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Dear Dr. Ito,

Please find attached our response to the reviewers for our manuscript "Modeling the impact of agricultural land use and management on U.S. carbon budgets." Within the response you will find references to the changes we made in the manuscript. Following is a marked up version of the manuscript which contains all the edits that were made to address the reviewer's comments. Please feel free to contact me if you have any questions.

Thank you,

Beth Drewniak

We thank the reviewer for the comments on our manuscript. We believe these comments will significantly improve the manuscript. Our point-by-point response to the review follows.

*The Drewniak et al. article is a modeling study of the effects of crop residue removal, as pertains to cellulosic biofuels, on soil organic carbon. The paper is well written and clearly presented. It is an interesting application of the CLM-Crop model. I suggest the following minor revisions (though the final suggestion could involve some more analysis of the existing model runs and would help enhance the article):*

*Comment: 1. Please cite Melillo et al. (2009) in the Introduction, which explored the effects of land use conversion due to cellulosic biofuels. ( Melillo, J. M., Reilly, J. M, Kicklighter, D. W., Gurgel, A. C., Cronin, T. W., Paltsev, S., Felzer, B. S., Wang, X., Sokolov, A. P., and Schlosser, C. A. 2009. Indirect emissions from biofuels: how important? Science. 326:1397-1399.)*

Response: Thanks for the suggestion, we have included the suggested reference to Melillo et al., in the Introduction (P. 13677, L. 10).

*Comment: 2. The sentence "The use of crop residues for bioethanol production shows promise for meeting U.S. energy needs" in the Introduction needs some further clarification – what is meant by U.S. energy needs exactly?*

Response: We have modified the text to reflect the renewable fuel goals, rather than energy needs (P. 13677 L. 16).

*Comment: 3. Change the color bar in Figure 1c so the numbers match up to the divisions. " In most regions, the percent difference between the data set and the model simulation is < 5 %" – from Figure 1c, a large portion of the Central Plains appear to be > 5%, not just boreal regions.*

Response: Thanks for the suggestion. We have updated the figure to scale more appropriately and to distinguish the 5% color change. There is a swath of the Great Plains where the percent difference is greater than 5%; however the percent difference is still less than 6% in this region.

*Comment: 4. I do like the validation efforts, so I am not asking for more because I know how difficult it is to get models to look exactly like the data. However, the use of "r" rather than "r2" in Figure 3 is nonstandard and makes the correlation look better than it is. I really see no correlation between modeled and observed values – is there any better r2 value for clay, sand, or silt independently? I might instead comment that the overall range of values is captured by the model, in addition to the model underestimate. How does this figure show the model captures the variability?*

Response: The R-square values were small (0.057), even for individual soil textures (Sand $R^2 = 0.03$, Silt $R^2 = 0.11$ and Clay $R^2 = 0.06$). Given the difficulty comparing point field observations with model data, we have modified our comparison approach and created an alternate figure by plotting the mean and standard deviation of observed SOC stocks at the model grid cell resolution, which replaces Figure 3 in the manuscript. The coefficient of determination between observed and predicted values is still small. Our use of the term variability was to highlight that the model predicted large spatial variability in SOC,

which is captured through a wide range of SOC values. We have updated the manuscript to clarify our meaning (P. 13684 L. 15-16). Our new approach using standard deviation demonstrates the large variability of SOC observations at the model grid scale.

*Comment: 5. Sentence in discussion: "Currently, individual agricultural plots typically lose 33–51% of SOC, and that loss increases to nearly 90% when residue is harvested" and in abstract: "After long periods of cultivation, individual plots growing maize and soybean lost up to 65%.". Where do these figures come from? They are not apparent from Figure 4, so I am unclear if they are referring to individual grids, or individual "plots" – do these represent data rather than the model?*

Response: Each modeled grid cell contains up to three crop types growing on independent soil columns. When we refer to "individual agricultural plots" we refer to the portion of the grid cell growing just one crop type as opposed to what is shown in the figures, which includes a weighted average of SOC of all the crop portions of the grid cell. We have revised the text to make this distinction more clear (P. 13687 L. 4).

*Comment: 6. I thank the authors for pointing out the negative effects of adding too much fertilizer in the discussion. It can also be pointed out the fertilizer use and production also leads to more N2O in the atmosphere, a powerful greenhouse gas.*

Response: We have modified the text to include this important loss of nitrogen inputs (P. 13687 L. 23).

*Comment: 7. Typo: Second to last paragraph, change "should a priority" to "should be a priority".*

Response: The text has been modified as suggested (P. 13688 L. 6).

*Comment: 8. Ultimately this is a very simple analysis of the effect of residue on soil organic carbon. I would think the model would also track the effect of that additional SOC on nitrogen – it would add something to this analysis if the authors could easily pull out net nitrogen mineralization rates, or plant nitrogen uptake, to track more precisely how the decreased residue affects nitrogen limiting conditions, and ultimately, crop yield. I would also think they could pull out some actual numbers on crop yield for these different runs, rather than just make the qualitative statements that more SOC leads to better crop yields. However, I am not sure if these output are actually saved on their current history files.*

Response: We do have data saved in our files for net nitrogen mineralization, plant nitrogen uptake, and crop yields. As suggested, we added two additional figures (Figs. 7 and 8) in the discussion section to highlight the decreasing nitrogen uptake and crop yields with increasing residue harvest. The major outlier was the simulation without fertilizer, which had much lower (~60%) yield compared to the current residue simulation. This supports our conclusion that decreasing residue returned to the soil results in decreased nitrogen availability for future plant uptake and retards plant growth and productivity in subsequent growing seasons (P. 13687 L. 6+).

We thank the reviewer for providing helpful comments to improve our manuscript. We have expanded our analysis to include the suggested revisions wherever possible, and when suggestions were not possible to include in current study due to the model capabilities, we have included additional text to address those issues in the discussion. Our point-by-point response to the review follows.

*Overall comments:*

*This discussion paper investigated potential of the effect of crop residue removal on changes in soil organic carbon (SOC) stock in land under agricultural usages, at a large geographical scale. Simulation experiment using CLM-Crop model was applied for this purpose, in combination with spatial and temporal inventories on historical climatic data, land-use/land-cover, and crop-calendar. By using the design of the simulation experiment very similar to that employed in previous study by Drewniak et al. (2013), this study focused on the changes in SOC stock. In addition, validation for the performance of the CLM-Crop model prediction for SOC stock over contiguous USA was conducted using gridded SOC stock data from IGBP-DIS and field observed SOC stock data from ISCN, respectively.*

*Challenges to improve earth system models to deal with agricultural ecosystems, and especially, SOC stock changes, are of interest for a wide range of scientific community. Especially, the attempt to conduct model validation using field observed SOC data would attract a great deal of interest.*

*My overall impression regarding to this manuscript is as follows.*

*1. First of all, some of the authors' interpretations on the result of validation on model performance to predict amount of SOC stock on lands under agricultural use (i.e. model predicted SOC stock vs. observed SOC stocks in agricultural lands in ISCN data; Fig. 3) are rather questionable. Although, the authors postulated that CLM-Crop can capture the SOC stock at various agricultural sites, however, I think it is difficult to conclude that such statement is supported by the results presented in this study. Rather, it should be interpreted that model simulation failed to predict variations in SOC stock at various agricultural fields.*

Response: The nature of global scale land surface models, such as the community land model (CLM) investigated here, is to represent large grid areas and cover different types of soil and landuse. The grid size is primarily driven by the need to simulate over hundreds of years and often coupled to an atmospheric model as a part of an earth system model. As these models are developed and improvements made to different components, we expect the resolution to increase and so would the ability to match data collected on a small 'sites' and at different depths. The primary focus of this manuscript and the model development is to represent in the model the basic features of the crops, their impact on carbon stocks above and below the soil at a model resolution. Given that, we have modified the text to reflect that the model results captured a wide range of SOC stock values of U.S. croplands, and stated that the model results showed substantial differences with individual field observations (P. 13684 L. 15-17). It would be difficult for any model formulated to be part of a global earth system modeling to capture the exact SOC value measured at any given location. Our intention was not to imply that the model could predict field observations perfectly, but it can capture a wide range of observed SOC values, making it a useful tool to evaluate the effects of management change on

SOC. We argue that this is sufficient for the task at hand i.e. calculate the changes due to agricultural management in SOC, not the absolute values of SOC's by themselves. We have also included additional analysis looking at the SOC stock correlation to temperature and precipitation (see our response to "suggestions for revision" – 4 below). Despite the lower SOC estimate by CLM, the model does capture the trends in SOC across temperature and precipitation zones (i.e. decreases in SOC stock over increasing temperature and precipitation). Further, we also noted in the discussion (P. 13688 L. 6) that the differences we found between observed and modeled SOC stocks, suggest improvements are needed in the model structure such that they can better capture the cropland SOC dynamics.

*2. In addition, methodology for model validation using the ISCN data was too simple and not appropriate for the purpose and the question addressed. From the experimental setup it is obvious that there is a large gap in the size of spatial entity between model simulation prediction (a 2.8 ×2.8 grid, with varying area of soil columns) and observed soil data set (a field). Therefore, I think authors should build more elaborate strategies to compare observed SOC data with model output by, for example, filling this gap, before concluding just that large variations in field observations made the model validation difficult. The same can be said to the method of comparison for SOC stock between model predictions and observations in ISCN applied in this study, which just simply compared averaged SOC stock of soil columns in a grid, with differing depth (e.g. 0-300 cm or deeper for model simulation; 0-15 or 0-30 cm for most of observations in ISCN; according to the body text), without any attempt to minimize the effect of this difference on the comparison of SOC stock of soil columns by, for example, using uniform depth of soil columns for SOC stock calculation for both model simulation and observations.*

Response: We are aware about the mismatch between point observations and a CLM grid cell. Since the spatially interpolated observation data to the model grid scale do not exist for the US croplands and taking into consideration the reviewers concerns, we have modified our validation approach and replaced Figure 3. We instead plotted the mean observed SOC for each model grid cell scale along with its standard deviation (see our response to "suggestions for revision - 1" below). Regarding soil depth, all of the ISCN data was for depths of 1 m; we have clarified this distinction in the paper (P. 13683 L. 24 and P. 13684 L. 25). Although CLM calculates SOC in a 3.8 m soil column, since most SOC is within the top meter (Jobbagy and Jackson, 2000) we feel that the depth mismatch between the simulations and observations will be minimal. As per the reviewer's suggestion, in this approach we didn't remove any observations.

*3. Although, authors postulated that CLM-Crop model could capture the range of SOC stocks observed in agricultural fields (Fig. 2), however, it is difficult for me to judge whether this was true because of above mentioned reason. I also have questions with regard to 1) reasons why observed data records in ISCN having SOC value greater than 50 kg C m-2 were excluded (Fig. 2 and Fig. 3), and 2) potential bias in the ISCN dataset, if any measures like stratified random sampling had not been employed in sampling sites setup (please see specific comment).*

Response: As stated previously, we used SOC observations to 1-m depth, which captures the bulk of SOC in the soil column. In addition, half of the observed SOC values were at or below 10 kg C/m2 and 75%

were at or below 15 kg C/m2, which is the range of the modeled output. Given this distribution, despite the underestimation of SOC in CLM, the model did capture a wide range of SOC in US croplands.

Of the over 4000 cropland data points from the ISCN that were included in the analysis, only a small portion (2.5%) had values greater than 50 kg C/m$^2$. Most of those observations did not fall within a CLM grid cell growing crops. With the new approach of gridding the data for Figure 3, we kept those points in the analysis (which are reflected in some of the large standard deviation calculations). We still excluded those points in Figure 2 only (to improve readability of the figure) since they are all outliers and cropland SOC values are typically less than 50 kg C m$^{-2}$ (Mishra et al., 2010, 9.5 kg m$^{-2}$; Kern 1994).

Most of the ISCN SOC data of continental US comes from the USDA-NRCS database. In this study, we included all the pedons that were from the croplands. A separate study is ongoing that is segregating the dataset into different land cover types, climate regions, major land resource area, etc., but this will not be complete for some time. In fact, studies such as this point to the need for more aggressively developing these datasets as more and more climate models represent croplands as one of the landuse types in their models. We do not expect our model would capture actual site SOC observations since our model cannot capture changes in land use or management practices over time.

*4. I believe that the above mentioned points (1-3) are crucial, as many of subsequent discussions on the size of the effect of residue removal on SOC stock change were based on the advocated good performance of the CLM-Crop model to predict SOC stock in land under agriculture. Therefore, I rate this point as a major flaw.*

Response: As discussed above, the type of models discussed here are a new breed of crop model implementations that would work within a coupled earth system model and provide the ability to distinguish a crop landuse type in these models. These models are currently in the process of being benchmarked with available datasets and developing new strategies for both improving the models and identifying data needs. We do agree with the reviewer that there is a need for higher resolution models that can be of a scale that will resolve individual croplands (several hundred meter resolution) and availability of data at these scales. Both of these are not possible at this moment (computational limitation on very high resolution climate models and unavailability of chronosequenced SOC data at very high resolutions). As better ways of representing available data becomes available and model resolutions improve we will be in a position to evaluate absolute values of SOC in the models. However, as long as we focus on perturbations to SOC due to various disturbances, a reasonable representation of SOC over large grid cells and over long time scales as was done here is a reasonable approach. We addressed the reviewer concerns within these constraints and included additional analysis with new and existing observational sets (for details see our response to "suggestions for improvement" below). We believe the analysis strengthens the manuscript and thank the reviewer for the suggestions.

*5. About SOC stock of all land, model predicted SOC stock over all land-use types over USA, 84 Pg C, was found to be comparable with previous estimation by Kern (78-85 Pg C; Kern, 1994). However, more detail explanation on the setup of model input data for historical land-use change is needed to interpret meaning of this result (please see specific comment).*

Response: The estimates of SOC stocks by Kern (1994) were based on data from several sources, between 1975-1990, whereas in our model land use data comes from Leff et al. (2004), which is representative of the early 1990's. We agree that this discrepancy will cause changes in model predictions, however CLM cannot support dynamic land use with functioning crops (this includes changes in cropland extent and crop type). As a result, we were only able to introduce land use change once after the model spinup. However, our simulations without cropland (i.e. crops represented as grass) indicate about 93 Pg C stored in US soils. Therefore the full range of SOC values between no cropland and the current cropland distribution could be between 93-84 Pg C, with the actual value somewhere in between. Since the bulk of SOC loss (20-50%) occurs in the first 40-50 years (Lal et al., 1999), we don't anticipate the SOC loss by the model to be exaggerated, which is why our prediction still falls within range of the estimates. As suggested by the reviewer, we have included additional information in Section 2 of the manuscript to clarify how historical land use was simulated by CLM (P. 13682, 1st paragraph). We have also expanded our discussion to include uncertainties in the CLM estimate of SOC from historical changes in land use, intensity of agriculture, and fertilizer usage (P. 13688 L. 10).

*6. In conclusion, I rate the paper is not acceptable in present form, and recommend that the paper should be revised so that it will be evaluated again whether or not it can be accepted for publication in BG. I recommend authors to revise the paper with taking into account the above mentioned points as well as specific comments shown below. I would like to encourage the revision, as a challenge to conduct validation of model performance to predict SOC stock change using field observed data is important and would attract a great deal of interest for scientific community. I included some suggestions for revision.*

Response: We have performed additional model validation per the reviewer's suggestions, which we believe strengthened the manuscript. Our findings indicate CLM can capture the change in SOC after conversion to cropland over long time periods, although the model does not simulate the initial rapid loss of SOC. Our additional analysis showed that CLM captures climate trends in SOC stocks; particularly, simulated SOC decreases with increasing temperature and precipitation as supported by observations. Finally, we extended the discussion section of the manuscript to address reviewer's suggestions that current CLM model structure does not permit and thus we were unable to accommodate (e.g. changes in land use) (P. 13688 L. 10).

*Specific comments:*

*Land-use change:*

*Please add more detail explanation on historical land-use change setup for the simulation. From the body text, it seems that land-use change (i.e. conversion of grasslands to croplands) was set to occur only once throughout the entire time sequence of simulation, and all at once at the end of spin-up (in 1850; if I understood correctly). However, land-use/land-cover data used to assign land-use conversion from grassland to cropland corresponds to early 1990s; e.g. land-use/land-cover dataset used for grass scenario (IGBP DISCover) corresponds to 1992-1993 (Loveland et al., 2000), whereas that for other scenarios represents the early 1990s (Leff et al., 2004). Therefore, I wonder whether the occurrence and*

*duration of cropland land-use was largely overestimated in the simulation. If this is the case, I do recommend revising the input data of historical land-use change to include several land-use change events to be more consistent with the changes in cropland area estimated by Ramankutty and Foley (1999) and to re-execute model simulation with the revised input (I am not sure whether the model can deal with land-use change to occur several times during the course of simulation, though). As the simulated SOC loss in a grid was found to correlate with area of agricultural lands in a grid, this point may be crucial.*

Response: We've added text to clarify how the land use conversion in CLM occurred (once during the simulation since CLM cannot support changes in land use at this time; P. 13682, 1st paragraph). The model spinup is designed to get the model in a steady state only and does not correspond to an end period year of 1850. The 171-year simulation is chosen to simulate the most intense agricultural land use over the U.S. We agree that using a modern land use map (representing early 1990's) over the entire period may overestimate the agriculture land area, but historical cropland land use peaked in 1940, followed by a decline (the strength varies with region; Waisanen and Bliss, 2002). Furthermore, agriculture land use was established prior to 1850 so we expect that the model may overestimate SOC in some grid cells where cultivation has been practiced longer. As such, we feel confident that our choice in land use is amenable given the model constraints. However, since the effect of land use change is important for SOC, we have modified our manuscript to include a discussion on historical land use change impacts on SOC (P. 13688 L. 10).

*Organic matter input to soils:*

*Input of manure from live-stock waste origin to soils was not taken into consideration in the model simulation. According to MacDonald et al. (2009), about 15.8 million acres of cropland, equivalent to about 5 percent of all U.S. cropland in 2006, were estimated to receive livestock manure. Although, this figure is just an estimate and showing that manure is used on only a small fraction of U.S. cropland, however, for some major crops the percent of the acreage received manure may not be negligible, such as corn (12 %), oats (9 %), as well as hay and grasses (7 %) (MacDonald et al., 2009). Although, input of manure, and in addition, sewage sludge, is taken into account in the estimation of SOC stock change in greenhouse gas inventory reporting of USA, I wonder whether these contribution can be considered as negligible or not. I also think that the title of the manuscript employing the term, 'US carbon budgets' is rather exaggerated.*

Response: We thank the reviewer for suggesting alternate source of nutrient addition to the croplands. However, in current model structure of CLM there is no mechanism for adding organic matter to soils through livestock manure although this is a focus for future model development. Therefore, we have considered this suggestion as a source of possible uncertainty in CLM results, and expanded the discussion section to address this issue (P. 13688 L. 10).

*Soil organic carbon stock:*

*P. 13683, L.6-8:*

*In "The total stored SOC over all land surface types in the United States, as calculated by CLM-Crop, is 84 Pg C, which falls within the range of previous estimates of 78–85 Pg C (Kern, 1994).", please explain for which year the prediction and the estimate was made, respectively. From Fig. 4, it seems around 2020 is refereed (i.e. 'Current Residue' in 2020 (i.e. 1850 + 170 = 2020) at around 85 Pg C) for the model prediction. If this is the case, I wonder if this corresponds to the year for which the land-use/land-cover estimation by Kern (Kern, 1994) was made.*

Response: See also our response under "Land-use change". We have removed the reference to 1850 in the manuscript since our intention was not to indicate that our simulation was starting at 1850, but to reference the intense period of agriculture production in the U.S. Our rational for running the model for 171 years was to compare the transient model state after heavy agriculture establishment with observations. Therefore, we have added clarification that our simulation doesn't correspond directly to the years 1850-2020. We think the Kern (1994) dataset is roughly representative of the 1990's, as it contains the pedons data collected by USDA-NRCS through a long period of time (1975 – 1990). Since we are aware that the uncertainty with this approach is substantial, we have included additional analysis (Section 3.2) that examines the change in SOC after cropland establishment to validate our model results.

*P.13683, L.28:*

*What is the reason to exclude the plots with SOC > 50 kg C m-2? Is this because ISCN data has problems in data quality control? Any organic soils included? Please explain.*

Response: Of the over 4000 data points from the ISCN that were included in our analysis, only a small portion (105 points, 2.5%) had values greater than 50 kg C/m$^2$. Since cropland SOC values are typically less than 50 kg C /m$^2$ (Kern 1994; Mishra et al., 2010, 9.5 Kg m$^{-2}$) we initially removed the higher values from our analysis. In addition, the land use designation in the ISCN data may not reflect the land use when the soil measurement was taken, which could result in erroneous data points collected for our analysis. Our modified analysis approach taking the mean SOC stock with SD now includes all observation data points (with the exception of Figure 2 to improve readability of the graph). We've added text to clarify (P. 13683 L. 28).

*Fig. 2 and Fig. 3:*

*I wonder whether the soil sampling site selection in ISCN employed stratified random sampling, with taking different land-use, management, soil types, and climate regimes into account, or not. If not, as is often the case with many of existing soil data set, the data should be dealt in a careful manner especially when the entire data is just simply compared with model output because of potential bias.*

Response: Most of the cropland SOC data in ISCN database comes the pedon data collected by USDA-NRCS. Stratified random sampling was not employed while collecting these samples but the idea was to represent different soil types using expert judgment of pedologists. As suggested by the reviewer, in additional analysis, we have analyzed the distribution of SOC samples across temperature and precipitation gradients (see our response under "Suggestions for revision – 4").

*Suggestions for revision:*

*1. Employing calculation for weighted means for SOC stock for each grid based on observed SOC data, of ISCN or including additional soil dataset, with taking into account relative distribution of different land-use type and history, soil types, management practices, etc., in each grid, if possible. Number of data may not be enough to conduct such calculation, though. It would be useful to consult methodologies used for the estimation of SOC stock change at country scale in the national greenhouse gas inventory reporting of USA (USEPA, 2014), which employs an 'expansion factor' for scaling of SOC stock (stock-change) from observation points to the entire country.*

Response: We agree that weighting the SOC stock from observations to aggregate to the grid scale is important for the comparison between observations and the model output; however, conducting this study is outside the scope of present study. We have reconsidered our analysis and replaced Figure 3. Rather than plotting all the observational points compared to the model, we averaged the observation data within each model grid cell and included the standard deviation of the observations in each grid cell. This demonstrates the large variability of SOC observations within each gridcell. With this additional analysis, we are also able to infer that the model tends to estimate higher SOC in sandy soils, and lower SOC for clay and silt soils, although it should be noted that the soil texture is determined from the model since observational data does not include soil texture. We include this additional analysis in Section 3.2

*2. Referring to figures of estimated SOC stock (stock-change) shown in the national greenhouse gas inventory reporting (US-EPA, 2014) and to compare it with that predicted in the model simulation in this study. Such information, and, in addition, corresponding discussions will be useful for readers.*

Response: We thank the reviewer for pointing out the US-EPA (2014) report, but note that the carbon fluxes estimated were also model-derived using the DSSAT model. Therefore, we found additional observational studies to compare our change in soil carbon from Wei et al. (2014). The dataset includes 453 site observations from 36 countries of SOC change when forests are converted to cropland. SOC stock change was reported for time periods ranging from 1-200 years from conversion. We include an additional figure in the manuscript (Figure 5), which shows the percent SOC loss over a 200-year period as reported in Wei et al. (2014) along with a random sample of 500 points from CLM. The data indicate that although CLM cannot simulate the initial rapid loss of SOC following land conversion, over long periods CLM does capture total SOC loss. Since decreases in SOC increase with increasing initial SOC concentration (Wei et al., 2014), we believe the initial modest decline in SOC is the result of lower initial SOC concentrations simulated by CLM. We have included this figure and accompanying discussion in section 3.2 of the manuscript.

*3. Use of information on land-use/land-cover, land-use history, and management practices of each sampling site in the ISCN data set when assessing the range, mean, or median of SOC stocks, if such data are available. Again, uniform depth of soil columns should be used in the calculation to compare it with model simulation output. As this study emphasized that differences in crop residue input to soils would have affected changes in SOC stock significantly, such information on land-use (and management, if available) should be included in the method for model validation.*

Response: We agree that segregating the data in the suggested manner would be informative, but is beyond the scope of this study. An effort to evaluate the data is ongoing and these results can be re-evaluated at that time. Although our soil depth in the model (3.8 m) is deeper than the observations (1 m), we feel that the mismatch has little impact on results since most SOC is in the top soil layers (Jobbagy and Jackson, 2000). Most field data is not collected beyond 1-m and the current CLM model structure doesn't have a vertical carbon profile. We addressed the issue of changing land use and management further in the discussion section of the manuscript (P. 13688 L. 10).

*4. In addition, assessing differences in SOC stock between different land-use types (e.g. cropland vs. grassland) at several different geographical zones having different climatic conditions (temperature, precipitation etc.), in model and observation, respectively, followed by making comparison between these two to explore model performance. I expect such approach would produce output that may highlight strength of the study applying earth system model and spatial and temporal inventories of climate and land-use over large geographical entity.*

Response: We thank the reviewer for this suggestion and have performed additional analysis to consider the impact of climatic conditions (temperature and precipitation) on SOC stock. Though the CLM simulates lower SOC stocks initially, the trend in SOC stocks over the different climate regimes mirrors that of the observations. High temperature and precipitation regions result in higher turnover rates of carbon (Wei et al., 2014) and result in lower SOC stocks. Over natural vegetation, the variability of SOC is quite high, but CLM hints that higher precipitation results in higher SOC. This could be the result of higher vegetative productivity when sufficient rainfall is present. A figure plotting the SOC stocks from model simulations and from data observations against annual mean temperature and total precipitation (Fig. 4) and accompanying discussion has been added to the manuscript in section 3.2.

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1    **Modeling the impact of agricultural land use and management on U.S. carbon budgets**

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**Abstract**

20

21 Cultivation of the terrestrial land surface can create either a source or sink of atmospheric $CO_2$,

22 depending on land management practices. The Community Land Model (CLM) provides a useful

23 tool to explore how land use and management impact the soil carbon pool at regional to global

24 scales. CLM was recently updated to include representation of managed lands growing maize,

25 soybean, and spring wheat. In this study, CLM-Crop is used to investigate the impacts of various

26 management practices, including fertilizer use and differential rates of crop residue removal, on

27 the soil organic carbon (SOC) storage of croplands in the continental United States over

28 approximately a 170-year period. Results indicate that total U.S. SOC stocks have already lost

29 over 8 Pg C (10%) due to land cultivation practices (e.g., fertilizer application, cultivar choice,

30 and residue removal), compared to a land surface composed of native vegetation (i.e.,

31 grasslands). After long periods of cultivation, individual ~~plots~~ subgrids (the equivalent of a field

32 plot) growing maize and soybean lost up to 65% of the carbon stored, compared to a grassland

33 site. Crop residue management showed the greatest effect on soil carbon storage, with low and

34 medium residue returns resulting in additional losses of 5% and 3.5%, respectively, in U.S.

35 carbon storage, while plots with high residue returns stored 2% more carbon. Nitrogenous

36 fertilizer can alter the amount of soil carbon stocks significantly. Under current levels of crop

37 residue return, not applying fertilizer resulted in a 5% loss of soil carbon. Our simulations

38 indicate that disturbance through cultivation will always result in a loss of soil carbon, and

39 management practices will have a large influence on the magnitude of SOC loss.

40

**1.    Introduction**

Bioenergy crops are promoted as a renewable energy source capable of improving energy security and mitigating greenhouse gas (GHG) emissions from fossil fuels. These crops are considered environmentally friendly and economically competitive, because $CO_2$ emitted by biofuel combustion is partially balanced by atmospheric uptake through photosynthesis (Hughes et al., 2010). The Renewable Fuel Standard of the U.S. Energy Independence and Security Act (EISA 2007) sets a national target of producing 136 billion liters of renewable fuels by 2022. Of this, at least 61 billion liters is expected to come from cellulosic ethanol (U.S. Environmental Protection Agency, 2010). Though maize grain and sugarcane are currently the major global sources for bioethanol production, maize production in the United States is not sufficient to meet the renewable fuel targets. Furthermore, recent studies suggest that production of ethanol from corn grain might in fact increase GHG emissions because of changes in land use (Searchinger et al., 2008; Kim et al., 2009; Melillo et al., 2009). For these reasons, cellulosic biofuels produced from cellulose and hemicellulose plant biomass are considered a viable alternative to conventional crop-based biofuels.

Cellulosic biofuels can be made from perennial feedstocks or from residues of annual cropping and forestry activities, thereby reducing or eliminating the need for additional agricultural land. The use of crop residues for bioethanol production shows promise for ~~meeting~~ fulfilling U.S. ~~energy~~ renewable fuel goals, but more research is needed on the effects on soil organic carbon (SOC) of crop residue removal from croplands (Mishra et al., 2013) and net GHG balance (McKone et al., 2011). Furthermore, crop residues play a crucial role in sustainability and resilience of agroecosystems (Karlen et al., 2009). Therefore, to understand the environmental consequences of using crop residues for bioenergy production on large spatial

3

64  scales, it is essential to know the impacts on the SOC pool of differential rates of crop residue

65  removal and nitrogenous fertilizer applications.

66      Crop residue is responsible for maintaining soil moisture, returning carbon and other

67  nutrients to soil, and erosion mitigation; in general, it provides a sustainable environment for

68  cultivation activities (Lal, 2009). Without residue cover, wind and water erosion will increase

69  (Van Pelt et al., 2013). Long-term residue harvest results in loss of yields and productivity by

70  decreasing the nutrient content of soils (Blanco-Canqui and Lal, 2009a). These arguments

71  demonstrate that using crop residues as a bioenergy fuel resource could have detrimental impacts

72  on agroecosystems (Blanco-Canqui and Lal, 2009a).

73      Globally, soils store more carbon than the atmosphere and biosphere combined, acting

74  both as a source and sink of atmospheric $CO_2$ (IPCC, 2013). However, cultivation loss of SOC

75  ranges from 50% to70% (Lal and Bruce, 1999). Over the U.S. Midwest, land conversion led to a

76  25-50% reduction of soil carbon (Houghton et al., 1999; Lal, 2002). The result is large carbon

77  payback times, ranging from a few years to several centuries (Fargione et al., 2008; Gibbs et al.,

78  2008; Searchinger et al., 2008). On the other hand, conversion from cultivation to native

79  grasslands, such as through enrollment in the Conservation Reserve Program, resulted in

80  increased soil carbon (Anderson-Teixeira et al., 2009; Pineiro et al., 2009). Therefore, it is

81  critical to evaluate the impact of agricultural land use and management on regional carbon

82  budgets.

83      The influence of agriculture on the carbon cycle is complex; carbon capture and storage

84  in croplands are dependent on management practices, including tillage, fertilizer applications,

85  residue management, and crop sequence (West and Post, 2002; Hooker et al., 2005; Dou and

86    Hons, 2006; Huggins et al., 2007; Khan et al., 2007; Kim et al., 2009). SOC stocks and fluxes at

87    a particular location are soil and site specific and reflect the long-term balance between organic

88    matter inputs from vegetation and losses due to decomposition, erosion, and leaching. Some

89    studies have attempted to quantify carbon sequestration from mitigation strategies such as no-till

90    or conservation tillage practices, residue management, use of cover crops, and restoration and

91    reserve actions (Conant et al., 2001; West and Post, 2002). These studies showed that as farming

92    techniques are improved to maximize yield and minimize disturbance, SOC can be maintained

93    and perhaps even increased over time.

94          However, the effect of altered management on agricultural soil's ability to store or emit

95    carbon is unresolved, largely as a result of conflicting evidence. For example, some studies on

96    the effects of nitrogen fertilizer indicated a decrease in SOC caused by increased decomposition

97    (Khan et al., 2007; Russell et al., 2009), while others reported an increase in SOC from increased

98    biomass returned to the soil after harvest (Jung and Lal, 2011; Halvorson et al., 1999; Wilts et

99    al., 2004). SOC increases when crop residue is returned to the land (Buyanovsky and Wagner,

100   1998; Wilhelm et al, 2004; van Groenigen et al., 2011), but residue can also increase

101   decomposition in warm, moist areas (Johnson et al., 2005). Perhaps the disagreement is the result

102   of the large variability and uncertainty of field measurements, which make developing

103   conclusions difficult (Karlen et al., 2011). For example, Smith et al. (2012) found no differences

104   between the residue-returned and residue-harvested treatments, and in some cases the residue-

105   harvested sites had increased SOC. Thorburn et al. (2012) also found no consensus regarding

106   residue harvest and SOC response. Nonetheless, most studies found a loss of SOC with residue

107   harvesting. Although the variability of SOC measurements can be attributed to any number of

108   effects — including topography (Senthilkumar et al., 2009b), SOC baseline (Senthilkumar et al.,

109  2009a), aggregate protection (Ananyeva et al., 2013), and even depth (Kravchenko and

110  Robertson, 2011; Syswerda et al., 2011) — it is generally agreed that if crop residue is used as

111  feedstock for biofuels, additional carbon losses can occur (Karlen et al., 2011).

112        SOC losses can be mitigated through recommended management practices, but studies

113  disagree on the limits of harvestable crop residue to maintain SOC levels in soils. Estimates of

114  harvestable non-grain biomass range from 13% (Tan et al., 2012) to 50% (Blanco-Canqui and

115  Lal, 2009a), with an average of about 25%, although that might require stabilization of SOC

116  (Tan et al., 2012). These estimates consider erosion, soil productivity, maintaining SOC, surface

117  crusting, porosity, aggregate breakdown, compaction, and soil temperature, but the wide range in

118  estimated biomass available for harvest leaves questions regarding the sustainability of cellulosic

119  ethanol. However, because the rate of SOC loss tends to increase with increased biomass harvest

120  (Lemke et al., 2010), harvesting small amounts of residue for biofuel might be feasible.

121        Modeling studies can supplement observational data and explore possible differences in

122  SOC by investigating idealized cases. A benefit is that the wide study area can be extended to

123  regional or global scales without resorting to geospatial methods of interpolating sparse data. In

124  this study, we evaluated the influence of cultivation on SOC by using the agriculture version of

125  the Community Land Model (CLM), CLM-Crop (Drewniak et al., 2013). Our analysis includes

126  impacts of changes in land use and also in management practices, such as crop residue harvesting

127  and fertilizer application. A description of the model and the simulations performed is presented

128  in Sect. 2, followed by results and a discussion in Sect. 3 and Sect. 4, respectively.

129  **2      Methods**

130  **2.1      CLM-Crop model description**

131      CLM-Crop, the agriculture version of CLM, includes representations of maize, spring

132  wheat, and soybean crop types with fully coupled carbon-nitrogen cycling (Drewniak et al.,

133  2013). The variation of carbon and nitrogen allocation to plant components with the growth

134  phase of crop development is based on the dynamic vegetation model Agro-IBIS (Kucharik and

135  Brye, 2003). The growth phases are defined as planting, emergence, grain fill, and harvest. Plant

136  date and growth period are determined from the Crop Calendar Dataset (Sacks et al., 2010), and

137  each phase is reached according to a phenological heat unit (PHU) method (see Drewniak et al.,

138  2013).

139      Several processes governing nitrogen cycling are included in CLM-Crop to represent

140  nitrogen retranslocation, fertilization, and nitrogen fixation in soybean. Nitrogen retranslocation

141  occurs during the grain fill growth phase, when nitrogen in the leaves and stem are mobilized to

142  meet organ demands. Fertilizer is applied during the emergence phase for 20 days at constant

143  rates of 150 kg/ha for maize, 80 kg/ha for spring wheat, and 25 kg/ha for soybean. The 20-day

144  fertilization period is designed to optimize nitrogen usage and reduce loss of excess nitrogen

145  through denitrification. Soybean nitrogen fixation allows soybean crops to behave as legumes

146  fixing additional nitrogen through roots — a treatment similar to that of the SWAT model

147  (Neitsch et al., 2005).

148      Harvest occurs as soon as maturity is reached. Grain is removed from the system to

149  represent the consumption of that plant component. The remaining stems and leaves are

150  considered residue and are split into litter and product pools. Litter is returned to the soil through

151  the decomposition process, while product is removed with the grain for uses such as biofuels,

152  animal bedding, etc. The amount of residue returned as litter can be varied for different

153  scenarios. High returns represent sustainable agriculture practices to maintain soil fertility, and

154  low returns are indicative of high cellulosic biofuel usage.

155  **2.2    Input data**

156  CLM-Crop requires two types of input: climate data and surface data. The climate data

157  from the National Center for Environmental Protection reanalysis for 1948-2004 (Kalnay et al.,

158  1996) include temperature, wind speed, humidity, precipitation, solar radiation, and surface

159  pressure at 3-hr intervals. Because the spin-up of the model requires over 600 yr of simulation,

160  we cycled through the reanalysis data to reach a steady state (Thornton and Rosenbloom, 2005).

161  Surface data sets assign the proportion of each land type and plant functional type in a

162  grid cell; crops are grown separately from natural vegetation to eliminate competition for

163  resources. Natural vegetation prescribed from Bonan et al. (2002) includes a generic crop area.

164  Crop distribution for 1992 from Leff et al. (2004) is used to construct maize, wheat, and soybean

165  coverage from the total generic crop area. Because the wheat coverage includes both spring and

166  winter wheat, we model winter wheat as spring wheat in CLM-Crop. Some crop areas

167  overestimated as double cropping in the data set might result in a crop area being counted twice.

168  In addition to land use, the surface data include the planting dates and growth period of

169  each crop type from the Crop Calendar Dataset (Sacks et al., 2010). Planting date is the average

170  day of year when planting occurs, aggregated from 0.5° resolution to 2.8° for CLM-Crop. In

171  regions where data are not available, Sacks et al. (2010) used nearest-neighbor extrapolation to

172  infer planting date. Growth period is calculated in Sacks et al. (2010) as the average number of

8

173    PHUs between the average planting date and the average harvest date for the 30-yr Climatic

174    Research Unit data set (New et al., 1999).

175    **2.3     Simulations**

176    CLM-Crop was run at a resolution of $2.8° \times 2.8°$ by using the spin-up procedure in

177    Thornton and Rosenbloom (2005). During spin-up, only natural vegetation was active, and

178    croplands were simulated as grass until a steady SOC state was reached. At the end of the spin-

179    up, the land use was converted to include agriculture, representative of the early 1990's land use

180    maps from Leff et al. (2004). CLM does not have a dynamic vegetation capability when crops

181    are active, so land use/land cover is held constant for the remaining simulations. and sSeveral

182    case studies were designed and run to evaluate the influence of management practices on SOC

183    (Table 1). Each case study was run for a total of 171 years (three complete cycles of the 1948-

184    2004 data) Since extensive cropland coverage for the United States did not occur until around

185    1850 (Ramankutty and Foley, 1999), each scenario was run for three complete cycles of the

186    1948-2004 climate data (a total of 171 years) at an hourly time step to reach a state

187    representative ofrepresent the most intense cultivation period current conditions for in North

188    America (Ramankutty and Foley, 1999). However, we consider only the last 57 yr of simulation

189    for analysis with averaged data. The control simulation, representing current fertilizer and

190    management practices over North America, is compared to an extension of the spin-up, with

191    crops represented as grass. Additional experiments compared the impact on soil carbon from four

192    agricultural practices (high, medium, and low residue levels and zero fertilizer) with our control

193    simulation.

194    To investigate the effects of land use changes on SOC, different residue management

195    practices, and varied fertilizer application, the results from six scenarios were analyzed (Table 1).

196    First, conventional crop management (control run, 70% residue) is compared with crops

197    simulated as grass (grass run). Second, effects of high (90%), medium (30-40%), and low (10%)

198    residue are compared with values for the control run. Third, the effect of no fertilizer application

199    (with 70% residue) is evaluated by comparison with the control run.

200    **3      Results**

201    **3.1     Soil organic carbon**

202    Simulated SOC values from the control run range from $< 2$ kg C m$^{-2}$ in the Southwest to

203    $> 20$ kg C m$^{-2}$ in the northern United States (Fig. 1). Average SOC values are lower in crop

204    ecosystems than in natural vegetation systems because of biomass removal and other land

205    management. The total stored SOC over all land surface types in the United States, as calculated

206    by CLM-Crop, is 84 Pg C, which falls within the range of previous estimates of 78-85 Pg C

207    (Kern, 1994). CLM-Crop-simulated SOC for agriculture sites over the contiguous United States

208    (CONUS) has a pattern similar to that of total SOC, with higher SOC in the northern part of the

209    country and lower SOC in the southern regions.

210    The general spatial pattern of the model-calculated SOC over CONUS is evaluated by

211    using available spatially gridded data sets of SOC. The data developed by the global soil carbon

212    International Geosphere-Biosphere Program (IGBP; Global Soil Data Task Group, 2000) for

213    CONUS are summarized in Fig. 1b. The SOC pattern and magnitude are similar to the model-

214    calculated values (Fig. 1a). The differences between the model-calculated SOC and the IGBP

215    data set are shown in Fig. 1c. In most regions, the percent difference between the data set and the

10

216    model simulation is < 5%. Areas with higher percent differences are in boreal regions, where

217    CLM tends to underestimate soil carbon (Koven et al., 2013).

218        Figure 1 includes both managed and natural lands. To evaluate the model-simulated SOC

219    over agricultural lands, we selected self-identified measurements of SOC from agricultural lands

220    available from the International Soil Carbon Network (ISCN; 2014). This data set has over 4,000

221    unique SOC measurements to 1-m depth from croplands over CONUS. Although CLM soil

222    depth (3.8 m) is deeper than the observations (1 m), we feel that the mismatch has little impact

223    on results since most SOC is in the top soil layers (Jobbagy and Jackson, 2000). Because the

224    ISCN data were collected over a wide variety of soils, at different points in the crop cycle and

225    different times since the change in land used, variability is large, and the number of outliers from

226    the median of the sample is significant. We filtered out outliers with SOC measurements > 50 kg

227    C m$^{-2}$. The plot in Fig. 2 shows the range of values with significant occurrences in the upper

228    quartile and above the 90th percentile of the distribution. We filtered out outliers with SOC

229    measurements > 50 kg C m$^{-2}$ in this figure only to improve readability of the graph, since only a

230    small portion (2.5%) of the measured values were higher than 50 kg C m$^{-2}$ and SOC in

231    agriculture lands is typically less than 50 kg C (Kern et al., 1994; Mishra et al., 2010). The model

232    results for the grid cells identified as cropland are included in Fig. 2. The model results have a

233    much less variabilitysmaller range than the ISCN data, as would be expected for SOC values

234    extracted at the end of the simulation period and post-harvest. In addition, the SOC in the model

235    is less variable because of the larger grid cells with uniform soil type. Nevertheless, the median

236    SOC values simulated by CLM-Crop fall within range of the middle 50% of the ISCN

237    measurements (Fig. 2), and thus the simulated values are comparable, on average, with the

238    observations.

239     In a further evaluation of the model's performance over agricultural lands, we completed

240     a site-by-site comparison of modeled SOC to observed SOC. We applied a filter to separate soil

241     over the modeling domain into three types (clay, sand, and silt), to examine the model behavior

242     against the different textures. Figure 3 plots simulation results versus observations of SOC for

243     values selected as described above. Each point indicates the mean observational SOC stock at the

244     model grid scale with the standard deviation. The plot indicates that although the model does

245     tend to underestimate the variability of soil carbon over croplands, CLM does reasonably well at

246     catching a the variabilitywide range of SOC values at agricultural sites for all soil textures. The

247     model does not capture the individual site observations well, due to the high spatial variability.

248     In addition, CLM captures soil carbon better at mid latitude than at low and high latitude (data

249     not shown), because cropland areas are smaller in the latter regions. CLM tends to simulate high

250     SOC in sandy soils, low SOC for silt soils, and clay SOC in between, however the soil texture is

251     determined from the model data and therefore may not accurately represent the soil texture of the

252     observations. This result is encouraging, in view of difficulties in comparing CLM-Crop-

253     simulated SOC with observations at agriculture sites. (correlation coefficient is 0.24 with an

254     RMSE of 8.8 kg C m$^{-2}$). First, the large grid size used in the model simulation cannot resolve the

255     small-scale variability between farm-scale measurements, which are apparent from the large

256     standard deviation in observations. Second, the model is run with static management for long

257     time periods and cannot capture changes in management or land use over long temporal and

258     large spatial resolutions while observations are taken over various time frames with vastly

259     different land use history. Finally, most measurements are taken only to 15- or 30 cm1 m depth,

260     and CLM-Crop estimates SOC for the total soil column (> 300 cm). Despite these challenges,

261 CLM can capture the range of SOC present at many agriculture sites and in many cases CLM

262 SOC estimates fall within the standard deviation of the observations.

263      In order to explore the model performance further, we examined the effect of climate

264 variability on SOC stocks. CLM SOC stocks decrease with increasing mean annual temperature

265 and total annual precipitation (Fig. 4), which is also supported by observations. Higher

266 temperatures and soil moisture generally result in higher below ground activity and therefore

267 faster turnover of soil carbon (Wei et al., 2014). Natural vegetation follows the same temperature

268 trends, but regions with higher annual precipitation indicate higher SOC stock. This is possibly

269 the result of increased productivity when precipitation is high, however the variability in natural

270 vegetation is quite high making conclusions difficult.

271      Finally, we also consider the ability of the model to capture temporal changes in SOC

272 from land use conversion. Percent SOC loss since conversion from forest to agriculture, as

273 summarized in Wei et al. (2014), is plotted in Fig. 5 over temporal periods ranging from 1-207

274 years with a subset (500 points) of CLM SOC percent loss taken from random grids and time

275 periods. Although CLM does not simulate the rapid loss of SOC that occurs in some field

276 observations, by the end of the simulation, CLM does capture the range of SOC loss as seen in

277 observations. Initial lower SOC stocks likely cause the initial modest decline in SOC simulated

278 by the model, since SOC loss increases with increasing initial SOC concentration (Wei et al.,

279 2014). This result highlights CLMs ability to capture changes in SOC over long time periods.

280 **3.2 CLM-Crop-simulated changes in soil carbon**

281      Most grid cells lost between 3% and 45% of total SOC, averaged across the grid cell. The

282 amount of SOC lost was correlated with the size of the agriculture land base; higher agriculture

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283　land use resulted in larger SOC loss. Individual crop soil columns indicate high losses of SOC,

284　up to a maximum of 75% of total SOC, although average soil loss is 33-51%. Total loss also

285　varied with crop type; maize and wheat lost about 10% less SOC than soybean. This is

286　understandable, given the low residue of soybean crops, although this result varied with location.

287　For example, total simulated SOC loss over maize and soybean soil columns at the Bondville site

288　in Illinois was 48%. At the Mead, Nebraska, site, losses of SOC for maize and soybean columns

289　were approximately 44% and 52%, respectively.

290　　　While these site-level SOC losses are comparable with observations (Lal, 2004),

291　comparison with the SOC values in the control simulation might be exaggerated as a result of the

292　subgrid hierarchy, because the accumulated SOC estimated by the grass simulation was

293　influenced by all vegetation types in the soil column, while the soil column in the control

294　simulation only included one crop type. In addition, Ramankutty and Foley (1999) showed that

295　most early croplands from the late 1800s were formed through deforestation and later prairie

296　removal. This implies that our estimation might be exaggerated, because grassland ecosystems

297　can hold more carbon than forests (Schlesinger, 1997). Overall, a 10% loss in total SOC over the

298　United States between the control run and the grass run accounts for a nationwide carbon loss of

299　more than 8 Pg (Fig. 64).

300　　　Residue management can have the largest impact on soil carbon. Increasing the residue

301　left on the field to 90% results in a 2.6% increase of SOC, but allowing a 10% residue amount

302　(as a potential result of increased cellulosic biofuel demand) leaves an SOC decrease of over

303　5.7%. The difference between these two scenarios is over 7 Pg C, almost the same amount as the

304　total carbon loss due to agricultural land use. Interestingly, we found no notable differences

305　between crop responses. Even a more modest decrease in the residue returned to the field (30-

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306   40%) results in a 3.5% loss of SOC compared to the control simulation. Increasing the residue

307   harvest will increase the amount of SOC loss (Anderson-Teixeira et al., 2009; Blanco-Canqui

308   and Lal, 2009b). Harvesting residue results in the loss of not only soil carbon, but also soil

309   fertility, indicated by declining yields (data not shown). This implies that increased residue

310   harvest for cellulose might result in expansion of croplands to counter yield declines.

311         Eliminating fertilizer use showed the biggest impact on yields and SOC, simulating over

312   6% loss (Fig. 64). Globally, decreases in yields of roughly 60-70% occurred for maize and

313   wheat, but soybeans, relying less on fertilizer inputs, suffered a 22% decrease in yields. The

314   different response between plant types was large: individual maize and wheat soil columns lost

315   an average of 63% SOC, whereas soybean only lost 11%. Despite low yields, leaving 70%

316   residue allowed carbon inputs to maintain nearly the same SOC level as in the run with low

317   residue return. This indicates a critical role for fertilization in soil carbon storage, without which

318   an additional 5 Pg C might be lost due to cultivation. The observed result is not surprising, as

319   fertilizer contributes to the total biomass accumulated during crop development, and increased

320   biomass returned as residue will allow the soil to retain some of the nutrients taken up during

321   crop growth, improving the soil fertility.

322   **4.    Discussion**

323         CLM-Crop has proven to be a valuable tool for evaluating changes in soil carbon under

324   various management practices. Our results indicate that the SOC for agricultural sites will be

325   reduced through any management practice while disturbance continues, with the total amount

326   lost depending on the management practice. Model-estimated U.S. losses of SOC due to current

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327    cultivation practices are around 10%, with a potential for greater loss as the amount of harvested

328    residue increases.

329        The amount of biomass residue left on the field after grain harvest has the most

330    significant effect on SOC. Cellulosic biofuels rely on harvesting the stems and leaves of crops,

331    resulting in an additional 5% loss of carbon within the soil system. Currently, ~~individual~~

332    ~~agricultural~~ model ~~plots~~ subgrids growing a single crop type on an independent soil column

333    typically lose 33-51% of SOC, and that loss increases to nearly 90% when residue is harvested.

334    Over long time scales, this effect can degrade the sustainability of the soil for crop growth and

335    can negatively affect yield. For example, plant nitrogen uptake (Fig. 7) decreased linearly with

336    increasing residue harvest. The high residue returns uptake 7.4% more N than the current residue

337    runs, whereas medium and low residue returns have 6.6% and 15.6% lower N uptake,

338    respectively. When fertilizer is not included, the resulting N uptake is 57% lower. This impact is

339    transferred to yields (Fig. 8) resulting in 9% and 17% lower yields for the medium and low

340    residue returns, respectively. Thus, the effects of residue management on SOC are very

341    important, and increasing the amount of residue used for cellulosic ethanol production could

342    have a significant impact on soil carbon storage and ultimately plant productivity. Leaving plant

343    residue from crop production in the soil decreases the amount of carbon lost to the atmosphere.

344    However, meeting cellulosic biofuel demand through cultivation of managed grasses such as

345    switchgrass and Miscanthus has been shown to increase soil carbon storage over time

346    (Anderson-Teixeira et al., 2009), most likely because nutrient demands and management

347    practices are different for these types of biofuel crops.

348        Disagreement between studies about the possible effect of fertilizer on SOC leaves this

349    management practice open for further research. Our findings suggest that fertilizer use might

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350 improve yield and increase the amount of carbon returned to the soil in crop residue; however,

351 increased residue removal for biofuels could reduce this effect. As fertilizers improve and are

352 applied to maximize plant uptake while minimizing loss to leaching and denitrification, fertilizer

353 might provide an important tool for farmers to mitigate the soil carbon loss due to increasing

354 residue harvest for biofuel use. However, care must be taken to ensure that fertilizer inputs do

355 not exceed plant uptake, which could result in increased nitrogen leached into the groundwater

356 and increased greenhouse gas emission of $N_2O$ via nitrification and denitrification pathways. The

357 effect of increased decomposition when fertilizer is used also needs to be explored.

358       Expanding the model to incorporate other management practices (rotation, tillage,

359 irrigation, etc.) is important activity for future model development. Erosion, for example, is

360 expected to increase as a result of crop residue harvest (Lal and Pimentel, 2007). This secondary

361 effect of residue harvest can have multiple consequences. First, soil fertility will decline with the

362 loss or transport of soil organic matter. Second, erosion processes result in the breakdown of soil

363 aggregates promoting oxidation of SOC. Both effects will reduce nutrient and water holding

364 capacities of the soil (Lal and Pimentel 2008). Finally, the loss of nutrients will result in a

365 decline of crop productivity, further enhancing SOC loss. As such, our result should be

366 considered a lower bound estimate of SOC loss from residue harvest. Including these effects and

367 expanding agricultural models to a global scale should be a priority for future model

368 development. Given the challenges comparing with observations, focusing on model

369 developments that capture cropland SOC dynamics is equally important as developing datasets

370 that can be used for climate model validation, especially considering the increasing complexity

371 of ESMs that include cropland representation. Although the crop representation in CLM-Crop is

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372 flexible enough for expansion to a global scale, rigorous testing is needed to ensure that crop

373 behavior is consistent with regional observations.

374     There are some limitations to our modeling approach that lead to uncertainties in the

375 model prediction of SOC. For example, changes in land use and land cover are not included in

376 CLM. Historical changes in land use indicate a steady increase in cultivated land which peaked

377 in the 1940's and declined thereafter (Waisanen and Bliss, 2002). Using a modern land use cover

378 over the historical period may result in an over prediction of SOC loss, because the model will

379 overestimate the agricultural land base in some (early) years and the model won't capture

380 increases in SOC when agriculture land is abandoned. This also limits the influence of beneficial

381 agriculture practices such as crop rotation and fallowing. Historical changes in land management

382 are also not represented in the model, such as changes in residue harvest over time or organic

383 matter additions. For example, Lal et al. (1999) suggest early cultivation removed residue

384 following harvest until after 1940 when residue was returned to the field. The high spatial

385 variability and difficulty finding these types of historical data is a major challenge for trying to

386 add these features to CLM.

387     Finally, further research is needed for full evaluation of the importance of agro-

388 ecosystem impacts on soil carbon. We have shown here that SOC loss can vary greatly,

389 depending on management practices. Practices such as residue management can have significant

390 impact on SOC retained in agricultural soils, with higher residue removal from soil leading to

391 higher SOC losses. Use of fertilizer can compensate for some of the loss, but the benefit is

392 limited. Further modeling studies are important for simulating these competing effects on carbon

393 storage. Our study suggests that considerable care is needed in designing appropriate

394 management practices to realize the full carbon mitigation benefits of using biofuels from

395 cellulosic ethanol.

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Figure 1. (a) Total SOC (kg C m$^{-2}$) simulated by CLM-Crop over the contiguous United States. (b) Total SOC from the IGBP over the same domain as in (a). (c) Percent difference between (a) and (b).

Figure 2. Box plot of the weighted average total SOC over croplands, as simulated in CLM-Crop and in observations from the ISCN. Observations reporting > 50 kg C m$^{-2}$ were removed from the analysis.

Figure 3. CLM-modeled SOC (kg C m$^{-2}$) versus ISCN observations for model derived soil texture types clay, sand, and silt. Each point represents the mean observed SOC stockvalue in the grid cell; error bars show the with standard deviation at the model grid scale. The black line represents the 1:1 ratio.

Figure 4. Top: The effects of temperature on SOC stock from CLM crops (blue) and natural vegetation (green) and ISCN observations (red). Bottom: The effects of precipitation on SOC stock from CLM crops (blue) and natural vegetation (green) and ISCN observations (red).

Figure 5. Percent decrease of SOC after conversion from natural vegetation to cropland. Percent decrease data from Wei et al. (2014) are in red (US points are orange) and CLM percent loss is blue.

Figure 64: Simulated change in total U.S. SOC (Pg C) due to agricultural land management for all scenarios.

Figure 7. The effect of agricultural land management change on crop annual average nitrogen uptake.

Figure 8.The effect of agricultural land management change on annual crop yield.

604     Table 1. CLM-Crop simulations performed.

| Run name | Land use | Fertilizer | Residue |
|---|---|---|---|
| Control | Leff et al., 2004 | Yes | 70% — all crops |
| High residue | Leff et al., 2004 | Yes | 90% — all crops |
| Medium residue | Leff et al., 2004 | Yes | 30% — maize 30% — wheat 40% — soybean |
| Low residue | Leff  et al., 2004 | Yes | 10% — all crops |
| No fertilizer | Leff  et al., 2004 | No | 70% — all crops |
| Grass | Bonan  et al., 2002 | Not applicable | Not applicable |

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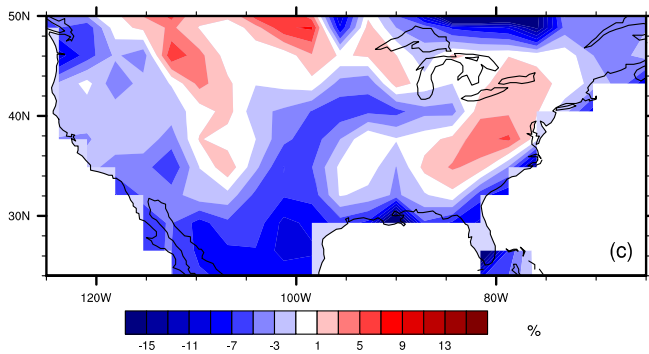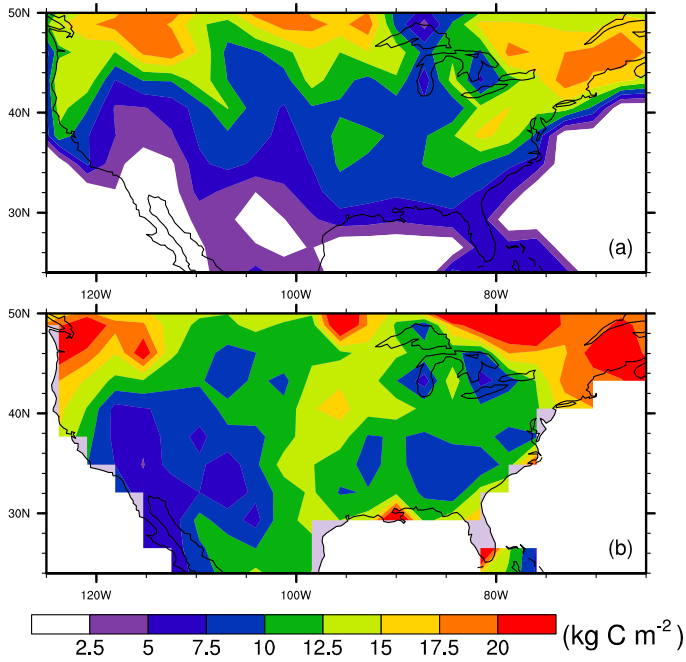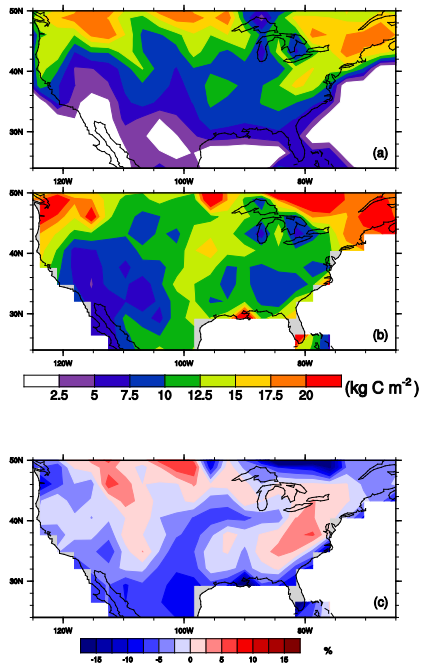
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609    Figure 1. (a) Total SOC (kg C m$^{-2}$) simulated by CLM-Crop over the contiguous United States. (b) Total

610    SOC from the IGBP over the same domain as in (a). (c) Percent difference between (a) and (b).

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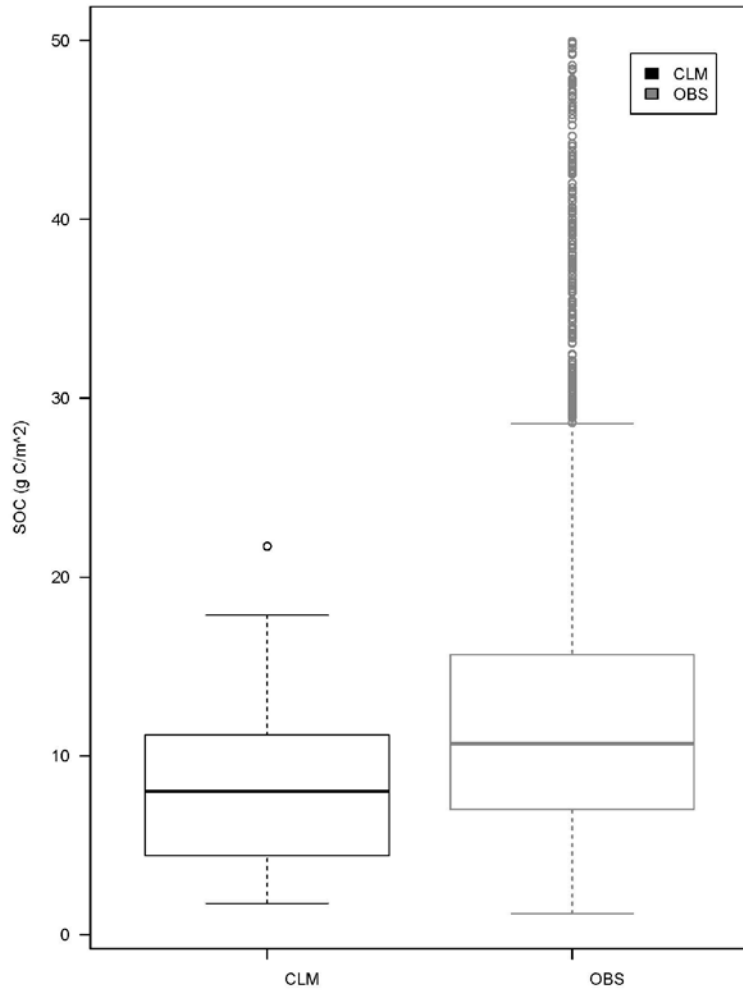


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Figure 2. Box plot of the weighted average total SOC over croplands, as simulated in CLM-Crop and in

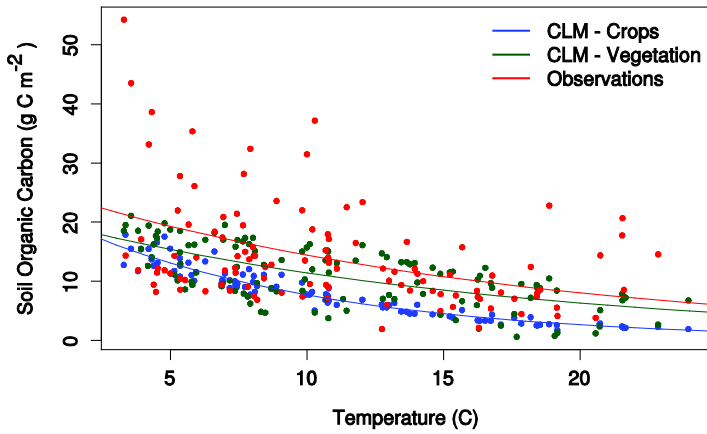observations from the ISCN. Observations reporting > 50 kg C m$^{-2}$ were removed from the analysis.

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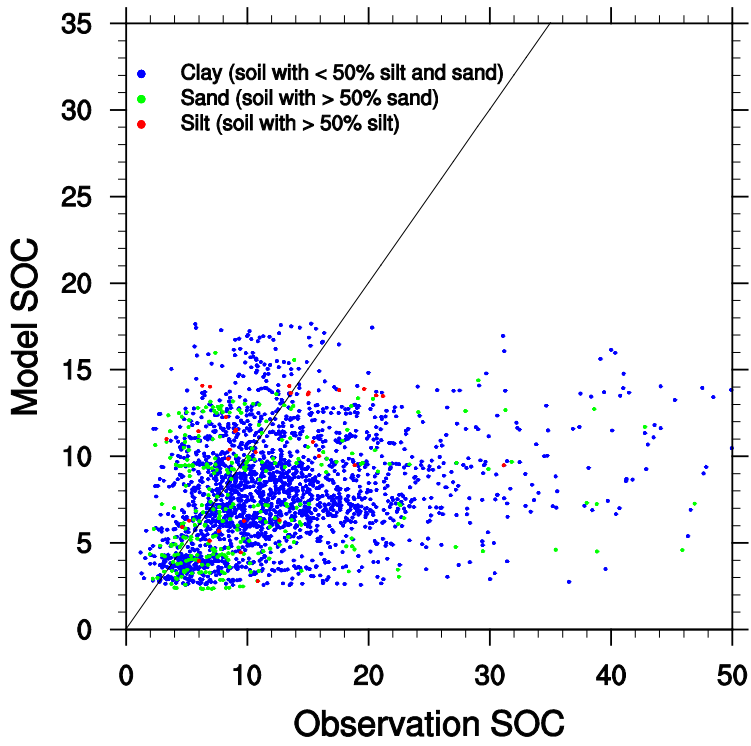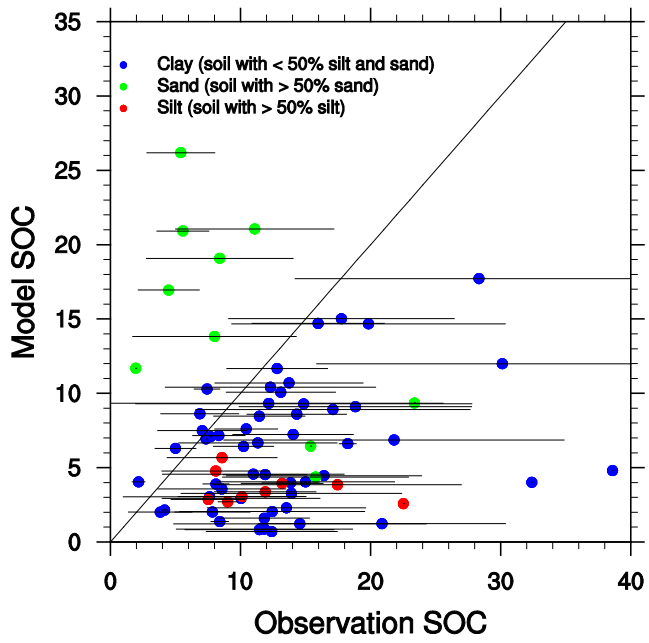
618  Figure 3. CLM-modeled SOC (g C m$^{-2}$) versus ISCN observations for soil texture types clay, sand, and
619  silt. The black line represents the 1:1 ratio.

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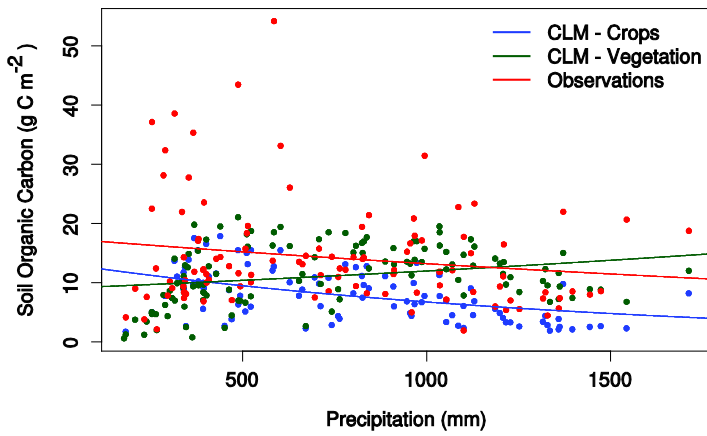
Figure 4. The effects of temperature (top) and precipitation (bottom) on SOC stock from CLM crops

623    (blue) and natural vegetation (green) and ISCN observations (red).
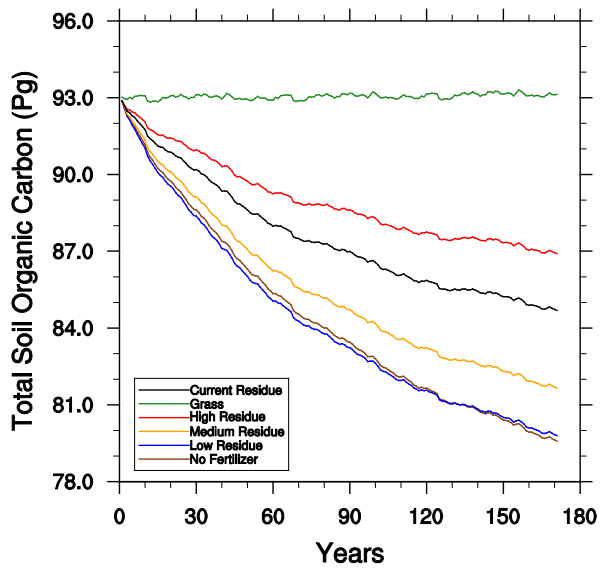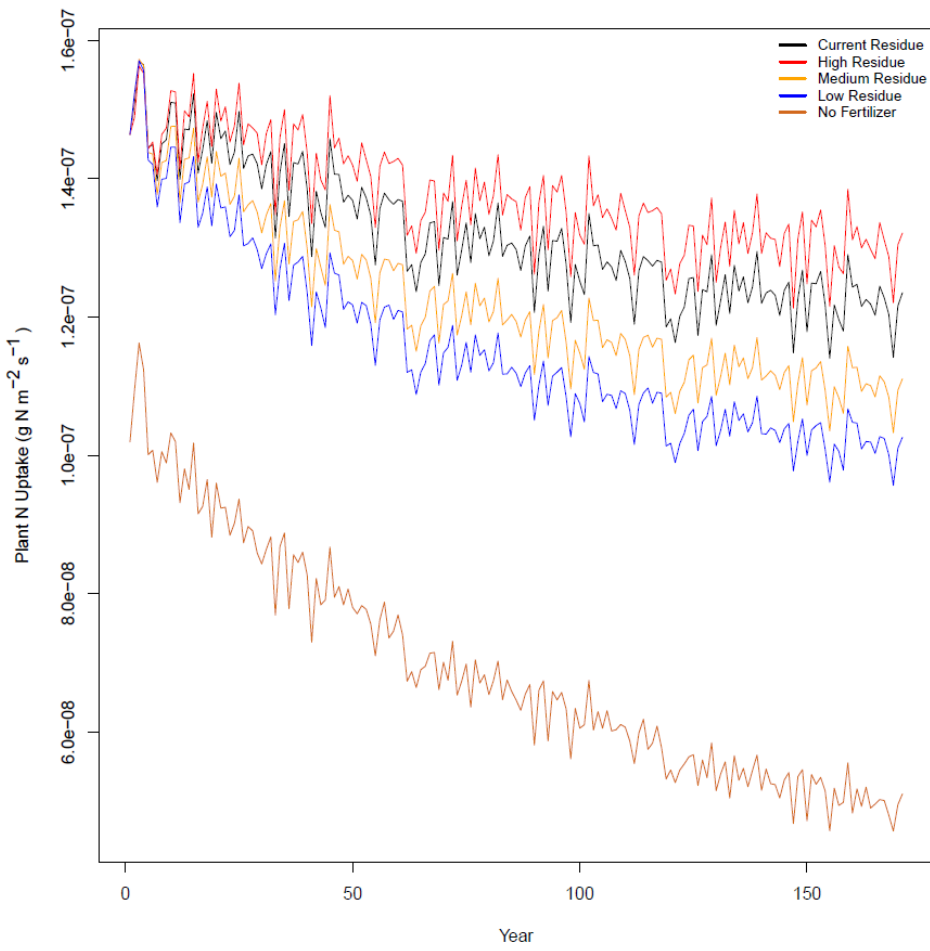
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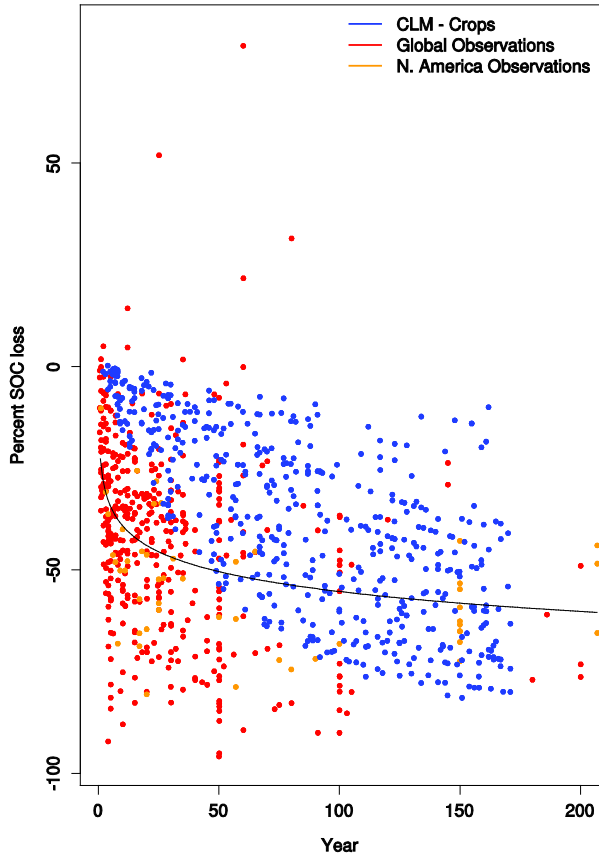
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Figure 5. Percent decrease of SOC after conversion from natural vegetation to cropland. Percent decrease

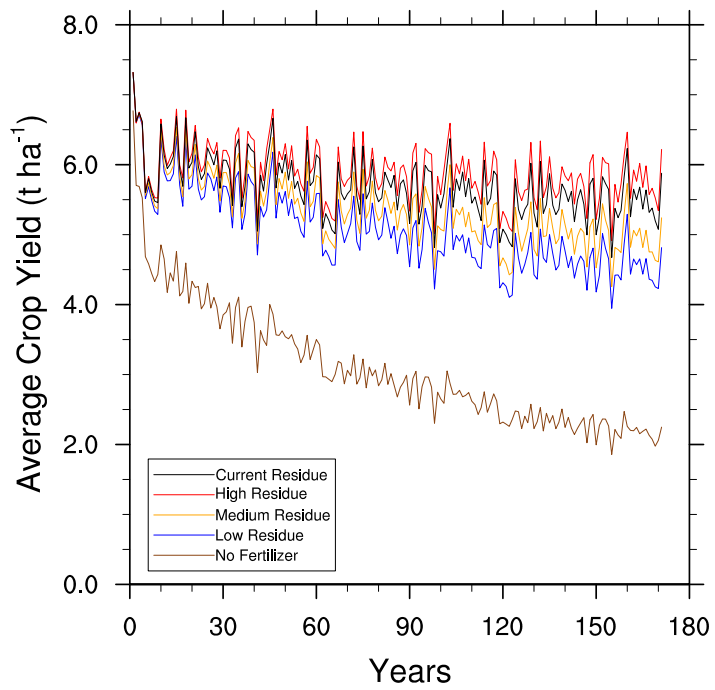data from Wei et al. (2014) are in red (US points are orange) and CLM percent loss is blue.

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Figure 46: Simulated change in total U.S. SOC (Pg C) due to agricultural land management for
all scenarios.

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634 Figure 7. The effect of agricultural land management change on crop annual average nitrogen uptake.

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Figure 8.The effect of agricultural land management change on annual crop yield.

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