nature climate change

LETTERS

PUBLISHED ONLINE: 20 APRIL 2014 | DOI: 10.1038/NCLIMATE2187

Biofuels from crop residue can reduce soil carbon and increase CO_2 emissions

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Removal of corn residue for biofuels can decrease soil organic carbon (SOC; refs 1,2) and increase CO_2 emissions[3] because residue C in biofuels is oxidized to CO_2 at a faster rate than when added to soil[4,5]. Net CO_2 emissions from residue removal are not adequately characterized in biofuel life cycle assessment (LCA; refs 6–8). Here we used a model to estimate CO_2 emissions from corn residue removal across the US Corn Belt at 580 million geospatial cells. To test the SOC model[9–11], we compared estimated daily CO_2 emissions from corn residue and soil with CO_2 emissions measured using eddy covariance[12–14], with 12% average error over nine years. The model estimated residue removal of 6 Mg per ha^{-1} yr^{-1} over five to ten years could decrease regional net SOC by an average of 0.47–0.66 Mg C ha^{-1} yr^{-1}. These emissions add an average of 50–70 g CO_2 per megajoule of biofuel (range 30–90) and are insensitive to the fraction of residue removed. Unless lost C is replaced[15,16], life cycle emissions will probably exceed the US legislative mandate of 60% reduction in greenhouse gas (GHG) emissions compared with gasoline.

Crop residues are abundant feedstocks that are used for biofuel production globally[17,18]. By 2022, the US Energy Independence and Security Act (EISA) mandates production capacity for cellulosic ethanol and advanced biofuels to be 61 billion litres per year (bly) and 19 bly, respectively[17]. Corn residue is predominantly used in US cellulosic ethanol biorefineries, with a combined capacity of 0.38 bly in 2014 (ref. 19). An additional 0.42 bly of US hydrocarbon biofuels mostly uses wood[19], but could also be derived from crop residue[20]. Absolute changes in soil organic carbon (SOC) from corn residue removal have been estimated in LCA (ref. 6), but few have estimated net changes in SOC and CO_2 emissions compared with no residue removal[7,8,21,22], as required by consequential LCA (ref. 23).

Recent research suggests soil CO_2 emissions from residue removal could produce life cycle GHG emissions for cellulosic ethanol that exceed the mandated emissions reduction[8]. Incubation experiments with soil and corn residue showed that SOC is oxidized to CO_2 at 0.54–0.80 Mg C ha^{-1} per season when residues are completely removed[3]. Modelled removal of all corn residue in Austria projected an SOC loss of 0.35 Mg C ha^{-1} yr^{-1}, which represents nearly 50% of life cycle GHG emissions from a biorefinery system[24]. Modelled SOC oxidation to CO_2 from removal of sweet sorghum residue showed these emissions could eliminate all GHG emissions benefits of the resulting biofuel compared with gasoline[25]. Similar net losses of C stocks have also been projected for biofuels from forestry in some cases[26].

Changes in SOC occur by two dominant processes: soil erosion by water and wind, and soil respiration where SOC is oxidized to CO_2 (refs 4,5). Soil erosion has significantly depleted SOC across the US Corn Belt, with a recent loss of 1.7 billion tons of soil in the US in 2007 (ref. 27). Crop residue has conventionally been left on the field after harvest to reduce soil erosion and maintain the SOC stocks and soil fertility of the Corn Belt[1]. Although some soil measurements in the Corn Belt have shown that complete residue removal reduces SOC compared with no removal[28,29], other studies found no significant differences[16]. Measuring SOC change accurately is limited owing to the high spatial variability in SOC stocks, the inability to detect a small annual percentage change, short-term studies, and failure to express SOC results in an equivalent mass basis to account for changes in soil bulk density[30,31]. Furthermore, when crop residue is removed, it is essential to determine whether SOC loss is due to erosion or respiration, to accurately estimate the resulting net CO_2 emissions.

Models are necessary to confidently estimate small percentage annual changes in regional SOC stocks due to respiration[30,31], as extensive gas exchange measurements are too costly. Although soil moisture and texture are often used in SOC models[4], a robust model can estimate daily changes in SOC due to oxidation to CO_2 based on initial SOC (C_0), C inputs from agricultural crops (C_i), and average daily temperature (T_a), as shown below[9–11]. The SOC model used here is based on exponential oxidation coefficients for SOC (k_s, S_s) and cereal crop residues (k_r, S_r) from 36 field studies across North America, Europe, Africa and Asia[10] (see Supplementary Table 1 and Methods). An additional term in the equation is added for each year of new C inputs to the soil from residue and roots.

$$C_t = C_0 \cdot e^{-k_s \cdot \left(\Sigma Q_{10}^{\frac{T_a - T_r}{10}} \cdot t\right)^{1-S_s}} + C_i \cdot e^{-k_r \cdot \left(\Sigma Q_{10}^{\frac{T_a - T_r}{10}} \cdot t\right)^{1-S_r}}$$

To test the model in the central US, we compared model results with measured CO_2 emissions, residue biomass, and SOC from an irrigated no-till continuous corn field experiment in eastern Nebraska (Mead) from 2001 to 2010 (refs 12–14). The model estimated that 83% of initial residue C input was oxidized during the first three years, which closely agreed with field measurements that found an average of 20% remained[14] (Supplementary Fig. 1) Cellulose, hemicellulose and protein in residue rapidly oxidize, whereas the more recalcitrant lignin fraction (~18% dry matter[6]) undergoes a slower oxidation process and contributes to SOC (ref. 4). The model estimated 80.9% of initial SOC remained after nine years (56.1 of 69.4 Mg C ha^{-1}) in the 0–30 cm depth, and net C from residue (8.53 Mg C ha^{-1}) contributed to the maintenance of a total of 93.2% of the initial SOC stock (Fig. 1). When compared with soil measurements, the model predicted net SOC loss within

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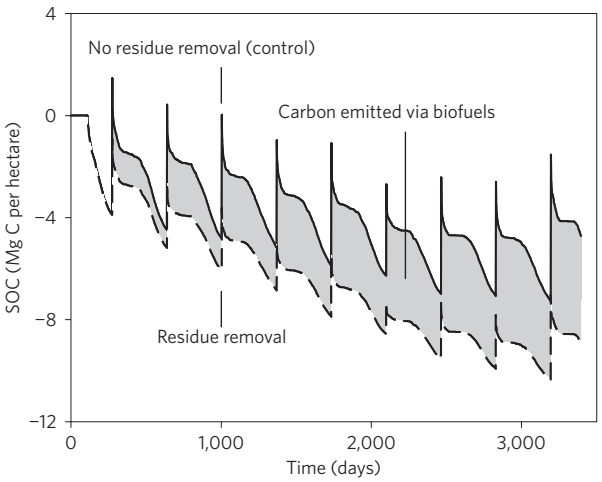

Figure 1 | Modelled soil organic carbon decrease due to removal of 6 Mg corn residue per hectare per year over nine years compared with no removal under irrigated continuous corn. Daily modelled oxidation of soil organic carbon (SOC) and residue to CO_2 is based on field measurements of initial SOC (0–30 cm soil depth), corn residue input, and temperature at Mead, Nebraska. The average annual net loss of SOC is 0.47 Mg C ha^{-1} yr^{-1}, but declines exponentially from 1.13 to 0.25 Mg C ha^{-1} yr^{-1} over the first eight years.

17% accuracy during the first four years of the experiment (Supplementary Table 2). Eddy covariance was used to measure net CO_2 fluxes to the atmosphere to estimate ecosystem respiration, which was partitioned into emissions from crop respiration and from soil and residue[32] (Methods). The model predicted annual measured net CO_2 emissions to the atmosphere from soil and residue with an error of 12.4% on average (range 34 to −22%; Supplementary Tables 3 and 4). While using coefficients for SOC oxidation derived from a global span of field measurements, the modeled SOC dynamics agreed well with the field measurements of CO_2 emissions, residue remaining, and SOC. The global character of the model assumptions combined with these regional tests indicates the model has enough accuracy to confidently estimate the average direction of change in net CO_2 emissions and SOC from residue removal across the Corn Belt.

The model was used to estimate geospatial changes in SOC from hypothetical residue removal under continuous corn across the Corn Belt. Input data included measurement-derived estimates of initial SOC stock (C_0), C inputs from county crop yields (C_i) (2001–2010), and monthly average temperature (T_a, Methods). Four supercomputer simulations (R1–R4) applied the SOC model at 580 million grid cells of size 30 m × 30 m ($> 52 \times 10^6$ ha in total), at monthly intervals from 2001 to 2010: R1 estimated baseline SOC change with no residue removal, and R2, R3, and R4 correspond to 2, 4 and 6 Mg ha^{-1} yr^{-1} residue removal, respectively, with the highest being ∼50–100% removal. To simulate each dry metric ton of residue harvested, C_i was reduced by 0.4 Mg C ha^{-1} yr^{-1}, resulting in a modelled decrease in SOC compared with no removal[33].

To test the geospatial application of the model, we compared simulated oxidation of SOC based on field measurements of initial SOC, crop yield, and temperature at Mead with the geospatial method for the same site. Modelled removal of 6 Mg residue ha^{-1} yr^{-1} based on site measured parameters resulted in an average loss of 0.47 ± 0.29 (s.d.) Mg C ha^{-1} yr^{-1} (range 0.25–1.13) over the nine years compared with no removal (Fig. 1) and the geospatial application found a similar average loss of 0.50 ± 0.34 Mg C ha^{-1} yr^{-1} (Supplementary Fig. 2). This comparison suggests geospatial application of the model using independently derived gridded data agrees well with site-specific modelling based on field measurements for the same site.

Simulated R4 removal across the entire Corn Belt resulted in an average loss of 0.66 ± 0.08 Mg C ha^{-1} yr^{-1} (range 0.17–0.79, Fig. 2b) over the first five years and an average of 0.47 ± 0.4 Mg C ha^{-1} yr^{-1} (range 0.22–0.56, Fig. 2b) for ten years compared with no removal (R1), owing to decreasing C loss over time as SOC reaches a new equilibrium (Fig. 2a,b and Supplementary Table 5). Estimated average trends in SOC across the larger region unexpectedly agreed well with the Nebraska site. Importantly, this loss of SOC as respiration corresponds to only 0.3–0.4% per year of initial average SOC stock for the Corn Belt at 73.8 Mg C ha^{-1} yr^{-1} (0–30 cm depth) (Supplementary Fig. 3 and Table 6). The actual amount of SOC loss to CO_2 on average across the region could be greater than or less than estimated here, but these results indicate the likely direction of change and relative magnitudes. The resulting map indicates that Minnesota, Wisconsin and Iowa have the highest net loss of SOC (Fig. 2a). This region has high SOC stocks from low temperatures, which slow oxidation of SOC and residue, and increase the relative change in SOC from residue removal.

In LCA, emissions of CO_2 from SOC loss in grams per megajoule of biofuel energy (g CO_2 MJ^{-1}) can be determined by dividing the average geospatial emissions by the simulated biofuel energy yield[8]. Cellulosic ethanol yields per ton of residue were from current and expected future commercial production[34]. More energy dense hydrocarbon fuels (for example, FT-diesel) from crop residue have similar energy yields per ton of residue compared to ethanol but they generally have a lower volume yield[20] (Supplementary Table 8). Owing to the LCA calculation, when net SOC losses are divided by the energy yields, R1–R4 estimated CO_2 emissions average 70 ± 6.4 g CO_2 MJ^{-1} (range 30–90, Fig. 2c) and are similar over the first five years for all three residue removal levels (R1–R4, R1–R3, R1–R2). Over ten years, average emissions estimates are lower at 49 ± 4.3 g CO_2e MJ^{-1} (range 33–63) owing to declining C loss over time. Importantly, for the same time interval, the average intensity of CO_2 emissions per amount of residue removed is roughly the same for all removal levels; less residue removed causes less decrease in SOC but is associated with a smaller biofuel energy yield. On a relative basis, biofuels from crop residue yield a low amount of energy and oxidize a large C pool, producing high CO_2 emissions per unit energy, which is similar to the previously identified phenomenon for indirect land use change from biofuels[23,35].

Adding the five-year average emissions to other net production emissions (for example, biorefinery) of about 30 g CO_2-equivalent per megajoule (g CO_2e MJ^{-1}) results in net GHG emissions for cellulosic ethanol at 100 g CO_2e MJ^{-1} (Fig. 3 and Supplementary Tables 7 and 8). The average value is 7% greater than gasoline (93.7 g CO_2e MJ^{-1}; ref. 7), and 62 g CO_2e MJ^{-1} above the 60% GHG reduction set by EISA. The range of SOC loss modelled is 30–90 g CO_2e MJ^{-1} (Fig. 2c and Supplementary Fig. 4), which makes cellulosic ethanol 60–120 g CO_2e MJ^{-1}; decreasing the time interval would further increase these values (Fig. 1). Whereas previous estimates for single locations do not represent regional variability in CO_2 emissions from residue removal[21,22], these average geospatial estimates for the region can be applied to US Environmental Protection Agency standards for the industry (or see Supplementary Fig. 4), irrespective of the amount of crop residue removed, assuming a consistent time interval; these estimates assume that crop residue is removed and no mitigation action is taken, which seems to predominantly occur.

To meet the EISA mandate for cellulosic ethanol and advanced biofuel from corn residue (79.5 bly by 2022), 46 million hectares with a yield of 6 Mg ha^{-1} yr^{-1} is needed, which is 88% of the Corn Belt area modelled. Emissions of CO_2 from SOC in this area would be 81.8–117 Tg CO_2 yr^{-1} (10–5 year average loss rates), equivalent to 1.4–2.0% of net US GHG emissions in 2011.

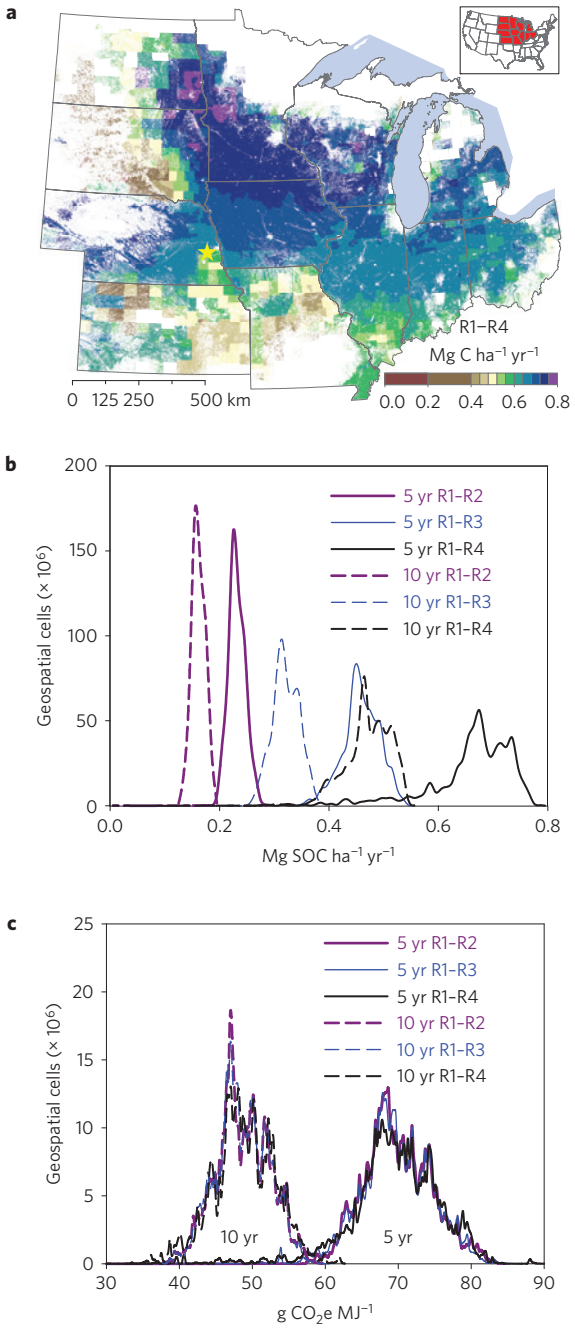

Figure 2 | Modelled soil organic carbon respiration to CO_2 in the US Corn Belt from corn residue removal. **a**, Geospatial modelling of soil organic carbon (SOC) loss from 6 Mg ha^{-1} yr^{-1} of residue removal (first five years) relative to no removal (580 million cells; Mead, Nebraska, is indicated). **b**, Loss of SOC compared with no removal by removal level and time. **c**, CO_2 emissions increase in the biofuel life cycle corresponding to **b**.

Instead of increasing CO_2 emissions and reducing agricultural SOC stocks, an alternative strategy would be to make vehicles more efficient and decrease fuel demand (consistent with the 2012 US CAFE standards), thus potentially making the expanded fuel supply from the RFS2 unnecessary[36]. Alternatively, development of other bioenergy systems, such as perennial grasses or forestry resources, may provide feedstocks that could have less negative impacts on SOC, GHG emissions, soil erosion, food security and biodiversity than from removal of corn residue[36–39].

Soil CO_2 emissions from residue removal, however, can be mitigated by a number of factors and management options. As

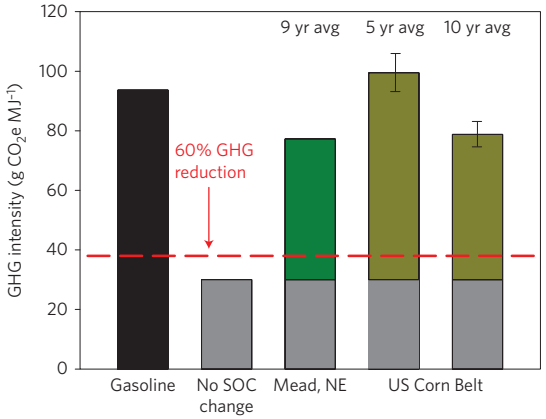

Figure 3 | Contribution of modelled CO_2 emissions from SOC to the life cycle of biofuel from corn residue. Error bars are ± one standard deviation, based on Fig. 2c. Data are also from Fig. 1 and Supplementary Tables 7 and 8.

residue is a source of N_2O emissions, residue removal would lower these emissions by ~4.6 g CO_2e MJ^{-1}, or ~8% of SOC emissions (Supplementary Table 8). The lignin fraction of residue can also potentially be burned to produce electricity, off-setting coal-generated electricity and saving emissions of up to ~55g CO_2 e MJ^{-1} (ref. 7). Furthermore, use of improved soil and crop management practices, such as no-till cover crops, forage-based cropping systems, animal manure, compost, biochar and biofuel co-products, could replace the estimated SOC loss after residue removal[15,16]. These management options require more research under different residue removal practices to ensure SOC stocks are maintained where crop residue is removed.

Methods

Soil organic carbon model. Oxidation rate coefficients were estimated for soil organic matter (SOM) and plant residue (k_S and k_r, respectively) and the rate of ageing of SOM and plant residue (S_S and S_r, respectively) from 306 datasets from 36 studies covering a wide range of residue substrates, soil types and climatic conditions globally[10] (Supplementary Table 1). Average oxidation response due to temperature (Q_{10}) is based on previous research. Decomposition rates were modelled for all C components (nine years of residue inputs and initial SOC) at the field site based on daily average temperature data and measured C_0 and C_i values (Supplementary Fig. 1 and Tables 2,3). If T_a is greater than the reference temperature (T_r, 10 °C), T_a is subtracted from T_r and divided by 10, 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 0 °C. The sum of T_{co} (total heat accumulated) determines the amount of C remaining at time t.

Comparison of model with field CO_2 measurements. Fluxes of CO_2 were measured using tower eddy covariance above continuous corn from 2001 to 2010 at Mead, Nebraska. Inputs of C to soil at Mead were estimated based on measured grain and residue yield, and estimated root biomass (Supplementary Table 3). Measured ecosystem total respiration was partitioned into emissions from: live root and aboveground biomass of the growing crop, irrigation water, and SOC and crop residue (Supplementary Table 4). The gas measurements account for net CO_2 flux from the entire soil profile depth, and modelling of CO_2 emissions from the top 0–30 cm is expected to underestimate measured flux emissions; but as the majority of SOC is often in the top 30 cm in the Corn Belt, modelling the dynamics of this zone would probably account for the majority of emissions.

Geospatial data and supercomputer simulations. A 10 m Soil Survey Geographic grid (gSSURGO) of representative 30 cm depth SOC values was resampled to 30 × 30 m and converted to Mg C ha^{-1} (30 cm)$^{-1}$ (Supplementary Fig. 2). All other spatial inputs were resampled to 30 m and aligned with the SOC grid space using zero-valued SOC masks of the area planted in corn or soybean in 2010. Monthly maximum and minimum average temperatures from the PRISM database (2001–2010) were used. Rainfed county corn grain yield estimates from NASS (2001–2010) were converted to Mg C ha^{-1} yr^{-1} using a harvest index (0.53), and estimated C from roots was added (Supplementary Fig. 2 and Table 3). Simulated removal of C was limited to the actual amount of aboveground C estimated in each grid per year.

A massive amount of data was used to produce these results. Processing on a PC with ESRI's ArcGIS 9.3 limited input file size to the state level (1-2 gigabytes (GB)). Data were analysed using high-performance computer clusters in the Holland Computing Center (HCC) at University of Nebraska-Lincoln (http://hcc.unl.edu) that employ parallel programs to speed up computation. The uncompressed input data totalled ~3 terabytes (TB) and the uncompressed output data totalled > 30 TB. The program split each state's input file into ~40 megabyte (MB) files, and then executed computations on the smaller files in parallel. The output files were then joined together in a single state file, for each of the 12 states. If input files had not been split, the computational speed would have been significantly reduced owing to opening and closing of files and because loading an entire large disk file into memory at once is infeasible.

Received 13 August 2013; accepted 5 March 2014; published online 20 April 2014

References

1. Wilhelm, W. W., Johnson, J. M. F., Karlen, D. L. & Lightle, D. T. Corn stover to sustain soil organic carbon further constrains biomass supply. *Agronomy J.* **99,** 1665–1667 (2007).
2. Anderson-Teixeira, K. J., Davis, S. C., Masters, M. D. & DeLucia, E. H. Changes in soil organic carbon under biofuel crops. *GCB Bioenergy* **1,** 75–96 (2009).
3. Kochsiek, A. E. & Knops, M. H. Maize cellulosic biofuels: Soil carbon loss can be a hidden cost of residue removal. *GCB Bioenergy* **4,** 299–233 (2012).
4. Kutsch, W. L., Bahn, M. & Heinemeyer, A. *Soil Carbon Dynamics: An Integrated Methodology* (Cambridge Univ. Press, 2009).
5. Conant, R. T. *et al.* Temperature and soil organic matter decomposition rates–Synthesis of current knowledge and a way forward. *Glob. Change Biol.* **17,** 3392–3404 (2011).
6. Sheehan, J. *et al.* Energy and environmental aspects of using corn stover for fuel ethanol. *J. Indust. Ecol.* **7,** 117–146 (2004).
7. Spatari, S. & MacLean, H. L. Characterizing model uncertainties in the life cycle of lignocellulose-based ethanol fuels. *Environ. Sci. Tech.* **44,** 8773–8780 (2010).
8. Liska, A.J. in *Sustainable Biofuels: An Ecological Assessment of Future Energy* (eds Bhardwaj A. K., Zenone T. & Chen J. K.) (Walter De Gruyter, in the press).
9. Yang, H. S. & Janssen, B. H. A mono-component model of carbon mineralization with a dynamic rate constant. *Eur. J. Soil Sci.* **51,** 517–529 (2000).
10. Yang, H. S. & Janssen, B. H. Relationship between substrate initial reactivity and residues ageing speed in carbon mineralization. *Plant Soil* **239,** 215–224 (2002).
11. Vleeshouwers, L. M. & Verhagen, A. Carbon emission and sequestration by agricultural land use: A model study for Europe. *Glob. Change Biol.* **8,** 519–530 (2002).
12. Verma, S. B. *et al.* Annual carbon dioxide exchange in irrigated and rainfed maize-based agroecosystems. *Agr. For. Metereol.* **131,** 77–96 (2005).
13. Suyker, A. E. & Verma, S. B. Coupling of carbon dioxide and water vapor exchanges of irrigated and rainfed maize–soybean cropping systems and water productivity. *Agr. For. Metereol.* **150,** 553–563 (2010).
14. Kochsiek, A. E., Knops, J. M. H., Brassil, C. E. & Arkebauer, T. J. Maize and soybean litter-carbon pool dynamics in three no-till systems. *Soil Sci. Soc. Am. J.* **77,** 226–236 (2012).
15. Fronning, B. E, Thelen, K. D & Min, D. Use of manure, compost, and cover crops to supplant crop residue carbon in corn stover removed cropping systems. *Agronomy J.* **100,** 1703–1710 (2008).
16. Blanco-Canqui, H. Crop residue removal for bioenergy reduces soil carbon pools: How can we offset carbon losses? *BioEnergy Res.* **6,** 358–371 (2013).
17. Panoutsou, C., Bauen, A. & Duffield, J. Policy regimes and funding schemes to support investment for next-generation biofuels in the USA and the EU-27. *Biofuel Bioprod. Bioref.* **7,** 685–701 (2013).
18. Solomon, B. D., Barnes, J. R. & Halvorsen, K. E. Grain and cellulosic ethanol: History, economics, and energy policy. *Biomass Bioenergy* **31,** 416–425 (2007).
19. Brown, T. R. & Brown, R. C. A review of cellulosic biofuel commercial-scale projects in the United States. *Biofuel Bioprod. Bioref.* **7,** 235–245 (2013).
20. Cherubini, F. & Strømman, A. H. Production of biofuels and biochemicals from lignocellulosic biomass: Estimation of maximum theoretical yields and efficiencies using matrix algebra. *Energy Fuel* **24,** 2657–2666 (2010).
21. Kim, S., Dale, B. E. & Jenkins, R. Life cycle assessment of corn grain and corn stover in the United States. *Int. J. Life Cycle Assess.* **14,** 160–174 (2009).
22. Gramig, B. M., Reeling, C. J., Cibin, R. & Chaubey, I. Environmental and economic trade-offs in a watershed when using corn stover for bioenergy. *Envir. Sci. Tech.* **47,** 1784–1791 (2013).
23. Liska, A. J. & Perrin, R. K. Indirect land use emissions in the life cycle of biofuels: Regulations versus science. *Biofuel Bioprod. Bioref.* **3,** 318–328 (2009).
24. Cherubini, F. & Ulgiati, S. Crop residues as raw materials for biorefinery systems—A LCA case study. *Appl. Energy* **87,** 47–57 (2010).
25. Wortmann, C. S. *et al.* Dryland performance of sweet sorghum and grain crops for biofuel in Nebraska. *Agronomy J.* **102,** 319–326 (2010).
26. Hudiburg, T. W., Law, B. E., Wirth, C. & Luyssaert, S. Regional carbon dioxide implications of forest bioenergy production. *Nature Clim. Change* **1,** 419–423 (2011).
27. National Resources Conservation Service, *National Resources Inventory, 2007 Annual NRI, Soil Erosion on Cropland.* (US Department of Agriculture, 2010).
28. Clapp, C. E., Allmaras, R. R., Layese, M. F., Linden, D. R. & Dowdy, R. H. Soil organic carbon and 13C abundance as related to tillage, crop residue and nitrogen fertilization under continuous corn management in Minnesota. *Soil Till. Res.* **55,** 127–142 (2000).
29. Karlen, D. L *et al.* Crop residue effects on soil quality following 10-years of no-till corn. *Soil Till. Res.* **31,** 149–167 (1994).
30. Falloon, P. & Smith, P. in *Soil Carbon Dynamics: An Integrated Methodology* (eds Kutsch, W. L., Bahn, M. & Heinemeyer, A.) 221–244 (Cambridge Univ. Press, 2009).
31. Smith, W. N. *et al.* Crop residue removal effects on soil carbon: Measured and inter-model comparisons. *Agr. Ecosyst. Environ.* **161,** 27–38 (2012).
32. Biscoe, P. V., Scott, R. K. & Monteith, J. L. Barley and its environment. III. Carbon budget of the stand. *J. Appl. Ecol.* **12,** 269–293 (1975).
33. Johnson, J. M. F., Allmaras, R. R. & Reicosky, D. C. Estimating source carbon from crop residues, roots and rhizodeposits using the national grain-yield database. *Agronomy. J.* **98,** 622–636 (2006).
34. Kazi, F. K. *et al.* Techno-economic comparison of process technologies for biochemical ethanol production from corn stover. *Fuel* **89,** S20–S28 (2010).
35. Searchinger, T. *et al.* Use of US croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science* **319,** 1238–1240 (2008).
36. Liska, A. J. & Heier, C.D. The limits to complexity: A thermodynamic history of bioenergy. *Biofuel Bioprod. Bioref.* **7,** 573–581 (2013).
37. Blanco-Canqui, H. Energy crops and their implications on soil and environment. *Agronomy. J.* **102,** 403–419 (2010).
38. Tilman, D. *et al.* Beneficial biofuels—the food, energy, and environment trilemma. *Science* **325,** 270–271 (2009).
39. Smith, P. *et al.* How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals? *Glob. Change Biol.* **19,** 2285–2302 (2013).

Acknowledgements

This research was funded by the US Department of Energy (DE-EE0003149) and the Agricultural Research Division of the University of Nebraska and made use of the Holland Computing Center of the University of Nebraska-Lincoln.

Author contributions

A.J.L., H.Y., M.M. and S.G. designed the research; A.J.L., H.Y., M.M., S.G. H.Z., M.P.P., X.X.F. and A.E.S. performed the research; A.J.L., H.Y., M.M., S.G., H.Z., M.P.P., X.X.F. and A.E.S. analyzed the data; and A.J.L., H.Y., M.M., H.B.-C., and A.E.S. wrote the paper.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to A.J.L.

Competing financial interests

The authors declare no competing financial interests.