots.	CMZ	No. Rots.	CMZ	No. Rots.	CMZ	No. Rots.
01	15	12	1	23	2	36	1	46	5	59	14
02	72	13	5	24	15	37	27	47	6	60	6
03	36	14	11	25	8	37.1	27	48	6	62	5
04	5	15	13	26	2	38	35	49	7	63	10
4.1	5	15.1	13	27	7	38.1	35	50	8	64	15
05	15	16	6	28	10	39	22	51	8	65	10
06	7	17	12	29	7	40	21	52	6	66	22
07	15	18	6	30	30	41	14	53	7	67	25
08	7	19	19	32	10	42	24	54	6	68	5
09	4	20	5	33	26	43	2	55	12	69	18
10	11	21	1	34	20	44	6	57	22	70	6
11	17	22	9	35	8	45	1	58	15	71	1

3.3.5 Tillage Management Practices

Tillage practices can impact sustainable residue removal (Wilhelm et al., 2010). One of the primary reasons tillage operations are performed is to incorporate residues into the soil creating more manageable soil surface conditions for planting of the next crop. Because of this sustainable residue removal can potentially reduce the need for tillage operations. To investigate the impacts and opportunities associated with tillage management practices, three tillage regimes were modeled for every crop rotation-residue removal scenario in the assessment. The three regimes represent standard practices by CMZ and crop rotation as defined by NRCS. The standard practices were collected from the NRCS standard management database specified in Table 3.1. For each CMZ the specific tillage equipment, the dates that operations were performed, and number of passes were extracted for each crop and tillage regime. This data is used to create CMZ and crop specific rules and populate the

specific set of tillage operations for each CMZ-crop rotation-tillage regime combination. The tillage regimes used in this study are categorized as conventional, reduced, or no-till. These tillage regimes in all cases are consistent with the tillage definitions provided by the Conservation Technology Information Center (CTIC) (CTIC, 2011). Conventional tillage is the most invasive tillage regime including at least one full-width complete soil inversion tillage operation resulting in less than 15% residue on the soil surface after planting. Conventional tillage typically involves multiple tillage passes. Reduced tillage includes at least one full-width tillage pass, but leave up to 30% residue on the soil surface after planting. No-till is defined as the minimum soil disturbance required for input of the following crop. The specific set of operations for each tillage regime is determined based CMZ and crop rotation using the NRCS rule set described previously. Figure 3.5 shows the percentage of acres in reduced tillage practices for the 2011 sustainable residue removal projections. The correlating data is available for conventional and no-tillage practices.

3.3.6 Residue Removal Practices

The agricultural residue removal rate scenarios used in this study follow the schema developed by Muth and Bryden, 2011. They included five standard residue removal methods for each crop rotation–tillage combination. These residue removal methods each utilize existing equipment and methods to remove residues from the field. Table 3.3 lists and describes each of these five removal rates. The decision to use existing equipment configurations is an important distinction between the assumptions used in this assessment and those used in past regional and national scale analyses. The environment process models need an accurate representation of the orientation of the material left on the field. Often only the quantity of material left on the soil is considered when investigating sustainable residue

removal limits. In many scenarios the orientation of the remaining material is as or more important than the quantity. The clearest examples of this dynamic is that water erosion is best controlled with residue covering as much of the soil surface as possible, while wind erosion is best controlled by leaving taller standing stubble in the field to reduce the kinetic energy of the wind prior to interaction with the soil surface. There are two advantages to selecting existing harvest methods, 1) the models are provided with an accurate representation of residue quantity and orientation after harvest and 2) the results of the assessment represent the current state of technology by implementing commercially available removal operations.

Table 3.3. Description and approximate residue removal rates for the five residue harvest methods used in this study.

Residue Harvest Level	Residue Collection Equipment and Process	Approximate Residue Collection Rate
No Residue Harvest (NRH)	Combine harvester functions as normal.	0%
Harvest Grain and Cobs (HGC)	Combine harvester internal mechanisms are set to break apart cobs and collect with the grain.	22%
Moderate Residue Harvest (MRH)	Combine harvester residue chopper and spreader are disengaged leaving a windrow behind the machine. In a second pass a baler picks up the windrow making 3'x4'x8' square bales.	35%
Moderately High Residue Harvest (MHH)	Combine harvester residue chopper and spreader are disengaged leaving a windrow behind the machine. A rake is used to collect additional surface residue into a single windrow. In a third pass a baler picks up the windrow making 3'x4'x8' square bales.	52%
High Residue Harvest (HRH)	Combine harvester residue chopper and spreader are disengaged leaving a windrow behind the machine. A flail shredder is used to cut standing stubble and collect surface residue into a single windrow. In a third pass a baler picks up the windrow making 3'x4'x8' square bales.	83%

3.3.7 Yield Scenarios

County average crop yields are used for all crops in this study. Yield assumptions at the county level for residue producing crops match those used for the US Billion Ton Update (DOE, 2012) that utilized the USDA Economic Research Service (ERS) Agricultural Baseline Projections (USDA ERS, 2012). The ERS Baseline Projections provide projections for ten years. The 2030 yield assumptions were linearly extrapolated from the ten-year projection to 2030. For crops that were not considered in the US Billion Ton Update county level average yields were acquired from USDA NASS using 2008–2010 reported averages and no yield increases between 2011 and 2030 was assumed. This assumption is reasonable because these crops typically have less historical data to support yield increase projections and these are not residue producing crops, but are crops that are in rotation with residue producing crops.

3.3.8 Determining Sustainable Removable Rates

A residue removal rate is considered sustainable in this analysis if the combined soil loss from wind and water erosion is less than or equal to the tolerable soil loss (T-value) reported in SSURGO and soil organic matter is not being depleted. For each removal rate scenario the wind and water erosion outputs from the models were combined to a total erosion value and then compared with the soil T-value from SSURGO. Following this the integrated model output for the SCI was tested to be greater than or equal to zero. If the combined soil loss was less than the soil T-value and the SCI was greater than or equal to zero then a removal rate scenario was considered sustainable.

3.3.9 County and State Level Results

Establishing county level sustainable agricultural residue removal results requires aggregating the soil/crop rotation/tillage/yield scenarios to county level sustainable residue quantities and removal rates. First the maximum sustainable removal rate for each soil/crop rotation/tillage/yield was determined using the sustainability metrics discussed earlier. Following this the sustainable removal managements were attributed to the soils in a county. Each SSURGO soil is given a relative area percentage for the county based on the map unit acres variable from the SSURGO database. This assumes that all crop rotations and tillage management practices for a county are evenly distributed across each soil in that county. The county average sustainable residue removal rates for each crop, CR_i , are calculated for each of the i crops in a county as follows

$$CR_i = \sum_j \left(\alpha_j \sum_k \left(\alpha_{k,i} \sum_l \left(\alpha_l cr_{i,j,k,l} \right) \right) \right) \quad (3.1)$$

where α_j is the fraction of area of each j soil, $\alpha_{k,i}$ is the fraction of area for crop i that is in k type of rotation, α_l is the fraction of area in l tillage regime, and $cr_{i,j,k,l}$ is the sustainable residue removal rate for crop i in j soil in k type of rotation and l tillage regime. The CR_i are then summed over the county to determine the total sustainable residue available in each county.

$$TR = \sum_i CR_i A_i \quad (3.2)$$

where TR is the total sustainable residue in a county, and A_i is the area of the county producing crop i . State level sustainably removable residue totals are determined by summing the sustainable residue available in each of the state's counties. National total

sustainably removable residue quantities are established by summing sustainable residue for each of the conterminous states.

3.4 RESULTS

Using the assessment procedure discussed above nearly 100 million unique scenarios creating a spatially comprehensive representation of the conterminous US were examined. The complete set of runs for this study was distributed on a 48-node computing cluster comprised of 3.0 GHz Intel Xeon Quad-Core rack-mounted machines running Microsoft Server 2008™ with no other computational duties. The wall clock run time for the entire assessment was nearly 10 weeks. Figure 3.5 shows the results for the 2011 scenario. The top map in Fig. 3.5 shows county level annual sustainable residue availability in terms of metric tons. As shown large sections of the Corn Belt, Great Plains, and Pacific Northwest have the potential to contribute significant quantities of agricultural residues sustainably for bioenergy production. Specifically, 503 counties combined in the 2011 scenario sustainably provide over 100,000 metric tons of residues sustainably on an annual basis. The lower portion of Fig. 3.5 shows the county level sustainable residue removal rates, in metric tons per hectare, for each of the five residue producing crops from this study. Higher removal rates will typically result in increased economic viability for residue removal operations and removal rates of 2.25 metric tons per hectare will often provide the best opportunity for economic viability (Hess et al, 2009a, Hess et al., 2009b). For all five residue producing crops the majority of counties have a sustainable removal rate of less than 2.25 metric tons per hectare for 2011 yield and land management scenario. Corn stover residue shows the greatest potential for higher removal rates primarily because of high total biomass production with corn. Barley and wheat have potential for removal rates above 2.25 metric tons per hectare on irrigated

production in the Great Plains and Pacific Northwest. Rice residue production is limited to the South Central US and areas in California, and removal rates above 2.25 metric tons per hectare are found in these regions. Sorghum residue is available across a large region of the South Central US and Great Plains, but removal rates for sorghum do not exceed 1.14 metric tons per hectare for any county in the country. Table 3.4 shows the sustainable residue removal potential by state for the 2011 and 2030 scenarios, as well as providing a hypothetical scenario for 2030 that assumes all acres adopt no tillage practices. The Corn Belt states of Iowa, Illinois, Nebraska, Minnesota, and Indiana provide 60% of the sustainably available residue nationally for the 2011 scenario. This result is consistent with the by crop residue totals shown in Table 3.5. Corn stover residue accounts for 81.9% of the sustainably available residue in the 2011 scenario nationally.

The results for the 2030 scenario are shown in Fig. 3.6. The county level sustainable residue quantities are significantly higher across the country due to higher grain crop yields in the 2030 scenario. In this scenario 605 counties nationally produce 100,000 metric tons or greater sustainable residue. As shown in Fig. 3.6 areas in the Corn Belt show significant increases in sustainable residue removal potential as compared to 2011. This occurs because increasing corn grain yields have the greatest potential impact on sustainable residue availability. Table 3.5 shows that corn stover residue grows to 84% of the total residue available in the 2030 scenario. The by-crop removal rate maps in Fig. 3.6 show nearly the same spatial distribution of residue as the by-crop removal rate maps in Fig. 3.5. The primary result is that increased yields provide higher sustainably removal rates for each crop. Corn stover residue removal rates approach 11 metric tons per acre for extremely high yielding counties under irrigated production. Sorghum residue removal rates remain low with the

highest county average at less than 1.3 metric tons per hectare. Table 3.4 shows that the by-state sustainable residue for the 2030 scenario increase between 30% and 50% for the highest producing states with a national increase in sustainable residue of 38%. An interesting note is the slight decrease in residue available from Montana. This is a result of the tillage assumptions associated with higher crop yields.

Tables 3.4 and 3.5 also provide the sustainably removable residue quantities for a 2030 scenario that assumes all acres use no tillage management practices. This scenario is only intended to provide a hypothetical upper bound for the sustainable residue removal potential accounting for the management practices considered in this study. The total sustainable residue potential under this assumptions increases 43% from the standard 2030 management assumptions to nearly 300 million metric tons of residues. Considering the individual crop results shown in Table 3.5, no tillage management practices provide the largest increases in sustainably removable residue for sorghum and rice at 210% and 132% increases respectively. The sustainable corn stover residue removal potential increases 40% nationally with the all no tillage management practice assumption.

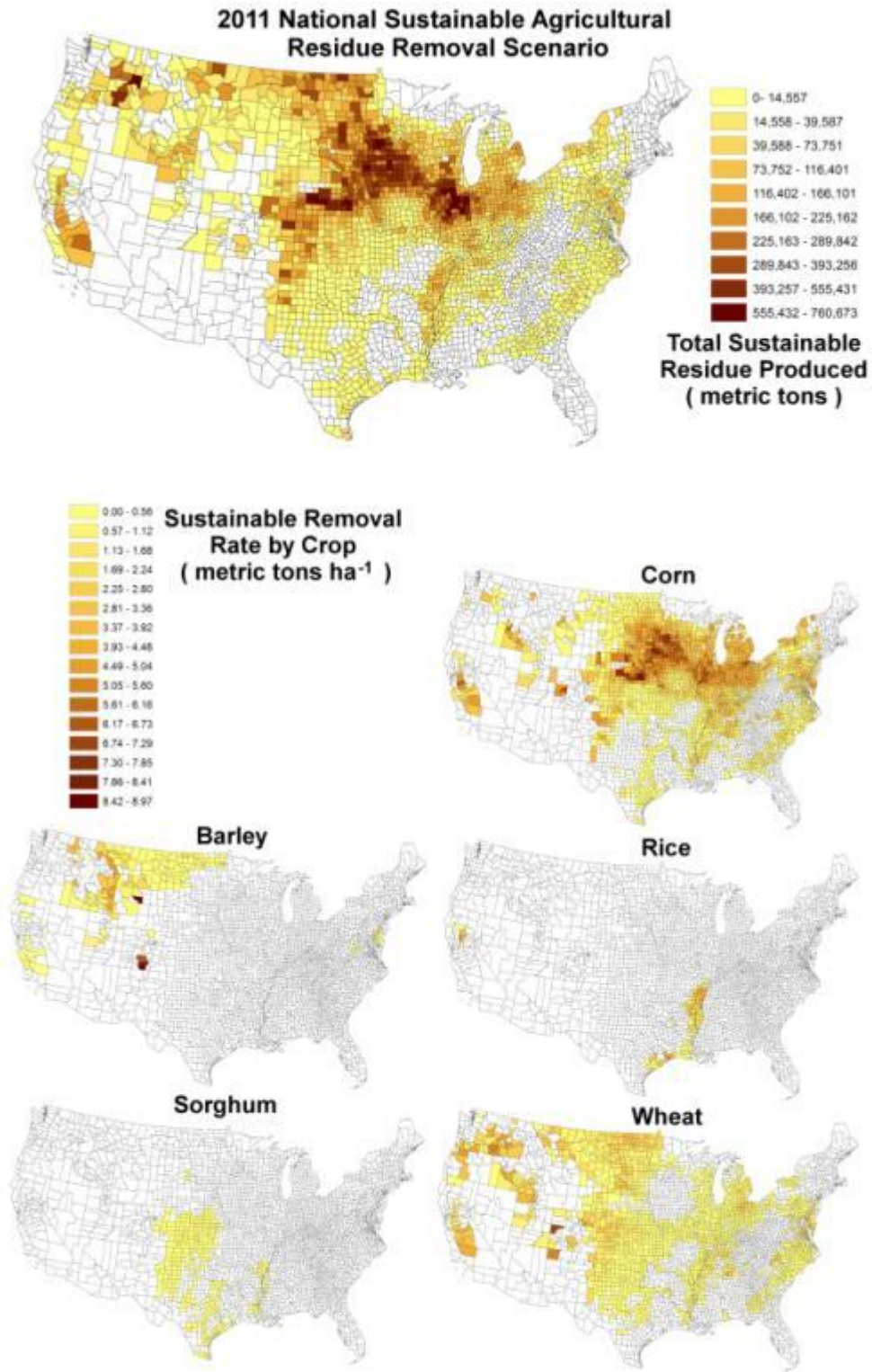


Figure 3.5. 2011 sustainable residue scenario results.

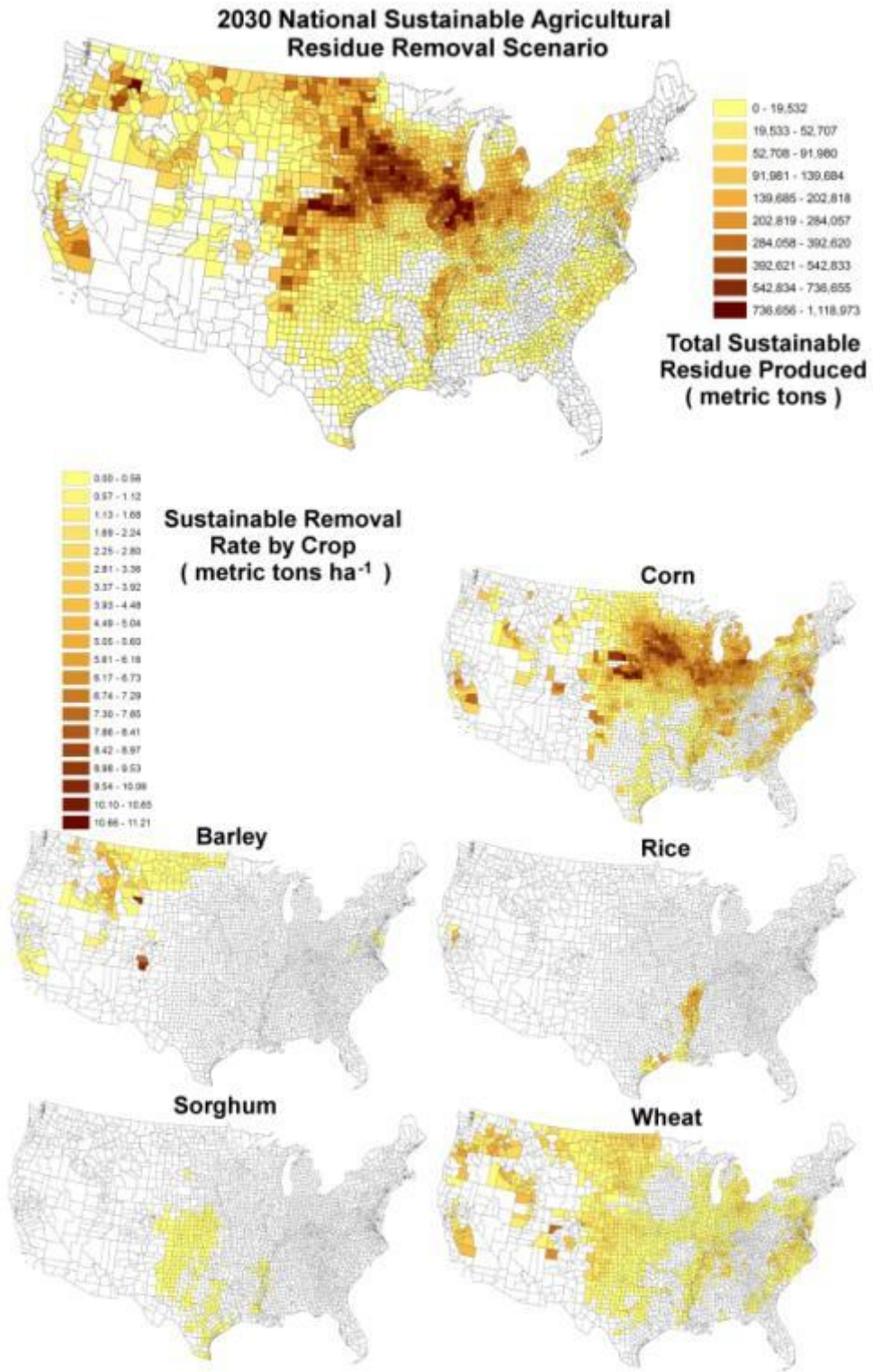


Figure 3.6. 2030 sustainable residue scenario results

Table 3.4. State and US total sustainable residue available in 2011 and 2030 scenarios. Also included is a projection assuming 100% of acres adopt no-tillage practices.

State	2011 Sustainable Residue (1000 metric tons)	2030 Sustainable Residue (1000 metric tons)	Percentage Increase from 2011 to 2030	2030 Sustainable Residue – All No Till Assumption (1000 metric tons)
IA	25,916	37,321	44%	49,761
IL	20,935	29,995	43%	44,071
NE	18,609	25,147	35%	31,542
MN	16,006	21,252	33%	27,925
IN	8,615	12,457	45%	18,218
SD	9,215	11,437	24%	12,890
ND	7,333	8,614	17%	10,953
OH	5,687	8,225	45%	10,620
KS	6,491	8,170	26%	13,156
WI	4,262	6,392	50%	11,590
MI	3,200	4,375	37%	7,220
TX	2,282	3,342	46%	7,296
MO	2,252	3,303	47%	6,456
AR	1,792	2,934	64%	6,405
CO	2,674	2,926	9%	3,474
KY	1,516	2,413	59%	3,273
WA	1,863	2,240	20%	2,711
MT	2,104	2,036	-3%	2,208
CA	1,575	1,903	21%	2,121
ID	1,586	1,813	14%	2,184
NY	938	1,257	34%	2,799
PA	764	1,246	63%	3,525
NC	458	1,120	144%	1,701
OR	961	1,070	11%	1,439
MD	597	1,022	71%	1,445
TN	589	1,012	72%	1,443
OK	362	787	117%	2,821
LA	448	767	71%	2,654
MS	401	749	87%	1,762
VA	296	615	108%	815

State	2011 Sustainable Residue (1000 metric tons)	2030 Sustainable Residue (1000 metric tons)	Percentage Increase from 2011 to 2030	2030 Sustainable Residue – All No Till Assumption (1000 metric tons)
SC	186	448	141%	618
AL	221	350	59%	404
DE	203	336	65%	600
GA	105	239	128%	405
NM	169	230	36%	285
UT	133	148	12%	178
WY	85	103	21%	251
NJ	46	71	54%	210
WV	21	37	75%	63
FL	3	3	21%	7
US Total	150,897	207,905	38%	297,499

Table 3.5. Results split out by crop.

Crop	2011 Sustainable Residue (1000 metric tons)	Percentage of Total 2011 Residue Provided by Each Crop	2030 Sustainable Residue (1000 metric tons)	Percentage of Total 2030 Residue Provided by Each Crop	2030 Sustainable Residue – All No Till Assumption (1000 metric tons)
Barley	1,220	0.8%	1,382	0.7%	1,721
Corn	123,515	81.9%	174,625	84.0%	244,628
Rice	2,602	1.7%	3,939	1.9%	9,123
Sorghum	636	0.4%	682	0.3%	2,113
Wheat	22,924	15.2%	27,277	13.1%	39,914
Total	150,897	100.0%	207,905	100.0%	297,499

3.5 SUMMARY

This study utilized an integrated environmental process modeling strategy to investigate sustainable agricultural residue removal potential in the conterminous US. Soil erosion from wind and water forces, and soil organic carbon constraints were considered to determine sustainability of residue removal. Scenarios were developed for sustainable residue removal for 2011 and 2030 crop yield projections. SSURGO soil map units represent the base spatial

unit for the assessment and provided the soils data across the country for each of the models in the integrated framework. Crop rotations for each county were established by processing the CDL land use data from USDA NASS. Land management scenarios were built using NRCS CMZ rules for determining operational timing and equipment systems. Three tillage regimes were included in the land management scenarios for each crop rotation. Residue removal equipment configurations utilized NRCS standard assumptions and included five residue removal rates. The integrated modeling framework was iteratively executed resulting in nearly 100 million residue removal scenarios to provide a spatially comprehensive assessment of sustainably residue removal potential across the country. The assessment concluded that over 150 million metric tons of agricultural residues could be sustainably removed in 2011 with 82% of that material coming from corn stover. The assessment also concluded that yield increases and changing tillage management practices will create the potential for nearly 208 million metric tons of residue to be sustainably removed in 2030. Corn stover residue accounts for 84% of the sustainable residue in 2030.

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CHAPTER 4. MODELING THE IMPACT OF VARIABILITY AT THE SUB-FIELD SCALE ON SUSTAINABLE AGRICULTURAL RESIDUE REMOVAL

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ABSTRACT

This paper develops 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 based on soil erosion from wind and water, and soil organic matter constraints. Agricultural residues are the largest potential near term source of biomass for bioenergy production. Sustainable use of agricultural residues for bioenergy production requires consideration of the important role that residues play in maintaining soil health and productivity. Several previous analysis studies have developed methodologies and tools to estimate sustainable agricultural residue removal by considering important environmental constraints such as soil loss from wind and water erosion and soil organic carbon at field scale or larger but have not considered variation at the sub-field scale. Increased availability of sub-field scale datasets such as grain yield data, high fidelity digital elevation models, and soil characteristic data provides an opportunity to investigate the impacts of sub-field scale variability on sustainable agricultural residue removal. Using three representative fields in Iowa, this paper contrasts the results of current NRCS conservation

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management planning analysis with sub-field scale analysis for rake and bale removal of agricultural residue. The results of the comparison show that the field average assumptions used in the 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 sub-field scale sustainable agricultural residue removal including the development of real-time variable removal technologies for agricultural residue.

4.1 INTRODUCTION

The Energy Independence and Security Act, 2007, requires annual US biofuel production to increase to more than 136 billion liters by 2022. Nearly 80 billion liters of this production must come from non-cornstarch feedstock. Given a conversion rate of 330 liters of biofuel per metric ton of biomass feedstock (Aden et al., 2002; Phillips et al., 2011), meeting this target will require the development and utilization of over 240 million metric tons 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). However, sustainable removal of agricultural residue 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 carbon, 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

Izaurrealde, 2010; Muth and Bryden, 2012). The focus of these studies has been establishing the potential availability of agricultural residues over 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 sub-field scale.

This paper presents a modeling strategy that integrates together the individual models and databases required to evaluate sustainable agricultural residue removal potential at a sub-field scale based on specific crop yield, soil characteristics, and surface topography data. Following a discussion of this computational model, sustainable agricultural residue removal from three typical Iowa fields is examined using both the current NRCS guidelines and the sub-field modeling process discussed here, and the results are contrasted.

4.2 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 Natural Resource Conservation Service (NRCS) of the US Department of Agriculture (USDA). Larson used the Universal Soil Loss Equation in 1979 to perform the first major assessment of the sustainability of removing agricultural residues. This study examined soils and production systems in the Corn Belt, the Great Plains, and the Southeast US. 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 carbon levels, was not considered. This study used area-weighted averages for soil, climate, and crop yields across USDA's Major Land

Resource Areas (MLRAs) (USDA, 2006). The MLRAs investigated by Larson et al. were comprised of groups of approximately 5–20 counties. Soils were averaged to the MLRA level by extracting the primary erodibility factors for each soil from 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 in 2002 to estimate sustainable removal rates of corn (*Zea mays* L.) stover and wheat (*Triticum aestivum* L.) straw. This study expanded Larson's analysis through the use of the Soil Survey Geographic (SSURGO) Database (USDA-NRCS, 2012b), an open access national soil survey database provided by NRCS. Nelson's methodology considered water and wind induced erosion at the SSURGO soil map unit spatial scale for reduced and no tillage management practices. This 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. This analysis found that in 1997 the midwestern and eastern United States could have sustainably supplied more than 58 million metric tons of corn stover and wheat straw. In 2004, Nelson et al. expanded this assessment with two additions: (1) including five one- and two-year crop rotations (e.g., corn-soybean [*Glycine max* (L.) Merr.]) and (2) calculating 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 acres were in a corn-soybean rotation using reduced tillage practices; nearly 398 million

metric tons 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 Nelson's methodology to perform a nationwide corn stover availability assessment. The spatial scale of data and analysis assumptions were consistent with Nelson's, but an additional constraint was added to this by restricting stover removal from non-irrigated production in dry climates. This constraint was included based on an assumption that for non-irrigated 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 metric tons 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 (USDA-ARS, 2010). The new model was the Revised Universal Soil Loss Equation, Version 2 (RUSLE2) (USDA-NRCS, 2011b). 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 RUSLE. Through the development of 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) (USDA-ARS and NRCS, 2008), and Soil Conditioning Index (SCI) (USDA-NRCS, 2012) models in conjunction with RUSLE2 for conservation management planning. The NRCS field office implementation of RUSLE2, WEPS, and SCI utilizes representative soil and slope, and field average yield assumptions to analyze a management plan for a particular field (USDA-NRCS Iowa, 2008). The choice for a representative soil and slope are based on

selecting the “dominant critical” soil area. The NRCS field office technical note describes the dominant critical soil area as having the following characteristics, (1) it is significantly large enough to effect a change in management, (2) it is not an average of the field characteristics, (3) it is not the worst case scenario, and (4) 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 greater than 0, which qualitatively suggests that soil organic carbon 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 carbon 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 (USDA-ARS, 2009), WINDGEN (Wagner, 1992), and NRCS management practice (USDA-NRCS, 2011a) databases. Figure 4.1 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 metric tons 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.

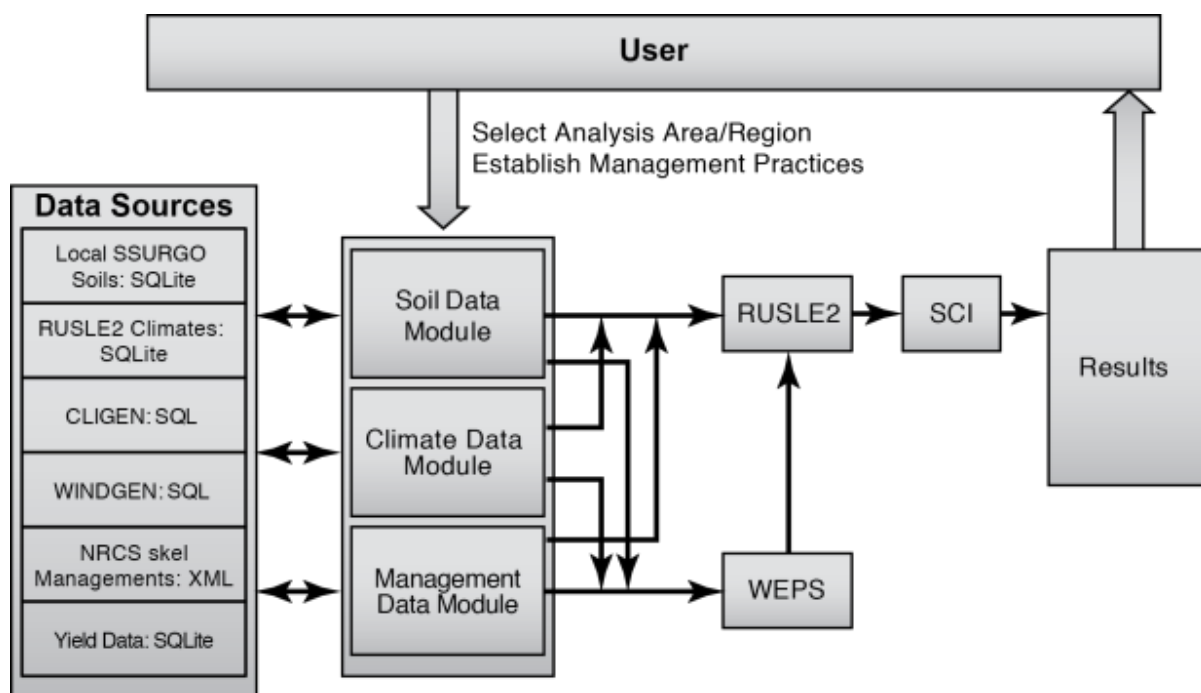


Figure 4.1. Integrated residue removal modeling framework.

None of the current modeling approaches supports analysis of the impact of sub-field scale variability on sustainable residue removal. However, the high fidelity spatial data necessary to perform sub-field scale analyses are becoming increasingly available. The high fidelity spatial data available for these analyses include crop yield data from combine

harvesters and high resolution digital elevation models (DEMs) describing surface topography.

4.2.1 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 datasets are acquired directly from harvester yield monitors in the form of ESRI™ shape files (ESRI, 2012). These datasets provide significant detail at a sub-field scale. For example, a typical ESRI™ shape file can contain over 400 yield measurements per hectare, and point-to-point yield across the field may vary by a factor of more than 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., 1994; 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 U.S. Geological Survey (USGS) produced national datasets (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 (GeoTREE, 2011). LiDAR mapping is the highest fidelity surface slope data currently available and provides a more accurate representation of relatively low slope agricultural land than the USGS produced DEMs (USGS, 2010). Based on this, LiDAR data assembled through the GeoTREE project are utilized in the work presented here.

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

4.3 THE INTEGRATED MODELING PROCESS AT THE SUB-FIELD 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 sub-field variability in sustainable agricultural residue removal rates. This paper develops an integrated model for sub-field variability of sustainable agricultural residue removal. This model includes the current modeling tools (i.e., RUSLE2, WEPS, and SCI), the existing data sources (i.e., SSURGO soils, CLIGEN, WINDGEN, and NRCS managements), 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 sub-field 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 from different spatial scales. The starting place for the sub-field model developed here is 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 4.2 shows the dataflow within the sub-field integrated model. As shown, the computational challenge of iteratively computing sustainable residue removal is handled by 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 (ESRI 1998). Following completion of this task, the second loop uses the data and RUSLE2, WEPS, and SCI models to simulate the environmental processes for each spatial location and management scenario of interest. For this study about 1,200 model executions per hectare (400 spatial elements, 1 management scenario, 3 model executions [RUSLE2, WEPS, SCI] per spatial element) are required. Upon completion of the scenario runs, the model results are provided back 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.

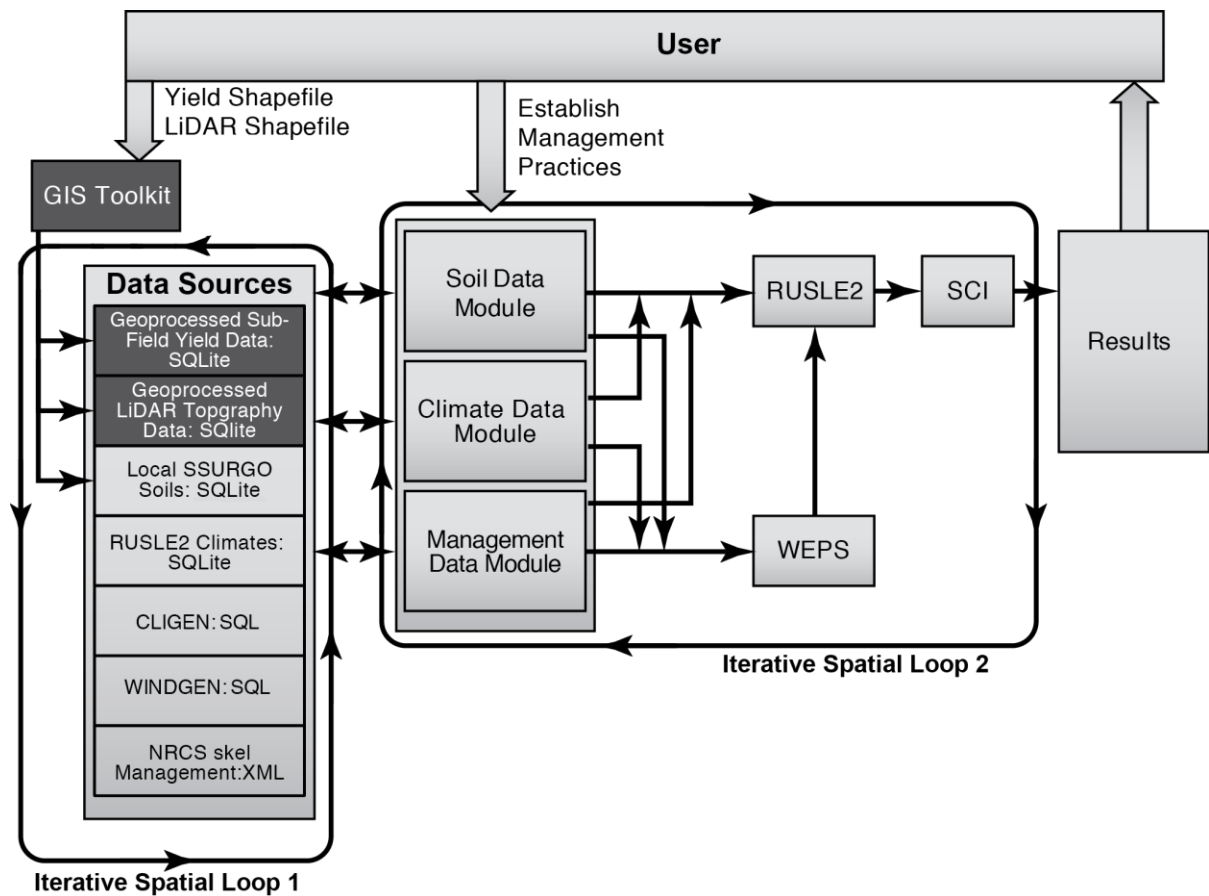


Fig. 4.2. The sub-field scale modeling process.

The geoprocessing tool used in this project is ESRITM ArcGIS 10. ESRITM ArcGIS 10 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 datasets. 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 between the various databases. RUSLE2 has been developed with the base computation unit as a single overland flow path along a hill slope 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 RUSLE2 requires selection of a representative soil, slope, slope length, and yield that are considered constant for the field. To use RUSLE2 at the sub-field 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 are 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 RUSLE2, WEPS, and SCI at a spatial element basis. A similar assumption is made for the WEPS model. 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 sub-field scale integrated model is 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 sub-

factors calculated by RUSLE2 and WEPS using the assumptions as stated. The specific spatial details of each database are as follows:

1. Yield data is input directly as received from the harvester output. The crop yield datasets represent the base spatial discretization for the sub-field scale integrated model. Each yield data point represents a spatial element at the meter scale. Ground speed of harvesting equipment, variability in surface slope, and yield variability have each been found to create error 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 compared to characteristics of the fields such as soil carbon and slope that provide insight into potential productivity, and the yields correlated well with expectations. Based on this, the high fidelity yield data used here is as-recieved 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 (GeoTREE, 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 soil database provides soil characteristic data at the 10–100 meter scale. 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 is 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 is a field scale characteristic and is taken as constant across the spatial elements. The NRCS management database provides the crop rotation, tillage practice, fertilizer application, and harvest practice management data.

4.3.1 Model Validation

The initial integrated model coupling RUSLE2, WEPS, and SCI was verified to provide the same conclusions as the NRCS field office versions of the models as described in Muth and Bryden (2012). However, in the case of sub-field sustainability of agricultural residue removal, 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 is used in the NRCS field office implementation. The code was then run and summarized at the sub-field scale, demonstrating that the code properly called, formatted, computed, and assembled the data needed. In each case the integrated sub-field 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 for reasonableness and to ensure the results could be explained. This is discussed further in Section 4.

4.4 RESULTS

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

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 are 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 is 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 datasets, the location of the fields in Iowa ensures access to LiDAR surface topography data, and they provide a range of sub-field scale variability. Field 1 has highly variable soil and slope characteristics. Field 2 has uniform soils and slope but variability in crop yield. The characteristics of Field 3 have more moderate variability.

4.4.1 Conservation Management Planning Results

NRCS conservation management planning guidelines (USDA-NRCS Iowa, 2008) were used to evaluate 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 4.1 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 SSURGO 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 earlier and listed for each field in Table 4.1. Table 4.2 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 only happens 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 4.2, soil loss due to erosion for each field is less than the T value. For Field 1 the SCI is less than zero, which results in a determination that rake and bale residue removal would not be sustainable management in the field. For Fields 2 and 3 the SCI is greater than 0. This leads to the conclusion that rake and bale residue removal would be approved as sustainable by NRCS for Fields 2 and 3.

Table 4.1. List of soils and primary assumptions for each field NRCS conservation management assessment.

Field	List of SSURGO Soils (In order of area: high to low)	Dominant Critical Soil	Dominant Critical Slope	Field Average Yield (Mg ha ⁻¹)	Tillage	Crop Rotation	Residue Harvest Operations
1	84 Clyde silty clay loam, 0 to 2 percent slopes 198B Floyd loam, 1 to 4 percent slopes 173 Hoopston fine sandy loam, 1 to 3 percent slopes 83B Kenyon loam, 2 to 5 percent slopes 407B Schley loam, 1 to 4 percent slopes 175B Dickinson fine sandy loam, 2 to 5 percent slopes 41B Sparta loamy fine sand, 2 to 5 percent slopes	83B Kenyon loam	4.0%	10.85	Reduced	Corn-Soybean	Rake and Bale
2	688 Koszta silt loam, 0 to 2 percent slopes 587 Chequest silty clay loam, 0 to 2 percent slopes	688 Koszta silt loam	1.0%	12.60	Reduced	Continuous Corn	Rake and Bale
3	587 Chequest silty clay loam, 0 to 2 percent slopes 687 Watkins silt loam, 0 to 2 percent slopes 88 Nevin silty clay loam, 0 to 2 percent slopes 7 Wiota silty clay loam, 0 to 2 percent slopes 133 Colo silty clay loam, 0 to 2 percent slopes 688 Koszta silt loam, 0 to 2 percent slopes 8B Judson silty clay loam, 2 to 5 percent slopes 422 Amana silt loam, 0 to 2 percent slopes 54 Zook silty clay loam, 0 to 2 percent slopes	587 Chequest silty clay loam	1.0%	12.40	Conventional	Continuous Corn	Rake and Bale

Table 4.2. Sustainability of rake and bale removal evaluated under NRCS conservation management planning guidelines.

Field	Residue Removal Rate (Mg ha ⁻¹)	Water Erosion (Mg ha ⁻¹)	Wind Erosion (Mg ha ⁻¹)	Combined Erosion (Mg ha ⁻¹)	Soil T Value (Mg ha ⁻¹)	SCI	Sustainable Residue Removal Practice
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

4.4.2 Sub-Field Scale Data

To examine the impact of sub-field scale variability of soil characteristics, surface topography, and grain yield on residue removal sustainability in each of these fields, the sub-field integrated model used the same management practices and climate information as the NRCS management guidelines (USDA-NRCS, 2008). The yield, slope, and soil information were obtained from the high spatial fidelity crop yield, LiDAR, and SSURGO data as described earlier. The results of these analyses are shown in Figs. 4.3, 4.4, and 4.5 for Fields 1, 2, and 3; respectively.

As shown in Table 4.1, seven different SSURGO soil types comprise Field 1. The SSURGO data for the organic matter and sand fraction in the top horizon are shown in Figs. 4.3a and 4.3b. The dominant critical soil used for the NRCS conservation management planning guidelines for Field 1 is 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 previously because it is the lowest slope, least erosive, and highest organic matter soil in the field. The next largest soil in terms of area in the field is map unit 198B Floyd loam which comprises about 13 ha, or 20% of the field. This soil

also is low slope, and has high organic matter compared to other soils in the field and subsequently was not selected as dominant critical. The SSURGO slope for 83B Kenyon loam is 4.0% and is used as the representative slope for the field based on NRCS conservation management planning guidelines. As shown in Fig. 4.3c, there is significant variability in the slope of this field. Figure 4.3d shows that the corn yields on this field for the 2010 growing season vary from less than 4.3 Mg ha^{-1} to over 15 Mg ha^{-1} . The lower yield ranges seen in Fig. 4.3d can be generally associated with lower organic matter soils shown in Fig. 4.3a. A similar relationship is found between lower yields and higher sand fraction soils shown in Fig. 4.3b. The correlation between lower yields in Fig. 4.3d and higher slope areas shown in Fig. 4.3c 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 varieties have a higher grain to residue ratio (Wilhelm et al., 2011), in this study it is assumed, consistent with NRCS guidelines, that the corn grain to residue rate is 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 ranges from $0.0\text{--}3.92 \text{ Mg ha}^{-1}$. The result of this is shown in Fig. 4.3e where rake and bale residue removal is a direct reflection of Fig. 4.3d, 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 4.3f summarizes at a sub-field scale where rake and bale removal will be sustainable in Field 1 and where one or more sustainability criteria will be violated. Specifically, Fig. 4.3f shows where (1) SCI values are less than zero, which simulates a soil carbon issue; (2)

combined wind and water erosion are greater than the T-value for the soil; and (3) SCI is less than zero, and erosion is greater than the T-value, thus simulating that both a soil loss and a soil organic carbon issue exist. As shown, the primary sustainability issue for rake and bale residue removal in this field is soil organic carbon. This is in agreement with the sustainability analysis performed using NRCS conservation planning guidelines. However, it is interesting to note 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 the soil sand fraction is above 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 carbon 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. This is not surprising because the dominant critical soil area selection criteria for this field result in a representative soil with relatively high slope and moderate organic matter. The largest soil in terms of 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 Figs. 4.3a and 4.3f. The only areas of Field 1 where rake and bale removal is sustainable are those with levels of high soil organic matter. The lowest soil carbon, highest sand fraction, highest surface slope, and lowest grain yield are all found in the same parts of the field.

Field 2 is comprised of two SSURGO soils, as listed in Table 4.1. Both soils have a representative organic matter of 3.5% (Fig. 4.4a) and a relatively low sand fraction of less than 20% (Fig. 4.4b). Over 90% of the area in this field is less than 2.5% slope (Fig. 4.4c). The 2010

corn grain yield data averaged 12.6 Mg ha^{-1} , but ranged from less than 4 Mg ha^{-1} to nearly 17 Mg ha^{-1} (Fig. 4.4d). Figure 4.4e shows the residue removed across the field spatial elements using the NRCS assumptions for grain to residue ratio (1:1) and rake and bale residue removal operations (approximately 52% removal rate). Figure 4.4f shows where rake and bale removal will be sustainable for Field 2 and where one or more sustainability criteria will be violated. The majority (89%) of Field 2 is 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 sub-field analysis does find some soil carbon constraints on sustainability with rake and bale removal in pockets where grain yields are lower. As noted earlier, there are some questions about the accuracy of yields 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 carbon processes are continuous across larger areas than the small pockets seen in Fig. 4.4f. One solution to this may be aggregating soil carbon results to a larger reporting scale (e.g., averaging or other aggregation techniques) than the soil erosion results. Different environmental processes will likely 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.

As shown in Table 4.1, nine SSURGO soils comprise Field 3. As shown in Figs. 4.5a and 4.5b, the organic matter of these soils ranges from 3% – 6%, and all of the soils have a relatively low sand fraction (less than 20%). Surface slopes in this field are generally less than 2.5% with small regions near the field edge having slopes near 8% (Fig. 4.5c). The average corn grain yield

in 2010 was 12.4 Mg ha^{-1} . Yields ranged from less than 3 Mg ha^{-1} to more than 15 Mg ha^{-1} (Fig. 4.5d). As noted earlier 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 carbon 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 indicate that rake and bale removal for Field 3 would be sustainable. Figure 4.5e shows the residue removed across the field spatial elements using NRCS assumptions for grain to residue ratio (1:1) and rake and bale residue removal operations (approximately 52% removal rate). Figure 4.5f 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, sub-field scale analysis indicates 62% of Field 3 is sustainable with rake and bale removal. In contrast to Fields 1 and 2, erosion is a significant constraint for Field 3 (Fig. 4.5f). Considering that Field 3 has relatively low slopes, 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. 4.5b 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. However, the sub-field average yield for the areas of 587 Chequest silty clay loam in this field 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.

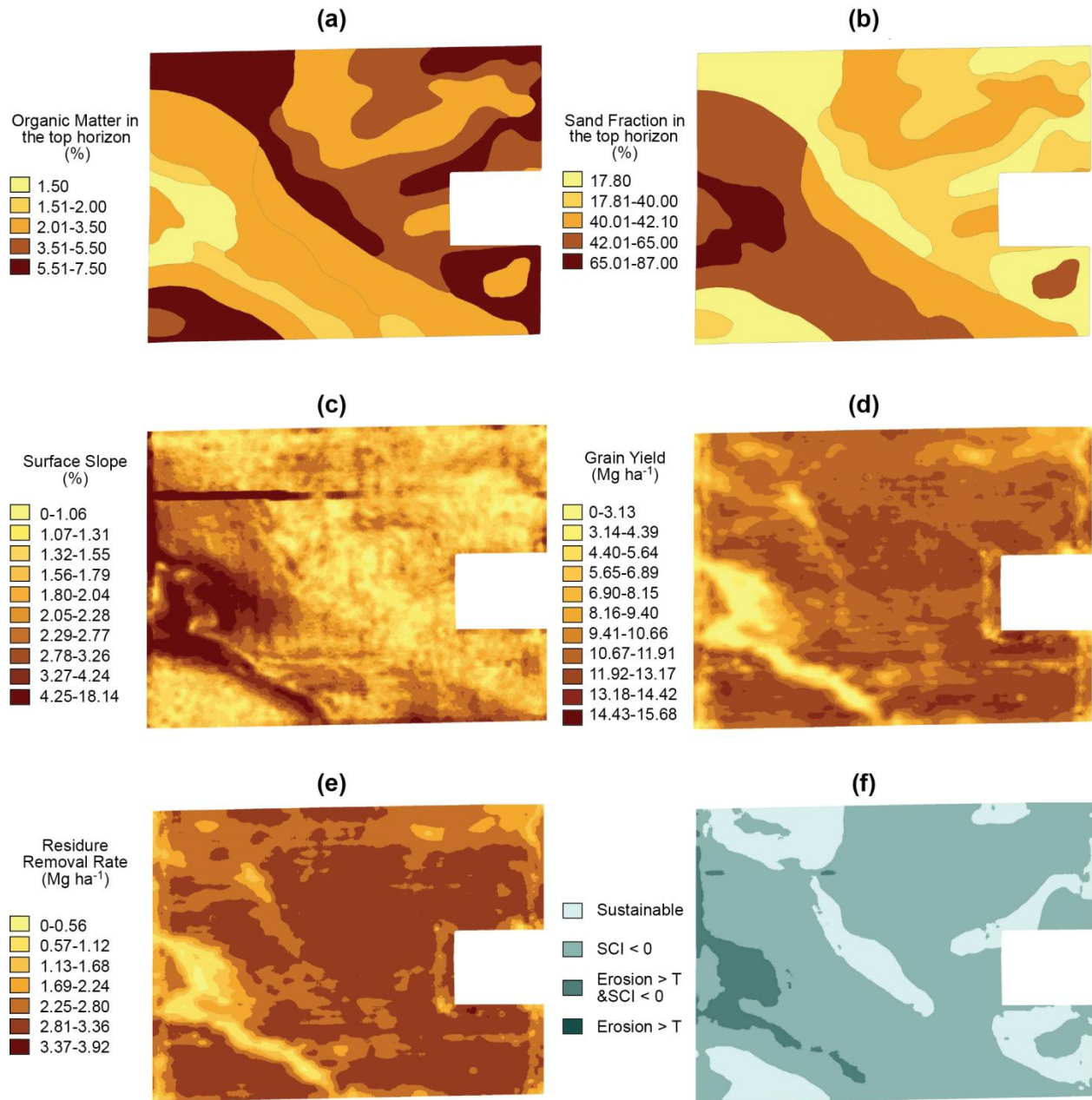


Figure 4.3. Residue removal results, key soil properties, and crop yield for Field 1.

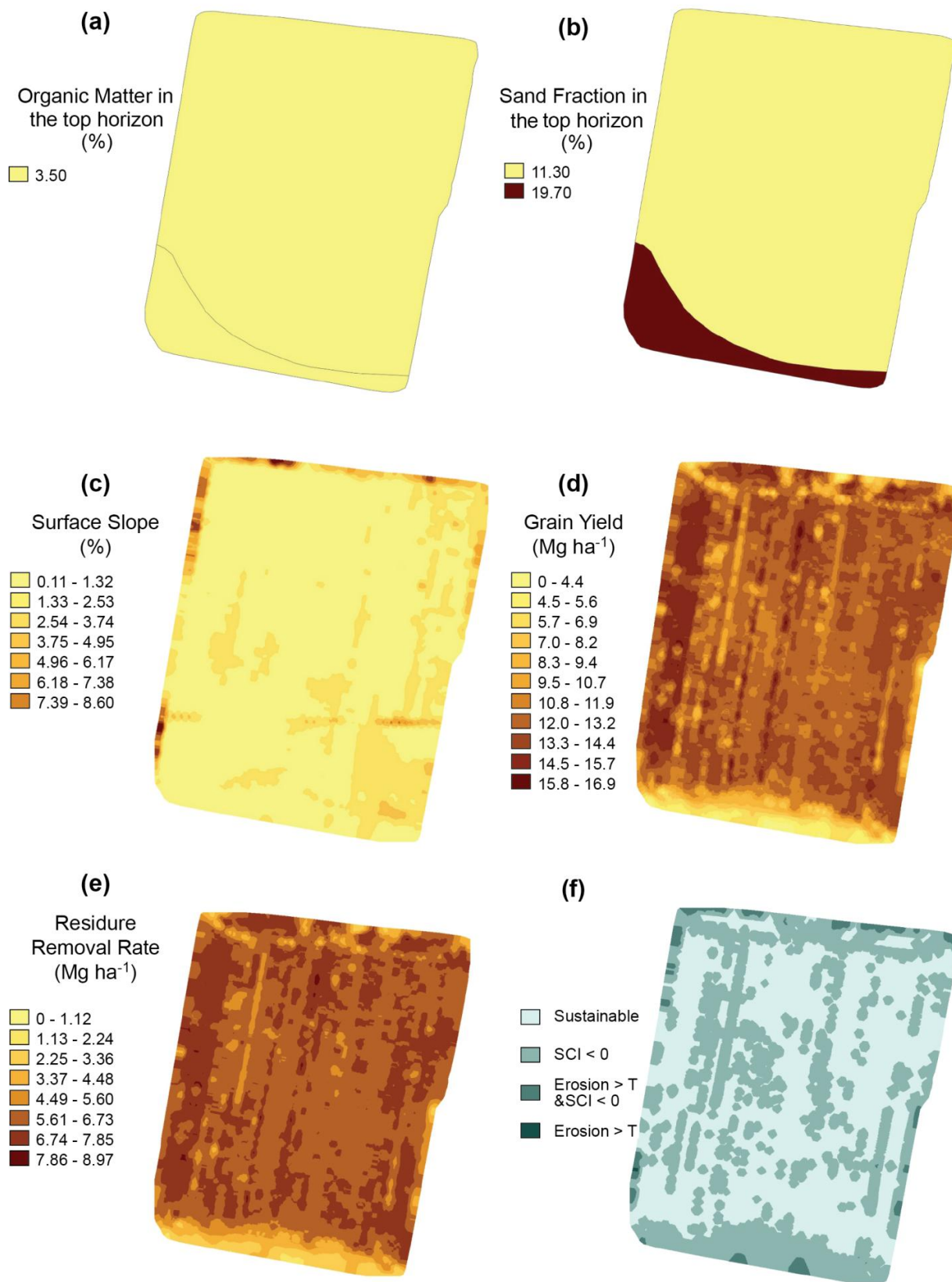


Figure 4.4. Residue removal results, key soil properties, and crop yield for Field 2.

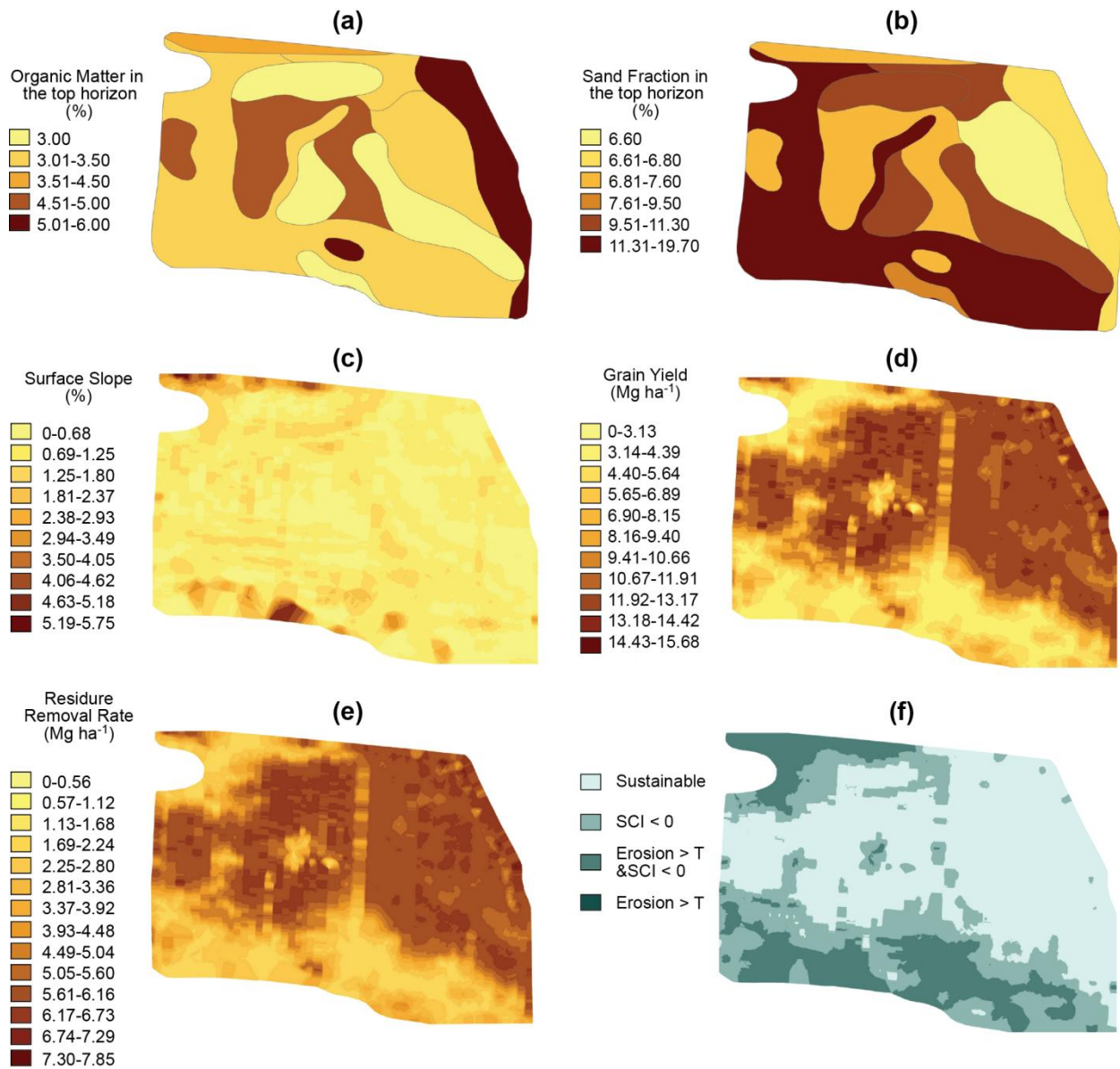


Figure 4.5. Residue removal results, key soil properties, and crop yield for Field 3.

4.5 SUMMARY

Tables 4.3 and 4.4 summarize the results from comparing the NRCS conservation management planning guidelines and the sub-field scale analysis of sustainable agricultural residue removal for the fields investigated in this study. Each of the three fields raises different issues when the sub-field scale analysis is compared with the conservation management planning guidelines. As shown in Table 4.3 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 sub-field analysis of Field 1 shows that 23% of this potentially available residue would be removed sustainably and Table 4.4 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.

Table 4.3. Available agricultural residue using rake and bale collection for each field.

Field	Total Residue Available if Sustainability is not Considered (Mg)	Sustainable Residue Available Based on NRCS Guidelines (Mg)	Sustainable Residue Available Based on Sub-field Analysis (Mg)	Fraction of Total Residue Available for Sustainable Removal Based on Sub-field Analysis
1	152	0	35	23%
2	119	119	106	89%
3	387	387	279	72%

Field 2 represents a situation where conservation management planning guidelines and the sub-field analysis of sustainable agricultural residue removal generally agree. Field 2 has much less variability in soil and slope. As shown in Table 4.3, the rake and bale operations would remove 119 Mg of residue. Sub-field analysis indicates that 89% would be removed sustainably and Table 4.4 shows that 83% of the 19 ha in Field 2 would be being managed sustainably. The sub-field analysis shows pockets where soil carbon is an issue. However, organic carbon dynamics in the soil are understood to work over more continuous extents than these pockets.

This raises questions about how to apply and report the sub-field scale model results for the SCI.

In Field 3 the assumption of a field average grain yield is inconsistent with the sub-field scale data for significant portions of the field. As discussed previously the assumption in this analysis is the the grain to residue ratio for corn is 1:1. As a result, although the NRCS guidelines indicate that rake and bale residue removal would be sustainable, the sub-field analysis shown in Table 4.3 for Field 3 finds that 72% of the 387 Mg of residue would be removed sustainably and Table 4.4 shows that 62% of the 77 ha would be managed sustainably.

Table 4.4. Field Area That Can Be Sustainably Managed Using Rake and Bale Collection Based on Sub-field Analysis.

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

4.6 CONCLUSIONS

This paper develops a computational strategy to model the impact of sub-field scale variability on sustainable agricultural residue removal. The computational strategy integrates together data inputs from multiple spatial scales, geoprocessing tools to facilitate interaction with high fidelity sub-field 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 sub-field scale. The model was then used to examine three representative fields in Iowa to examine the relationship between sub-field variability and the current NRCS conservation management planning guidelines. For Field 1 the conservation management planning guidelines found that rake and bale residue removal of agricultural residue is unsustainable. The sub-field analysis showed that these assumptions protect the majority of the field from unsustainable practices, but do

understate residue removal potential for significant portions of the field. In Field 2 the sub-field 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, the soil organic carbon dynamics and the spread of agricultural residue occur on larger spatial scales. Based on this, a validated methodology for applying the SCI at sub-field scale needs to be developed. Field 3 was found to have significant areas in which the sub-field analysis and the NRCS conservation management planning guidelines disagreed as to the sustainability of rake and bale residue removal. Based on these observations, additional research is needed to investigate the following issues and questions:

1. The current conservation management planning approach using representative soil, representative slopes, and field average yields 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 sub-field analysis found that over 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 sub-field scale model results. As highlighted by the small pockets where soil carbon issues are identified in Field 2, the spatial scale of precision farming and the spatial scale of soil carbon

dynamics are not directly comparable. Validated modeling algorithms need to be developed that address this issue.

In addition, the application of the sub-field 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. However, the sub-field model developed in this work 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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**CHAPTER 5. AN INVESTIGATION OF SUSTAINABLE VARIABLE RATE
AGRICULTURAL RESIDUE REMOVAL**

A paper submitted to *Journal of Environmental Quality*

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ABSTRACT

Agricultural residues have near-term potential as a feedstock for bioenergy production, but removal of agricultural residues must be managed carefully to maintain soil health and productivity. Recent studies have shown that sub-field scale variability in soil characteristics, surface slope, and grain yield can significantly impact the amount of residue that can be sustainably removed at different areas within a single field. This study examines the potential of a conceptual variable rate residue removal equipment configuration capable of on-the-fly residue removal rate adjustments from 0%–80% by modeling residue removal at thirteen removal rate levels: 0% and 25%–80% at 5% increments. The variable rate residue removal operations are simulated with a sub-field scale integrated modeling framework that evaluates residue removal sustainability considering wind erosion, water erosion, and soil carbon constraints. Three Iowa fields with diverse soil, slope, and grain yield characteristics were examined and the sustainable removal rate of agricultural residue using the conceptual variable rate removal equipment was 2.35, 7.69, and 5.62 Mg ha⁻¹. In contrast, the sustainable removal rates using rake and bale removal for the entire field were 0.0, 6.40, and 5.06, respectively. In addition, the variable rate residue removal sustainably managed 100% of the land area in all three fields. In contrast, Field 1 could not be sustainably managed using rake and removal, and 83% of land area of Field 2 and

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62% of the land area of Field 3 were managed sustainably using rake and bale removal for the entire field.

5.1 INTRODUCTION

Over the past three decades, significant discussion and debate have taken place regarding the opportunity for sustainable removal of agricultural residues for bioenergy production. The latest motivation for investigating agricultural residue removal potential comes from the Energy Independence and Security Act of 2007, which requires annual U.S. biofuel production to increase to more than 136 billion liters by 2022. Non-cornstarch feedstock such as agricultural residues must comprise nearly 80 billion liters of this production. If a production rate of 330 liters of biofuel per metric ton of biomass feedstock is assumed (Aden et al., 2002; Phillips et al., 2011), meeting this target will require the development and utilization of over 240 million metric tons of non-cornstarch biomass resources annually. Many in the bioenergy community consider sustainable agricultural residues to be the cellulosic resource with the greatest near-term potential for bioenergy production (Perlack et al., 2005; Aden et al., 2002). Agricultural residues provide a number of functions within the agronomic system that are critical to maintaining soil health (Karlen et al., 2003; Johnson et al., 2006; Wilhelm et al., 2007; Clay et al., 2010), and excessive residue removal can negatively impact the long term productivity of soil resources (Wilhelm et al., 2010; Sheehan et al., 2004; Mann et al., 2002; Khan et al., 2007).

A number of previous efforts have investigated the issue of sustainable residue removal across a wide range of spatial scales and analysis approaches. These have identified that significant amounts of agricultural residues are potentially available for bioenergy production. An early study performed by Larson (1979) examined agricultural residue removal potential across the Corn Belt, Great Plains, and the Southeast of the United States. Because of data and

computational limitations, this study used area-weighted averages for soil characteristics, climate conditions, and crop yields across the U.S. Department of Agriculture (USDA) identified Major Land Resource Areas (MLRAs) (USDA-NRCS, 2012a) for the regions investigated. The scale of MLRAs is typically groups of 5–20 counties. To do this, Larson aggregated the soils data available to create a composite set of erodibility factors representing each MLRA and estimated that nearly 49 million metric tons of agricultural residues could be sustainably harvested over the regions assessed at that time. After an extended period in the 1980s and 1990s during which agricultural residue removal received limited research focus, Nelson (2002) used the Soil Survey Geographic (SSURGO) Database (USDA-NRCS, 2011c), an open access national soil survey database provided by the USDA Natural Resources Conservation Service (NRCS) to investigate residue removal potential for 37 states from the Great Plains to the East Coast. Nelson developed a methodology using “county average, hectare-weighted fields.” This methodology aggregated the range of soil characteristics for each county and concluded at that time the 37 states investigated could annually produce approximately 58 million metric tons of residue sustainably. Continued progress with data management and environmental modeling tools enabled Nelson et al. (2004) to adapt the 2002 Nelson study to (1) include additional crop rotations and (2) calculate erosion at the SSURGO soil type spatial scale (10 m–100 m). Based on this, Nelson et al. (2004) concluded that 30.2 million dry metric tons of corn (*Zea mays* L.) stover and 13.4 million dry metric tons of wheat (*Triticum aestivum* L.) straw were available for removal annually across the 10 states investigated over the five-year span from 1997–2001. In 2007, Graham et al. utilized the methodology developed by Nelson et al. (2004) to investigate corn stover residue removal across the United States. The 2007 study by Graham et al. used the same spatial scale, or scenario tools, as the 2004 study by Nelson et al., and included an additional

constraint of soil moisture. Graham et al. (2007) also found that soil organic carbon was an important consideration, but noted the computational limitations to including it. They stated “in its current form with manual input, the Soil Conditioning Index is not practical to run for the thousands of corn production situations that occur in the USA” (p. 1). The study concluded that 58.3 million metric tons of stover could be sustainably removed annually.

Cruse and Herndl (2009) noted that developing a sustainable and profitable cellulosic biofuels industry using corn stover will require the ability to determine spatially variable sustainable removal rates and harvest technology that can remove residue at these rates. Significant work has been done looking at both single-pass and multi-pass residue removal system configurations and quantifying the generalized removal potential of the different systems. These systems have generally not been capable of variable rate removal. Single pass configurations have much more potential for on-the-fly adjustments of removal rate than multipass configurations, and some investigations of variable rate single pass configurations have been performed. Karkee et al. (2010) presented a study in which sub-field removal adjustments were made using the single pass equipment configuration used by Hoskinson et al. (2007). Similar to variable rate seeding (Fountas et al., 2006; Bullock et al., 1998), variable rate fertilizer application (Hong et al., 2006; Koch et al., 2004), and variable rate chemical application (Anglund and Ayers, 2003), the availability of high spatial fidelity agriculture datasets provides significant motivation for developing variable residue removal equipment. Based on single pass technologies that include removal rates from 25% (Zych, 2008) to more than 80% (Hoskinson et al., 2007), the study presented here assumes an adjustable on-the-fly removal rate of 25%–80% in 5% increments, with a 0% removal option.

Muth et al. (2012) developed an integrated modeling approach that utilizes high fidelity agricultural datasets to examine the variability of sub-field agricultural residue removal. This integrated model coupled the Revised Universal Soil Loss Equation, Version 2 (RUSLE2) (USDA-NRCS, 2011a), Wind Erosion Prediction System (WEPS) (USDA-ARS and NRCS, 2008), and Soil Conditioning Index (SCI) (USDA-NRCS, 2012b) models with a multi-scale set of databases describing crop yield, surface topography, soil characteristics, climate, and land management data. The sustainability of rake and bale residue removal of three fields in Iowa was examined using the current NRCS conservation management planning guidelines (USDA-NRCS, 2011b) and the sub-field modeling approach. The NRCS conservation management planning analysis concluded that rake and bale removal would be sustainable for two of the three fields. The sub-field model found that there was significant variability in the sustainability of rake and bale removal across individual fields. As a consequence, the study concluded that the dominant critical soil and slope, and field average yield assumptions used in the NRCS conservation management planning may lead to unsustainable residue removal decisions for portions of some fields and reduced residue removal in other fields.

One potential approach for dealing with sub-field scale variability in sustainable residue removal rates is to use equipment that can perform controlled, on-the-fly removal rate adjustments. Although it is becoming more broadly recognized that removal rates will vary from field to field, and within fields (Cruse and Herndl, 2009), limited work to date has focused on identifying the impact and value of equipment with this capability. This paper investigates sustainable variable rate residue removal at the sub-field scale for three representative Iowa fields. Specifically, the impact of a conceptual single-pass residue harvester configuration that can make on-the-fly removal rate adjustments is investigated using the sub-field scale model

developed by Muth et al. (2012). The results of variable rate harvest using this conceptual machine are compared with sustainable rake and bale removal of agricultural residue using NRCS planning guidelines.

Table 5.1. List of soils and primary assumptions for each field NRCS conservation management assessment.

Field	List of SSURGO Soils (In order of area: high to low)	Dominant Critical Soil	Dominant Critical Slope	Field Average Yield (Mg ha ⁻¹)	Residue Harvest Operation
1	84 Clyde silty clay loam, 0 to 2 percent slopes 198B Floyd loam, 1 to 4 percent slopes 173 Hoopston fine sandy loam, 1 to 3 percent slopes 83B Kenyon loam, 2 to 5 percent slopes 407B Schley loam, 1 to 4 percent slopes 175B Dickinson fine sandy loam, 2 to 5 percent slopes 41B Sparta loamy fine sand, 2 to 5 percent slopes	83B Kenyon loam	4.0%	10.85	Rake and Bale
2	688 Koszta silt loam, 0 to 2 percent slopes 587 Chequest silty clay loam, 0 to 2 percent slopes	688 Koszta silt loam	1.0%	12.60	Rake and Bale
3	587 Chequest silty clay loam, 0 to 2 percent slopes 687 Watkins silt loam, 0 to 2 percent slopes 88 Nevin silty clay loam, 0 to 2 percent slopes 7 Wiota silty clay loam, 0 to 2 percent slopes 133 Colo silty clay loam, 0 to 2 percent slopes 688 Koszta silt loam, 0 to 2 percent slopes 8B Judson silty clay loam, 2 to 5 percent slopes 422 Amana silt loam, 0 to 2 percent slopes 54 Zook silty clay loam, 0 to 2 percent slopes	587 Chequest silty clay loam	1.0%	12.40	Rake and Bale

Table 5.2. Field descriptions for the three fields.

Field	Location	Area (ha)	Crop Rotation	Tillage
1	Cerro Gordo County, Iowa	57	Corn-Soybean	Reduced
2	Iowa County, Iowa	19	Continuous Corn	Reduced
3	Iowa County, Iowa	77	Continuous Corn	Conventional

5.2 BACKGROUND

In this study the integrated model developed by Muth et al. (2012) to support sustainable sub-field scale residue removal assessments is used to examine sustainable variable rate agricultural residue removal. Specifically, agricultural residue removal based on NRCS guidelines is contrasted with variable rate residue removal in the same three Iowa fields and using the same management practices evaluated by Muth et al. (2012). These fields are described in Tables 5.1 and 5.2. These three fields were chosen for this series of studies because of the availability of high fidelity sub-field scale data and because they exhibit a wide range of sub-field scale variability of soil conditions, surface topography, and yield. This earlier study examined how sub-field scale variability in soil characteristics, surface slope, and grain yield impacted the sustainability of rake and bale residue removal within the three fields. Two of the fields are in a continuous corn crop rotation, and the other is in a corn-soybean (*Glycine max* (L.) *Merr.*) rotation. The list of operations used to describe these two rotations is shown in Table 5.3. These operation lists are consistent with the NRCS standards in the region where all three of the fields are located. As shown in Table 5.3, two of the fields are modeled with reduced tillage practices and one is modeled with conventional tillage practices. The SSURGO soils that make up each field are shown in Table 5.1. The model assumptions and configurations for each tillage regime are consistent with the tillage definitions provided by the Conservation Technology Information Center (CTIC) (CTIC, 2012). Conventional tillage includes full width tillage passes and results in less than 15% of the residue remaining on the soil surface after planting the next crop. Reduced tillage again involves full width tillage passes, but leaves up to 30% of the residue on the soil surface after planting.

The sub-field model utilizes high fidelity input data sets providing soil characteristics, surface slope, and grain yield. Crop yield data are supplied from the combine harvester yield monitor systems. Each crop yield data point is a base spatial unit for the sub-field scale integrated model, and each of these points represents a spatial element at the 1 m scale. Surface topography data are supplied by light detection and ranging (LiDAR) through airborne laser scanning (Vitharana et al., 2008; McKinion et al., 2010). LiDAR data for the state of Iowa is provided by the GeoTREE LiDAR mapping project and managed in an SQLite database within the integrated model (GeoTREE, 2011). The LiDAR data is also provided at the 1 m scale. Soil characteristics data is provided by the Soil Survey Geographic (SSURGO) Database (USDA-NRCS, 2011c), an open access national soil survey database provided by NRCS. SSURGO data is at the 10–100 m scale. Climate data is represented in the integrated model at the county scale (approximately 10,000–100,000 m) and is provided by three sources: NRCS managed RUSLE2 climates, CLIGEN, and WINDGEN. For an individual field, the centroid latitude and longitude is used to establish the climate input data. The RUSLE2 climate data is pulled in for the county where the centroid is located. The CLIGEN and WINDGEN databases use an interpolation algorithm to calculate climate data based on triangulation of nearby weather stations. Land management data is provided by an NRCS-managed database, which is housed in the integrated model as an XML data structure. Management data is a field scale characteristic.

The variable rate removal operations were modeled as a direct bale unit where a large square baler is pulled and powered by the combine harvester and receives residue material directly from the separations units within the harvester. This was modeled assuming machine adjustments through the header and the separations units. For removal rates from 25%–50%, the header height was assumed to be standard for current commercial harvest operations and a control

system within the harvester separation unit was assumed to adjust the quantity of material entering the baler. For removal rates from 50%–80%, the header height was assumed to be adjusted lower, moving more of the plant residue through the harvester and then to the baler. The standard corn header was exchanged for a row crop header, and machine performance impacts of this configuration were not considered in this study. Based on this, the direct bale residue harvest operation was modeled from 25%–80% removal at 5% increments. Including the potential for no removal, this creates thirteen potential removal rates.

The integrated model was run at each yield data point within a field for the complete set of crop rotation/residue removal combinations. The residue removal combinations as described previously are 25%–80% removal at 5% increments. This schema creates 13 residue removal rate bins. Sustainable removal rates from 0%–25% are modeled and binned at 0% removal; 25%–29.9% are binned at 25% removal with that schema continuing to 79.9% removal. Sustainable removals from 80%–100% are binned at 80% removal. Residue harvest at each yield point was evaluated for sustainability, thus requiring total wind and water induced soil erosion to be less than or equal to the tolerable soil loss level identified by NRCS for the particular soil and the SCI to be greater than or equal to zero. The highest removal rate satisfying these criteria was established as the removal rate for each yield point with the assumption that the harvesting equipment could make these adjustments on the fly. Executing this analysis resulted in approximately 15,600 model executions per hectare (400 spatial elements, 13 residue removal scenarios, and 3 model executions per spatial element).

Table 5.3. Continuous corn and corn-soybean crop rotations modeled in this study with reduced tillage assumptions.

Continuous Corn		Corn/Soybean	
11/1 Year 1	Chisel Plow	4/20 Year 1	Fertilizer Application
4/25 Year 2	Fertilizer Application	5/1 Year 1	Field Cultivation
5/1 Year 2	Field Cultivation	5/1 Year 1	Plant Corn
5/1 Year 2	Plant Corn	10/11 Year 1	Harvest Corn Grain DB Residue
10/11 Year 2	Harvest Corn Grain DB Residue	11/1 Year 1	Chisel Plow
		5/15 Year 2	Plant Soybeans
		10/1 Year 2	Harvest Soybeans

5.3 RESULTS

The sub-field scale model scenarios discussed in Section 3 were run for each of the three fields and the results are shown in Figs. 5.1–5.3. As shown in Fig. 5.1, Field 1 has diverse soil characteristics with soil organic matter ranging from 1.5% to 7.5% and sand fractions ranging from 17.8% to 87.0% in the top horizon of the soil. Areas of low organic matter and high sand fraction correlate with the higher surface slopes shown in Fig. 5.1c. These field characteristics have a negative impact on grain yield, as shown in Fig. 5.1d. Muth et al. (2012) determined that only 21% of Field 1 would be managed sustainably with rake and bale residue removal due to the significant diversity in soil and surface slope characteristics and because the NRCS guidelines find that rake and bale residue removal is not sustainable for this field. Figure 5.1e shows the sustainable residue removal fraction across Field 1 for the land management assumptions as listed in Table 5.2. Figure 5.1f shows sustainable residue removal ranging from 0 to over 5 Mg ha⁻¹. As shown, those areas with low grain yield do not sustainably support any residue removal. Specifically, for grain yields below approximately 5 Mg ha⁻¹ the minimum removal rate of 25% modeled for the conceptual variable rate removal configuration is too high for sustainable removal. It is also shown that sustainable removal fraction increases in areas of the field where soil organic matter is higher. The SSURGO soil map units shown in Fig. 5.1a are soil survey data, and the explicit transitions between different organic matter levels seen in Fig. 5.1a will be continuous in the field. In the same way, the explicit transitions to higher residue removal rates for the variable rate harvester in Fig. 5.1e will have transitions that are more continuous.

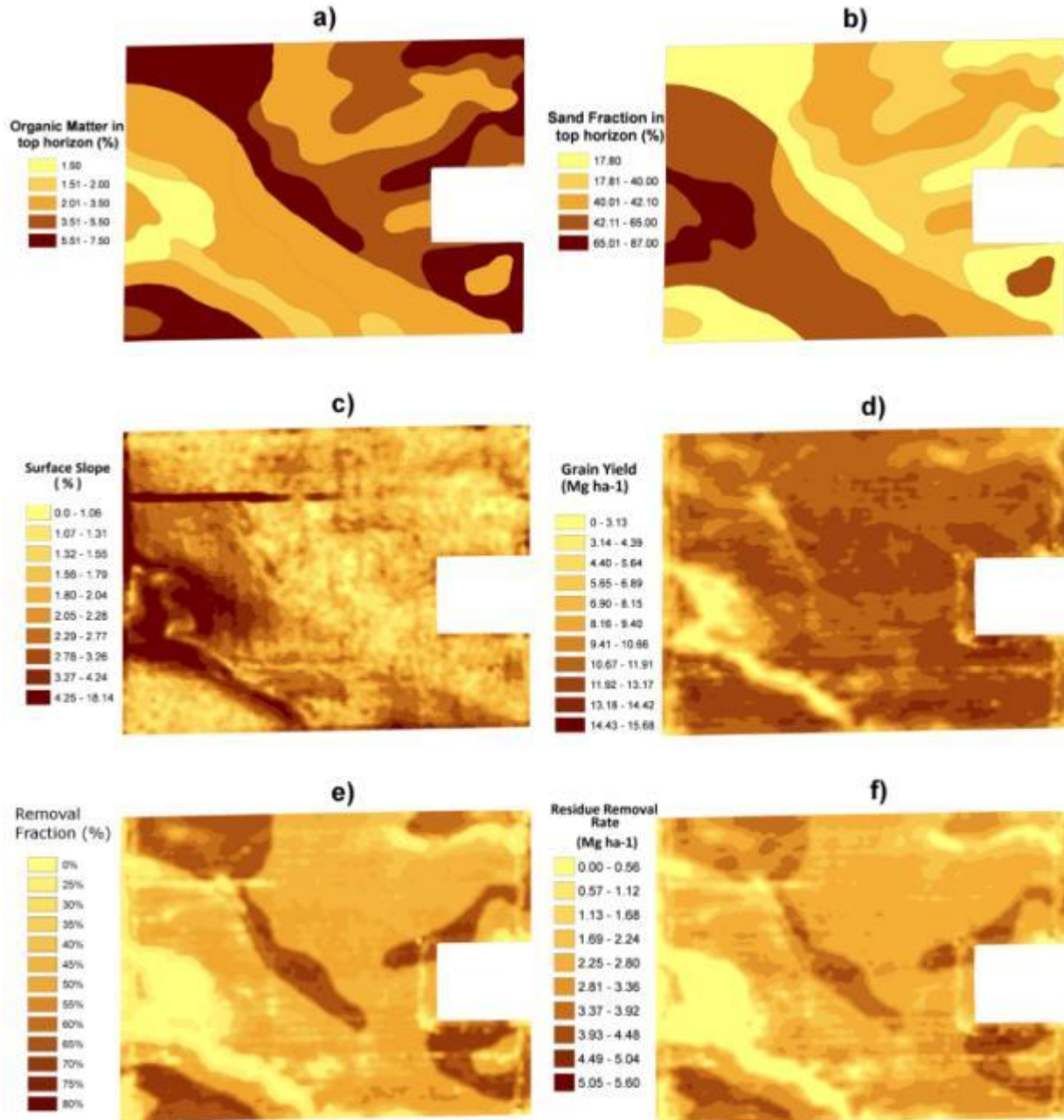


Figure 5.1. Field 1 characteristics and variable rate removal results.

Field 2 is managed with a continuous corn rotation and reduced tillage practices, as shown in Table 5.2. As shown in Fig. 5.2, this field has minimal soil and surface slope diversity. Grain yields are generally high in this field, and the rake and bale residue removal operations were found to be sustainable for 83% of Field 2 using the sub-field scale integrated model (Muth et al., 2012). The fractional residue removal map using the conceptual variable rate residue harvester is

shown in Fig. 5.2e, and the sustainable residue removal rate is shown in Fig. 5.2f. Because soil and surface slope conditions in Field 2 are generally uniform, the residue removal rates look similar to the grain yield map (Fig. 5.2d). Small pockets of lower grain yields along the edges of and in locations within Field 2 lead to little or no residue sustainably available with the variable rate harvester in these areas. The majority of Field 2 can sustainably provide residue removal of approximately 5 Mg ha⁻¹ or greater.

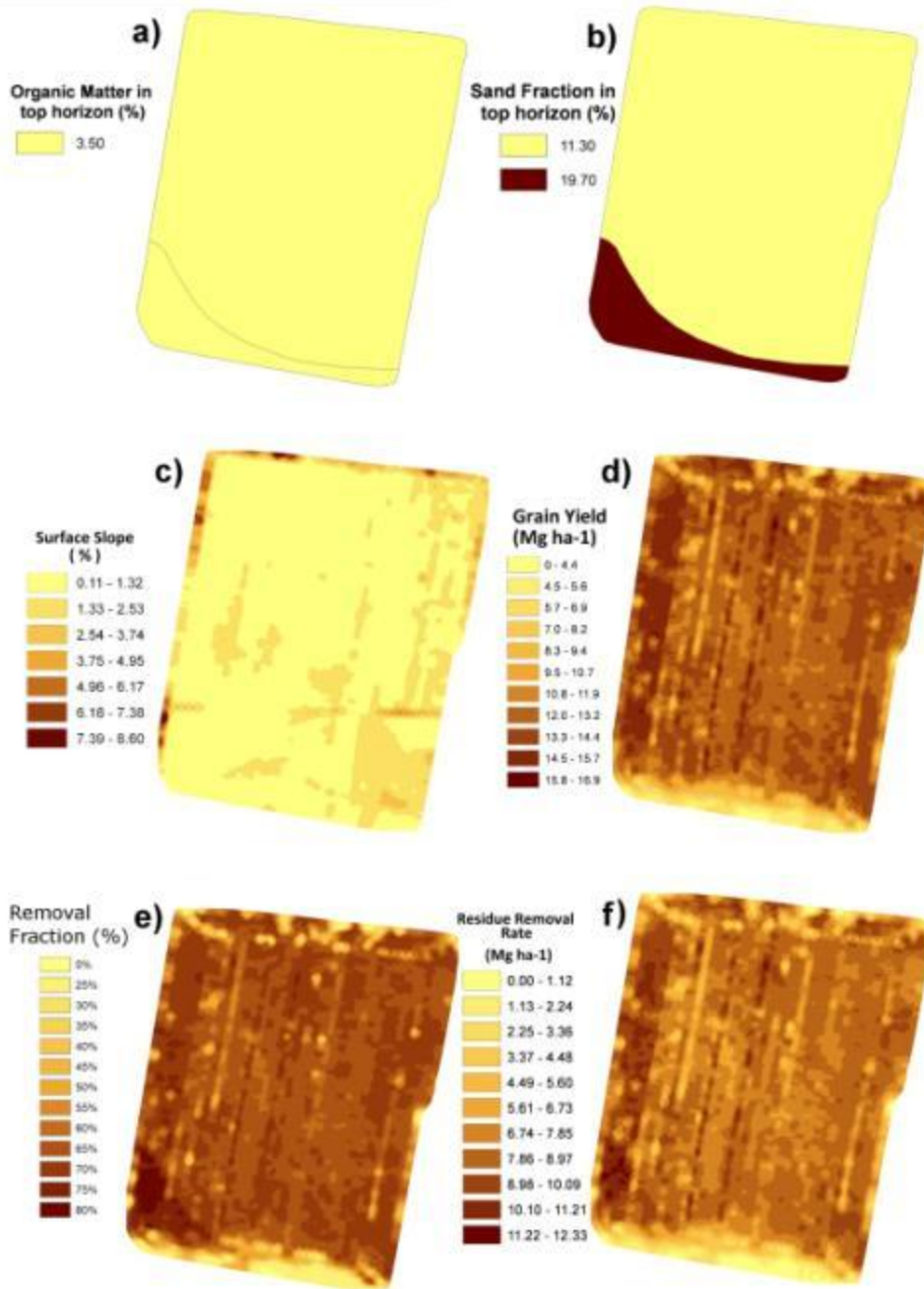


Figure 5.2. Field 2 characteristics and variable rate removal results.

Field 3 is modeled in a continuous corn rotation using conventional tillage practices. As shown in Figs. 5.3a and 5.3b, Field 3 has moderate diversity in soil characteristics compared to Fields 1 and 2. Surface slope in Field 3 is generally uniform and low at less than 1.5% for most of the field, as shown in Fig. 5.3c. Grain yield, shown in Fig. 5.3d, is highly variable in Field 3. Significant portions of the field had grain yields less than 4.5 Mg ha^{-1} , and large areas of Field 3 also had relatively high grain yields above 13 Mg ha^{-1} . The sustainable residue removal fraction using the variable rate residue harvester shown in Fig. 5.3e shows that areas of high grain yield correlate with high removal fractions above 65%. The removal rate map in Fig. 5.3f directly relates to the grain yield variability in Fig. 5.3d. A significant area in Field 3 cannot have any residue removed sustainably, but large portions of the field can sustainably provide over 8.5 Mg ha^{-1} of residue.

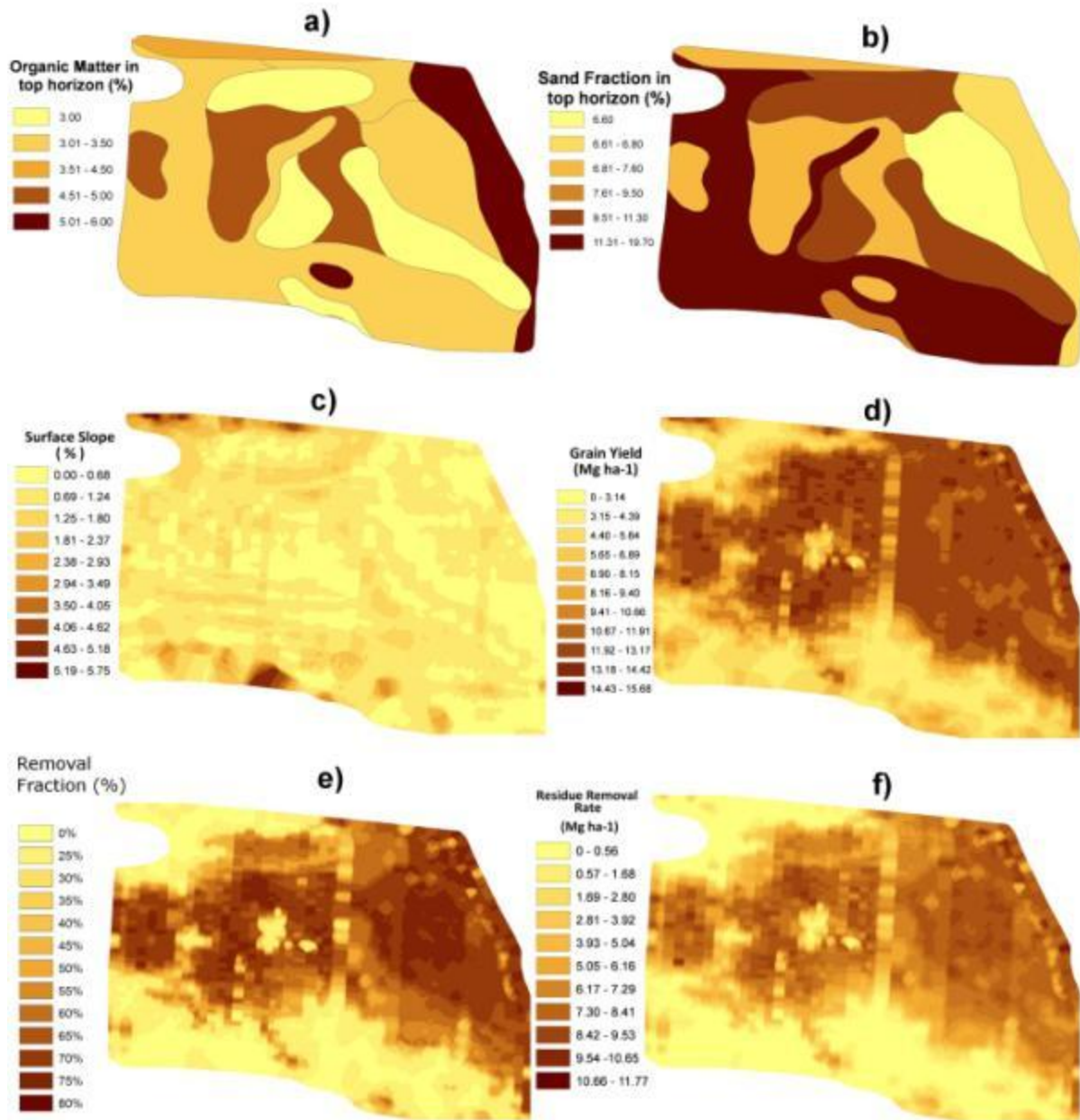


Figure 5.3. Field 3 characteristics and variable rate removal results.

Figures 5.4a through 5.4c show the mass fraction of residue removed sustainably and the area fraction of residue harvested by bin for each of the three fields. As shown in Fig. 5.4a, nearly 13% of the area in Field 1 requires a 0% removal rate to be sustainably managed. The 45% removal rate covers the most area and provides the most residue mass for Field 1 of the range of removal rates. Higher removal rates provide more residues per unit area, and Fig. 5.4a

shows that although the 65% removal rate is only used for about 12% of the field, it provides nearly 20% of the total residue mass sustainably available in Field 1. The results in Fig. 5.4a show that in order to collect 90% of the sustainably removable residue, the variable removal rate harvester would need to be capable of on-the-fly rate adjustments from 40% to 65%. The requirements are different when considering harvester performance for sustainably managing a land area. In this case the variable rate harvester would need to be able to make on-the-fly adjustments down to 0% removal to achieve sustainable removal for 100% of the area in Field 1. Accounting for both maximizing residue mass collected and sustainably managing a land area requires a robust and dynamic variable rate residue harvester in Field 1.

Figure 5.4b shows that lower diversity in the sub-field characteristics found in Field 2 create different variable rate residue harvester performance requirements than the more diverse Field 1. Looking at Fig. 5.4b, the 65% removal rate is used for over 40% of Field 2. When 5% removal rate adjustments to 60% and 70% are included, nearly 80% of Field 2 is represented. Figure 5.4b shows that if the harvester has the ability to adjust between 60% and 70% removal rates, over 90% of the sustainably removable residue mass would be collected in Field 2. These results show that the uniform sub-field characteristics in Field 2 result in much less intense variable rate residue harvester performance requirements to achieve sustainable practices and maximize residue removed than found for Field 1.

Over 15% of the area in Field 3 requires no residue harvest, and over 35% of the area in the field requires removal rates at or below 50% (Fig. 5.4c). In contrast, the majority of the sustainably available residue mass will be collected at removal rates at 60% or above. Field 3 presents a scenario where on-the-fly removal rate adjustments within the variable rate harvester

need to cover the full range of the modeled assumptions to meet both goals of sustainably managing the land and maximizing sustainably removed residue mass.

One question that arises is whether the full range of 25%–80% is needed or if a smaller range of residue removal would be nearly as effective. In Field 1, a variable rate harvester with the capability to adjust between 40%–65% residue removals would collect 91% of the sustainably removable residue mass. Within Field 2, the variable rate harvester would need to adjust between 60%–70% removal rates to collect 92% of the sustainably removable material. For Field 3 to achieve 90% removal of the sustainably available residue would require removal rate adjustments from 50%–70%. Therefore, if the variable rate harvester was able to make on-the-fly adjustments from 40%–70% removal rates, more than 90% of the sustainably available residue would be removed from each of these fields.

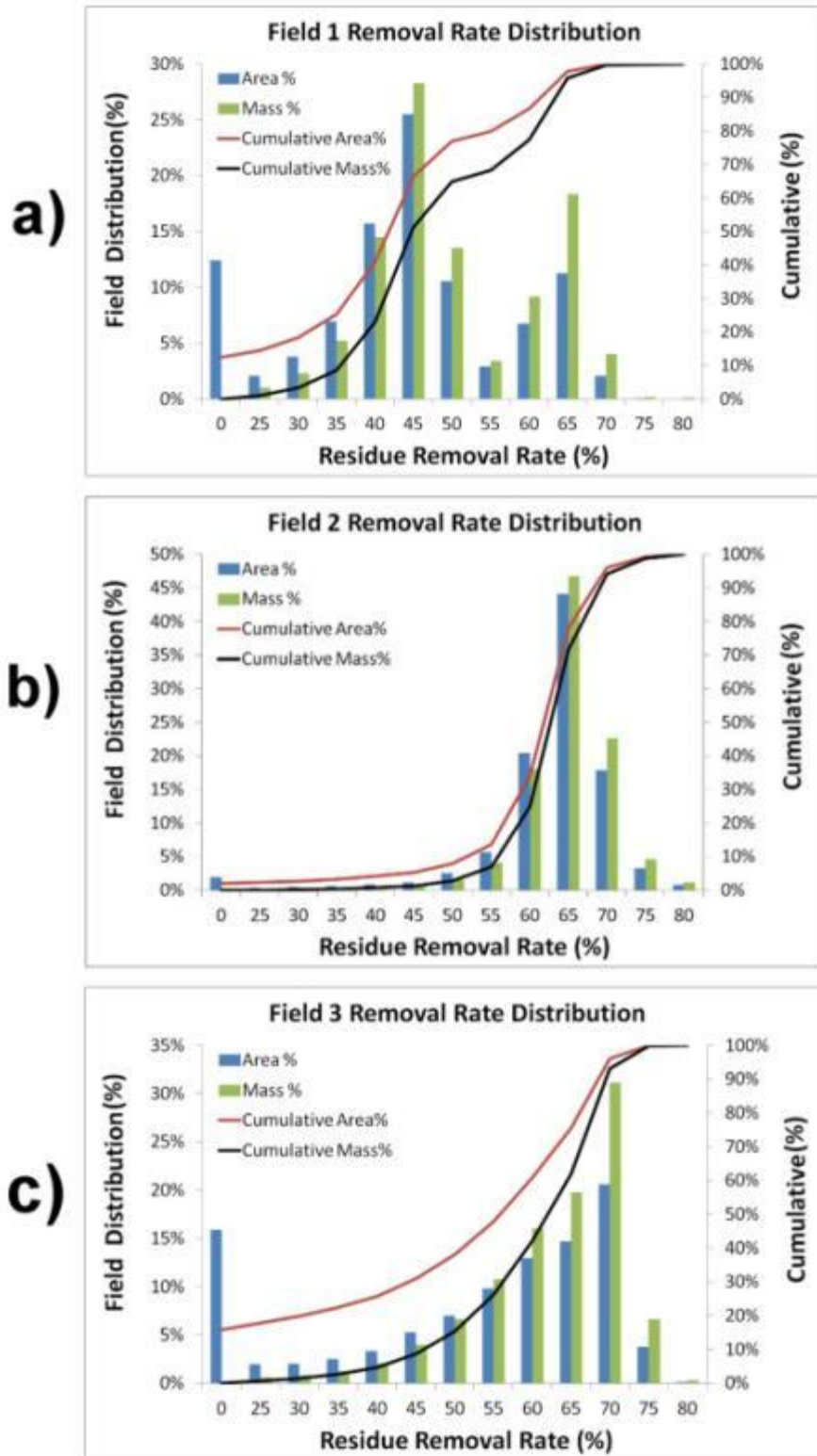


Figure 5.4. Removal fraction distribution for variable rate harvest scenarios in each of the three fields.

For each of the three fields, Table 5.4 compares the variable rate residue removal scenario in this study to the current NRCS guidelines for sustainable rake and bale removal of the entire field and the selective sub-field rake and bale single rate residue removal scenario discussed in Muth et al. (2012). The sustainable removal rate of agricultural residue for the conceptual variable rate removal equipment was 2.35, 7.69, and 5.62 Mg ha⁻¹ for Fields 1–3, respectively. In contrast, the sustainable removal rates using rake and bale removal and NRCS guidelines for the entire field were 0.0, 6.40, and 5.06 for Fields 1–3, respectively. In addition, the variable rate residue removal sustainably managed 100% of the land area in all three fields. In contrast, Field 1 could not be sustainably managed using rake and removal, and 83% of the land area of Field 2 and 62% of the land area of Field 3 were managed sustainably using rake and bale removal for the entire field. The selective rake and bale residue removal harvest of 21% of Field 1 provided 0.62 Mg ha⁻¹, and as a consequence, it is likely that this field could not be harvested sustainably and economically. Selective rake and bale harvest of Fields 2 and 3 managed the entire land sustainably but only harvested 83% and 62% of the land area, respectively, and provided lower residue yields (5.70 and 3.65 Mg ha⁻¹, respectively) relative to current NRCS practice.

Table 5.4. Sustainable residue removal potential for the three fields compared to rake and bale as reported by Muth et al. (2012).

Field	Total Residue Available with Rake and Bale if Sustainability is not Considered	Sustainable Residue Available with Rake and Bale Based on NRCS Guidelines	Average Annual Sustainable Removal Rate with Rake and Bale Based on NRCS Guidelines	Sustainable Residue Removal with Selective Rake and Bale (Muth et al., 2012)	Average Annual Sustainable Removal Rate with Selective Rake and Bale (Muth et al., 2012)	Sustainable Residue Removal with Variable Rate Assumptions	Average Annual Sustainable Removal Rate with Variable Rate
	Mg	Mg	Mg ha ⁻¹	Mg	Mg ha ⁻¹	Mg	Mg ha ⁻¹
1	152	0	0.00	35	0.62	133	2.35
2	119	119	6.40	106	5.70	144	7.69
3	387	387	5.06	279	3.65	430	5.62

5.4 CONCLUSIONS

The paper examines the potential of variable rate residue removal technology for increasing sustainably removable residue, and characterizes the performance of the conceptual variable rate harvester required to maximize sustainable removal of residue. This analysis was performed for three representative Iowa fields. Sub-field scale variability in soil characteristics, topography, and yield significantly impact sustainably available residue removal rates in all three fields. In each of the fields, variability in one or more of these items led to a wide range in sustainable residue removal in different areas of the field. For Field 1 soil properties had a large impact on the residue availability, whereas in Fields 2 and 3 the sustainable residue removal rates correlated to grain yield. In each field there were areas where no residue was sustainably available and areas where large portions of the available residue could be removed sustainably.

It was found that variable rate residue harvest technologies support the challenging goals of optimizing residue removal for sustainable land management and bioenergy production. Compared with NRCS guidelines that suggest that no residue could be sustainably removed in Field 1, the conceptual variable rate residue harvester modeled here would sustainably manage 100% of the land area while providing an average of 2.35 Mg ha^{-1} of residue for energy use. In Fields 2 and 3, variable rate harvest provides 1.29 and 0.56 Mg ha^{-1} more residues, respectively, than NRCS guidelines using rake and bale removal while sustainably managing 100% of the land area. This suggests that variable rate removal of agricultural residue could sustainably provide more agricultural residue for energy production while improving sustainable management of land resources.

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CHAPTER 6. CONCLUSIONS AND FUTURE DIRECTIONS

This chapter presents a summary of the findings and conclusions from the research performed for this dissertation along with a discussion on the potential implications of these findings and conclusions for implementing sustainable agricultural residue removal practices across the nation. Also presented are future directions for this work. Specifically addressed are potential roles this work can have in supporting a transition toward sustainable, highly productive, integrated bioenergy production systems capable of meeting national bioenergy production goals.

6.1 SUMMARY

An integrated modeling strategy has been built and demonstrated for sustainable residue removal analyses. A framework was used to integrate multiple environmental process models and databases required to simulate agricultural residue removal scenarios and to assess sustainability for multiple potential limiting factors. The integrated modeling framework initially focused on utilizing NRCS developed models and databases: the RUSLE2 water erosion model, the WEPS wind erosion model, and the SCI soil carbon model. These choices were made because of the significant investments already made in developing and validating these models, the databases required for the models already exist, and NRCS field offices across the country currently use the models to implement conservation management required through Farm Bill legislation. The framework approach facilitates use of the models in executable form, which provides a number of advantages. These include leveraging the existing model validation efforts and allowing the seamless exchange of new or updated model versions. The integrated modeling strategy has been applied across multiple spatial scales. An initial application of the framework included an assessment of the sustainably

available residue for the state of Iowa. The study utilized SSURGO soil map units as the base spatial elements for the analysis and calculated the integrated model results for nearly five million scenarios. The results, which used assumptions about current land management and crop yield practices, showed nearly 26.5 million metric tons of agricultural residue as sustainably available in the state.

The integrated modeling strategy was then applied to a sustainable agricultural residue removal assessment for the entire conterminous United States. This assessment builds upon previous large scale assessments by providing a more comprehensive spatial and temporal analysis for the conterminous United States that considers multiple potential environmental limiting factors. SSURGO soil map units represent the base spatial elements for the analysis. The assessment incorporated the latest advancements in land cover and land use data by developing and integrating a methodology using the USDA Cropland Data Layer to establish accurate crop rotation practices. Three tillage regimes (conventional, reduced, and no tillage) were run. Each of the soil type/crop rotation/tillage regime/crop yield/removal rate scenarios was run through the integrated model, resulting in nearly 100 million total scenarios. This includes yield scenarios for 2011 and 2030. The results were aggregated to county level projections, and they showed that in 2030 over 200 million metric tons of agricultural residues could be sustainably removed. If no tillage management practices are universally adopted, the sustainably available residue could reach nearly 300 million tons. These results are useful for the emerging bioenergy industry making decisions about investments from two perspectives. First, the county level projections can support decisions identifying regions where sufficient quantities of biomass can be found to support bioenergy conversion facilities.

Second, the raw data calculated at the SSURGO soil map unit level can help identify sustainable removal practices within NRCS conservation management planning guidelines.

The integrated model was extended to use high fidelity spatial data at the sub-field scale, which has become readily available through precision agriculture. Specifically, geoprocessing tools that work with combine harvester yield monitor data, LiDAR surface slope data, and SSURGO soils data were used to adapt the integrated model for sub-field scale sustainable residue removal investigations. Sub-field scale residue removal assessments were performed for three representative Iowa fields. The results of the assessments show that variability in soil characteristics, surface slope, and grain yield can greatly impact sustainable residue removal within individual fields. The assessments investigated current NRCS conservation management planning guidelines that use dominant critical soil type selection, representative slope and slope length selection, and field average grain yield. The results of the sub-field assessments showed that these assumptions do not reflect sustainable removal rates for large portions of the fields. In some cases there are significant areas in a field that will have too much residue removed, and in others there are significant quantities of residue that could be sustainably removed above the recommendations. Primary conclusions of the sub-field assessments are that sustainable residue removal analysis must consider sub-field scale variability and that residue removal system configurations that can adapt to changing residue removal rates across a field could play an important role in maximizing the potential residue available while ensuring sustainable land management practices.

The sub-field scale integrated model was then applied to the three Iowa fields to investigate a variable rate residue harvesting concept as a mechanism for managing sub-field scale variability. The modeled system was based on single pass direct bale technologies and

assumed an ability to adjust between 25% and 80% residue removal on-the-fly. Using this conceptual configuration, significantly more residue was available in each of the fields, and all areas in each field were managed sustainably. The sub-field scale integrated model also informed potential machine requirements for this variable removal rate configuration. In each of the three fields the variable rate removal equipment needs to adapt from 0% to over 50% removal rates in order to get 80% of the sustainably available residue.

The general conclusions of this work are that large amounts of agricultural residues are sustainably available using commercially available equipment and current management practices. However, these systems are vulnerable to unsustainable removal practices due to sub-field scale variability in soil characteristics, surface slope, and grain yield. Furthermore, the conservation planning guidelines do not currently account for sub-field scale variability in these factors. Variable rate removal technologies have the potential to overcome these challenges as well as maximize residue removal while ensuring sustainability at the sub-field scale.

6.2 FUTURE DIRECTIONS

The future directions of this work fall into two categories. First is the continued development and extension of the environmental process modeling integration framework and associated computational methods. The second category is additional studies implementing the framework to investigate important questions that remain unanswered.

6.2.1 Modeling Framework Extensions

A primary extension required for the current integrated modeling framework is additional geoprocessing tools that are seamlessly coupled to the computational engine. This is important because additional spatial data continue to become available. This new data

better characterize the systems being investigated and create higher quality integrated model results. One example of this is supplementing SSURGO data with grid based soil sample data that many land managers are paying to attain. The capability to utilize these additional geospatial data sets also creates opportunities to investigate additional questions that are being asked by environmentalists and the bioenergy community. These include the impact of residue removal on water quality, green house gas emissions, and soil micronutrient levels. To support the examination of these questions, the framework also needs to be extended with additional model interfaces. The targeted models for integration interface development include Daycent, EPIC, and APEX. These models will support investigation of green house gas cycles, water quality, and quantitative soil carbon questions.

Another requirement for making the existing integrated model more extensible is increasing the computational efficiency to facilitate the distributed use of the toolset for on-the-fly control systems. As shown with the sub-field scale studies, it will be important to calculate removal rates on the harvesting equipment quickly as high fidelity precision agriculture data is being collected. There are several potential methods for developing and deploying this capability that need to be investigated and compared.

6.2.2 Additional Studies with the Existing Framework

Several studies utilizing the integrated modeling framework can be performed to examine remaining questions about sustainable agricultural residue removal, and more generally the optimal use of the productive landscape for bioenergy feedstock production. The first set of studies can be performed utilizing the integrated modeling framework with its current capability.

Another important consideration is the changes in the harvest index. As discussed in Chapter 2, there is evidence emerging that suggests advanced genetic modifications could be changing the ratio of grain to biomass in the residue producing crops. Although the exact relationship between increasing yields and changes in harvest index has not been established, a study investigating the large-scale impact of changes in the harvest index for residue-producing crops will provide useful information for the bioenergy community.

Variable rate residue removal was shown to sustainably harvest more residue than commercially available residue removal equipment configurations. A study investigating the larger geographic impact of variable rate residue removal could provide useful information for several participants in the bioenergy community including land managers, equipment manufacturers, and biorefiners. Another innovative management strategy that has received attention for potentially increasing sustainable residue removal potential is the use of cover crops.

Cover crop systems can reduce soil erosion and support soil organic matter cycles, thus facilitating higher residue removal rates. Two studies investigating the impact of cover crops on sustainable residue removal potential would be useful. First, examining the impact of cover crop managements across a large geographic region (state or nation) could provide perspective on the importance of continued agronomic research developing cover crop management systems. Second, investigating the impact of cover crops while considering sub-field scale variability could inform land managers considering residue removal.

This work has focused on identifying sustainable agricultural residue removal potential, but has generally not considered the economic viability of the systems examined. The large geographic assessments and sub-field scale data provided by this work can provide

information for economic analyses of residue harvest and logistics operations for bioenergy systems. These economic analyses are critical for determining the ultimate viability of agricultural residue removal systems.

6.2.3 Additional Studies with the Enhanced Framework

Another set of additional studies that could provide useful information to the bioenergy research community will require the framework extensions mentioned above. Specifically of interest are the green house gas impacts of residue removal. The primary concern is that removing residue will require additional nitrogen application to replace the physiological nitrogen within the residue that would have broken down and become available in the soil. The additional nitrogen application could potentially result in higher N₂O emissions from the soil surface to the atmosphere. A study that utilizes an ecosystem model such as Daycent to simulate the N₂O emissions for residue removal operations could inform the extent of this potential problem and provide guidance on mitigating any issues that become apparent. Another concern that emerges when considering additional nitrogen application requirements is water quality. Current agricultural production systems are known to cause increased nitrogen loading in watersheds, particularly tile drained systems in the Corn Belt. Integration of the models mentioned above will facilitate studies that can simulate watershed nitrogen loading for a number of different management practices associated with residue removal.

Each of these proposed studies considers part of a broad set of ecosystems services provided by the agricultural landscape. Bioenergy production systems, including agricultural residue removal, forest resources, dedicated herbaceous energy crops, and dedicated woody energy crops have the potential to enhance the ecosystem services provided by the agricultural landscape. The integration of sub-field scale geoprocessing tools with a broad set

of environmental process models as described through this work have the potential to support the agronomic and soil science communities in designing optimal landscape configurations which maximize feedstock production for bioenergy while enhancing the ecosystem services provided by the agricultural landscape. This is a bold and challenging objective which will require strong collaborations between large groups of researchers collecting data, developing models, and integrating the collective knowledge for enhanced decision making. The integration framework approach developed in this work has potential to help achieve this objective.

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