Biogeosciences Discuss.,
doi:10.5194/bg-2016-473-AC2, 2017

Biogeosciences
Discussions

Interactive comment on "No significant changes in topsoil carbon in the grasslands of northern China between the 1980s and 2000s" *by* Shangshi Liu et al.

Shangshi Liu et al.

ssliu@ibcas.ac.cn

Received and published: 11 April 2017

[General Comments] In this manuscript, the authors set out to examine the changes in SOC density in the upper 30 cm of the grasslands of northern China between the 1980s and 2000s, using two computer models algorithms. They utilize soil and atmospheric data from a national database (1980s) and a field campaign (2000s) to compare the net and rate of change in SOCD. The authors conclude that northern grasslands in China remained a neutral SOC sink between the 1980s and 2000s. Overall I believe that the content of the manuscript is important for the further understanding of the global C system and may prove useful in applying models to predict C behavior in soil systems. However, I have many concerns with the manuscript in its current state. Perhaps the largest concern is that the datasets used to develop the models to determine SOCD changes over time are not from the same locations, and differences between the datasets that are due to the spatial differences will result in a bias in the results that cannot be accounted for in the current model.

[Response] Thank you very much for your supportive comments. Regarding the datasets used to develop the ANN/RF models, we agree with your concern that the differences of locations between two periods of datasets could lead to potential uncertainty in our results; however, we think this bias induced by these two periods of observations has been almost eliminated.

As you know, to directly verify SOC stock and its dynamic, repeated soil sampling is still essential and valid methods. However, only a few repeated consistent soil samplings have been conducted at national or regional scales (Bellamy et al., 2005, SEPA, 2011, Nielsen et al., 2012, Gruneberg et al., 2014). Moreover, only parts of the original sampling sites were resampled among most of these studies (Bellamy et al., 2005, Yang et al., 2010), and therefore strongly limited the role of repeated soil sampling in monitoring SOC dynamic. Thus, it is important to develop appropriate methods to compare these mismatching soil observations at different time periods, to predict SOC stock of sites in the two periods.

In our study, we used machine learning algorithms (i.e., ANN and RF) to extrapolate the SOCD in 2000s at sites with the same location as that being surveyed in 1980s, and vice versa. Thereby, comparable matched SOCD profiles were projected by these models. The algorithms produced promising predictions with high coefficient of determination (r2) and and low RMSE. Compared to other widely used spatial extrapolation method such as Kriging-based interpolation, which mainly consider the spatial relevant relationship of sites, machine learning method combined with multiple relevant database has shown better performance in theory and practice (Nello & John, 2000, Drake et al., 2006, Li et al., 2013, Yang et al. 2014). Therefore, the uncertainty led by the different sampling plots could be considerably reduced in this study.

[General Comments] Second, many parameters in the dataset are never discussed nor invoked in the model (or never stated that they are), and may play large roles in the output that are not investigated.

[Response] Thank you for your comments. Following your comments, we will further discuss those parameters in the updated MS.

In this MS, we combined SOCD data with its relevant spatial position (i.e., longitude, latitude, altitude), climate (i.e., Temperature and Precipitation), edaphic (i.e., soil texture) and vegetation database (i.e., NDVI) to construct models. We previously focused on how climate and vegetation parameters affected C dynamic, and we will further investigate the role of spatial position and edaphic factors in estimating SOCD changes in the revised MS.

In brief, in temperate grasslands, SOCD changes were negatively correlated with latitude ($P < 0.01$) and longitude ($P < 0.05$), but positively correlated with altitude ($P < 0.01$). However, no significant geographical variation was found in alpine grasslands. Moreover, t-test results shown SOCD changes were no significant correlated with soil texture in our study area.

[General Comments] Additionally, other absent parameters (e.g. respiration rates) may play critical roles in the modeling output, but are never discussed. These limitations need to critically discussed in the manuscript.

[Response] We agree that some parameters such as respiration rate play important roles in C dynamic. Unfortunately, more detailed measurements of soil respiration rates for this region were not available for this study. We will add descriptions on these limitations in the updated MS.

[General Comments] Third, a better test of the model would be to utilize the model to predict a SOCD for an area with a known vegetation type, and then directly measure the SOCD in that location to determine the accuracy of the model. Most of the modeling

optimization is performed using calculated C values, not direct measurements. For more detailed comments and concerns, see “Specific Comments” below.

[Response] Thanks for the comments. Actually, this approach of model test has been used in our MS. The detail of model test process will be more clearly clarified in revised MS as follows.

Firstly, we collected all direct soil C measurements of each period, and divided this data set into two parts (i.e., training dataset and test dataset). Secondly, the training dataset (90% of all data) was used to construct and validate the RF and ANN models. Lastly, we input data from the test dataset (10% of all data) into the constructed model and generated prediction, and the comparison of measurement C values and predicted C values were used to present the reliability of the two approaches.

Specific Comments

[comment 1] Introduction: A sentence or two should be added discussing and quantifying the importance of soil C in northern China. How much C is here? How much is estimated to be fluxing in or out of the grasslands here? Is it small compared to other global fluxes, or is it significant? If it’s small, why should anyone bother with investigating this region?

[Response] Thank you for your suggestion. The importance of soil C in northern China grasslands will be more clearly stated in the revision as follows.

Grasslands account for about 22 percent of global soil carbon stock (Jobbágy & Jackson, 2000). As an important component of global grassland ecosystems, China not only ranks the third in grassland area in the world, but also contains various grassland biomes, thus provides a unique opportunity to study the soil C dynamic of the grassland.

[comment 2] Line 50: “Previous studies”, but no references provided

[Response] Yes, we will do it.

[comment 3] Line 127: Why the top 30 cm? How was this number determined? What is its significance to the study?

[Response] Given that topsoil stores the most part of the carbon in whole soil and also is the most sensitive to environmental changes, data in the top 30 cm were used to detect SOCD changes in this study, as did in other studies (Goidts et al., 2007, 2009, Lettens et al., 2005, Prietzel et al., 2007)

[comment 4] Line 183: It is reported that the r2 values here as 0.73 and 0.62 for RF and ANN, respectively. These numbers are also provided in Table S1. However, in Figure 3, the reported values are 0.84 and 0.81. What is the difference between the two datasets being presented and compared here?

[Response] We are sorry for this confusion. This will be more clarified in Figure 3 captions. As stated in the manuscript, the r2 values of 0.73 and 0.62 were the average value of 5000 stimulations. Moreover, to intuitively present the precision of these models, we also schematically showed example data and provided relative static parameter in Figure 3, the r2 values of these example data are 0.82, 0.83, 0.81, 0.85, respectively.

[comment 5] Line 200, Table 2: In the different regions, calculated rates of change values range from -88.9 to 144.65, but the average was determined to be 3.7. How useful will the reported 3.7 value be in a region that exhibits rates closer to 144 or -89? Would it be more useful to account for the extreme spatial heterogeneity, or lump large sections together and utilize their average in global models? In what application are the results the most applicable and useful?

[Response] Thanks for your comments. We would like to mention that both these results (spatial heterogeneity pattern and average value) are applicable and useful. The application of these results will be further discussed in the revised MS.

On the one hand, to examine the driving force responsible for SOCD change, enough variability is required in this situation (Goidts et al., 2009). Therefore, we undertook

the calculation of the heterogeneity of SOCD changes of our sampling sites, and further explored the relationship between climate changes and C dynamics based on this calculation.

On the other hand, precise evaluation of the average value of SOC stock and its change is the prerequisite to understand the regional C budge, since a small change in SOC stock could significantly affect the regional C cycle. Thus, to answer this question, like other previous studies (Bellamy et al., 2005, Goidts et al., 2009), we integrated all sections in our study area, and used paired t-test to examine the average changes in regional SOCD between 1980s and 2000s, and further concluded that no significant changes in topsoil organic C in this region during our sampling period.

[comment 6] Section 3.3: The title of this section suggests that a comparison between soil geochemical parameters and SOCD will be made, but there is no discussion of geochemical parameters here, nor in the discussion section. I recommend simply deleting “and soil geochemistry” from the section title.

[Response] Thanks for your comment. “and soil geochemistry” will be removed in the revised manuscript.

[comment 7] Figures 6 & 7: C storage and stability is a function of several parameters (e.g. moisture, temperature, vegetation, etc.). Comparing one parameter (e.g. max temperature change) can not thoroughly elucidate information about the behavior and C in the soil, and predict its behavior in a model. Further, using the selected parameters is likely not the most appropriate comparison that can be made, given the dataset available.

[Response] we agree that the behavior of C storage was contributed by numerous environmental factors. Thus, mixed multilinear model will be used to investigate the influence of all environmental parameters on C behavior in soil in the revised MS.

[comment 8] It is stated that the relationship shown in Figure 9b is significant, with an r2 value of 0.16. Perhaps these data present a general trend, but I would be weary of making big claims about the relationship between MAP and NDVI from this dataset. Further, in lines 298-300, it is stated that Figure (9) demonstrates that alpine grasslands do not show a correlation between SOC and MAP, when Figure 9 shows NDVI (not SOC). Thus, the referenced data do not support the 'suggestion' in this passage. Additionally, the theory of additional precipitation leading to accelerated vegetation growth is valid, but the data in Figure 9 do not support this.

[Response] Thanks for your comments. Firstly, the Figure 9 shown the significant relationship between the temporal changes of MAP and NDVI rather than its spatial pattern. Although r2 value was not high, the positive effects of precipitation in soil C have been widely reported in temperate grasslands (Jobbágy & Jackson, 2000; Austin & Sala, 2002). In the revised MS, we will add more descriptions on the different relationship between annual precipitation change and SOCD change in temperate and alpine grasslands.

Secondly, the text in lines 298-300 we made some confusing statements mistakes and will change with "This suggests thatÂăincreased precipitation does not significantly influence the soil C input in alpine grasslands but couldÂăaccelerate vegetation growth and increase C input into the soil in temperate grasslands."

[comment 9] In lines 308-310, the authors conclude that a positive feedback was demonstrated in response to climate warming in temperate grasslands. Again, I would be very careful in making large claims based on such weak correlations (r2 = 0.1).

[Response] Thanks for your comments. Yes, the significant relationship indicated that climate factors can partly explain the SOCD change, but we will carefully describe this and revise it throughout the text in the updated MS.

[comment 10] It seems odd that the work done in this manuscript is focused on climate change and optimizing models to predict SOCD, but there is little discussion about application of the models and the results. The models use old data/calculations to

optimize, calibrate, and validate SOCD output, but for data that already exist and are known. So how can this model then be used to look forward and help "unravel SOC dynamics under climate change", as discussed in the introduction?

[Response] Thanks. Yes, we did not explain this in the discussion section in some details. We will add some more details about how this model framework can be applied to SOCD dynamic observation under the climate change scenario in the updated MS.

Our model framework has three important implications for unravelling the SOC dynamic under a climate change scenario. First, this study developed an advanced methodology which could be used to compare unmatched soil inventories between different time periods. Our results suggested combining systematic soil C measurements with machine learning approaches (i.e., ANN and RF) is a promising method to estimate SOCD change and could also be applied to other regions around the world. Second, the database generated by this model could be used for understanding the feedback loop between the grassland carbon cycle and climate change (i.e., climate warming, precipitation pattern shifts). Our finding shows varied relationships between SOCD changes and climate changes among alpine and temperate grasslands, thus highlighting that climatic controls over SOCD dynamics depend on vegetation types. Finally, our findings demonstrate that some seasonal climate parameters (i.e., summertime drought, spring and summertime max temperature) played a much more important role in comparison to annual average climate data in constraining soil C changes. To gain further insight into SOC behavior, future model studies should focus more on how these seasonal climate changes have control over the SOC dynamic.

[comment 11] The results and discussion addressing the third objective of this manuscript, to answer "How these changes are associated with climatic factors and vegetation types", is not satisfying. The 6 different ecological classifications are generically lumped into two throughout the paper, though each of the ecological domains is likely to have a distinct vegetation structure and communities. I would expect that these variables would be discussed and investigated in more detail, and justification be made for the 2-class generalization used throughout the paper if it was appropriate.

[Response] Thanks. Yes, we will add new tables to present these relationships in more details among 6 different grassland types in the updated MS.

[comment 12] The supplemental figures are never introduced nor discussed.

[Response] Thank you! We will do it.

Technical Corrections 1) Line 58: Delete period after “soil” 2) Line 66: “nature” should be “natural” 3) Line 67: accounts 4) Line 121: Delete period after “season)” 5) Line 163: Delete “s” from “sites” 6) Line 165: “were” should be “was” 7) Line 166: “extrapolated model predictions” 8) Line 168: Delete “s” from “sites” 9) Line 168: “were” should be “was” 10) Line 169: Use “absence” instead of “lackness” 11) Line 172: “. . .generated by those sites which had not been. . .” 12) Line 173: Delete “s” from “sites” 13) Line 235: “an” should be “a” 14) Lines 284, 285: A “,” should be added after “et al.” in both references 15) Line 298: Figure 9? Figure 7 is referenced, but it does not apply. 16) Line 484: Space between “Figure 7”

[Response] We thank the referee for the detailed technical corrections which helped a lot to improve the manuscript. We will make all these changes as suggested.

[References]

Austin A.T. and Sala O.E. (2002) Carbon and nitrogen dynamics across a natural precipitation gradient in Patagonia, Argentina. Journal of Vegetation Science, 13, 351–360.

Bellamy, P.H., Loveland, P.J., Bradley, R.I., Lark, R.M. and Kirk, G.J. (2005) Carbon losses from all soils across England and Wales 1978-2003. Nature, 437, 245-248.

Ding, J., Li, F., Yang, G., Chen, L., Zhang, B., Liu, L., Fang, K., Qin, S., Chen, Y., Peng, Y., Ji, C., He, H., Smith, P. and Yang, Y. (2016) The permafrost carbon inventory on the Tibetan plateau: a new evaluation using deep sediment cores. Global Change Biology,

22(8).

Drake J.M., Randin C. and Guisan A. (2006) Modelling ecological niches with support vector machines. Journal of Applied Ecology, 43, 424–432.

Goidts, E., Wesemael, B. V., and Oost, K. V. (2009). Driving forces of soil organic carbon evolution at the landscape and regional scale using data from a stratified soil monitoring. Global Change Biology, 15(12), 2981-3000.

Goidts E.and Wesemael B.V. (2007) Regional assessment of soil organic carbon changes under agriculture in southern Belgium (1955–2005). Geoderma, 141, 341-354.

Grüneberg, E., Ziche, D., and Wellbrock, N. (2014). Organic carbon stocks and sequestration rates of forest soils in germany.ÂăGlobal Change Biology,Âă20(8), 2644-62.

Jobbágy, E.G. and Jackson, R. B. (2008). The vertical distribution of soil organic carbon and its relation to climate and vegetation.ÂăEcological Applications,Âă10(2), 423-436.

Lettens, S., Orshoven, J. V., Wesemael, B. V., Vos, B. D., and Muys, B.(2005) Stocks and fluxes of soil organic carbon for landscape units in Belgium derived from heterogeneous data sets for 1990 and 2000. Geoderma, 127, 11-23

Li, Q., Yue, T., Wang, C., Zhang, W., Yu, Y., Li, B., Yang, J. and Bai, G. (2013) Spatially distributed modeling of soil organic matter across China: An application of artificial neural network approach. Catena, 104, 210-218.

Nello C., John S.T. (2000) An Introduction to Support Vector Machines and Other Kernel- based Learning Methods. Cambridge University Press, New York, USA.

Nielsen O.K., Mikkelsen M.H., Hoffmann L. et al. (2012) Denmark’s National Inventory Report 2012. Emission Inventories 1990-2010 - Submitted under the United Nations Framework Convention on Climate Change 1990-2008. National Environmental Research Institute, Aarhus, 1168.

Prietzel, J., Stetter, U., Klemmt, H. J., and Rehfuess, K. E. (2006). Recent carbon and nitrogen accumulation and acidification in soils of two scots pine ecosystems in southern germany.ÂăPlant and Soil,Âă289(1), 153-170.

SEPA (2011) National Inventory Report 2011 Sweden. Submitted under the United Nations Framework Convention on Climate Change and the Kyoto Protocol. National Inventory Report 2011, Swedish Environmental Protection Agency.

Yang, Y., Fang, J., Ma, W., Smith, P., Mohammat, A., Wang, S. and Wang, W. (2010) Soil carbon stock and its changes in northern China's grasslands from 1980s to 2000s. Global Change Biology, 16, 3036–3047.

Yang, Y., Li, P., Ding, J., Zhao, X., Ma, W., Ji, C. and Fang, J. (2014) Increased topsoil carbon stock across China's forests. Global Change Biology, 20, 2687-2696

Interactive comment on Biogeosciences Discuss., doi:10.5194/bg-2016-473, 2017.