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Modeled and Measured Ecosystem Respiration in Maize–Soybean Systems Over 10 Years

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Abstract

Crop residue is an abundant resource for the potential production of biofuels, but a better understanding of its use on net carbon emissions must be developed to mitigate climate change. This analysis combines two established crop growth models (Hybrid-Maize and SoySim) with a simple soil and crop residue respiration model to estimate daily ecosystem respiration (ERe) from maize and soybean; ERe was estimated to be the sum of CO₂ emissions from the oxidation of the growing crop, crop residue, and soil organic carbon (SOC). Model-estimated CO₂ fluxes from irrigated continuous maize and irrigated maize–soybean cropping systems in eastern Nebraska were compared with tower eddy covariance measurements of CO₂ fluxes from 2001 to 2010 from those fields. Modeled C emissions closely estimated measured seasonal patterns of CO₂ dynamics and measured daily ERe (R^2 : 0.87, 0.84). Measured and modeled annual ERe values were also compared and better agreement was found in maize compared to soybean. As there are limited comparisons of modeled soil emissions with eddy covariance measured CO₂ fluxes, this study is important for the validation of these types of models and to support their potential use in quantifying emissions from crop residue for biofuels.

Core Ideas:

- The combination of crop and soil models can predict daily measured CO₂ emissions.
- Crop residue is the main source of carbon inputs to soil and largely determines soil organic carbon.
- Where residue is removed for biofuels, increased carbon emissions will occur.

Abbreviations:

CARB	California Air Resources Board
DM	dry matter
ERe	ecosystem respiration
GPP	gross primary production
GHG	greenhouse gas
LAI	leaf area index
LCA	life cycle assessment
ME	modeling efficiency
NAE	normalized average error
NEE	net ecosystem exchange
NMAE	normalized mean absolute error
Re	respiration
RMSE	root mean square error
SOC	soil organic carbon
SOM	soil organic matter
T	temperature



Federal and state policies seek to reduce greenhouse gas (GHG) emissions from transportation fuels, but the estimation of emissions from biofuels has been highly controversial due to data scarcities, uncertainty in designating systems boundaries and timescales, and the need to account for dispersed biospheric C emissions (Liska, 2014b, 2015). Bioenergy is often not 'C neutral' because it can reduce the amount of C stored in terrestrial ecosystems and thus contribute net C emissions to the atmosphere (Searchinger et al., 2008; Haberl et al., 2012). Some analyses have indicated that water and nutrient inputs to agriculture can produce excess crop residue above that needed to maintain soil organic carbon (SOC), thus contributing net C sequestration (Wilhelm et al., 2007; Johnson et al., 2014). Yet the amount of C input from residue needed to maintain SOC is spatially variable, with areas of high SOC requiring greater C inputs (Liska et al., 2014a). Furthermore, some proponents of residue use for biofuels suggest that excess residue from continuous maize (*Zea mays*) in some locations is disruptive to continuously high crop yields, and should be removed. These circumstances raise a number of questions: How much

does crop residue use for biofuels reduce agricultural SOC stocks and how does this impact net C emissions to the atmosphere? How C-intense are the resulting biofuels and what factors determine this intensity? Research suggests that crop residue use for biofuels reduces SOC and increases C emissions, and these emissions are probably significant relative to other emissions in the life cycle, although many conflicting circumstances and interpretations may limit the estimated magnitude of these emissions (Liska et al., 2014a, 2014b; Jones et al., 2017; Ruis and Blanco-Canqui, 2017; Qin et al., 2018; Adler et al., 2015). To better understand variable site-specific C dynamics, modeling of C emissions is essential to geographically estimate the rate of conversion of SOC and crop residue to CO₂, and to generalize results to a larger region as guidance for relevant biofuel producers.

Quantification of marginal changes in C emissions from biofuel production using crop residue must follow similar precedents in the life cycle assessment (LCA) of biofuel emissions. A paradigm shift in the accounting of biofuel emissions came with the recognition that indirect land use change and associated C emissions can be consistently estimated using econometric models (Searchinger et al., 2008; Hertel et al., 2010; Liska, 2015). Quantification of indirect land use emissions assumes that a marginal increase in demand from a new biofuel industry will transmit a commodity price increase to global agricultural markets that in turn will drive a marginal conversion of forests to agricultural land, largely in the tropics, with a resulting marginal increase in net C emissions to the atmosphere (Liska, 2015). The inclusion of these indirect land use emissions in the rule-making of the Renewable Fuel Standard by the USEPA and in the Low Carbon Fuel Standard by the California Air Resources Board (CARB) has made recognition of these marginal emissions a precedent in biofuel emissions accounting. Similar marginal C emissions from crop residue for biofuels should be quantified and included in life cycle emissions used by regulators (Liska et al., 2014a, 2014b).

When crop residues are removed and converted to biofuels, they are burned to CO₂ within roughly a year, and are converted to CO₂ significantly faster than when left on the field where decomposition is a slower process (Liska et al., 2014a). Regional average emissions estimates are needed for regulators, because regulators have tended to not have the resources to evaluate every individual producer; however, where biofuel producers reduce energy use in refining, CARB does allow individual biofuel producers to submit individual processing efficiencies. The USEPA and CARB currently do not recognize marginal residue C emissions from biofuels made with crop residue. Absolute changes in SOC are strictly

not relevant for these emissions estimates (as there can be slight gains or losses), because LCA needs to estimate the relative change in emissions compared to a counterfactual circumstance; i.e., changes in emissions from the use of crop residue need to be estimated relative to the site-specific emissions where residue has not been removed, according to similar methods used in econometric models (Liska et al., 2014b). Marginal C emissions then must be normalized to quantify C emissions per unit energy in biofuel, a metric used by regulators. Because similar amounts of C are burned per unit of energy, all crop residue removal levels have been found to produce the same C emissions per unit of biofuel energy, which means that lowering residue removal levels to reduce total C emissions does not change the marginal C intensity of biofuels from crop residue calculated in regulatory LCAs (Liska et al., 2014a).

In *Factors of Soil Formation* (Jenny, 1941), Hans Jenny, former President of the Soil Science Society of America, first used a first-order kinetic equation to describe the exponential decomposition rate of change of SOC to CO₂ (Nieder and Benbi, 2008). Modifications of this simple equation have been shown to reliably estimate SOC decomposition in a range of soils and climates (Jenkinson et al., 1991; Greenland et al., 1992; Vleeshouwers and Verhagen, 2002; Kutsch et al., 2009; Lal and Stewart, 2010). These equations are a simple approach to help us understand the rate that both crop residues and SOC decompose to CO₂. Exponential coefficients for use in a modified equation were independently derived from 306 measured data sets from 36 studies from Europe, North America, Asia, Africa, Australia, New Zealand, and South America (Yang and Janssen, 2000, 2002; Liska et al., 2014a). Use of these coefficients in the model have been shown to estimate annual tower eddy covariance measured CO₂ emissions from SOC and crop residue with ~10% error in a long-term continuous maize field experiment (Liska et al., 2014a). The model estimates that whereas only ~10% of SOC under continuous maize in Nebraska is oxidized after 10 yr, ~45% of maize residue has oxidized after 1 yr, ~70% of residue has oxidized after 2 yr, 80% after 3 yr, and ~90% after 10 yr; these values closely correspond to field measurements of biomass (Fig. S1 in Liska et al., 2014a).

Quantification of CO₂ fluxes into and from agroecosystems due to photosynthesis and respiration can be estimated with continuous long-term tower eddy covariance measurements. These techniques provide reasonably accurate point-scale measurements of the net exchange of CO₂ in agroecosystems (Goulden et al., 1996; Baldocchi, 2003; Richardson and Hollinger, 2005; Papale et al., 2006), but these micrometeorological

methods cannot directly distinguish between different crop and soil processes contributing to the measured ecosystem respiration (ERe) (Verma et al., 2005; Suyker and Verma, 2010, 2012). Alternatively, soil and crop process models can differentiate among different sources and sinks to estimate changes in ERe and SOC (Liska et al., 2014a; Kutsch et al., 2009; Yang and Janssen, 2000, 2002; Vleeshouwers and Verhagen, 2002; Yang et al., 2004, 2006a, 2006b; Setiyono et al., 2010). For model validation, long-term CO₂ flux measurements associated with extensive supplementary field measurements are considered more accurate and precise than direct soil measurements of SOC over interannual timeframes and for those changes on a timescale of roughly 5 yr (Rodeghiero et al., 2009; Falloon and Smith, 2009; Liska et al., 2014b). The accuracy of soil measurements of SOC are limited due to the high spatial variability in SOC stocks, the inability to detect a small annual percentage change, and failure to express SOC measurements on an equivalent soil mass basis to account for changes in soil bulk density, among numerous other methodological issues (Leifeld and Fuhrer, 2010; Falloon and Smith, 2009; Rodeghiero et al., 2009). There has also been relatively little stringent testing of SOC process models using CO₂ flux measurements from tower eddy covariance, since the original development (~70 yr ago) of these types of models (Falloon and Smith, 2009; Kucharik, 2006). Models are necessary to confidently estimate small percentage interannual changes in regional SOC stocks due to respiration (Falloon and Smith, 2009), as extensive gas exchange measurements are too costly. Agricultural C dynamics are mostly determined by crop physiology and phenology (Yang et al., 2004; Setiyono et al., 2010), soil variables (Kutsch et al., 2009; Falloon and Smith, 2009), climatic variables (Kutsch et al., 2009; Verma et al., 2005; Suyker and Verma, 2010, 2012; Falloon and Smith, 2009), and management practices (Liska et al., 2014a; Powlson et al., 2014). In practice, it is well understood that SOC can be increased by increasing C inputs from residue (Lal, 2004). Alternatively, where crop residue is removed for biofuels compared to no removal, C inputs to soil can be significantly reduced and life cycle C emissions can be increased, due to biomass processing and use as biofuels.

The goal of this study is to compare a relatively simple soil C model with daily C emissions measured by eddy covariance to better estimate changes in emissions from the use of crop residue for biofuels (Liska et al., 2014a). Specifically, the objectives of this study were to test the daily accuracy of a soil model for estimating C emissions from soil and crop residue by combining this model with two crop models to estimate ERe.

To evaluate the accuracy of the combined models, estimated emissions were then compared to eddy covariance flux measurements of ecosystem respiration in maize–soybean (*Glycine max*) systems over 10 yr in Nebraska. Overall, this analysis sought to build confidence in the accuracy of relatively simple modeling approaches that may be useful in addressing C emissions from the use of crop residue.

Materials and Methods

Experimental Maize and Soybean Field Sites

Two large production-scale fields sites (~50 ha each) located near Mead, NE, have been in no-till or limited tillage since 2001. Both fields, US-NE1 (doi:10.17190/AMF/1246084) and US-NE2 (doi:10.17190/AMF/1246085), are a part of the Ameriflux Network (<http://ameriflux.lbl.gov/>). In 2005, US-NE1 was tilled due to declining yields associated with continuous maize production and conservation plow methods were introduced and continued each year thereafter. Crop management practices (i.e., plant populations, herbicide and pesticide applications, irrigation) have been employed in accordance with the standard best management practices prescribed for production-scale maize–soybean systems in the region (Verma et al., 2005; Suyker and Verma, 2010, 2012). Each year, maize and soybean yield and total dry matter were measured, and harvest index was calculated. The C content for each organ of maize and soybean were determined as previously described (Verma et al., 2005). The amounts of crop residue C on each site were estimated using measured yield and the harvest index, then the amount of root C kept in the field was estimated using the root-to-shoot ratio of 0.16 at physiological maturity (Amos and Walters, 2006) to conform to methods by Biscoe et al. (1975); see below. Dates of planting/emergence/harvest, plant population, crop yield, and crop C sequestration were recorded (Table 1).

Measurements from 2001 to 2010 reported here include daily CO₂ flux measurements using eddy covariance and crop residue biomass (Table 1). Daily maize and soybean respiration (Crop Re) was modeled using the Hybrid-Maize and Soysim models, respectively, and Eq. [7], and CO₂ from crop residue (Residue Re) and SOC (Soil Re) were estimated using Eq. [3] for both experimental field sites based on field micrometeorological measurements and previously derived parameter values (Table 2); further details on the modeling approach are below.

Table 1. Measured maize and soybean yields and carbon inputs at the two experimental field sites. Root C inputs were estimated, see *Methods*. For data 2001–2008, see Suyker and Verma (2010, 2012).

Year	Planting/emergence/ harvest dates	Crop yield Mg ha ⁻¹	GPP g C m ⁻²	Grain C g C m ⁻²	Residue C g C m ⁻²	Root C g C m ⁻²
Maize						
2001	10 May/16 May/18 Oct.	13.51	1929	521	486	78
2002	9 May/18 May/4 Nov.	12.97	1799	503	446	71
2003	15 May/27 May/27 Oct.	12.12	1676	470	438	70
2004	3 May/13 May/15 Oct.	12.24	1664	470	382	61
2005	4 May/17 May/13 Oct.	12.02	1617	447	436	70
2006	5 May/16 May/5 Oct.	10.46	1622	401	327	52
2007	10 May/18 May/5 Nov.	12.80	1900	487	416	67
2008	29 Apr./9 May/18 Nov.	11.99	1781	447	407	65
2009	20 Apr./5 May/9 Nov.	13.35	1952	501	520	83
2001	11 May/18 May/22 Oct.	13.41	1736	518	446	71
2003	14 May/25 May/23 Oct.	14.00	1898	538	454	73
2005	2 May/14 May/17 Oct.	13.24	1704	488	407	65
2007	2 May/11 May/5 Nov.	13.21	1848	496	416	67
2009	21 Apr./6 May/10 Nov.	14.18	1981	531	556	89
Soybean						
2002	20 May/28 May/7 Oct.	3.99	1071	183	268	43
2004	2 Jun/8 June/18 Oct.	3.71	935	171	163	26
2006	12 May/23 May/5 Oct.	4.36	983	199	377	60
2008	15 May/25 May/9 Oct.	4.22	899	188	266	43

Modeling of Soil Organic Carbon and Crop Residue Oxidation

One of the simplest models of SOC dynamics quantifies the change in SOC relative to the quantity of the initial soil C pool (C_s) multiplied by a negative rate constant ($-k_1$) to account for oxidative loss to CO_2 , plus C inputs from new plant substrates (C_r) at a specified rate (k_2) (Paustian et al., 1997; Bayer et al., 2006; Kutsch et al., 2009; Nieder and Benbi, 2008), where t is an annual interval, as shown:

$$\frac{dC}{dt} = -k_1 C_s + k_2 C_r \quad [1]$$

To predict SOC amounts due to soil oxidation at any time t (without C inputs), the first term of Eq. [1] can be integrated, as shown in Eq. [2]. A more developed form of the Eq. [2] is Eq. [3], where Q_{10} is the temperature coefficient with actual (T_a) and reference (T_r) temperatures, respectively ($Q_{10}^{(T_a - T_r)/T_r} \cdot t$). Oxidation of SOC to CO_2 is estimated based on initial SOC (C_{s0}), C inputs from agricultural residue and roots (C_{r0}), and average

daily temperature (T_a) (Liska et al., 2014a; Yang and Janssen, 2000, 2002; Vleeshouwers and Verhagen, 2002); C_t is the SOC pool (g C m^{-2}) at a given time in Eq. [2] and Eq. [3]:

$$C_t = C \cdot e^{-k \cdot t} \quad [2]$$

$$C_t = C_{s0} \cdot e^{-k_s \cdot \left[\sum Q_{10}^{(T_a - T_r)/T_r} \cdot t \right]^{(1-S_s)}} + C_{r0} \cdot e^{-k_r \cdot \left[\sum Q_{10}^{(T_a - T_r)/T_r} \cdot t \right]^{(1-S_r)}} \quad [3]$$

Exponential oxidation coefficients in Eq. [3] for SOC (k_s , S_s) and cereal crop residues (k_r , S_r) were derived from field measurements (306 datasets from 36 field studies) across North America, Europe, Africa, and Asia, covering a wide range of residue substrates, soil types, and climatic conditions globally (Yang and Janssen, 2002). The cellulose, hemicellulose, and protein in crop residue rapidly oxidize, and the exponential term ($1 - S$) reduces k through time to simulate the declining rate of oxidation of plant material (Conant et al., 2011), with relatively stable lignin being ~18% of maize residue mass (Liska et al., 2014a). The initial average rate coefficients for soil organic matter (SOM) and plant residues are k_s and k_r (units, $\text{day}_{(1-S)}$) and the speed of ageing of SOM and plant residues are S_s and S_r (unitless for $0 \leq S \leq 1$), respectively (Table 2). An additional term in the equation is added for each year of new C inputs to soil from residue and roots, making Eq. [3] a multi-pool SOC model.

The SOC decomposition rate, like most biological reactions, tends to double for every 10°C rise in temperature ($Q_{10} = 2$) (Davidson and Janssen, 2006; Kutsch et al., 2009). If the actual daily average temperature (T_a) is greater than the reference temperature (T_r , 10°C), T_r is subtracted from T_a and divided by T_r and placed as an exponent on Q_{10} in the model; this term is the temperature coefficient (T_{co}). If T_a is less than T_r then T_{co} is assumed to change linearly with T_a , with a rate of 0.1 per degree of T_a ; no oxidation occurs below a measured temperature of 0°C . The sum of T_{co} (total heat accumulated) determines the amount of C remaining at time t in Eq. [3].

Decomposition rates were modeled for all C components (initial SOC and 9 yr of residue inputs) at both field sites based on measured daily average temperature data and measured C_{s0} and C_{r0} values (Table 1). Inputs of C to soil at Mead were based on measured grain and residue yield, and estimated root biomass (Suyker and Verma 2010, 2012; see above, Amos and Walters, 2006). The dynamics of SOC and crop residue were estimated to only 30 cm of soil depth, which is estimated to contain ~66%

Table 2. Model inputs and major parameters for estimation of crop and soil respiration.†

	<i>Crop models: Hybrid-Maize/SoySim</i>			<i>Soil model</i>	
	<i>Maize</i>	<i>Soybean</i>		<i>residue</i>	<i>SOC</i>
Inputs					
Daily weather data	Tmax, Tmin, solar radiation, precipitation, wind speed, humidity			Tmax, Tmin,	
Field management	Planting date, cultivar maturity, plant density			crop residue C input, date	
Soil characteristics	Soil texture, soil bulk density				Initial SOC
Location	Latitude, longitude			–	
Parameters					
Coefficients, maintenance respiration (fR_m , g CH ₂ O respired g ⁻¹ DM d ⁻¹)	Stover	0.007	0.026(V3,V5), 0.02(R1), 0.01(R3.5), 0.008(R5), 0.005(R7)	–	
	Grain	0.005	0.01	–	
	Root	0.005	0.01(V3, V5), 0.01(R1), 0.01(R3.5), 0.008(R5), 0.005(R7)	–	
Coefficients, growth respiration (fR_g , g CH ₂ O respired g ⁻¹ DM d ⁻¹)	Stover	0.51	0.65	–	
	Grain	0.49	1.17	–	
	Root	0.45	0.56	–	
k (day ^(1-S))	–	–	–	0.149	0.0024
S (dimensionless)				0.66	0.462
Q10		2	2	2	2
Tref (°C)		25	25	10	10

† SOC, soil organic carbon; k, rate constant; S, rate constant; Q10, rate constant; Tref, reference temperature; Tmax, maximum temperature; Tmin, minimum temperature.

of root C in maize and soybean (Yang et al., 2006b). To increase the accuracy of the estimation of CO₂ emissions from crop residue, a 10-d lag time was used before oxidation would begin in all of the simulations.

Models for Maize and Soybean Growth and Respiration

Hybrid-Maize and SoySim are process models that simulate maize and soybean phenology and leaf area index (LAI) under growth conditions, dry matter production from photosynthesis, and maximum yield potential that is not limited by nutrient deficiencies, toxicities, insect pests, disease, or weeds (Yang et al., 2004, 2006a, 2006b; Setiyono et al., 2010). Phenology, LAI, and dry matter production components interact dynamically and each is influenced by daily weather variables. Model inputs include weather data (i.e., daily solar radiation, maximum and minimum temperatures), planting and harvest dates, and plant population density (Table 1).

Crop respiration was assumed to be the sum of daily maintenance respiration and growth respiration during the growing season. The rate of maintenance respiration (R_m , g C respired m⁻²) differs among different plant organs, and is affected by the amount of live biomass and

temperature (Cannell and Thornley, 2000). The R_m for each organ at day i of the crop growth period is calculated by Eq. [4]:

$$R_{mi} = \text{DMI}_i \times fR_m \times fT_i \quad [4]$$

The effect of temperature (fT_i) on R_m follows the Q_{10} function (Kropff and van Laar, 1993), as shown in Eq. [5], in which T_{ai} is the daily average temperature at day i of the crop growth period, T_r is the reference temperature of 25°C, and Q_{10} is the fractional increase or decrease in respiration rate per 10°C change in temperature:

$$fT_i = Q_{10}^{(T_{ai} - T_r)/10} \quad [5]$$

In Eq. [4], fR_m is the respiration rate per unit of live biomass at T_r (fR_m , g C respired g^{-1} DM d^{-1}). Each organ has a specific coefficient for maintenance respiration. The default values of fR_m used for maize and soybean in our calculations were obtained from the Hybrid-Maize and SoySim models (Table 2). DMI_i is the dry matter of the specific living organ at day i (g m^{-2}), which was calculated on the basis of the daily dry matter of the organ calculated from the Hybrid-Maize and SoySim models. Before the maximum LAI occurred, the modeled daily dry matter of the organ was used as the DMI_i . After the maximum LAI occurred, the ratio of LAI_i at day i to LAI_{\max} was used to calibrate the modeled DM of that day, and their product was assumed as the DMI_i .

Growth respiration (R_g , g C respired m^{-2}) is defined as the amount of carbohydrates respired in processes of converting primary photosynthate to specific organ tissues. This includes the production of energy transfer molecules and reductant for biosynthetic processes, transport processes, and nutrient uptake and reduction. R_g was calculated as the following equation at i day of crop growth period:

$$R_g = \text{netDMI}_i \times fR_g \quad [6]$$

where netDMI_i is a net biomass gain between i day and $i+1$ d of crop growth period ($\text{g m}^{-2} \text{d}^{-1}$) and fR_g is the respiration rate per unit of net biomass gain in dry matter for the specific organ (fR_g , g C respired g^{-1} DM d^{-1}).

Total crop respiration ($TCrop Re$, g C respired m^{-2}) is the sum of maintenance respiration and growth respiration during the period of planting date to harvesting date. It can be calculated as the following:

$$TCrop\ Re = \sum_{i = emergence\ date}^{harvesting\ date} Rmi + \sum_{i = emergence\ date}^{harvesting\ date} Rgi \quad [7]$$

Hybrid-Maize and SoySim were used to predict maximum crop yield potentials under specific climatic and management conditions. The modeled daily dry matter yields were higher than the actual crop yields, because the models estimate maximum crop yield potential as opposed to actual crop yields. The estimated yield was always higher for both maize and soybean with normalized mean absolute error (NMAE) ranging 8–19% for both crops at both field sites. Thus, the ratio of modeled yield to measured yield was used to down scale the modeled daily crop growth and crop respiration: modeled maize in US-NE1 was reduced an average of 19%, maize at US-NE2 by 13%, and soybean at US-NE2 by 8%. Scaled-down yields were used to more accurately reflect actual crop yields at the time to enable a better comparison with eddy covariance measurements.

Estimation of Carbon Budgets for Cropping Systems

On the basis of daily predictions of crop and soil respiration, daily and annual gross primary production (GPP), ERe, and net ecosystem exchange (NEE) of different cropping systems were modeled and compared with the measured values from tower eddy covariance systems. Predictions of daily and annual GPP obtained from Hybrid-Maize for maize and SoySim for soybean were scaled down according to grain yield to improve comparison with CO₂ measurements, using the same method as for respiration. Daily modeled ERe from the cropping systems was the sum of the daily respiration predicted from the crop (Eq. [7]) and from soil and residue (Eq. [3]).

Statistical comparison of daily eddy-covariance-measured ERe and modeled ERe was based on previous methods (Janssen and Heuberger, 1995). Multiple errors metrics were calculated: root mean square error (RMSE), normalized average error (NAE), normalized mean absolute error (NMAE), modeling efficiency (ME), and coefficient of determination (R^2). RMSE indicates accuracy based on the bias of the predictions, whereas NAE, NMAE, and R^2 reflect the level of precision, such that increases in RMSE, NAE, NMAE and decreases in R^2 correspond to increased prediction errors. ME is a measure of the coincidence of observed and modeled data and is sensitive to systematic deviations between model predictions

and observations; ME can range from -1 to 1 , where 1 corresponds to perfect agreement between model predictions and observations.

Dataset Repository

The complete dataset for this article contains calculations for soil organic modeling and comparison of estimated CO_2 emissions with eddy covariance-measured emissions at three field sites, and related measurements and data analysis (doi:10.5061/dryad.r9n6hg4).

Results and Discussion

Modeled oxidation of crop residue and initial SOC indicate that net soil SOC levels remained relatively constant over 10 yr for both continuous maize and maize–soybean rotations (Fig. 1); the model-estimated dynamics were 17% greater compared to limited soil C measurements at US-NE1 conducted in 2001 and 2005 (Liska et al., 2014a). Each individual component of the multi-pool SOC model is reduced over time via oxidation to CO_2 , and the total C remaining in the soil system is the sum of the individual components at any specific time; i.e., at the end of the 10 yr, nine crop residue pools, each at a different stage of decomposition, are summed with the remaining initial SOC pool to estimate total remaining SOC. During the soybean years of rotation at US-NE2, less C was added to soil compared to the maize years of rotation, which led to lower relative levels of SOC. Reduced C inputs to soil from maize residue removal would similarly reduce SOC over time, and the modeled differences between SOC with and without maize residue removal were previously used to estimate C emissions in the LCA of biofuels from crop residue using the same model as applied here (Liska et al., 2014a).

Of the three respiration components, Crop Re had the highest CO_2 flux values, which corresponded to measured and modeled seasonal GPP (data not shown) and stopped at harvest (Figs. 2A, 2C). Maximum maize Crop Re tended to be similar across years and sites, and tended to be higher than soybean Crop Re, as soybean has an average of roughly one-third of the grain and biomass yield of maize (Egli, 2008). Modeled Soil Re was highest in 2001, $3.6\text{--}4.4 \text{ g C m}^{-2} \text{ d}^{-1}$ for the two sites, and had an exponential response to temperature, with minimums of $<0.6 \text{ g C m}^{-2} \text{ d}^{-1}$ in 2010; this is the only modeled continuous variable throughout the entire time span (Figs. 2A, 2C). Crop residue emissions (Residue Re) were between the intensities of Crop Re and Soil Re, with peak intensities at

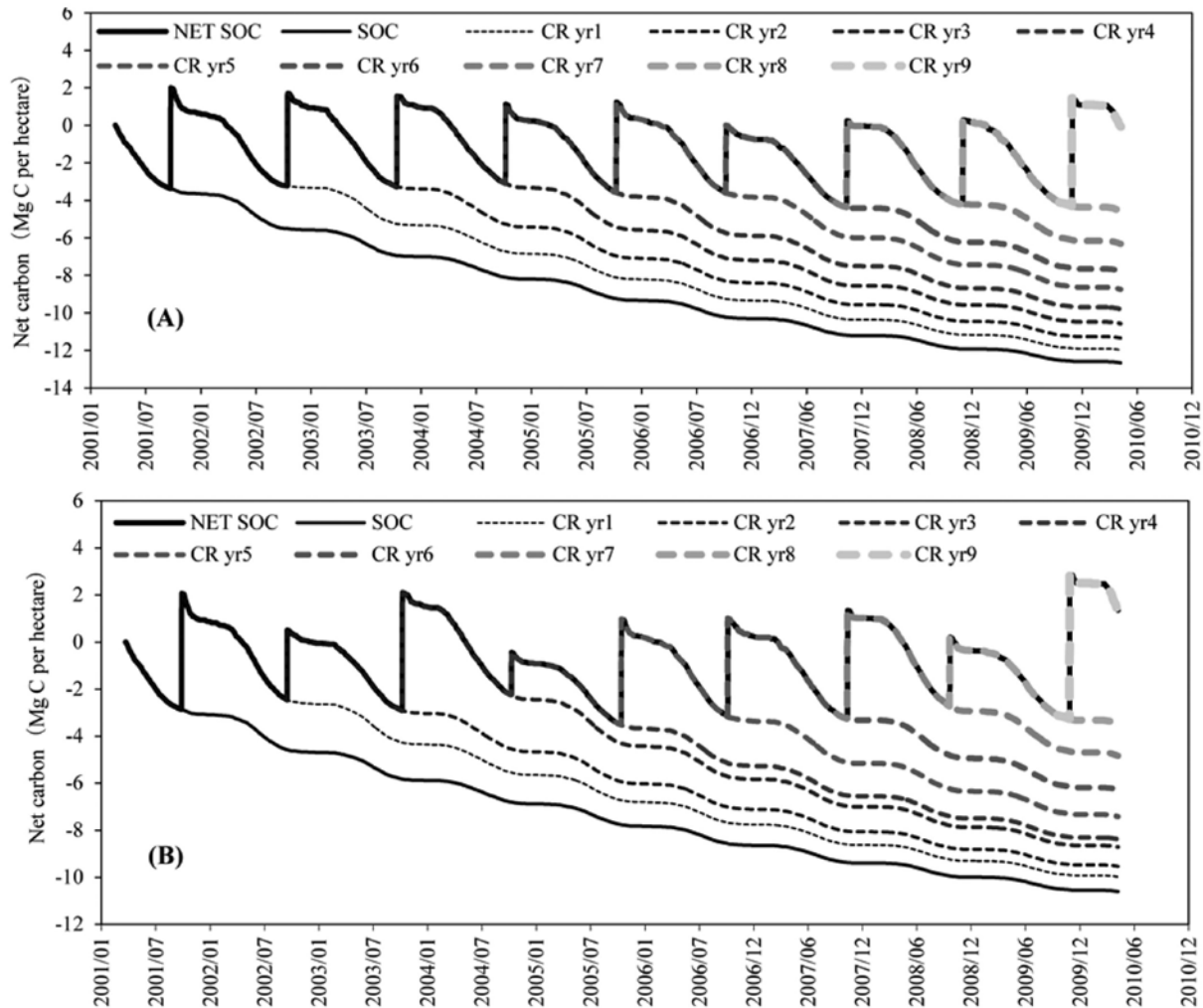


Fig. 1. Crop residue C and soil organic carbon remaining after oxidation in continuous maize (A) and maize-soybean rotations (B). Modeled daily oxidation used Eq. [3] at US-NE1 (A) and US-NE2 (B) from 2001 to 2010, based on measured SOC, crop residue input (CR), and temperature.

harvest when crop residue was first introduced into the system. At grain harvest each year, the component of modeled Residue Re began due to the transition of non-grain crop biomass from photosynthetic metabolism to respiration in crop residue and continued to oxidize until the end of the time span (Figs. 2A, 2C).

The three respiration components for both maize and soybean were summed to estimate daily ERe at both sites (Figs. 2B, 2D). Comparison of eddy-covariance-measured ERe and modeled ERe over time show similar seasonal patterns and maxima and minima for both maize and soybean for both sites (Figs. 2B, 2D). Modeled and measured crop yields

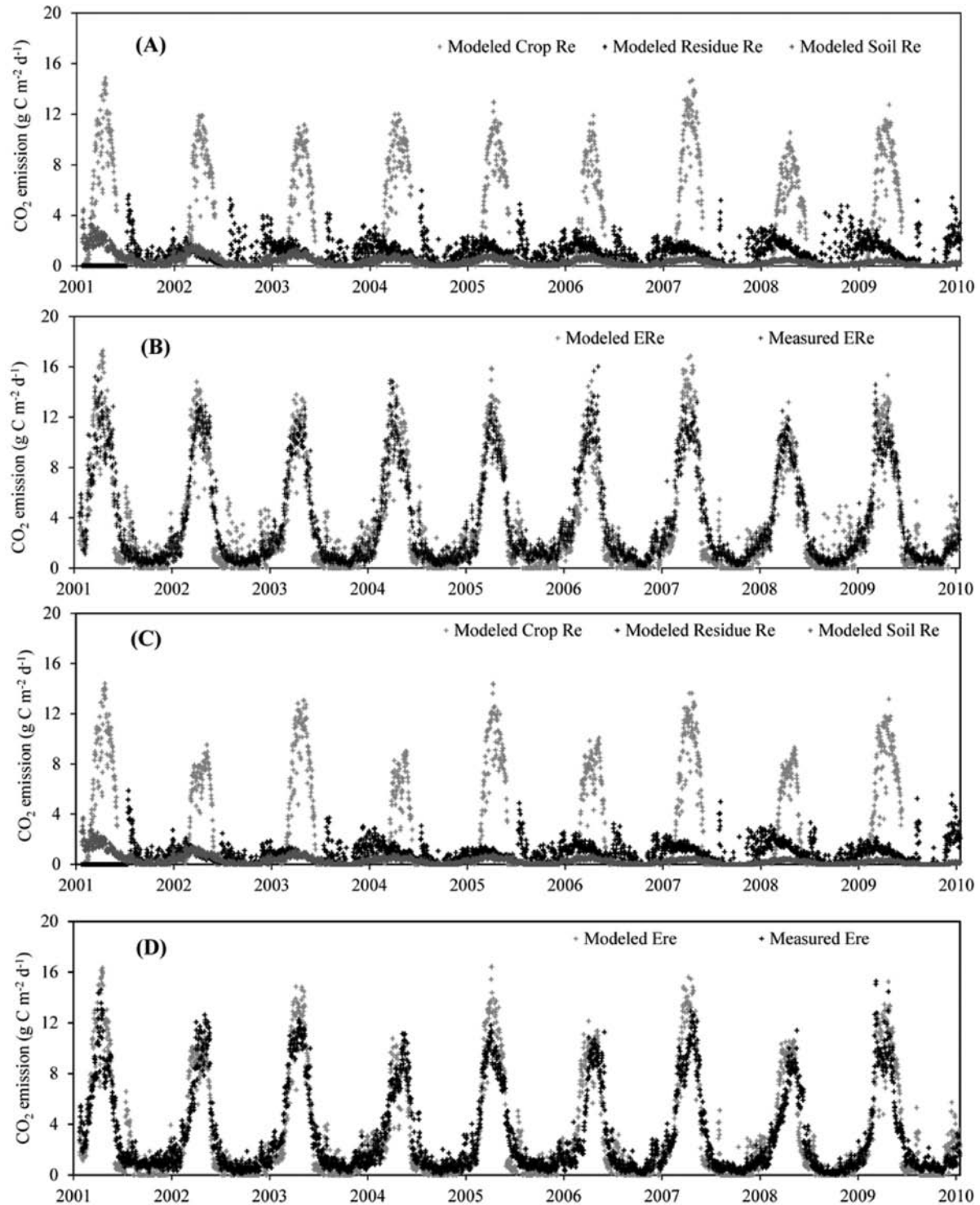


Fig. 2. Daily modeled respiration from maize and soybean (Crop Re), crop residue (Residue Re), and soil organic carbon (Soil Re) at US-NE1 (A) and US-NE2 (C) from 2001 to 2010; (A) and (C) show Residue Re and Soil Re emissions data from Fig. 1A and 1B, in comparison with Crop Re from crop growth models. The three components in (A) and (C) are summed to estimate modeled daily ERe for comparison with eddy-covariance-measured ecosystem respiration (ERe) for US-NE1 (B) and US-NE2 (D) from 2001 to 2010.

were also compared each year and their NMAE were used to down scale the modeled respiration and crop GPP (see *Methods*). From 2001 to 2010, daily values for modeled and measured ERe were highly correlated across both field sites (R^2 : 0.84–0.87; RMSE: 1.52–1.65 $\text{g C m}^{-2} \text{d}^{-1}$; NAE: –9–16%; ME: 0.76–0.84), with the strongest correlation at US-NE1 (Fig. 3A). These measurements and analysis were also conducted at a third field site with dryland maize–soybean rotation, where similar results were found (data not shown), but these results are not shown in the present study due to space limitations.

Modeled daily ERe values were also summed to estimate average annual ERe dynamics (Fig. 4). Modeled ERe for irrigated continuous maize at US-NE1 ranged from 1112–1409 $\text{g C m}^{-2} \text{yr}^{-1}$ with reasonable error compared to annually summed measurements (RMSE: 109 $\text{g C m}^{-2} \text{yr}^{-1}$). US-NE2 had similar modeled values for maize (ERe: 870–1350 $\text{g C m}^{-2} \text{yr}^{-1}$, RMSE: 104 $\text{g C m}^{-2} \text{yr}^{-1}$) and lower values for soybean. Modeled annual ERe had a close agreement with measured annual ERe at both field sites (NAE: –4–3%; NMAE: 3–12%) over the entire study period. Measured ERe was separated into Crop Re and Soil-Residue Re components by subtracting the mass of measured biomass at harvest (grain, residue, and root) from CO_2 fluxes, according to previous methods (Biscoe et al., 1975; Liska et al., 2014a); here measured crop biomass was subtracted from total downward flux, where the remaining downward flux

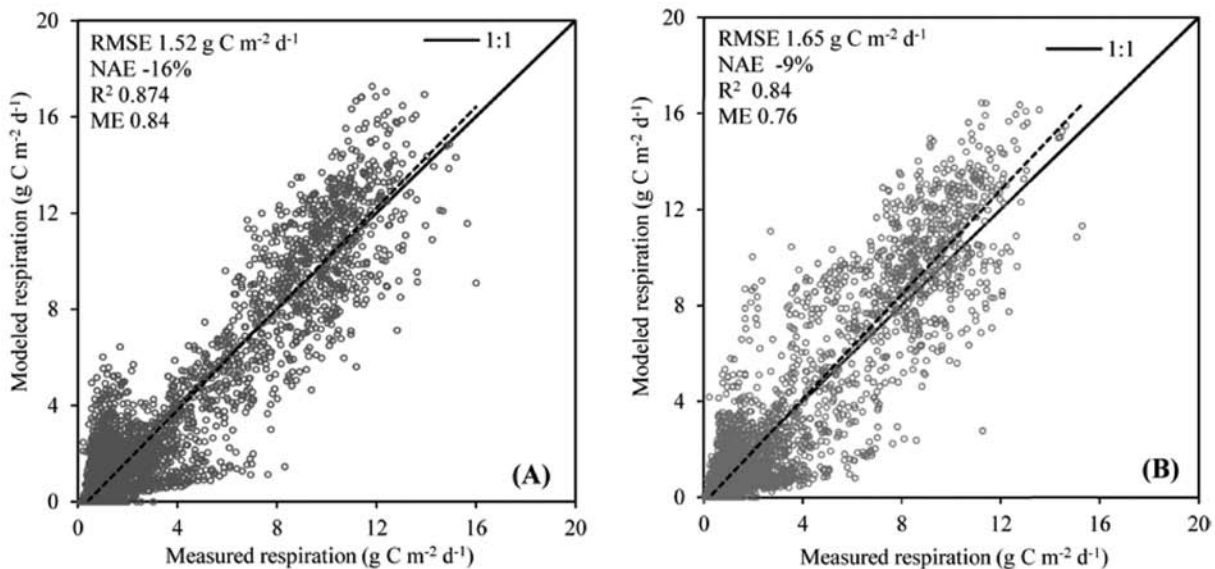


Fig. 3. Statistical comparison of daily eddy-covariance-measured and modeled ecosystem respiration at US-NE1 (A) and US-NE2 (B) ($n = 3285$ per site) from 2001 to 2010, with dashed trend line, based on data shown in Fig. 2B and 2D.

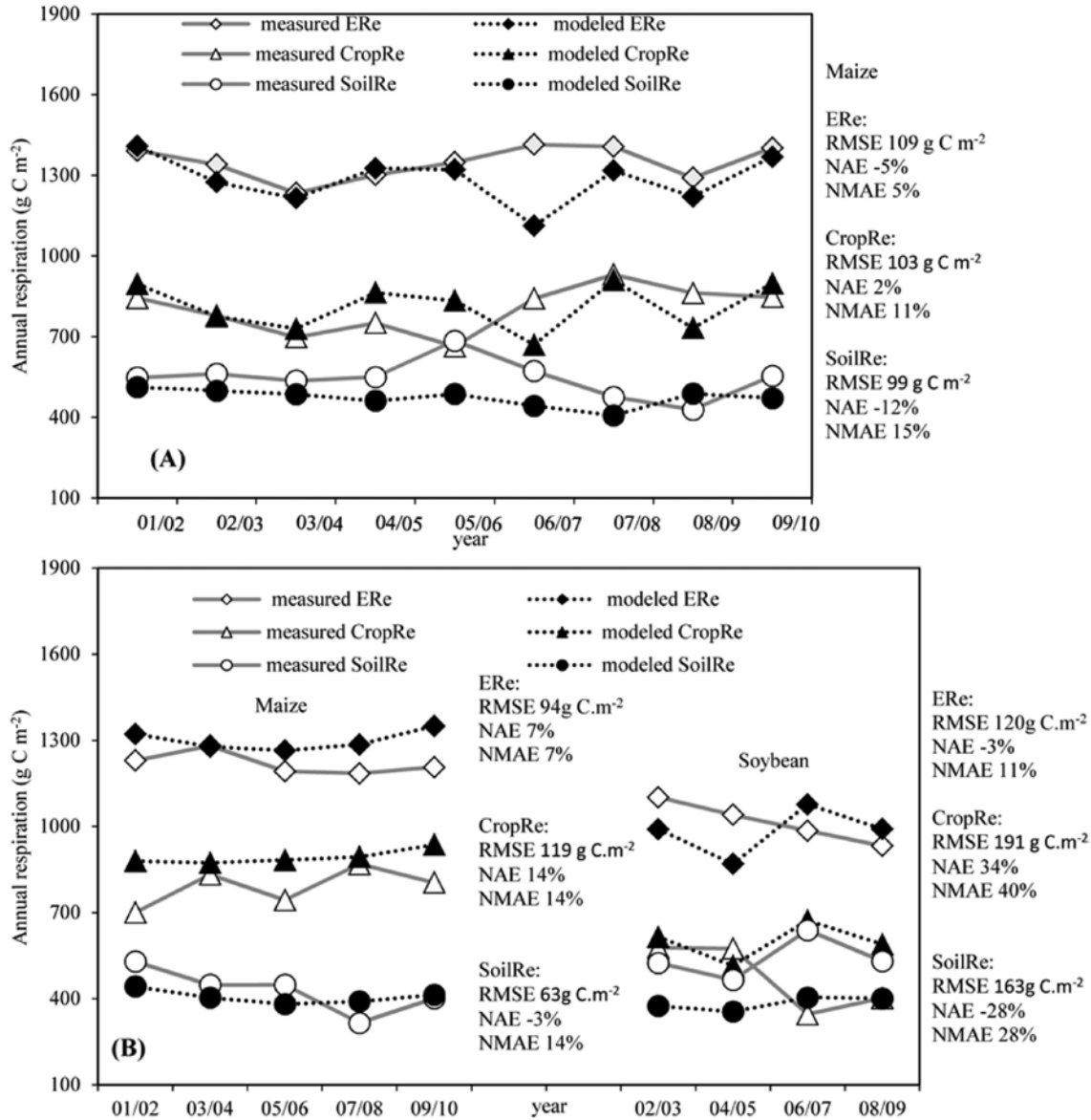


Fig. 4. Statistical comparison of annual eddy-covariance-measured and modeled ecosystem respiration at US-NE1 (A) and US-NE2 (B) from 2001 to 2010. The ERe was separated into emissions from the growing crop (CropRe) and emissions from soil and crop residue (SoilRe), based on data shown in Fig. 2.

not captured in biomass was estimated to be emitted as crop respiration; crop respiration was then subtracted from total upward flux (ERe) to estimate emissions from crop residue and soil (Fig. 4). For irrigated maize, crop respiration contributed 61–70% of modeled annual ERe and 57–73% of measured. The models slightly overestimated annual maize Crop Re

by 2% at US-NE1 and 14% at US-NE2 compared to the measured values. There was close agreement between the contribution of the modeled and measured Soil-Residue Re to ERe at US-NE1 (modeled:measured, 37%:40%); however, for US-NE2 the modeled Soil-Residue Re (35%) contributed less to ERe than measured (45%). Based on daily modeling, crop residue was found to contribute 71% of modeled Soil-Residue Re at US-NE1 and US-NE2 (Fig. 2A,2C), which is 26 and 25% of modeled ERe, respectively. While there may be close agreement between the percentage of Soil-Residue Re contributions to ERe, the soil models underestimated annual Soil-Residue Re at both field sites (NAE: -12 to -15%). In addition, in 2006, an unknown error in the measurement of crop residue appears to have produced a relative increase in Soil Re, based on the relatively increased estimated C input to soil (Fig. 1B).

The measurements and modeling shown here indicate that crop residue is a significant fraction of C emissions from both continuous maize (26%) and maize-soybean (25%) fields. Under continuous maize, both SOC and crop residue contributed ~40% of ERe (Fig. 4), and crop residue contributed ~71% of these emissions (Fig. 2A,2C). As C inputs from maize and soybean roots were estimated with a shoot-to-root ratio of 0.16 (see *Methods*), and comprised 10.6% (66% of 0.16) of residue C inputs to soil at 30 cm depth (Table 1), the mass of this relatively uncertain C pool only contributes an average of 5% of ERe at US-NE1; if actual root C were greater, then C inputs in residue would increase accordingly and increase estimated ERe; in a previous geospatial analysis using this model, a shoot-to-root ratio of 0.29 was used to not underestimate total C inputs to soil (Liska et al., 2014a, 2014b); but to separate soil and residue emissions from the growing crop emissions, 0.16 was used to estimate C captured in biomass at physiological maturity in accordance with previous methods to estimate annual emissions for comparison with the eddy covariance flux data (Liska et al., 2014a; Biscoe et al., 1975). Furthermore, the soil model also only estimated changes in the top 30 cm of soil, based on initial measurements of SOC, and modeling to deeper depths would also increase the C input to soil and increase estimated ERe. These approximations used here are still able to estimate the soil and residue ERe fraction with remarkable accuracy compared to the eddy covariance flux data when combined with predominantly standard parameters in the crop and soil models (Table 2). Yet the crop-specific parameters in Hybrid-Maize and SoySim vary with crop varieties and agricultural practices such as fertilization and irrigation; the weaker confidence and accuracy of modeled crop respiration for soybean compared to maize may

be associated with these crop-specific parameters (Fig. 4). While there is uncertainty in the soil and residue ERe models, some of this error can be attributed to the eddy covariance flux data, which includes both instrumentation and modeling uncertainty when estimating GPP, ERe, and NEE (Loescher et al., 2006; Verma et al., 2005).

Overall, these results strongly support previous findings concerning increased emissions from the use of crop residue for biofuels (Liska et al., 2014a); where residue is removed and burned, even greater emissions occur off-site because the C that would have remained in the field is more quickly oxidized to CO₂. Where crop residue is removed for biofuels, modeling shows that this would reduce C input to soil and lower SOC over time (Fig. 1). This analysis shows that use of a relatively simple SOC and residue model is able to estimate the daily rate at which crop residue and SOC oxidize to CO₂ with a high confidence, and further adds to existing models (Conant et al., 2011; Kutsch et al., 2009). These results also demonstrate that the use of residue for biofuels can impact the net C emissions and should be included in LCA results by regulators (Liska et al., 2014a, 2014b; Qin et al., 2018). New C inputs, such as in the form of cover crops, will also be necessary to maintain or increase SOC stocks where residue is removed (Ruis and Blanco-Canqui, 2017).

Conclusions

The analysis finds that the dynamics of crop residue oxidation are well predicted with a high accuracy, and modeling relationships clearly show that crop residue removal for biofuels causes a decrease in C inputs to soil and resulting SOC levels, and an associated increase in C emissions to the atmosphere because the removed C is oxidized at a faster rate as biofuel than when it is returned to soil. Where crop residue is used for biofuels, accelerated C emissions from biofuel oxidation during processing and use will require new C inputs to sustain SOC levels. Where new C inputs are not used, increased C emissions should be included in the regulatory LCAs used by the USEPA and CARB for estimating the emissions from the production of biofuels from crop residue.

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