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An integrated model for assessment of sustainable agricultural residue removal limits for bioenergy systems☆

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A B S T R A C T

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 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 rotation 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. Previously published results have shown residue availability from 22 million Mg to over 50 million Mg in Iowa.

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Software availability

The VE-Suite software is freely available under the GNU LGPL license. Documentation and software are available at www.VE-Suite.org.

The models and databases used are listed in Table 1.

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

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[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, 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 land 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.* 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. Background

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 (Larson, 1979). 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 Larson's study. Nelson (2002) used the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1996) 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 [NRCS, 2011c]) 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 Izaurralde, 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 used for cropland, pastureland, rangeland, and disturbed forestland applications (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 N_2O 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 and Hornbaker, 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 min typically), which makes then viable within an integrated multi-model decision framework.

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.

Model integration frameworks have been developed and used extensively for environmental modeling applications. Several examples of integrated modeling frameworks used for hydrology and water resource management applications include pesticide development in tile-drained fields (Branger et al., 2010), investigating the impacts of wildfires on flow and constituent loading (Feikema et al., 2011), a dam break scenario (Malleron et al., 2011), water requirement determinations (Hughes and Louw, 2010), and microbial respiration in floodplain landscapes (Tritthart et al., 2011). Additional applications of integrated environmental modeling frameworks have focused on supporting policy and water resource allocation decisions (van Delden et al., 2011; Ramin et al., 2011; Goodall et al., 2011; Merot and Bergez, 2010). Frameworks that integrate environmental models with economic models have also been developed to investigate land use (Schweitzer et al., 2011) and water management at the catchment scale (Kragt et al., 2011) Considerable attention has also focused on defining and evaluating integrated environmental modeling frameworks (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 et al., 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) 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 of 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.

3. Models and methodology

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, waterdrops falling from plant canopy, and surface runoff.

Fig. 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. Each of the data elements in Fig. 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 ith day is presented in Eq. (1).

$$a_i = r_i k_i l_i S c_i p_i \quad (1)$$

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. Eq. (1) provides the daily soil loss, or total "Sediment Out" in Fig. 2, but Eq. (1) does not calculate the deposition component of the mass balance. Eq. (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. (3). With these parameters established, the steady-state conservation of mass (Eq. (4)) is used to establish net detachment and deposition. Eq. (5) is then used to aggregate the daily time-steps determining the average annual soil loss.

$$D_p = \left(\frac{V_f}{q}\right)(T_c - g) \quad (2)$$

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).

$$T_c = K_T q s \quad (3)$$

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

$$g_{out} = g_{in} + \Delta x D \quad (4)$$

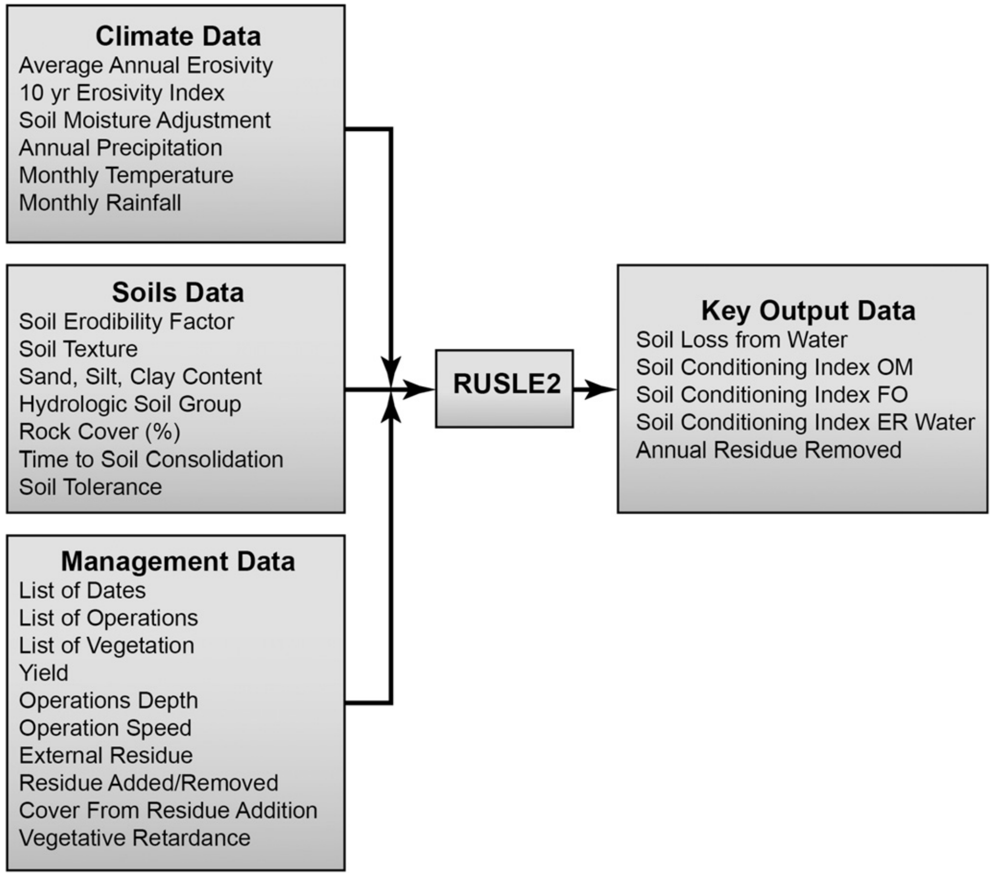


Fig. 1. Information input and output for RUSLE2.

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 segment, and D is the net detachment or deposition within a segment.

$$A = \frac{\left(\sum_{i=1}^{365} a_i\right)}{m} \tag{5}$$

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. (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.

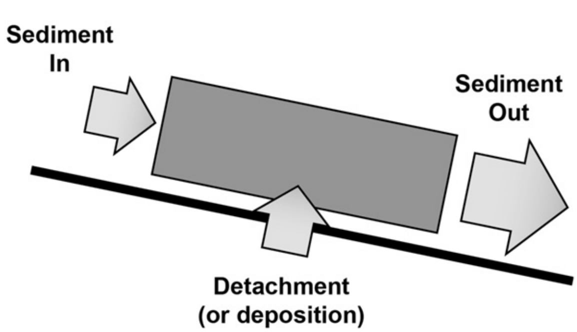


Fig. 2. Conservation of mass principles in the RUSLE2 simulations.

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. 3). Fig. 4 shows the information flow into and out of the WEPS model.

As shown in Fig. 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 (0.1–2.0 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. 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. 4. The submodels in Fig. 5 utilize the data inputs from Fig. 4 to provide the detailed site characterization parameters to the conservation of mass equations within the erosion submodel. Eq. (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}).

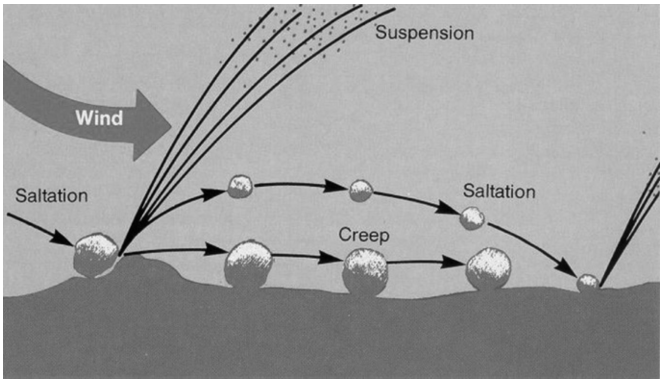


Fig. 3. WEPS mathematically simulates the mechanisms for soil loss caused by wind using a process-based daily time-step simulation (Hagen et al., 1996).

$$\frac{\partial(\overline{CH})}{\partial t} = -\frac{\partial q_x}{\partial x} - \frac{\partial q_y}{\partial y} + G_{en} + G_{an} - G_{tp} - G_{ss} \tag{6}$$

where x *and* y equal 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 (kg/m^{2}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. 5 for the next time-step. The other conservation equations, for suspension and PM-10 size classes, work functionally the same as Eq. (6) within the control volume, but with size class specific source and sink terms.

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. (7) as follows:

$$\mathrm{SCI} = (0.4\ \mathrm{OM}) + (0.4\ \mathrm{FO}) + (0.2\ \mathrm{ER}) \tag{7}$$

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 ≥ 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

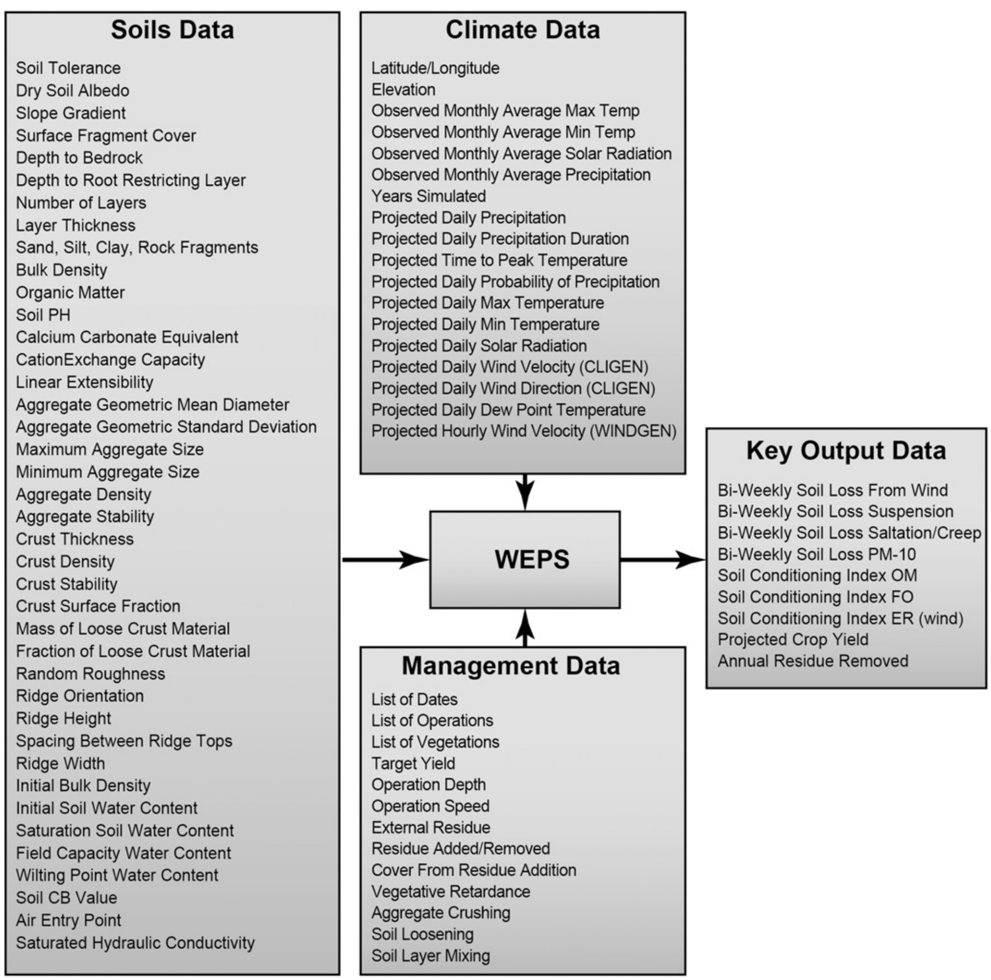


Fig. 4. The WEPS model requires extensive soils, climate, and management data to perform wind erosion calculations. (PM-10 = particulate matter less than 10 micrometers, OM = Organic matter, FO = field operation, ER = erosion).

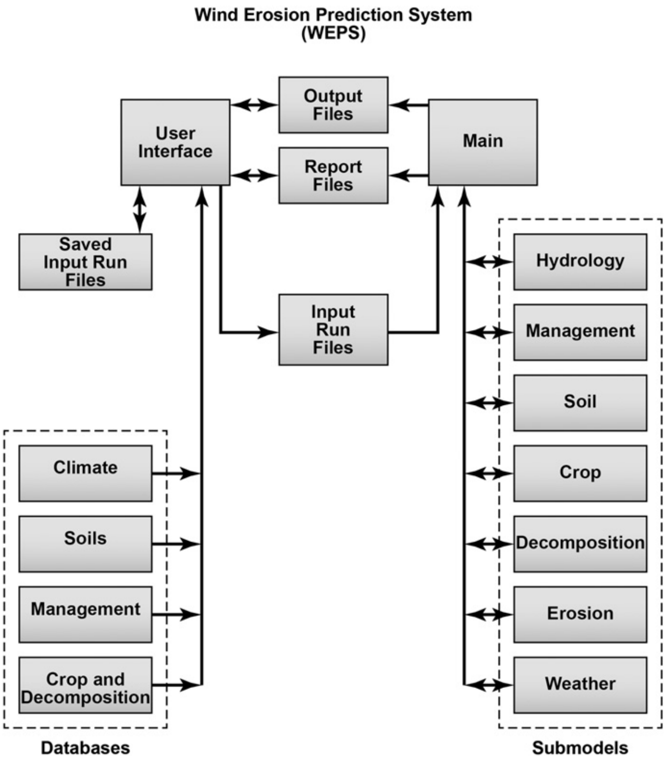


Fig. 5. WEPS core models are built on a Fortran 77 infrastructure that implements a modular set of submodels to calculate losses due to wind erosion (Hagen et al., 1996).

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.

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) 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.

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. Fig. 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.

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 1 lists the databases and models required for the integrated residue removal systems model.

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

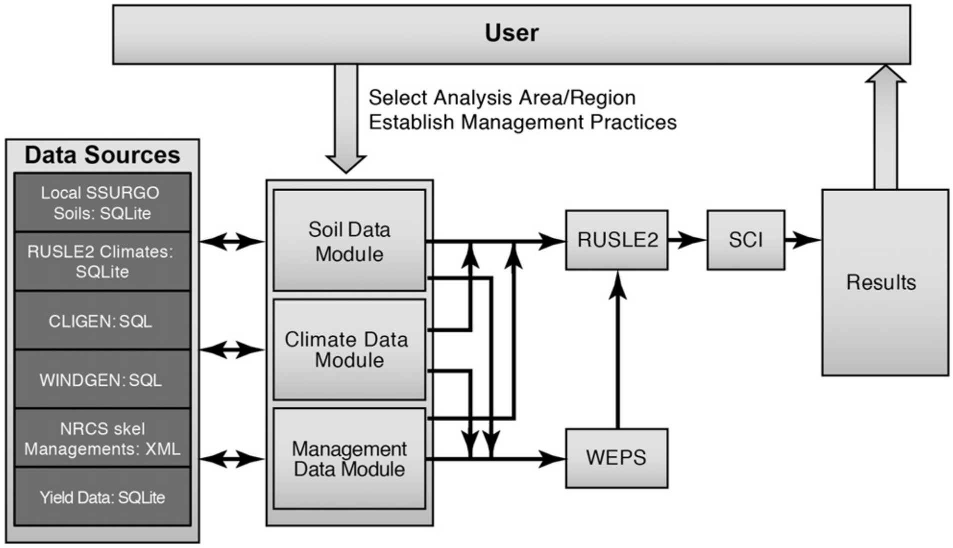


Fig. 6. Representation of the data flow through the integrated residue removal systems model.

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. 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. 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.
- *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. 8 (USDA, 2011a; Wagner et al., 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.

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.

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).

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

Table 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

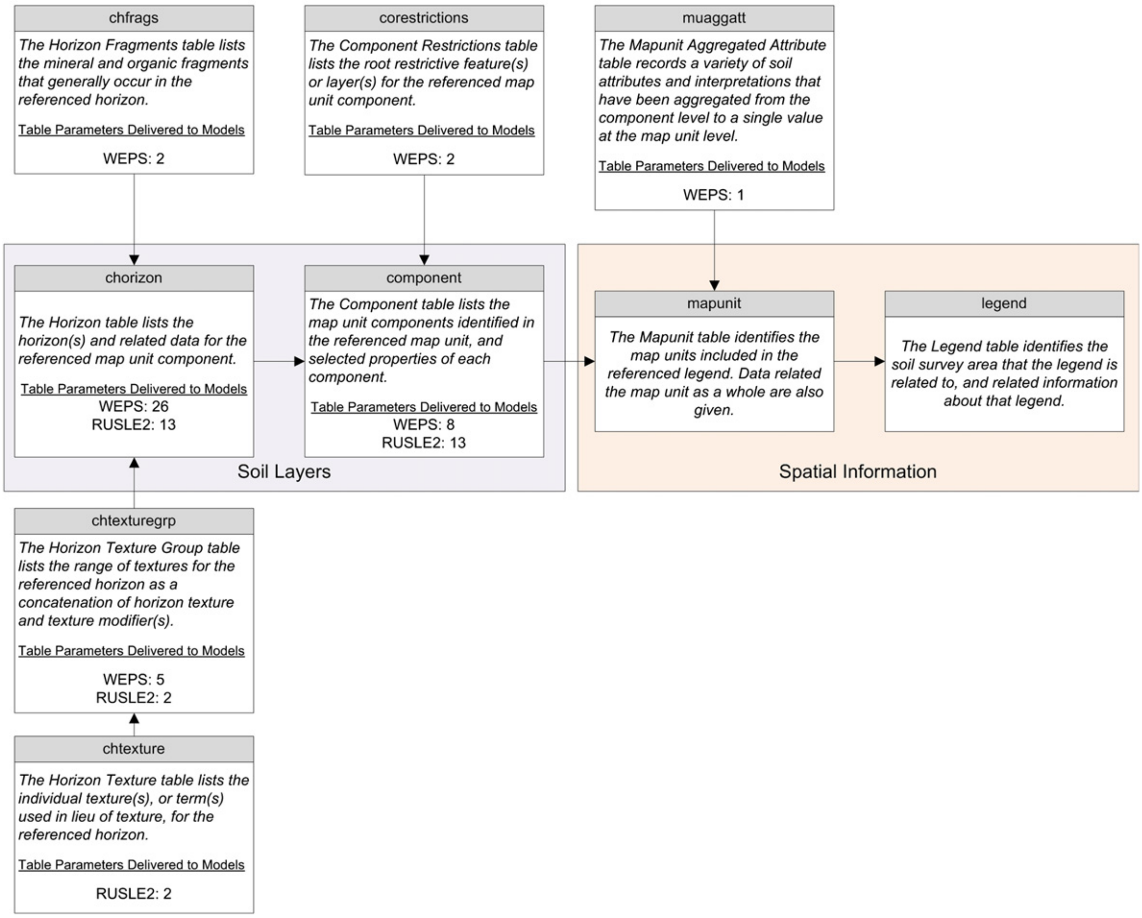


Fig. 7. Schematic representation of the locally managed SQLite SSURGO database managed by the Soils Data Module.

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. 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 and 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.

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 m 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. Fig. 9 shows the basic process flow for the functions performed by the framework interface for the WEPS model. Within the

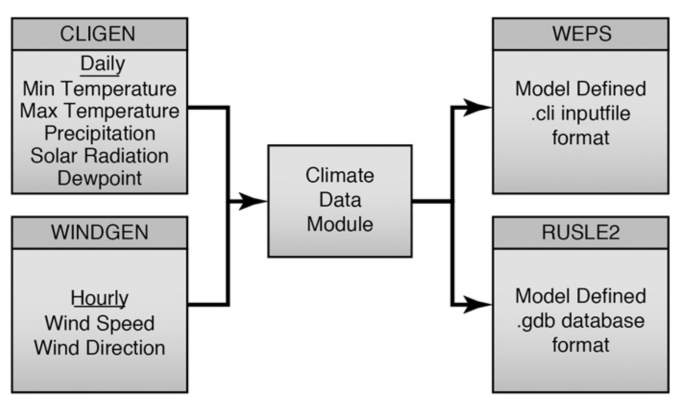


Fig. 8. Block diagram of the climate module functionality.

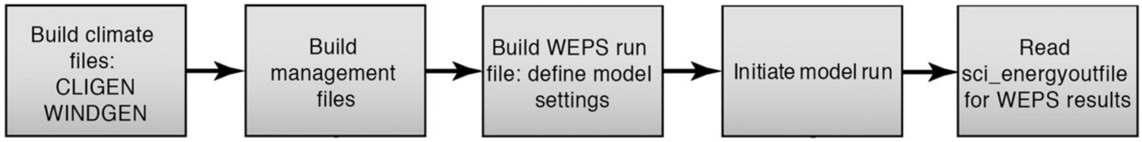


Fig. 9. The WEPS model wrapper within the toolkit utilizes the data provided through the previously described models to perform all necessary functions setting up the WEPS model run scenario.

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.

Upon completion of the WEPS model execution, RUSLE2 then runs and completes the analysis flow as shown in Fig. 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 s 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.

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. 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.

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.

3.6.1. Define and assemble the analysis scenarios

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, 2011c). 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 these rotations produce corn, soybeans, and winter wheat.

3.6.1.2. Tillage management practices. As shown in Table 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 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%.

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 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.

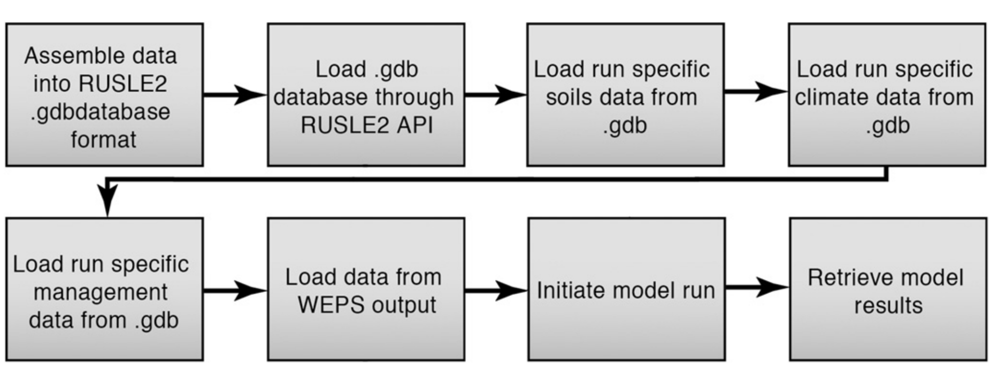


Fig. 10. The basic functional flow of the RUSLE2 API wrapper is shown.

Table 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

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 2–4. 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, 4 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 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.

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 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 6) (2006–2010) provided by USDA NASS (USDA, 2011c). 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. 11.

3.6.2. Model execution

Section 3.6.1 described how the model scenarios are defined and assembled. The following sub-sections describe the integrated model execution steps for the model scenarios. Specifically, the spatial scale for soils and climate data are presented for the state of Iowa case study. Model performance and the methodology for spatial aggregation of results are also presented.

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. Fig. 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. Fig. 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.

Table 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

Table 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 $3' \times 4' \times 8'$ 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 $3' \times 4' \times 8'$ 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 $3' \times 4' \times 8'$ square bales.	83%

Fig. 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 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.

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.

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.

Table 5
For the four crop rotations identified in Table 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		

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.

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) 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 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. 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. 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. This equation set is represented in matrix form in Eq. (8). Within Eq. (8) CG represents corn grain, SB represents soybeans, and WW represents winter wheat.

$$\begin{bmatrix} \left(\dfrac{1-\dfrac{WW_{area}}{CG_{area}}}{4}\right) & 0 & 0 \\ \left(\dfrac{1-\dfrac{WW_{area}}{CG_{area}}}{4}\right) & \left(\dfrac{1-\dfrac{WW_{area}}{SB_{area}}}{1.25}\right) & 0 \\ \left(\dfrac{1-\dfrac{WW_{area}}{CG_{area}}}{2}\right) & \left(\dfrac{1-\dfrac{WW_{area}}{SB_{area}}}{5}\right) & 0 \\ \left(\dfrac{WW_{area}}{CG_{area}}\right) & \left(\dfrac{WW_{area}}{SB_{area}}\right) & 1 \end{bmatrix} \begin{bmatrix} CG_{area} \\ SB_{area} \\ WW_{area} \end{bmatrix} = \begin{bmatrix} Rot1_{area} \\ Rot2_{area} \\ Rot3_{area} \\ Rot4_{area} \end{bmatrix} \tag{8}$$

The rotation designations match those listed in Table 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. Eq. (9) is the matrix representation of the equation set for counties without winter wheat production.

$$\begin{bmatrix} \left(\dfrac{1-\dfrac{0.2SB_{area}}{2.0CG_{area}}}{2}\right) & 0 \\ \left(\dfrac{1-\dfrac{0.2SB_{area}}{2.0CG_{area}}}{2}\right) & 0.8 \\ \left(\dfrac{0.2SB_{area}}{2.0CG_{area}}\right) & 0.2 \end{bmatrix} \begin{bmatrix} CG_{area} \\ SB_{area} \end{bmatrix} = \begin{bmatrix} Rot1_{area} \\ Rot2_{area} \\ Rot3_{area} \end{bmatrix} \tag{9}$$

An example application of this methodology is shown in Eq. (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. (8) is used.

$$\begin{bmatrix} 0.238 & 0 & 0 \\ 0.238 & 0.850 & 0 \\ 0.476 & 0.094 & 0 \\ 0.048 & 0.055 & 1 \end{bmatrix} \begin{bmatrix} 29,542 \\ 25,617 \\ 1416 \end{bmatrix} = \begin{bmatrix} Rot1_{area} \\ Rot2_{area} \\ Rot3_{area} \\ Rot4_{area} \end{bmatrix} \tag{10}$$

From Eq. (10), the 2008 hectares harvested were 29,542; 25,617; and 1416 respectively for corn grain, soybeans, and winter wheat. The results are provided in Table 7.

Fig. 13 represents the structure assembled for these steps to be executed within the integrated residue removal systems model results database. The results

Table 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

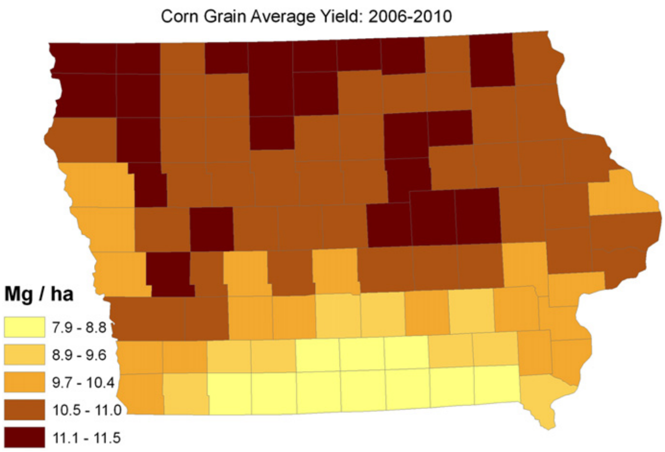
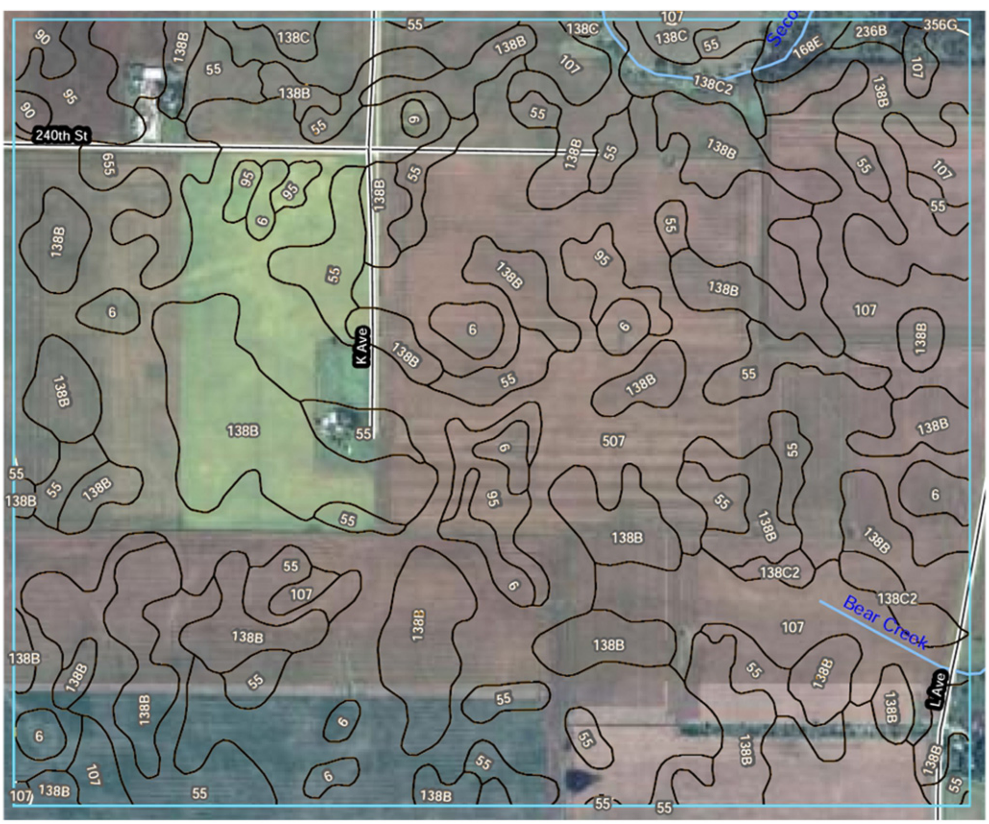


Fig. 11. County level average corn grain yields.

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.



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%

Fig. 12. SSURGO map unit for a roughly 330 hectare area in central Boone County, IA (USDA, 2011b).

Table 7
Rotation area (ha) for Lee County, IA using 2008 production statistics.

Continuous Corn Rotation	7031
Corn/Soybean Rotation	28,812
Corn/Corn/Soybean Rotation	16,483
Corn/Soybean/Winter Wheat Rotation	4249

4. Results and discussion

4.1. Determining the impacts of tillage management decisions

Fig. 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 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. (11) shown in column 1 of Table 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.

$$AY = \frac{\sum_{i=1}^{99} AY_i}{99} \tag{11}$$

The mass weighted average, AY_{MW} from Eq. (12) shown in column 2 of Table 8 considers not just the county average yields, but also the total mass produced in each county. In Eq. (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.

$$AY_{MW} = \frac{\sum_{i=1}^{99}\left(\frac{AY_i \times TM_i}{TM_S}\right)}{99} \tag{12}$$

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, 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. 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 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}.

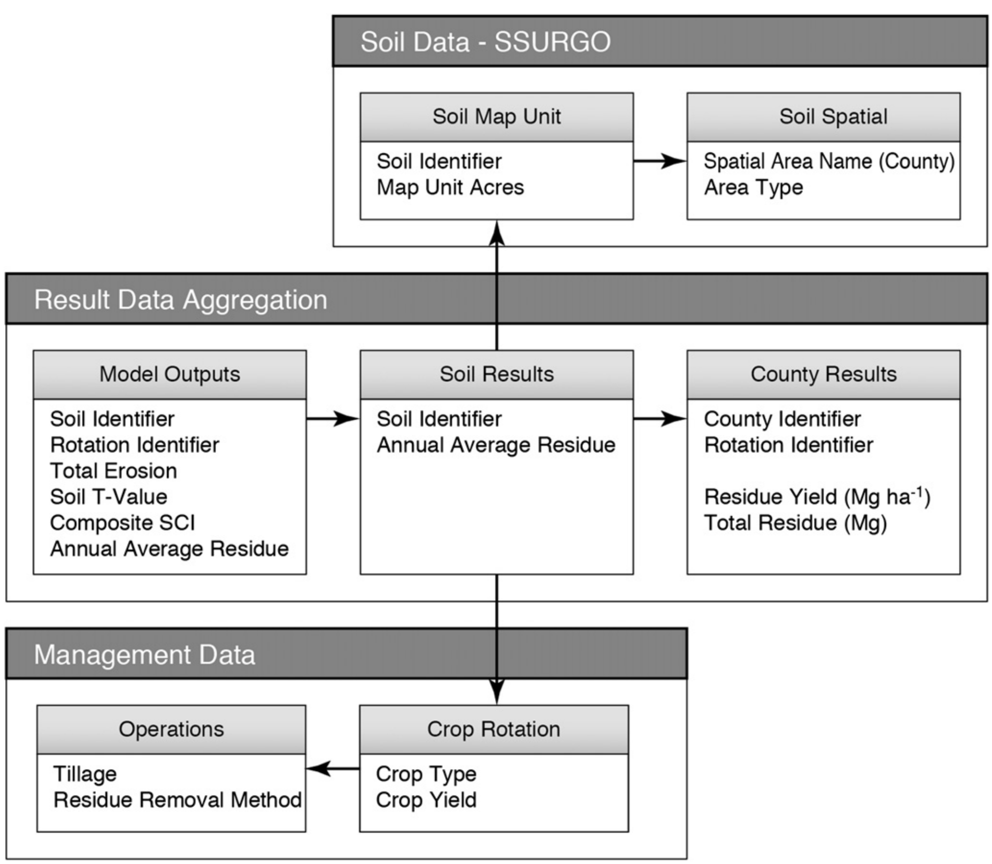


Fig. 13. The "by soil type" results were written to an SQLite database and the pictured query structure was developed to process the results for scenarios of interest.

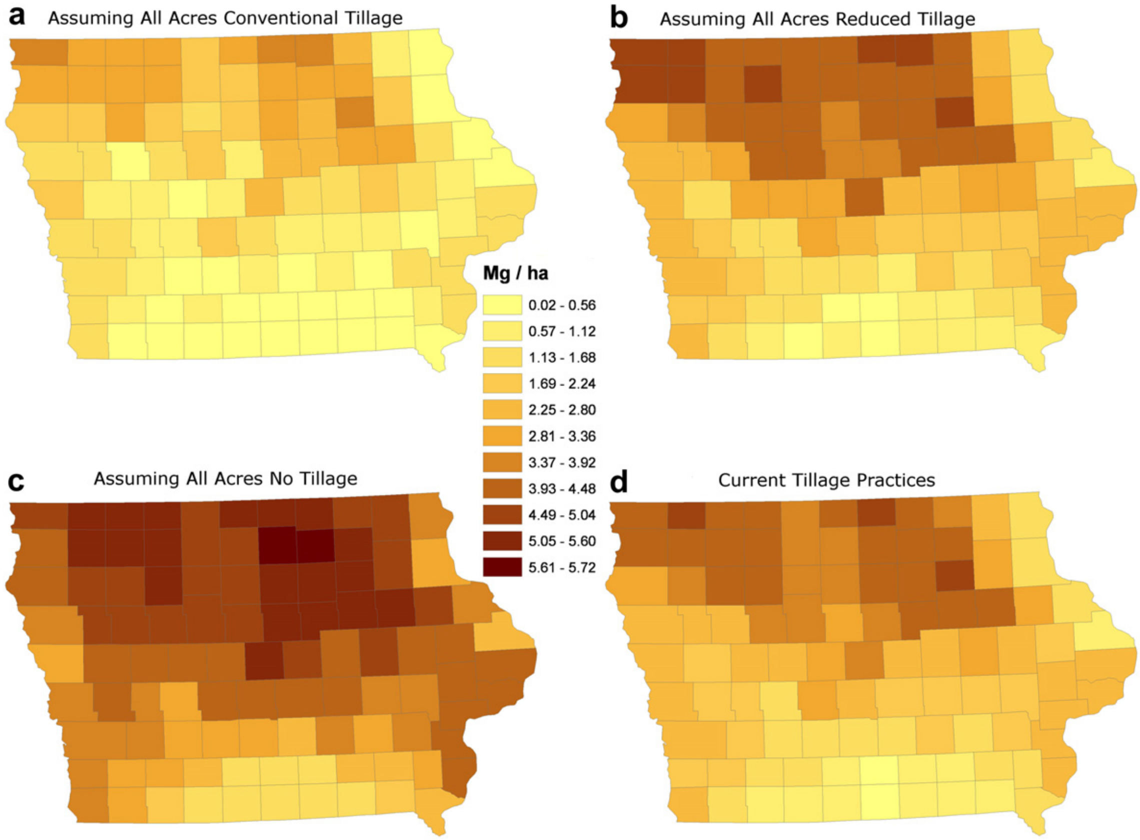


Fig. 14. County level residue yield for each of the three tillage management approaches, and the current tillage practices scenario are presented.

The current total removal potential equates to 27% of the residue produced.

The final column of Table 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 utilizes crop production data from 1995 to 2000, and this study uses data from 2006 to 2010. Because of this, the Graham et al. study is based on significantly less 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 2000 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 (8.8 liters gasoline equivalent [lge]). Recent International Energy Agency projections estimate advanced biofuel production capacity will reach more than 35 billion lge by 2020 (International Energy Agency, 2012). The results from this study show that sustainable

Table 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

agricultural residue removal in the state of Iowa can provide nearly one quarter of the feedstock required for this estimate. 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.

Comparing the tillage scenarios in Fig. 14 provides several conclusions. Counties in the northwest and north central parts of the state show less sensitivity to tillage. Fig. 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. Eq. (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.

$$TS_i = \left(\frac{AY_{i_{CT}}}{AY_{i_{NT}}}\right) \tag{13}$$

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. 11) and tillage sensitivity (Fig. 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. 15 in conjunction with the final column of Table 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.

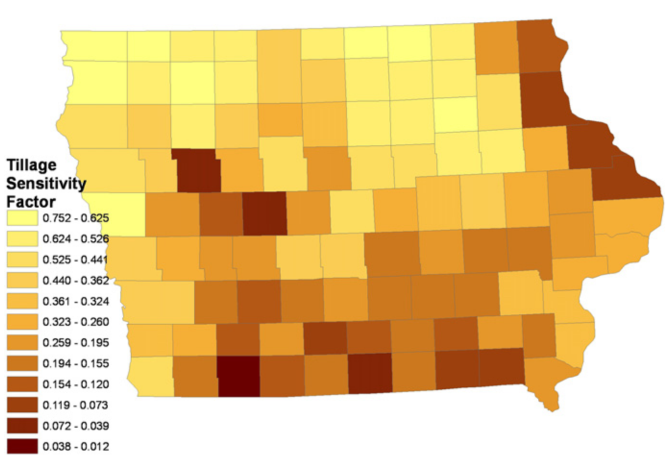


Fig. 15. Identifying if residue removal in a particular area is sensitive to tillage is important because that area may require management changes from current practices to establish sustainable residue harvest. Lower sensitivity to tillage is desirable in this scenario.

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 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 9 presents a subset of these comparisons. Specifically, Table 9 shows two unique soils from Adair County, Iowa. The "876B Ladoga silt loam, benches, 2–5 percent slopes" represents a higher organic matter and moderate slope soil, while the "175C2 Dickinson fine sandy loam, 5–9 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 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 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

Table 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, 2–5 percent slopes
Corn–Soybean Rotation: Reduced Tillage Practices

Corn Yield: 10.03 Mg ha^{-1} Soybean Yield: 2.82 Mg ha^{-1}							Corn Yield: 7.53 Mg ha^{-1} Soybean Yield: 1.88 Mg ha^{-1}						
Removal Rate	Model Outputs (Erosion Rates in Mg ha^{-1})						Removal Rate	Model Outputs (Erosion Rates in Mg ha^{-1})					
	WEPS Integrated	WEPS NRCS	RUSLE2 Integrated	RUSLE2 NRCS	SCI Integrated	SCI NRCS		WEPS Integrated	WEPS NRCS	RUSLE2 Integrated	RUSLE2 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	MHH	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}						
Removal Rate	Model Outputs (Erosion Rates in Mg ha^{-1})						Removal Rate	Model Outputs (Erosion Rates in Mg ha^{-1})					
	WEPS Integrated	WEPS NRCS	RUSLE2 Integrated	RUSLE2 NRCS	SCI Integrated	SCI NRCS		WEPS Integrated	WEPS NRCS	RUSLE2 Integrated	RUSLE2 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	MHH	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

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 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 9, the sustainable residue removal conclusions were the same between the NRCS field office and integrated models.

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 be able 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.

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 straightforward with the existing framework. Models without 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 models available 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. For example, the frequency and intensity of extreme events such as high winds and intense rainfall associated with climate change could increase the negative environmental impacts of residue removal, specifically erosion (Bates et al., 2008). 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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References

Aden, A., Ibsen, K., Jechura, J., Neeves, K., Sheehan, J., et al., 2002. Lignocellulosic Biomass to Ethanol Process Design and Economics Utilizing Co-current Dilute Acid Prehydrolysis and Enzymatic Hydrolysis for Corn Stover. NREL/TP-510-32438.

Adler, P.R., Del Grosso, S.J., Parton, W.J., 2007. Life-cycle assessment of net greenhouse-gas flux for bioenergy cropping systems. Ecol. Appl. 17 (3), 675–691.

Allan, B., Armstrong, R., Lefantzi, S., Ray, J., Walsh, E., Wolfe, P., 2005. Ccaffeine: A CCA Component Framework for Parallel Computing. Common Component Architecture Forum. http://www.cca-forum.org/ccafe (last retrieved accessed 15.06.11.).

Argent, R.M., Voinov, A., Maxwell, T., Cuddy, S.M., Rahman, J.M., Seaton, S., et al., 2006. Comparing modelling frameworks—a workshop approach. Environ. Modell. Softw. 21 (7), 895–910.

Arnaud, R., Barnes, M.C., 2006. COLLADA: Sailing the Gulf of 3D Digital Content Creation. A. K. Peters, Ltd., Wellesley, MA.

Ascough II, J.C., Flanagan, D.C., David, O., 2005. Assessing the potential of the object modeling system (oms) for erosion prediction modeling. In: Proceedings 05-211. 2005 ASAE Annual International Meeting, Tampa, FL.

AspenTech, 2011. http://www.aspentech.com (last accessed 15.06.11.).

Bates, B., Kundzewicz, Z.W., Wu, S., Palutikof, J. (Eds.), 2008. Climate Change and Water. Technical Paper of the Intergovernmental Panel on Climate Change. IPCC Secretariat, Geneva.

Bauen, A., Kaltschmitt, M., 2001. Current use and potential of solid biomass in developing countries and their implications for CO_2 emissions. In: Proceedings of the 1st World Biomass Conference. James & James, London.

Bernholdt, D.E., Allan, B.A., Armstrong, R., Bertrand, F., Chiu, K., Dahlgren, T.L., et al., 2006. A component architecture for high-performance scientific computing. Int. J. High Perform. Comput. Appl. 20, 162–202.

Branger, F., Braud, I., Debionne, S., Viallet, P., Dehotin, J., Henine, H., Nedelec, Y., Anquetin, S., 2010. Towards multi-scale integrated hydrological models using the LIQUID® framework. Overview of the concepts and first application examples. Environ. Modell. Softw. 25 (12), 1672–1681.

Conservation Technology Information Center, 2011. University of Purdue. http://www.citc.purdue.edu/ (last accessed 21.06.11.).

Dabney, S.M., Yoder, D.C., Foster, G.R., Nearing, M.A., 2006. Application of RUSLE2 to pasturelands. In: Proceedings of the 14th International Soil Conservation Organization Conference, Marrakesh, Morocco.

David, O., Markstrom, S.L., Rojas, K.W., Ahuja, L.R., Schneider, I.W., 2002. The object modeling system. In: Ahuja, L., Ma, L., Howell, T.A. (Eds.), Agricultural System Models in Field Research and Technology Transfer. Lewis Publishers, Boca Raton, FL, pp. 317–331.

Del Grosso, S.J., Mosier, A.R., Parton, W.J., Ojima, D.S., 2005. DAYCENT model analysis of past and contemporary soil N_2O and net greenhouse gas flux for major crops in the USA. Soil Tillage Res. 83 (1), 9–24.

Distributed Interactive Simulation Committee of the IEEE Computer Society, 1998. IEEE standard for distributed interactive simulation – application protocols. IEEE Std. 1278. 1a-1998. doi:10.1109/IEEESTD.1998.88572.

Energy Independence and Security Act (EISA) of 2007. H.R. 6, 110th Cong.

Feikema, P.M., Sheridan, G.J., Argent, R.M., Lane, P.N.J., Grayson, R.B., 2011. Estimating catchment-scale impacts of wildfire on sediment and nutrient loads using the E2 catchment modelling framework. Environ. Modell. Softw. 26 (7), 913–928.
Foster, G.R., Yoder, D.C., Weesies, G.A., Toy, T.J., 2003. The design philosophy behind RUSLE2: evolution of an empirical model. In: Ascough II, J.C., Flanagan, D.C. (Eds.), Proceedings of the Soil Erosion Research for the 21st Century. Honolulu, HI. ASAE Proc. Int. Symp. Report No. 701P0007, St. Joseph, MI, pp. 95–98.
Foster, G.R., Romkens, M.J., Dabney, S.M., 2006. Soil erosion predictions from upland areas: a discussion of selected RUSLE2 advances and needs. In: Proceedings of the Sino-American Workshop on Advanced Computational Modeling in Hydroscience and Engineering, Beijing, China.
Gassman, P.W., Osei, E., Saleh, A., Rodecap, J., Norvell, S., Williams, J., 2006. Alternative practices for sediment and nutrient loss control on livestock farms in northeast Iowa. Agric. Ecosyst. Environ. 117 (2–3), 135–144.
Goodall, J.L., Robinson, B.F., Castronova, A.M., 2011. Modeling water resource systems using a service-oriented computing paradigm. Environ. Modell. Softw. 26 (5), 573–582.
Graham, R.L., Nelson, R., Sheehan, J., Perlack, R.D., Wright, L.L., 2007. Current and potential US corn stover supplies. Agron. J. 99, 1–11.
Gregersen, J.B., Gijsbers, P.J.A., Westen, S.J.P., 2007. OpenMI: open modelling interface. J. Hydroinformatics 9 (3), 175–191.
Gregg, J.S., Izaurralde, R.C., 2010. Effect of crop residue harvest on long-term crop yield, soil erosion, and nutrient balance: trade-offs for a sustainable bioenergy feedstock. Biofuels 1 (1), 69–83.
Hagen, L.J., 2004. Evaluation of the Wind Erosion Prediction System (WEPS) erosion submodel on cropland fields. Environ. Modell. Softw. 19 (2), 171–176.
Hagen, L.J., Wagner, L.E., Tatarko, J., 1996. Wind Erosion Prediction System (WEPS) Technical Documentation: BETA Release 95–08. http://www.weru.ksu.edu/weps/docs/weps_tech.pdf (last accessed 21.06.11.).
Hai-yan, L., Zheng-yi, H.U., Rui-jie, Z., Yu-wan, P., Xiao-feng, Y., Yong-hong, W.U., 2010. Spatial variability of nitrogen in soils in farmland adjacent suburban villages at northern bank of Dianchi Lake. J. Agro-Env. Sci. 8, 1618–1623.
Halim, R., Clemente, R.S., Routray, J.K., Shrestha, R.P., 2007. Integration of biophysical and socio-economic factors to assess soil erosion hazard in the Upper Kaligarang Watershed, Indonesia. Land Degrad. Dev. 18 (4), 453–469.
Hess, J., Kenney, K.L., Wright, C.T., Perlack, R., Turhollow, A., 2009a. Corn stover availability for biomass conversion: situation analysis. Cellulose 16 (4), 599–619.
Hess, J.R., Wright, C.T., Kenney, K.L., Searcy, E.M., 2009b. Uniform-Format Solid Feedstock Supply System: A Commodity-Scale Design to Produce an Infrastructure-Compatible Bulk Solid from Lignocellulosic Biomass. Idaho National Laboratory, USDOE. INL/EXT-09-15423.
Hughes, D.A., Louw, D., 2010. Integrating hydrology, hydraulics and ecological response into a flexible approach to the determination of environmental water requirements for rivers. Environ. Modell. Softw. 25 (8), 910–918.
International Energy Agency (IEA), 2011. Technology Roadmap: Biofuels for Transport. http://www.iea.org/papers/2011/Biofuels_Roadmap.pdf (last accessed 31.03.12.).
Ismail, J., 2008. RUSLE2 model application for soil erosion assessment using remote sensing and GIS. Water Resour. Manage. 22 (1), 83.
Johnson, J.M.F., Reicosky, D., Allmaras, R., Archer, D., Wilhelm, W., 2006. A matter of balance: conservation and renewable energy. J. Soil Water Cons. 61 (4), 120A–125A.
Johnson, J.M.F., Papiernik, S.K., Mikha, M.M., Spokas, K.A., Tomer, M.D., Weyers, S.L., 2009. Soil processes and residue harvest management. In: Lal, R., Steward, B. (Eds.), Advances in Soil Science: Soil Quality and Biofuel Production. CRC Press, Boca Raton, FL, pp. 1–44.
Karlen, D.L., Andrews, S.S., Wienhold, B.J., Doran, J.W., 2003. Soil quality: humankind's foundation for survival. J. Soil Water Cons. 58 (4), 171–179.
Karlen, D.L., Tomer, M.D., Neppel, J., Cambardella, C.A., 2008. A preliminary watershed scale soil quality assessment in north central Iowa, USA. Soil Tillage Res. 99 (2), 291–299.
Kragt, M.E., Newham, L.T.H., Bennett, J., Jakeman, A.J., 2011. An integrated approach to linking economic valuation and catchment modeling. Environ. Modell. Softw. 26 (1), 92–102.
Larson, W.E., 1979. Crop residues: energy production or control?. In: Effects of Tillage and Crop Residue Removal on Erosion, Runoff, and Plant Nutrients Soil Conservation Society of America Special Publication No. 25, pp. 4–6.
Lloyd, W., David, O., Ascough II, J.C., Rojas, K.W., Carlson, J.R., Leavesley, G.H., et al., 2011. Environmental modeling framework invasiveness: analysis and implications. Environ. Modell. Softw. 26 (10), 1240–1250.
LMS International, 2011. Solutions Overview: 3D Virtual Prototype Simulation – LMS Virtual Lab. LMS Engineering Innovation. http://www.lmsintl.com/virtuallab (last accessed 15.06.11.).
Malleron, N., Zaoui, F., Goutal, N., Morel, T., 2011. On the use of a high-performance framework for efficient model coupling in hydroinformatics. Environ. Modell. Softw. 26 (12), 1747–1758.
MathWorks, 2011. Simulink – Simulation and Model-Based Design. The MathWorks, Inc. http://www.mathworks.com/products/simulink/ (last accessed 27.06.11.).
McCool, D.K., Foster, G.R., Yoder, D.C., 2004. The Revised Universal Soil Loss Equation, Version 2 (RUSLE2). In: Proceedings of the 13th International Soil Conservation Organization Conference (ISCO 2004). Paper No. 665. Brisbane, Australia.
McCorkle, D.S., Bryden, K.M., 2007. Using the Semantic Web technologies in virtual engineering tools to create extensible interfaces. Virtual Reality 11 (4), 253–260.
Merot, A., Bergez, J.-E., 2010. IRRIGATE: a dynamic integrated model combining a knowledge-based model and mechanistic biophysical models for border irrigation management. Environ. Modell. Softw. 25 (4), 421–432.
Nelson, R.G., 2002. Resource assessment and removal analysis for corn stover and wheat straw in the Eastern and Midwestern United States: rainfall and wind-induced soil erosion methodology. Biomass Bioenergy 22, 349–363.
Nelson, R.G., Walsh, M.E., Sheehan, J.J., Graham, R.L., 2004. Methodology for estimating removable quantities of agricultural residues for bioenergy and bioproduct use. Appl. Biochem. Biotechnol. 113, 0013–0026.
NRCS, 2011a. Wind Erosion Equation—Management Period Method Microsoft Excel Spreadsheet. http://www.mt.nrcs.usda.gov/technical/ecs/agronomy/technotes/agtechnoteMT76/ (last accessed 15.06.11.).
NRCS, 2011b. Revised Universal Soil Loss Equation, Version 2 (RUSLE2). Official NRCS RUSLE2 Program. http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm (last accessed 15.06.11.).
NRCS, 2011c. Official NRCS-WEPS Site. Wind Erosion Prediction System. http://www.weru.ksu.edu/nrcs/wepsnrcs.html (last accessed 15.06.11.).
OpenDX, 2011. The Open Source Software Project Based on IBM's Visualization Data Explorer. http://www.opendx.org (last accessed 15.06.11.).
Osei, E., Gassman, P.W., Hauck, L.M., Jones, R., Beran, L., Dyke, P.T., et al., 2003. Environmental benefits and economic costs of manure incorporation on dairy waste application fields. J. Environ. Manage. 68 (1), 1–11.
Padula, S.L., Gillian, R.E., 2006. Multidisciplinary environments: a history of engineering framework development. In: Proceedings of the 11th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference. AIAA Report No. 2006-7083. Portsmouth, VA.
Parton, W.J., Hartman, M., Ojima, D., Schimel, D., 1998. DAYCENT and its land surface submodel: description and testing. Global Planet. Change 19, 35–48.
Pepper, D.A., Del Grosso, S.J., McMurtrie, R.E., Parton, W.J., 2005. Simulated carbon sink response of shortgrass steppe, tallgrass prairie and forest ecosystems to rising [CO_2], temperature and nitrogen input. Global Biogeochem. Cycles 19.
Perlack, R.D., Wright, L.L., Turhollow, A.F., Graham, R.L., Stokes, B.J., Erbach, D.C., 2005. Biomass as Feedstock for a Bioenergy and Bioproducts Industry: The Technical Feasibility of a Billion-Ton Annual Supply. DOE OBP. DOE/GO-102005-2135.
Phoenix Integration, 2008. PHX ModelCenter® 10.0. http://www.phoenix-int.com/software/phx_modelcenter.php (last accessed 15.06.11.).
Powers, S.E., Ascough, L.A., Nelson, R.G., 2008. Soil and water quality implication associated with corn stover removal and herbaceous energy crop production in Iowa. In: Proceedings of the 2008 ASABE Annual International Meeting. Paper No. 083916, Providence, RI.
Pro-Trax Suite Simulation Software, 2011. http://www.traxintl.com/simulator-systems/simulation-software (last accessed 15.06.11.).
Rahman, J.M., Seaton, S.P., Perraud, J.-M., Hotham, H., Verrelli, D.I., Coleman, J.R., 2003. It's TIME for a new environmental modelling framework. In: Post, D.A. (Ed.), MODSIM 2003 International Congress on Modelling and Simulation, 4, pp. 1727–1732.
Ramin, M., Stremilov, S., Labencki, T., Gudimov, A., Boyd, D., Arhonditsis, G.B., 2011. Integration of numerical modeling and Bayesian analysis for setting water quality criteria in Hamilton Harbour, Ontario, Canada. Environ. Modell. Softw. 26 (4), 337–353.
Rejesus, R.M., Hornbaker, R.H., 1999. Economic and environmental evaluation of alternative pollution-reducing nitrogen management practices in central Illinois. Agric. Ecosyst. Environ. 75 (1), 41–53.
Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., Yoder, D.C., coordinators, 1996. Predicting Soil Erosion by Water: a Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). USDA Agricultural Research Service, Agricultural Handbook Number 703. US Govt. Printing Office, Washington, DC.
Richard, T.L., Van Ouwerkerk, E., Anex, R., 2007. I-FARM – a decision tool for biomass production. In: 29th Symposium on Biotechnology for Fuels and Chemicals. Denver, CO.
Rizzoli, A.E., Leavesley, G., Ascough II, J.C., Argent, R.M., Athanasiadis, I.N., Brilhante, V., et al., 2008. Integrated modelling frameworks for environmental assessment and decision support. In: Jakeman, A.J., Voinov, A.A., Rizzoli, A.E., Chen, S.H. (Eds.), 2008. Environmental Modelling, Software, and Decision Support: State of the Art and New Perspectives, vol. 3. Elsevier, Amsterdam.
Schmitt, L.K., 2009. Developing and applying a soil erosion model in a data-poor context to an island in the rural Philippines. Environ. Dev. Sust. 11 (1), 19–42.
Schmitz, O., Karssenberg, D., van Deursen, W.P.A., Wesseling, C.G., 2009. Linking external components to a spatio-temporal modelling framework: coupling MODFLOW and PCRaster. Environ. Modell. Softw. 24 (9), 1088–1099.
Schweitzer, C., Priess, J.A., Das, S., 2011. A generic framework for land-use modelling. Environ. Modell. Softw. 26 (8), 1052–1055.
Scientific Computing and Imaging Institute (SCI Institute), 2011. SCIRun. http://www.sci.utah.edu/cibc/software/106-scirun.html (last accessed 15.06.11.).
Secchi, S., Babcock, B.A., 2007. Impact of High Crop Prices on Environmental Quality: a Case of Iowa and the Conservation Reserve Program. Center for Agricultural and Rural Development, Iowa State University. Paper No. 07-WP 447.
Simulia™, 2011. Execution Engine (formerly Fiper). http://www.simulia.com/products/see.html (last accessed 15.06.11.).
Soanes, C., Stevenson, A., 2005. Concise Oxford English Dictionary. Oxford University Press, New York.
Stehfest, E., Heistermann, M., Priess, J.A., Ojima, D.S., Alcamo, J., 2007. Simulation of global crop production with the ecosystem model DayCent. Ecol. Modell. 209 (2–4), 203–219.

Thomson, A.M., Izarrualde, R.C., West, T.O., Parrish, D.J., Tyler, D.D., Williams, J.R., 2009. Simulating Potential Switchgrass Production in the United States. Pacific Northwest National Laboratory, USDOE. Contract No. DE-AC05–76RL01830.

Tritthart, M., Welti, N., Bondar-Kunze, E., Pinay, G., Hein, T., Habersack, H., 2011. Modelling highly variable environmental factors to assess potential microbial respiration in complex floodplain landscapes. Environ. Modell. Softw. 26 (9), 1097–1111.

USDA, 2011a. Cligen Overview. http://www.ars.usda.gov/Research/docs.htm?docid=18094 (last accessed 15.06.11.).

USDA, 2011b. Web Soil Survey. http://websoilsurvey.nrcs.usda.gov/app/HomePage.htm (last accessed 21.06.11.).

USDA, 2011c. National Agricultural Statistics Service. http://www.nass.usda.gov/ (last accessed 27.06.11.).

van Delden, H., Seppelt, R., White, R., Jakeman, A.J., 2011. A methodology for the design and development of integrated models for policy support. Environ. Modell. Softw. 26 (3), 266–279.

Vaszita, E., Siki, Z., Gruiz, K., 2009. GIS-based quantitative hazard and risk assessment of an abandoned mining site. Land Contam. Rec. 17 (3–4), 513–529.

Wagner, L.E., Tatarko, J., 2001. Demonstration of the WEP 1.0 wind erosion model. In: Ascough II, J.C., Flanagan, D.C. (Eds.), Proceedings of the Soil Erosion Research for the 21st Century. Honolulu, HI, 3–5 January 2001. ASAE Proc. Int. Symp. Report No. 701P0007, St. Joseph, MI, pp. 372–375.

Wagner, L.E., Tartarko, J., Skidmore, E.L., 1992. WIND-GEN: a Statistical Database and Generator for Wind Data. ASAE 1992 International Summer Meeting. Paper No. 922111. Charlotte, NC.

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

Wilhelm, W.W., Hess, R.J., Karlen, D.L., Johnson, J.M.F., Muth, D.J., Baker, J.M., et al., 2010. Balancing limiting factors and economic drivers for sustainable mid-western agricultural residue feedstock supplies. Ind. Biotechnol. 6 (5), 271–287.

Williams, J.R., Arnold, J.G., Srinivasan, R., Ramanarayanan, T.S., 1998. APEX: a new tool for predicting the effects of climate and CO_2 changes on erosion and water quality. In: Boardman, J., Favis-Mortlock, D. (Eds.), Modelling Soil Erosion by Water. Springer-Verlag, Berlin, pp. 441–449.

Zobeck, T.M., Crownover, J., Dollar, M., Van Pelt, R.S., Acosta-Martinez, V., Bronson, K.F., et al., 2007. Investigation of soil conditioning index values for southern high plains agroecosystems. J. Soil Water Conserv. 62 (6), 433–442.

Zobeck, T.M., Halvorson, A.D., Wienhold, B., Acosta-Martinez, V., Karlen, D.L., 2008. Comparison of two soil quality indexes to evaluate cropping systems in northern Colorado. J. Soil Water Conserv. 63 (5), 329–338.