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Response of microbial decomposition to spin-up explains CMIP5 soil carbon range until 2100

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Abstract

Soil carbon storage simulated by the Coupled Model Intercomparison Project (CMIP5) models varies 6-fold for the present day. We show that this range already exists at the beginning of the historical simulations and demonstrate that it is mostly an artifact of the representation of microbial decomposition and its response during the spin-up procedure used by the models. The 6-fold range in soil carbon, once established, is maintained through the present and to 2100 almost unchanged even under a strong business-as-usual emissions scenario. By highlighting the role of the response of decomposition to spin-up in explaining why current CMIP5 soil carbon stores vary widely, we identify the need to better constrain the outcome of this procedure as a means to reduce uncertainty in transient simulations.

1 Introduction

The land surface currently absorbs about a third of anthropogenic emissions of CO_2 (Canadell et al., 2007; Le Quéré et al., 2009) and so helps to offset global warming. Future global warming may enhance microbial decomposition and emissions of CO_2 from respired soil organic carbon (SOC), the largest carbon pool in the terrestrial biosphere (Jobbágy and Jackson, 2000). Higher emissions from SOC could accelerate increases in atmospheric CO_2 concentrations even if plant carbon uptake by photosynthesis increased under higher atmospheric CO_2 (Ahlström et al., 2013; Nishina et al., 2013; Friedlingstein et al., 2014). Conversely, if the soil remains a carbon sink (Le Quéré et al., 2009; Lund et al., 2010) the negative feedback on rising atmospheric CO_2 (Davidson and Janssens, 2006) would help limit rates of increase. How soil carbon is represented in models and how it responds to climate is critical to resolving whether the land will remain a sink or become a source of CO_2.

Recent model intercomparisons, such as the fifth phase the Coupled Model Intercomparison Project (CMIP5; Taylor et al., 2012), or the Inter-Sectoral Impact Model

Intercomparison Project (ISI-MIP; Warszawski et al., 2013) have highlighted a lack of consensus among models on whether the soil carbon sink will be sustained during the 21st century (Friedlingstein et al., 2014; Nishina et al., 2014;). These models also exhibit large discrepancies in stores of SOC they simulate. For example, Todd-Brown et al. (2013) report that total SOC simulated by CMIP5 models for the present day represents a 6-fold variation ranging from ~ 510 to ~ 3040 Pg C. Another large range (~ 1090 to ~ 2645 Pg C) exists in the present day SOC simulated by ISI-MIP models despite being driven by a harmonized weather dataset (Nishina et al., 2014). These latter results indicate that a significant fraction of the uncertainty in estimates of total SOC arises from the representation of land processes rather than differences in climate drivers.

Soil carbon pools of widely different sizes have the potential to react differently to future climate change. We therefore examine the likely reasons for the large differences between CMIP5 models in their simulation of SOC. Understanding why these models differ so significantly in the amount of SOC, and subsequently in the total amount of C mobilized in the global cycle, would enable an improvement in model projections of the resilience of SOC pools and improve our confidence in the sign of the soil carbon feedback in the future.

2 Material and methods

2.1 SOC in Earth System Models

In all global terrestrial models participating in recent intercomparison projects such as CMIP5 and ISI-MIP, the SOC balance and its change (ΔSOC) are derived in a similar way. First, inputs of carbon into the soil are derived from plant pools. Plant carbon uptake and turnover times respond to climate change, climate variability and atmospheric CO_2 independent of the size of the SOC pools. Meanwhile, modeled microbial decomposition releases carbon by heterotrophic respiration (R_h). The balance can be summarized by

$$\Delta SOC = SOC_{in} - R_h \tag{1}$$

where SOC_{in} is the input to the SOC pools from plant and litter pools.

Microbial decomposition is commonly represented as a first-order process and applied to a succession of pools. In each pool, a parameter k reflects the specific baseline residence time (Xia et al., 2013; Exbrayat et al., 2013a, b) at a reference soil temperature and non-limiting moisture conditions. Then, the decay rate is adjusted at each time step by an environmental scalar (Todd-Brown et al., 2013; Xia et al., 2013; Exbrayat et al., 2013a, b; Nishina et al., 2014) that describes the instantaneous response of microbial activity to the soil physical state as the product of a soil temperature (f_T) and a soil moisture respiration function (f_W). Various formulations of f_T and f_W have been implemented in model codes (Lloyd and Taylor, 1994; Falloon et al., 2011; Todd-Brown et al., 2013; Exbrayat et al., 2013a, b; Nishina et al., 2014) usually assuming a space and time-invariant response to the same conditions. Their effect on decay rate varies according to local soil conditions and therefore climate.

The actual decay rate ($k \times f_T \times f_W$) is applied to the amount of substrate available, SOC, to determine the amount of microbial decomposition D_m at each model time step:

$$D_m = k \times f_T \times f_W \times SOC \tag{2}$$

where $k \times f_T \times f_W$ is equivalent to the fraction of respired substrate, the inverse of the residence time SOC/R_h. A part of the decomposed organic matter is routed to pools with longer residence time and the rest is emitted as CO_2. There may be variations between models in the number of pools they represent (Nishina et al., 2013; Todd-Brown et al., 2013) and the formulations of the environmental response functions (Falloon et al., 2011; Exbrayat et al., 2013a) but at the ecosystem scale, R_h is proportional to the amount of substrate, i.e. SOC, available in the soil. This parameterization may be inconsistent with our current understanding of microbial decomposition (Allison et al.,

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2010; Schmidt et al., 2011; Wieder et al., 2013) because it lacks the representation of processes like microbial activity and priming effect (e.g. Xenakis and Williams, 2014). However, the first-order dependency of R_h on SOC, soil temperature and moisture is able to explain complex phenomenon like the apparent acclimation of decomposers to warming by quick depletion of the most labile substrate pools (Luo et al., 2001; Kirschbaum, 2004; Knorr et al., 2005).

2.2 CMIP5 data

From the CMIP5 archive we downloaded monthly soil carbon density (cSoil in metadata), litter carbon density (cLitter) and heterotrophic respiration (rh) for 15 CMIP5 models from 10 international institutions. A list of models can be found in Table 1 while further details about models and land components have been summarized in Table 2. We note that four of these models, namely BCC-CSM1.1 (model A), CCSM4 (model C), NorESM1-M (model N) and NorESM1-ME (model O), represent nitrogen limitation on plant productivity while the others do not. We selected data for the historical (1850–2005) and the most intensive Representative Concentration Pathway 8.5 (RCP 8.5, 2006–2100) experiments. A total of 79 simulations for the historical experiment, including 34 simulations continuing for RCP 8.5 (Table 1) were available. When cLitter was reported, we added it to cSoil as both pools are parameterized to generate R_h following first-order kinetics.

To calculate stock sizes we first multiplied spatially explicit data of cSoil and cLitter in $\mathrm{kg\,C\,m^{-2}}$ by corresponding grid-cell areas (areacella in metadata) and integrated their values globally. Similarly, we calculated global fluxes of R_h by multiplying monthly fluxes in $\mathrm{kg\,C\,m^{-2}}$ by grid-cell areas and integrating them globally. Fluxes were summed to obtain annual averages. Annual soil carbon input ($\mathrm{SOC_{in}}$) from above ground biomass was not available from the database. Therefore, we calculated it by inverting the SOC balance:

$$\mathrm{SOC_{in}} = \Delta\mathrm{SOC} + R_h \tag{3}$$

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As models did not start their historical simulations at the same time, we focus our analyses on the overlapping period of 1861–2100. We also averaged all realizations of the same model to retain one estimate per structure and account for model dependence (Bishop and Abramowitz, 2013) that may bias relationships presented hereafter toward the most represented model. We examined whether averaging models from the same institution led to different results but our conclusions were not affected by this choice. Therefore, we decided to treat these models as independent as they were labelled differently by their respective developers.

In the following, we report values of stocks and fluxes averaged for three periods of time, the pre-industrial (1861–1870), modern (1996–2005) and future (2091–2100) periods. While the period 1861–1870 is not part of the pre-industrial control runs sensu stricto, the minor increase in atmospheric CO_2 between pre-industrial times (i.e. before 1850) and 1870 is unlikely to have led models to simulate a strong change in the greenhouse effect and terrestrial C fluxes. Values are shown in Table 3.

2.3 Harmonized World Soil Database

HWSD (FAO, 2012) is a global dataset of dominant soil units at a 30 s arc resolution, providing soil properties for the top (0–30 cm) and sub-soil (30–100 cm). We use version 1.21 and follow the approach by Todd-Brown et al. (2013) to obtain global values. First, we regridded the HWSD by selecting dominant soil units in a 0.5° latitude × 0.5° longitude grid. Then, we multiply the organic carbon content of the dominant soil units (in % weight) by the bulk density (provided in kg dm^{-3}) to obtain the carbon density (in kg C m^{-2}) in each 0.5° × 0.5° grid cell. We multiply the density by the surface area of each grid cell and sum results to obtain a total soil carbon content of ∼ 1170 Pg C. Following Todd-Brown et al. (2013), a confidence interval of 29 % below the mean (i.e. ∼ 830 Pg C) to 32 % above the mean (i.e. ∼ 1550 Pg C) was considered to take variations in soil carbon content and the mapping processes into account. The range we obtain is slightly smaller than reported by Todd-Brown et al. (2013) (890–1660 Pg C)

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because we use an updated version of the HWSD and did not replace bulk density values for Andisols and Histosols.

3 Results

We compare total SOC for pre-industrial (1861–1870), modern (1996–2005) and future (2091–2100) periods. Figure 1 compares the total SOC range in CMIP5 models for 1861–1870 (563–2938 Pg C), 1996–2005 (576–3047 Pg C), and 2096–2100 (2582–3266 Pg C, derived using the RCP 8.5 scenario). All three periods show very similar distributions of SOC among the models and the present day and future ranges already exist at the beginning of the historical simulations. Figure 1 highlights that the size of SOC pools of individual CMIP5 models remain largely consistent over the three time periods. Indeed, pre-industrial SOC predicts modern SOC, modern SOC predicts future SOC and pre-industrial SOC predicts future stocks with a high degree of precision (Fig. 1). Also represented in Fig. 1 is the 95 % confidence interval of total SOC estimated from HWSD that we use as a reference for modern total SOC (i.e. in 1996–2005). We note that only four models fall within this range: BCC-CSM1.1 (model A), CanESM2 (model B) and the two versions of the model HadGEM2 (models G and H). Models based on the CLM4 land surface model (i.e. models C, N and O) underestimate modern SOC while all remaining models overestimate it. Note that models C, N and O include nitrogen limitation of the vegetation response to increasing CO_2.

4 Discussion

Despite the change imposed on boundary conditions during global warming experiments (Anav et al., 2013; Friedlingstein et al., 2014), CMIP5 present day and projected SOC stocks are largely determined by their initial conditions (Fig. 1). This was not unexpected due to the slow response of SOC pools but it clearly shows that modern and future stocks are defined by initial states. Further, as SOC in 1860 is unknown, CMIP5

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models use a spin-up procedure assuming steady pre-industrial boundary conditions (Xia et al., 2012) to obtain an equilibrated state for pre-industrial SOC. In order to reach equilibrium, iterative or semi-analytical methods (e.g. Xia et al., 2012) are employed to reach the pool sizes required to balance input (SOC_{in}) and output fluxes (R_h). Steady-state is assumed when the trend in ΔSOC becomes negligible. Hence, it is not the actual value of SOC that defines the equilibrium but its lack of variation in time (Xia et al., 2013; Exbrayat et al., 2013b).

A simple explanation for the CMIP5 range of total pre-industrial SOC stocks might be that models are not all at equilibrium, especially the outliers. Figure 2 shows the relationship between pre-industrial SOC_{in} and R_h, a relationship that is highly significant ($R^2 = 1$; $p < 0.001$) and strongly suggests that all models were equilibrated under pre-industrial boundary conditions. The 6-fold CMIP5 range is therefore more likely linked with the internal terrestrial processes represented in these models, something that we now examine.

Following Eqs. (1) and (2), the model-specific value of SOC obtained by a model via spin-up depends on two factors. First, if SOC_{in} is large, a larger SOC pool is required to offset it through microbial decomposition and R_h, for a given decay rate, $k \times f_T \times f_W$. Conversely, low values of SOC_{in} lead SOC pools to equilibrate to lower values for a particular decay rate. Second, if the decay rate is high (short residence time) during spin-up, SOC pools will remain small, for a given SOC_{in}. Conversely, low decay rates, or long residence time, will require large pools of substrate to offset the same input SOC_{in}. Both factors are model-specific: SOC_{in} is derived from plant primary productivity fluxes (Davidson and Janssens, 2006) while the baseline decay rate k and the shape of the response functions f_T and f_W are highly model-dependent (Falloon et al., 2011; Exbrayat et al., 2013a, b; Todd-Brown et al., 2013).

The relationship between SOC_{in} and total SOC during the pre-industrial period is shown in Fig. 3. Overall, the relationship is not significant ($R^2 = 0.01$; $p = 0.776$). Further, the models that equilibrate with the largest total SOC stock (models M, K, L) are not the models with the largest SOC input. Similarly, the small equilibrated SOC pool

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size of models C, N and O seems unrelated to SOC_{in} despite these models integrating N limitations on plant productivity and SOC_{in}. In short, the amount of SOC_{in} cannot explain the size of the initial pools.

In Fig. 4, we present the relationship between the pre-industrial SOC residence time (i.e. the inverse of the decay rate expressed as SOC/R_h) and total SOC. The relationship is highly significant ($p < 0.001$) and linear ($R^2 = 0.83$). As expected, models with a longer residence time, i.e. a low decay rate, require larger pools to offset the same SOC input, and vice-versa.

Overall, the large range exhibited by CMIP5 SOC is principally due to the response of microbial decomposition during the spin-up process (a long process that corresponds to multiple centuries of steady climate conditions). Model-specific parameter k and environmental response functions f_T and f_W drive SOC pools to the size required to compensate for SOC_{in}. The resulting equilibrated state obtained prior to the initiation of CMIP5 transient simulations propagates through the present and into the future even when using RCP 8.5. Therefore, a simple solution to reduce the uncertainty in simulated SOC stocks would be to modify model parameters, especially those related to SOC_{in} and SOC turn-over, to obtain a steady-state with SOC values representative of pre-industrial conditions. Because these are unknown and as simulated SOC does not vary much during historical experiments, we suggest that one could use current estimates provided by HWSD, or other estimates (e.g. Shangguan et al., 2014). For example, the 95 % confidence interval of total SOC derived from HWSD could be used as prior knowledge to constrain microbial decomposition parameter and response functions to generate adequate steady-state solutions of models. As decomposition processes are represented following first-order kinetics, simulating more realistic initial SOC stocks would likely lead models to represent more correct modern stocks, and improve confidence in projections of future stocks, corresponding fluxes and feedback on climate change.

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5 Conclusions

We have demonstrated that the 6-fold range in SOC stocks simulated by CMIP5 models can be explained by the model-specific response of microbial decomposition to spin-up under pre-industrial conditions. Model dependent parameter and response functions drive the size of the pools to the amount required by decay rates to offset SOC_{in} under the steady-state assumption. Once established, the resulting pool sizes remain similar through to the present and into the future even under the high-emissions RCP8.5 scenario that generates future conditions the least similar to current ones. We therefore identify the spin-up procedure, and especially the response of microbial decomposition during this very long model integration, as a key source of uncertainty in the simulation of SOC in CMIP5 models.

A model that equilibrates to a soil carbon store well outside the observed range should be examined with care. A very large amount of stored carbon increases the potential for the land surface to become a source as even a tiny relative change in decay rate can strongly enhance R_h and possibly reach a tipping point where it offset increases in SOC_{in}. Conversely, a very small SOC store increases the likelihood that it will remain a sink. Such results are likely to be artefacts of model implementation when SOC values are largely inconsistent with observed ranges.

In conclusion, we recommend that future intercomparisons should constrain model parameters so that each model achieves an equilibrated state similar to observations as the outcome of the spin-up procedure. This would remove a degree of freedom in initial conditions when comparing differences in projected changes.

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Table 1 of this paper) for producing and making available their model output. For CMIP the US Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

References

Ahlström, A., Smith, B., Lindström, J., Rummukainen, M., and Uvo, C. B.: GCM characteristics explain the majority of uncertainty in projected 21st century terrestrial ecosystem carbon balance, Biogeosciences, 10, 1517–1528, doi:10.5194/bg-10-1517-2013, 2013.

Allison, S. D., Wallenstein, M. D., and Bradford, M. A.: Soil-carbon response to warming dependent on microbial physiology, Nat. Geosci., 3, 336–340, doi:10.1038/ngeo846, 2010.

Anav, A., Friedlingstein, P., Kidston, M., Bopp, L., Ciais, P., Cox, P., Jones, C., Jung, M., Myneni, R., and Zhu, Z.: Evaluating the land and ocean components of the global carbon cycle in the CMIP5 Earth System Models, J. Climate, 26, 6801–6843, doi:10.1175/JCLI-D-12-00417.1, 2013.

ARORA, V. K. and BOER, G. J.: Uncertainties in the 20th century carbon budget associated with land use change, Glob. Chang. Biol., 16, 3327–3348, doi:10.1111/j.1365-2486.2010.02202.x, 2010.

Bentsen, M., Bethke, I., Debernard, J. B., Iversen, T., Kirkevåg, A., Seland, Ø., Drange, H., Roelandt, C., Seierstad, I. A., Hoose, C., and Kristjánsson, J. E.: The Norwegian Earth System Model, NorESM1-M – Part 1: Description and basic evaluation of the physical climate, Geosci. Model Dev., 6, 687–720, doi:10.5194/gmd-6-687-2013, 2013.

Bishop, C. H. and Abramowitz, G.: Climate model dependence and the replicate Earth paradigm, Clim. Dynam., 41, 885–900, doi:10.1007/s00382-012-1610-y, 2012.

Canadell, J. G., Le Quéré, C., Raupach, M. R., Field, C. B., Buitenhuis, E. T., Ciais, P., Conway, T. J., Gillett, N. P., Houghton, R. A., and Marland, G.: Contributions to accelerating atmospheric CO_2 growth from economic activity, carbon intensity, and efficiency of natural sinks., P. Natl. Acad. Sci. USA, 104, 18866–70, doi:10.1073/pnas.0702737104, 2007.

Chylek, P., Li, J., Dubey, M. K., Wang, M., and Lesins, G.: Observed and model simulated 20th century Arctic temperature variability: Canadian Earth System Model CanESM2, Atmos. Chem. Phys. Discuss., 11, 22893–22907, doi:10.5194/acpd-11-22893-2011, 2011.

Clark, D. B., Mercado, L. M., Sitch, S., Jones, C. D., Gedney, N., Best, M. J., Pryor, M., Rooney, G. G., Essery, R. L. H., Blyth, E., Boucher, O., Harding, R. J., Huntingford, C., and Cox, P. M.: The Joint UK Land Environment Simulator (JULES), model description – Part 2: Carbon fluxes and vegetation dynamics, Geosci. Model Dev., 4, 701–722, doi:10.5194/gmd-4-701-2011, 2011.

Collins, W. J., Bellouin, N., Doutriaux-Boucher, M., Gedney, N., Halloran, P., Hinton, T., Hughes, J., Jones, C. D., Joshi, M., Liddicoat, S., Martin, G., O'Connor, F., Rae, J., Senior, C., Sitch, S., Totterdell, I., Wiltshire, A., and Woodward, S.: Development and evaluation of an Earth-System model – HadGEM2, Geosci. Model Dev., 4, 1051–1075, doi:10.5194/gmd-4-1051-2011, 2011.

Cox, P. M.: Description of the TRIFFID dynamic global vegetation model, Met Office Hadley Centre Tech. Note, 24, 17 pp., 2001.

Davidson, E. A. and Janssens, I. A.: Temperature sensitivity of soil carbon decomposition and feedbacks to climate change, Nature, 440, 165–173, doi:10.1038/nature04514, 2006.

Doney, S. C., Lindsay, K., Fung, I., and John, J.: Natural variability in a stable, 1000-yr global coupled climate–carbon cycle simulation, J. Climate, 19, 3033–3054, doi:10.1175/JCLI3783.1, 2006.

Dufresne, J.-L., Foujols, M.-A., Denvil, S., Caubel, A., Marti, O., Aumont, O., Balkanski, Y., Bekki, S., Bellenger, H., Benshila, R., Bony, S., Bopp, L., Braconnot, P., Brockmann, P., Cadule, P., Cheruy, F., Codron, F., Cozic, A., Cugnet, D., Noblet, N., Duvel, J.-P., Ethé, C., Fairhead, L., Fichefet, T., Flavoni, S., Friedlingstein, P., Grandpeix, J.-Y., Guez, L., Guilyardi, E., Hauglustaine, D., Hourdin, F., Idelkadi, A., Ghattas, J., Joussaume, S., Kageyama, M., Krinner, G., Labetoulle, S., Lahellec, A., Lefebvre, M.-P., Lefevre, F., Levy, C., Li, Z. X., Lloyd, J., Lott, F., Madec, G., Mancip, M., Marchand, M., Masson, S., Meurdesoif, Y., Mignot, J., Musat, I., Parouty, S., Polcher, J., Rio, C., Schulz, M., Swingedouw, D., Szopa, S., Talandier, C., Terray, P., Viovy, N., and Vuichard, N.: Climate change projections using the IPSL-CM5 Earth System Model: from CMIP3 to CMIP5, Clim. Dynam., 40, 2123–2165, doi:10.1007/s00382-012-1636-1, 2013.

Dunne, J. P., John, J. G., Adcroft, A. J., Griffies, S. M., Hallberg, R. W., Shevliakova, E., Stouffer, R. J., Cooke, W., Dunne, K. A., Harrison, M. J., Krasting, J. P., Malyshev, S. L., Milly, P. C. D., Phillipps, P. J., Sentman, L. T., Samuels, B. L., Spelman, M. J., Winton, M., Wittenberg, A. T., and Zadeh, N.: GFDL's ESM2 global coupled climate–carbon earth system models, Part I: Physical formulation and baseline simulation characteristics, J. Climate, 25, 6646–6665, doi:10.1175/JCLI-D-11-00560.1, 2012.

Exbrayat, J.-F., Pitman, A. J., Abramowitz, G., and Wang, Y.-P.: Sensitivity of net ecosystem exchange and heterotrophic respiration to parameterization uncertainty, J. Geophys. Res. Atmos., 118, 1640–1651, doi:10.1029/2012JD018122, 2013a.

Exbrayat, J.-F., Pitman, A. J., Zhang, Q., Abramowitz, G., and Wang, Y.-P.: Examining soil carbon uncertainty in a global model: response of microbial decomposition to temperature, moisture and nutrient limitation, Biogeosciences, 10, 7095–7108, doi:10.5194/bg-10-7095-2013, 2013b.

Falloon, P., Jones, C. D., Ades, M., and Paul, K.: Direct soil moisture controls of future global soil carbon changes: an important source of uncertainty, Global Biogeochem. Cy., 25, GB3010, doi:10.1029/2010GB003938, 2011.

FAO/IIASA/ISRIC/ISSCAS/JRC: Harmonized World Soil Database (version 1.21). FAO, Rome, Italy and IIASA, Laxenburg, Austria, 2012.

Foley, J. A.: An equilibrium model of the terrestrial carbon budget, Tellus B, 47, 310–319, doi:10.1034/j.1600-0889.47.issue3.3.x, 1995.

Friedlingstein, P., Meinshausen, M., Arora, V. K., Jones, C. D., Anav, A., Liddicoat, S. K., and Knutti, R.: Uncertainties in CMIP5 Climate Projections due to Carbon Cycle Feedbacks, J. Climate, 27, 511–526, doi:10.1175/JCLI-D-12-00579.1, 2014.

Gent, P. R., Danabasoglu, G., Donner, L. J., Holland, M. M., Hunke, E. C., Jayne, S. R., Lawrence, D. M., Neale, R. B., Rasch, P. J., Vertenstein, M., Worley, P. H., Yang, Z.-L., and Zhang, M.: The Community Climate System Model Version 4, J. Climate, 24, 4973–4991, doi:10.1175/2011JCLI4083.1, 2011.

Giorgetta, M. A., Jungclaus, J., Reick, C. H., Legutke, S., Bader, J., Böttinger, M., Brovkin, V., Crueger, T., Esch, M., Fieg, K., Glushak, K., Gayler, V., Haak, H., Hollweg, H.-D., Ilyina, T., Kinne, S., Kornblueh, L., Matei, D., Mauritsen, T., Mikolajewicz, U., Mueller, W., Notz, D., Pithan, F., Raddatz, T., Rast, S., Redler, R., Roeckner, E., Schmidt, H., Schnur, R., Segschneider, J., Six, K. D., Stockhause, M., Timmreck, C., Wegner, J., Widmann, H., Wieners, K.-H., Claussen, M., Marotzke, J., and Stevens, B.: Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the coupled model intercomparison project phase 5, J. Adv. Model. Earth Syst., 5, 572–597, doi:10.1002/jame.20038, 2013.

Jenkinson, D. S.: The turnover of organic-carbon and nitrogen in soil, Philos. T. R. Soc. Lond., 329, 361–368, 1990.

Ji, J., Huang, M., and Li, K.: Prediction of carbon exchanges between China terrestrial ecosystem and atmosphere in 21st century, Sci. China Ser. D, 51, 885–898, doi:10.1007/s11430-008-0039-y, 2008.

Jobbágy, E. G. and Jackson, R. B.: The vertical distribution of soil organic carbon and its relation to climate and vegetation, Ecol. Appl., 10, 423–436, doi:10.1890/1051-0761(2000)010[0423:TVDOSO]2.0.CO;2, 2000.

Kirschbaum, M. U. F.: Soil respiration under prolonged soil warming: are rate reductions caused by acclimation or substrate loss?, Glob. Change Biol., 10, 1870–1877, doi:10.1111/j.1365-2486.2004.00852.x, 2004.

Knorr, W.: Annual and interannual CO_2 exchanges of the terrestrial biosphere: process-based simulations and uncertainties, Glob. Ecol. Biogeogr., 9, 225–252, doi:10.1046/j.1365-2699.2000.00159.x, 2000.

Knorr, W., Prentice, I. C., House, J. I., and Holland, E. A.: Long-term sensitivity of soil carbon turnover to warming, Nature, 433, 298–301, doi:10.1038/nature03226, 2005.

Krinner, G., Viovy, N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, P., Sitch, S., and Prentice, I. C.: A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system, Global Biogeochem. Cy., 19, GB1015, doi:10.1029/2003GB002199, 2005.

Le Quéré, C., Raupach, M. R., Canadell, J. G., Marland, G., Bopp, L., Ciais, P., Conway, T. J., Doney, S. C., Feely, R. A., Foster, P., Friedlingstein, P., Gurney, K., Houghton, R. A., House, J. I., Huntingford, C., Levy, P. E., Lomas, M. R., Majkut, J., Metzl, N., Ometto, J. P., Peters, G. P., Prentice, I. C., Randerson, J. T., Running, S. W., Sarmiento, J. L., Schuster, U., Sitch, S., Takahashi, T., Viovy, N., van der Werf, G. R., and Woodward, F. I.: Trends in the sources and sinks of carbon dioxide, Nat. Geosci., 2, 831–836, doi:10.1038/ngeo689, 2009.

Lawrence, D. M., Oleson, K. W., Flanner, M. G., Thornton, P. E., Swenson, S. C., Lawrence, P. J., Zeng, X., Yang, Z.-L., Levis, S., Sakaguchi, K., Bonan, G. B., and Slater, A. G.: Parameterization improvements and functional and structural advances in Version 4 of the Community Land Model, J. Adv. Model. Earth Syst., 3, M03001, doi:10.1029/2011MS000045, 2011.

Lloyd, J. and Taylor, J. A.: On the temperature dependence of soil respiration, Funct. Ecol., 8, 315–323, 1994.

Lund, M., Lafleur, P. M., Roulet, N. T., Lindroth, A., Christensen, T. R., Aurela, M., Chojnicki, B. H., Flanagan, L. B., Humphreys, E. R., Laurila, T., Oechel, W. C., Olejnik, J., Rinne, J., Schubert, P., and Nilsson, M. B.: Variability in exchange of CO_2 across 12 northern peatland and tundra sites, Glob. Chang. Biol., 16, 2436–2448, doi:10.1111/j.1365-2486.2009.02104.x, 2009.

Luo, Y., Wan, S., Hui, D., and Wallace, L. L.: Acclimatization of soil respiration to warming in a tall grass prairie., Nature, 413, 622–5, doi:10.1038/35098065, 2001.

Nishina, K., Ito, A., Beerling, D. J., Cadule, P., Ciais, P., Clark, D. B., Falloon, P., Friend, A. D., Kahana, R., Kato, E., Keribin, R., Lucht, W., Lomas, M., Rademacher, T. T., Pavlick, R., Schaphoff, S., Vuichard, N., Warszawaski, L., and Yokohata, T.: Quantifying uncertainties in soil carbon responses to changes in global mean temperature and precipitation, Earth Syst. Dynam., 5, 197–209, doi:10.5194/esd-5-197-2014, 2014.

Parton, W. J., Schimel, D. S., Cole, C. V. and Ojima, D. S.: Analysis of Factors Controlling Soil Organic Matter Levels in Great Plains Grasslands, Soil Sci. Soc. Am. J., 51, 1173–1179, doi:10.2136/sssaj1987.03615995005100050015x, 1987.

Parton, W. J., Stewart, J. W. B., and Cole, C. V.: Dynamics of C, N, P and S in grassland soils: a model, Biogeochemistry, 5, 109–131, doi:10.1007/BF02180320, 1988.

Raddatz, T. J., Reick, C. H., Knorr, W., Kattge, J., Roeckner, E., Schnur, R., Schnitzler, K.-G., Wetzel, P., and Jungclaus, J.: Will the tropical land biosphere dominate the climate–carbon cycle feedback during the twenty-first century?, Clim. Dynam., 29, 565–574, doi:10.1007/s00382-007-0247-8, 2007.

Randerson, J. T., Thompson, M. V., Conway, T. J., Fung, I. Y., and Field, C. B.: The contribution of terrestrial sources and sinks to trends in the seasonal cycle of atmospheric carbon dioxide, Global Biogeochem. Cy., 11, 535–560, doi:10.1029/97GB02268, 1997.

Sato, H., Itoh, A., and Kohyama, T.: SEIB–DGVM: a new Dynamic Global Vegetation Model using a spatially explicit individual-based approach, Ecol. Model., 200, 279–307, doi:10.1016/j.ecolmodel.2006.09.006, 2007.

Schmidt, M. W. I., Torn, M. S., Abiven, S., Dittmar, T., Guggenberger, G., Janssens, I. A., Kleber, M., Kögel-Knabner, I., Lehmann, J., Manning, D. A. C., Nannipieri, P., Rasse, D. P., Weiner, S., and Trumbore, S. E.: Persistence of soil organic matter as an ecosystem property, Nature, 478, 49–56, doi:10.1038/nature10386, 2011.

Shangguan, W., Dai, Y., Duan, Q., Liu, B., and Yuan, H.: A global soil data set for earth system modeling, J. Adv. Model. Earth Syst., 6, 249–263, doi:10.1002/2013MS000293, 2014.

Shevliakova, E., Pacala, S. W., Malyshev, S., Hurtt, G. C., Milly, P. C. D., Caspersen, J. P., Sentman, L. T., Fisk, J. P., Wirth, C., and Crevoisier, C.: Carbon cycling under 300 years of

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land use change: importance of the secondary vegetation sink, Global Biogeochem. Cy., 23, GB2022, doi:10.1029/2007GB003176, 2009.

Shindell, D. T., Pechony, O., Voulgarakis, A., Faluvegi, G., Nazarenko, L., Lamarque, J.-F., Bowman, K., Milly, G., Kovari, B., Ruedy, R., and Schmidt, G. A.: Interactive ozone and methane chemistry in GISS-E2 historical and future climate simulations, Atmos. Chem. Phys., 13, 2653–2689, doi:10.5194/acp-13-2653-2013, 2013.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An overview of CMIP5 and the experiment design, B. Am. Meteorol. Soc., 93, 485–498, doi:10.1175/BAMS-D-11-00094.1, 2012.

Thornton, P. E. and Rosenbloom, N. A.: Ecosystem model spin-up: estimating steady state conditions in a coupled terrestrial carbon and nitrogen cycle model, Ecol. Model., 189, 25–48, doi:10.1016/j.ecolmodel.2005.04.008, 2005.

Thornton, P. E., Lamarque, J.-F., Rosenbloom, N. A., and Mahowald, N. M.: Influence of carbon-nitrogen cycle coupling on land model response to CO_2 fertilization and climate variability, Global Biogeochem. Cy., 21, GB4018, doi:10.1029/2006GB002868, 2007.

Todd-Brown, K. E. O., Randerson, J. T., Post, W. M., Hoffman, F. M., Tarnocai, C., Schuur, E. A. G., and Allison, S. D.: Causes of variation in soil carbon simulations from CMIP5 Earth system models and comparison with observations, Biogeosciences, 10, 1717–1736, doi:10.5194/bg-10-1717-2013, 2013.

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., and Schewe, J.: The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP): project framework, P. Natl. Acad. Sci. USA, 111, 3228–32, doi:10.1073/pnas.1312330110, 2014.

Watanabe, S., Hajima, T., Sudo, K., Nagashima, T., Takemura, T., Okajima, H., Nozawa, T., Kawase, H., Abe, M., Yokohata, T., Ise, T., Sato, H., Kato, E., Takata, K., Emori, S., and Kawamiya, M.: MIROC-ESM 2010: model description and basic results of CMIP5-20c3m experiments, Geosci. Model Dev., 4, 845–872, doi:10.5194/gmd-4-845-2011, 2011.

Wieder, W. R., Bonan, G. B., and Allison, S. D.: Global soil carbon projections are improved by modelling microbial processes, Nat. Clim. Chang., 3, 909–912, doi:10.1038/nclimate1951, 2013.

Wu, T., Li, W., Ji, J., Xin, X., Li, L., Wang, Z., Zhang, Y., Li, J., Zhang, F., Wei, M., Shi, X., Wu, F., Zhang, L., Chu, M., Jie, W., Liu, Y., Wang, F., Liu, X., Li, Q., Dong, M., Liang, X., Gao, Y., and Zhang, J.: Global carbon budgets simulated by the Beijing climate center climate system model for the last century, J. Geophys. Res.-Atmos., 118, 4326–4347, doi:10.1002/jgrd.50320, 2013.

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7, 3481–3504, 2014

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Xenakis, G. and Williams, M.: Comparing microbial and chemical approaches for modelling soil organic carbon decomposition using the DecoChem v1.0 and DecoBio v1.0 models, Geosci. Model Dev. Discuss., 7, 33–72, doi:10.5194/gmdd-7-33-2014, 2014.
Xia, J. Y., Luo, Y. Q., Wang, Y.-P., Weng, E. S., and Hararuk, O.: A semi-analytical solution to accelerate spin-up of a coupled carbon and nitrogen land model to steady state, Geosci. Model Dev., 5, 1259–1271, doi:10.5194/gmd-5-1259-2012, 2012.
Xia, J., Luo, Y., Wang, Y.-P., and Hararuk, O.: Traceable components of terrestrial carbon storage capacity in biogeochemical models., Glob. Change Biol., 19, 2104–16, doi:10.1111/gcb.12172, 2013.

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Table 1. CMIP5 models and number of simulations used in this paper for historical and RCP 8.5 runs. The first column provides the letter code used in the figures. References and details about soil carbon components are provided in Supplement Tables 2 and 3.

	Model name	Institution	Number of model runs	
			Historical	RCP 8.5
A	BCC-CSM1.1	Beijing Climate Center (China)	3	0
B	CanESM2	Canadian Centre for Climate Modelling and Analysis (Canada)	5	5
C	CCSM4	National Center for Atmospheric Research (USA)	6	6
D	GFDL-ESM2G	Geophysical Fluid Dynamics Laboratory (USA)	1	1
E	GISS-E2-H	NASA Goddard Institute for Space Studies (USA)	17	3
F	GISS-E2-R		25	3
G	HadGEM2-CC	Met Office/Hadley Centre (UK)	1	1
H	HadGEM2-ES		3	3
I	IPSL-CM5A-LR	Institut Pierre Simon Laplace (France)	6	4
J	IPSL-CM5B-LR		1	1
K	MIROC-ESM	Japan Agency for Marine-Earth Science and Technology (Japan)	3	1
L	MIROC-ESM-CHEM		1	1
M	MPI-ESM-LR	Max Planck Institute (Germany)	3	3
N	NorESM1-M	Bjerknes Centre for Climate Research (Norway)	3	1
O	NorESM1-ME		1	1

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Table 2. Details about the CMIP5 models terrestrial and soil component and associated references.

	Model name	Terrestrial component	Soil biogeochemistry	# of pools L	# of pools S	N limitations
A	BCC-CSM1.1 (Wu et al., 2013)	AVIM2 (Ji et al., 2008)	Based on CENTURY (Parton et al., 1987)	2	6	Yes
B	CanESM2 (Chylek et al., 2011)	CTEM (Arora and Boer, 2010)	CTEM (Arora and Boer, 2010)	1	1	No
C	CCSM4 (Gent et al., 2011)	CLM4-CN (Lawrence et al., 2011)	CN module (Thornton et al., 2007) based on Biome-BGC 4.1.2 (Thornton and Rosenbloom, 2005)	3	3	Yes
D	GFDL-ESM2G (Dunne et al., 2012)	LM3.0 (Shevliakova et al., 2009)	Based on CENTURY (Parton et al., 1987)	–	2	No
E	GISS-E2-H (Shindell et al., 2013)	NCAR-CSM1.4 (Doney et al., 2006)	Based on CASA (Randerson et al., 1997)	–	9	No
F	GISS-E2-R (Shindell et al., 2013)			–	9	No
G	HadGEM2-CC (Collins et al., 2011)	JULES (Clark et al., 2011)	Based on TRIFFID (Cox, 2001) and RothC (Jenkinson, 1990)	–	4	No
H	HadGEM2-ES (Collins et al., 2011)			–	4	No
I	IPSL-CM5A-LR (Dufresne et al., 2013)	ORCHIDEE	STOMATE (Krinner et al., 2005) and CENTURY (Parton et al., 1988)	3	4	No
J	ISPL-CM5B-LR (Dufresne et al., 2013)			3	4	No
K	MIROC-ESM (Watanabe et al., 2011)	SEIB-DGVM (Sato et al., 2007)	Based on DEMETER-1 (Foley et al., 2005)	–	2	No
L	MIROC-ESM-CHEM (Watanabe et al., 2011)			–	2	No
M	MPI-ESM-LR (Giorgetta et al., 2013)	JSBACH (Raddatz et al., 2007)	Based on Bethy (Knorr, 2000) and CENTURY (Parton et al., 1988)	1	1	No
N	NorESM1-M (Bentsen et al., 2012)	CLM4-CN (Lawrence et al., 2011)	CN module (Thornton et al., 2007) based on Biome-BGC 4.1.2 (Thornton and Rosenbloom, 2005)	3	3	Yes
O	NorESM1-ME (Bentsen et al., 2012)			3	3	Yes

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Table 3. Model specific values of SOC_{in}, R_h and SOC used in Figs. 1 to 4. Values are averaged over the indicated years. All data are rounded to whole numbers. Values for 2091–2100 are from the Representative Concentration Pathway 8.5 (RCP 8.5) simulations.

Model	SOC_{in} [Pg C yr^{-1}]			R_h [Pg C yr^{-1}]			Total soil carbon [Pg C]		
	1861–1870	1996–2005	2091–2100	1861–1870	1996–2005	2091–2100	1861–1870	1996–2005	2091–2100
A	75	87	–	75	86	–	1273	1351	–
B	57	64	84	56	65	85	1511	1541	1490
C	46	49	56	46	49	57	563	576	582
D	79	85	119	79	86	120	1798	1781	1785
E	45	56	59	46	55	62	1988	2187	1997
F	44	54	57	45	54	60	2237	2425	2238
G	66	85	139	66	83	136	1178	1282	1604
H	68	88	140	68	86	137	1179	1291	1588
I	81	93	130	82	93	130	1657	1686	1735
J	70	81	116	70	81	116	1538	1567	1684
K	57	56	71	56	55	74	2515	2566	2494
L	57	57	74	55	56	77	2502	2572	2521
M	66	75	100	66	74	99	2938	3047	3266
N	51	54	59	51	54	60	646	662	637
O	52	55	63	52	55	64	654	670	672

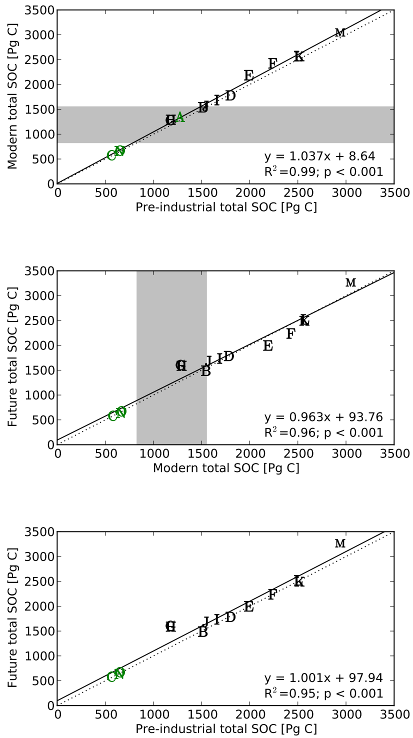

Figure 1. Relationship between total SOC in CMIP5 models at two different times: modern stocks as a function of pre-industrial stocks (upper panel), future stocks as a function of modern stocks (middle panel) and future stocks as a function of pre-industrial stocks (lower panel). Letters correspond to models as in Table 1 and models in green integrate nitrogen limitation. The gray area is the 95 % confidence interval of modern total SOC derived from the HWSD. Equation, R^2 and p values correspond to the linear relationship between stocks built using data from all models (solid line). The dotted line is the 1 : 1 line.

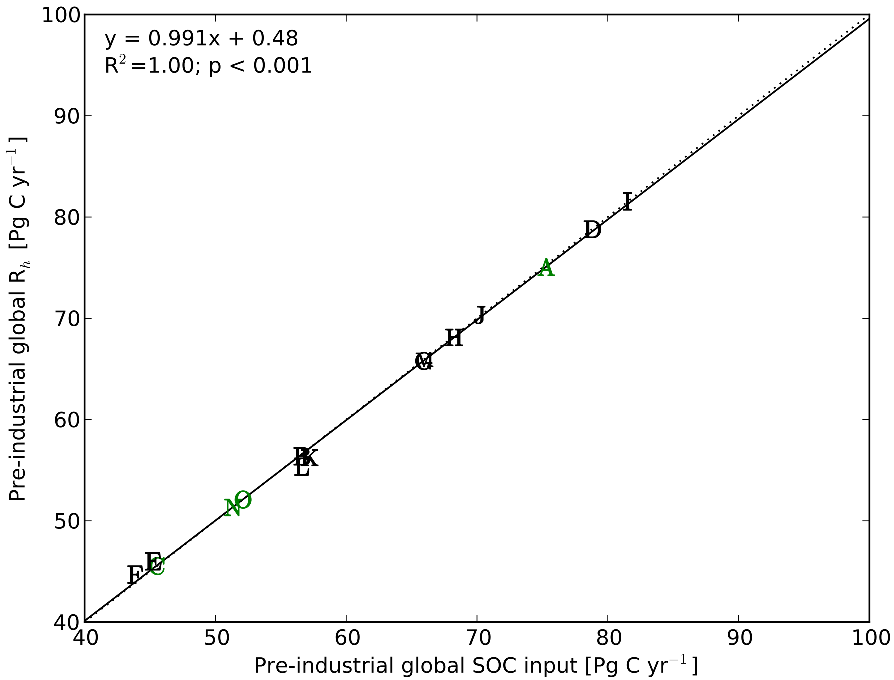

Figure 2. Relationship between pre-industrial global SOC input and pre-industrial R_h. Letters are the same as in Table 1 and models in green integrate nitrogen limitation. The solid line is a linear relationship constructed using all models with equation, R^2 and p values indicated in the top left corner. The dashed line represents the 1 : 1 relationship.

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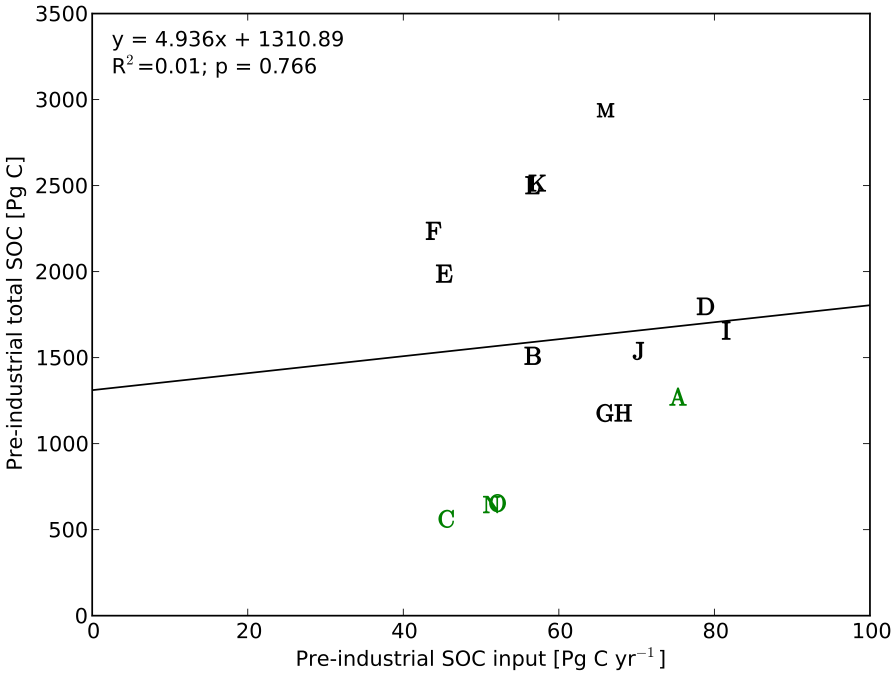

Figure 3. Relationship between pre-industrial SOC input and pre-industrial total SOC stocks at the beginning of the historical experiment. Letters correspond to the same models as in Table 1 and models in green integrate nitrogen limitation. The solid line is a linear relationship constructed using all models with equation, R^2 and p values indicated in the top left corner.

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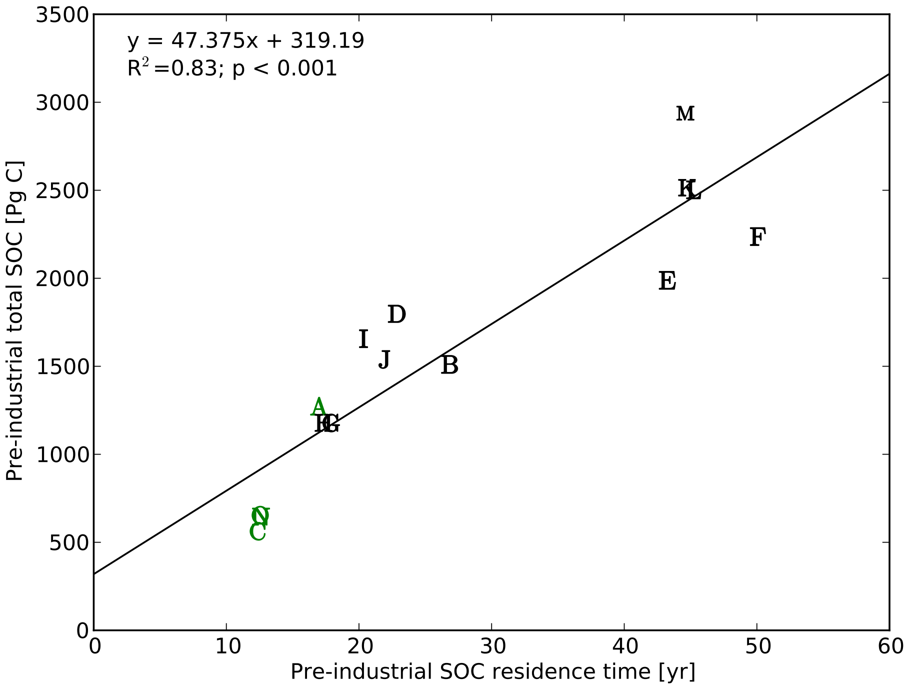

Figure 4. Relationship between pre-industrial global SOC residence time and total SOC. Letters correspond to the same models as in Table 1 and models in green integrate nitrogen limitation. The solid line is a linear relationship constructed using all models with equation, R^2 and p values indicated in the top left corner.