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Effects of model assumptions for soil processes on carbon turnover in the earth system

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Abstract

Soil organic matter (SOM) is the largest store of organic carbon (C) in the biosphere, but still the turnover of SOM is incompletely understood and not well described in global C cycle models. Here we use the Community Land Model (CLM) and compare the output for soil organic C (SOC) to estimates from a global data set. We also modify the assumptions about SOM turnover in two ways: (1) we assume distinct temperature sensitivities of SOC pools with different turnover time and (2) we assume a priming effect, such that decomposition rate of native SOM increases in response to a supply of fresh organic matter. The standard model predicted the global distribution of SOM reasonably well in most areas, but it failed to predict the very high stocks of SOM at high latitudes. It also predicted somewhat too much SOC in areas with high plant productivity, such as tropical rain forests and some mid-latitude areas. Assuming that the temperature sensitivity of SOC decomposition is dependent on the turnover rate of component pools reduced total SOC at equilibrium by a relatively small amount (< 1 % globally). Including a priming effect reduced total global SOC more (6.6 % globally) and tended to decrease SOC most in areas with high plant input (tropical and temperate forests), which were also the areas where the unmodified model overpredicted SOC (by about 40 %). The model was then run with climate change prediction for the standard and modified versions. Future simulations showed that differences between the standard and modified versions were maintained in a future with climate change (4–6 and 23–47 Pg difference in soil carbon between standard simulation and the modified with temperature sensitivity and priming respectively).

1 Introduction

Soil organic matter (SOM) is the largest store of organic carbon (C) in the biosphere (Batjes, 1996). Even relatively small percentage changes in this store can lead to large changes in atmospheric CO_2 concentrations. However, there is still large uncertainty associated with the response of SOM dynamics to perturbations such as changes in temperature, moisture and plant-derived inputs to soils that are predicted under environmental change (Billings et al., 2010; Heimann and Reichstein, 2008; Conant et al., 2011; Ostle et al., 2009; Zhu and Cheng, 2011). In large part, this uncertainty is a result of incomplete understanding of the complex chemical, physical and biological processes (and interactions) that govern SOM decomposition, and the influence of environmental factors on these processes (Dungait et al., 2012; Subke and Bahn, 2010; Paterson et al., 2009). This has limited the extent to which the processes mediating SOM decomposition have been represented explicitly in models, potentially limiting their accuracy in predicting impacts of environmental change across ecosystems.

Terrestrial models predict fluxes of C and water and more recently also nitrogen (N) and fire in the earth system. Several terrestrial models exist, such as Lund–Potsdam–Jena (LPJ), the Joint UK Land Environment Simulator (JULES) and the Community Land Model (CLM) (Sitch et al., 2003; Best et al., 2005; Oleson et al., 2010). These models can be integrated into Earth System Models (ESMs) to predict the biotic feedback to climate change. ESM studies have demonstrated that climate–carbon-cycle feedbacks over the next century may have a large impact on future CO_2 levels and climate (Cox et al., 2000; Friedlingstein et al., 2001), although this is not true in all simulations (Thornton, 2009). As well as being a tool in climate prediction, ESMs also provide tools for integration of knowledge about the land surface. A comparison of earth system models included in the Intergovernmental Panel on Climate Change (IPCC) showed that one of the largest uncertainties in predicting biotic feedback to climate change is how the soil will respond (Friedlingstein et al., 2006). The soil response to global warming is a critical parameter in determining future CO_2 concentrations and therefore the magnitude of feedbacks to the rate of future climate change (Jones et al., 2003) and represent a large uncertainty in future climate prediction overall, including physical climate effects (Huntingford et al., 2009). Improving the soil part of the model is therefore a priority for earth system modellers.

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Soils receive inputs of organic matter from plants via living roots (rhizodeposition) and senescent tissue (litter), whereas the dominant loss is as CO_2 from microbial decomposition of these inputs and of native SOM (Paterson et al., 2008, 2009; Yuste et al., 2007; Metcalfe et al., 2011). A large proportion of plant-derived inputs is rapidly mineralised to CO_2 (supporting the activities of diverse microbial communities) with the remainder contributing to the stock of SOM, and for soils in equilibrium, balancing the turnover of SOM pools. In simulation models, SOM is usually represented as 2–6 pools defined by their respective rates of turnover. In almost all models the temperature sensitivity of SOC turnover is assumed to be constant for all pools, irrespective of their mineralization rate, or other factors controlling relative turnover rates (e.g. Jenkinson et al., 1987; Parton et al., 1987, 1988, 1994; Williams, 1990; Li et al., 2000). In addition, SOC content is modelled to increase as a direct function of increasing rates of plant inputs, which makes the implicit assumption that the decomposition rates of individual pools do not affect each other, i.e. that there is no priming (Kuzyakov, 2010). However, in recent years, evidence derived from mechanistic studies of soil processes has challenged the validity of these assumptions. Firstly, some studies have now reported that SOC pools exhibit distinct temperature sensitivities, although this is still debated (Davidson and Janssens, 2006; Fang et al., 2005; Knorr et al., 2005; Reichstein et al., 2005; Waldrop and Firestone, 2004). Differential temperature sensitivity of SOC pools has been interpreted as being consistent with kinetic theory, where reactions with high activation energy (e.g decomposition of relatively recalcitrant SOC) have greater temperature sensitivity (Conant et al., 2011). Therefore, it has been suggested that incorporation of pool-specific temperature sensitivity into models could be approached through inclusion of an Arrhenius-form equation to modify pool turnover rates (Knorr et al., 2005). Secondly, increased decomposition of native SOM pools in response to fresh inputs from plants (priming effects) has now been demonstrated in many laboratory and field-based experiments (e.g. Fontaine et al., 2003, 2007, 2011; Zhu and Cheng, 2011; Kuzyakov, 2010; Paterson et al., 2008, 2011, 2013). It is increasingly recognised that such priming effects are general phenomena intrinsic to

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plant-soil interactions, but have only recently become reliably quantifiable (Paterson et al., 2009; Kuzyakov, 2010). Plant-mediated decomposition of native SOM is an important means of sustaining plant biomass production, through mobilisation of limiting nutrients from organic forms and may be a key process mediating the balance of ecosystem C-exchange (Paterson, 2003). Therefore, particularly under future environmental conditions where plant growth may be enhanced (e.g. in response to increased atmospheric CO_2 concentration) and result in increased inputs of plant-derived organic matter to soil, consideration of priming effects may be necessary for prediction of soil C-dynamics.

Here we use the Community Land Model (CLM) with Carbon–Nitrogen (CN) (Oleson et al., 2010; Thornton et al., 2007) to assess the potential global effects of changing the assumptions about temperature sensitivities of SOM pools and the effect of litter input on SOC mineralization rate. We assess the effects on a global scale and compare model output to available observational data at the global scale, and conduct simulations using both the standard and the modified versions with predicted climate change.

2 Materials and methods

2.1 Model

All model experiments were conducted with the terrestrial model CLM version 4.0, which simulates photosynthesis, C fluxes and storage, heat and water transfer in soils, and vegetation-radiation interactions (Oleson et al., 2010). The model has been updated to include an N cycle in addition to the C cycle (Thornton et al., 2007; Thornton, 2009). The model is described in detail in the CLM technical description and appropriate papers (Oleson et al., 2010; Thornton et al., 2007; Thornton, 2009).

The SOC sub-model in CLM is described in detail by Thornton and Rosenbloom (2005), structured as a converging cascade. The model has three litter pools and four SOC pools with different turnover time, similar to most SOM models. The fraction of

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plant litter allocated to each of the three litter pools depends on which plant functional type it is from. In addition, woody material is assumed to fractionate before it enters any litter pool, using a fractionation constant (K_{frag}). As the litter pools decompose, a fraction of the C is released as CO_2 and a fraction is transformed into the corresponding SOC pool. The SOC pools either mineralize to CO_2 or decompose to enter another SOC except the last (and slowest turning over SOC pool) that only mineralizes to CO_2. The response of the model to climate change in offline and fully coupled simulations has been explored (Thornton et al., 2007, 2009), and comparisons to detailed observations has been examined (Randerson et al., 2009). A version of this model was included in the Coupled Model Intercomparison Project (CMIP5) analysis prepared in part for the 5th Assessment report of Intergovernmental Panel on Climate Change (IPCC) (Lindsay et al., 2013), compared to other fully coupled models (e.g. Arora et al., 2013; Jones et al., 2013).

2.2 Modifications

The model was modified in two ways to assess the effect of other plausible assumptions about soil processes than those currently in the model. These modifications are described below.

2.2.1 Temperature sensitivity of pools

In the standard version of the model, decomposition rates of all soil and litter organic C pools are equally sensitive to temperature. Knorr et al. (2005) suggested how decomposition rates of pools could be calculated based on Arrhenius kinetics:

$$k = A \cdot e^{\frac{-E_a}{R \cdot T}}$$

where k is the decomposition rate, E_a is activation energy, R is the universal gas constant, T is temperature in Kelvin, and A is the theoretical decomposition rate at 0 K. Knorr et al. (2005) also developed an empirical formula for how activation energy can

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be calculated from turnover time. This therefore provides a methodology for how to calculate pool decomposition rates based on theoretical considerations from thermodynamics. Here we want to modify the temperature sensitivity, but keep the shape of the temperature response. We therefore set:

$$k_{\mathrm{mod}} = k \cdot A \cdot e^{\frac{-E_\mathrm{a}}{R \cdot T}}.$$

We use this to modify decomposition of pools so that the temperature response of the standard model is kept at 15 °C which is close to the global average temperature, that is, $k_{\mathrm{mod}} = k$. We divide k_{mod} by k setting k so that it does not cange at 15 °C. We then rearrange:

$$k_{\mathrm{mod}} = k \cdot e^{-\frac{E_\mathrm{a} \cdot (T - T_{15})}{R \cdot T \cdot T_{15}}}$$

where T_{15} is 15 °C in Kelvin degrees and k is the decomposition rate used in the standard model. With this formulation, decomposition rates of all pools will be more sensitive to temperature than the standard model. To make temperature sensitivity increase with pool turnover time, the fast decomposing pools should have unchanged or decreased temperature sensitivity, whilst the opposite should be true for the slowly decomposing pools. We therefore standardize it so that the temperature sensitivity of the intermediate litter pool and fast soil organic matter pool are unchanged:

$$k_{\mathrm{mod}} = k \cdot e^{\frac{(E_\mathrm{a} - E_\mathrm{a}/2) \cdot (T - T_{15})}{R \cdot T \cdot T_{15}}}.$$

The resulting decomposition rate is a function of temperature for the modified and standard response (Fig. 1).

2.2.2 Priming effect

Plants add C to the soil, broadly in proportion to their growth rate. In the standard model, this means that everything else being equal, C contents of soils will increase

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with increasing plant biomass production. However, there is evidence that input of fresh C can increase the decomposition rate of the C that is already there, through the priming effect (Kuzyakov, 2010). To account for priming of native SOM, we used data from a laboratory incubation experiment (Garcia-Pausas and Paterson, 2011). This experiment used ^{13}C-enriched glucose as a surrogate for plant-derived inputs allowing the mineralisation of native SOM to be quantified by isotopic mass balance (partitioning SOM-derived CO_2 efflux from that derived from the added glucose).

We expressed priming as a fractional increase in decomposition of all SOM pools as a function of the ratio between potential litter flux and potential SOM flux in terms of CO_2. If we further assume that the effect of increasing the amount of added substrate levels off at just above the highest sugar concentration in this experiment, we can fit a function to describe it: a continuous function that increases asymptotically to a maximum was fitted to the data:

$$\text{increase in SOM flux} = a \cdot \left(1 - e^{-b \cdot \text{litter/SOM}}\right)$$

where a and b are constants, here $a = 0.5$ and $b = 0.1291$ (Fig. 2). The assumption is that higher substrate addition rates than those used in this experiment would not increase the effect further. Therefore, the representation of the magnitude of priming effects can be considered conservative.

2.3 Simulation protocol

CLM simulations were conducted for long enough to reach equilibrium for the unmodified SOM model and for each of the modified versions. For these equilibrium simulations we used present-day land cover (Hurtt et al., 2006), atmospheric CO_2 concentration, and N and aerosol deposition. The terrestrial biosphere is forced from the atmosphere by prescribed temperature, precipitation, solar radiation, wind, specific humidity and air pressure, and data for this analysis were taken from the re-analysis by Qian et al. (2006). A 25 yr period (1972–2004) from the re-analysis is cycled throughout the CLM equilibrium simulations. The cycling was continued until the total global drift in net ecosystem C exchange was less than 0.05 $Pg\,C\,y^{-1}$ averaged over a 25 yr atmospheric forcing cycle. This "spin-up" procedure required approximately 1000 model years for all cases. The model was simulated at 1.9° latitude by 2.5° longitude horizontal grid spacing and a time step of 30 min.

Additional simulations were carried out with the modified and unmodified SOM model versions to explore how the different models predict future changes in SOM. These simulations were initialized from the final state of the corresponding equilibrium runs, but use transient atmospheric CO_2 and meteorological forcing. Output from the ECHAM5/MPI-OM CMIP3 runs (Roeckner et al., 2006) based on the SRES A1B greenhouse gas projection (Nakicenovic et al., 2000) was used to define future climate anomalies (relative to 1948–1972) for the quantities used in the atmospheric forcing (listed above). The climate anomalies are then applied to reanalysis for the years 1948–1972 that are cycled through four times from year 2000 to year 2100. This method retains observed climate diurnal, seasonal and interannual variability while applying model predicted future climate trends (Kloster et al., 2012; Ward et al., 2012). Transient CO_2 also follows the SRES A1B scenario.

2.4 Soil data

Soil data from ISRIC-WISE 5° (Batjes, 2005) were used to compare against output from the simulations. As the model generates SOC as a stock in each grid cell, whilst the data set gives SOC as percentage in each map unit within a grid cell, it was necessary to convert the map data set into SOC stocks. SOC stock in each map unit in each grid cell was calculated as follows:

$$C_s = d \cdot 10\,000 \cdot \left(1 - \frac{g}{100}\right) \cdot b \cdot C_p / 100$$

where C_s are SOC stocks ($g\,m^{-2}$), d is thickness of soil layer (cm), g is gravel content (%) b is bulk density ($g\,cm^{-3}$) and C_p is SOC content (%). The calculation was done

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separately for the two soil layers that the wise data set has data for (0–0.3 m and 0.3–1 m) The SOC content of both layers were summed, and a weighted average of C_s over the map units was calculated based on fractional area covered by each map unit.

3 Results and discussion

The unmodified CLM predicted about 26 % less SOC than estimated from the WISE data set (Table 1). It should be noted that the data set only has SOC in the top 1 m, so that real SOC storage and underprediction is even higher. The main reason for the underprediction is that the model is unable to predict the very high SOC contents in northern latitudes (Fig. 3). This is to be expected, as the model does not include effects of waterlogging, low pH and permafrost on SOC dynamics. However, the model also underpredicts slightly in many other areas. Exceptions are tropical rain forests in Amazonia and Africa and temperate forests in Asia and eastern United States where the model overpredicts SOC (Fig. 3). This suggests that in these areas plant productivity is weighted too strongly as a determinant of SOC stocks in the standard model (overall r^2 between net primary productivity – NPP – and the magnitude of the model overprediction of SOC compared to the observed was 0.56). It is also important to note that the standard model does not account for influences of soil texture and structure, which are strong determinants of stabilisation of SOC through constraining the access of decomposers to SOM (von Lutzow et al., 2006; Dungait et al., 2012). This could account for some of the unexplained variability in the distribution of SOC.

Inclusion of temperature and priming modifications did not dramatically alter predictions of total global SOC, but did affect the predicted distribution (Table 1; Fig. 4). While standard models have been calibrated to reproduce global SOC stocks, the lack of explicit representation of soil processes may limit their capacity to capture spatial variability in these stocks. That is, setting standard model functions to represent global means can reproduce global SOC stocks, but without further modification may be poor in the prediction of geographical variation. Such spatial variability would be expected

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where soil and environmental factors affect the relative importance of SOC-accrual and SOC-loss processes, causing deviation from mean responses on a global scale. In addition, analogously to predicting geographic variation in SOC, modelling impacts of environmental change on global SOC stocks may require more explicit representation of soil processes, as factors such as that CO_2 fertilisation and temperature rise may directly affect the balance of these soil processes.

The change in temperature sensitivity of SOC pools decreased SOC slightly in most areas (Table 1). In a few small areas, particularly on mountains the decrease was quite pronounced (Fig. 4), and these are also areas where the standard model overpredicted, so that this modification improved prediction of SOM distribution somewhat.

The inclusion of a simple priming effect function in the model reduced predicted global carbon stocks more than the changes in temperature sensitivity (Table 1, Fig. 4). Importantly the land areas where the priming had the greatest effect on SOC were those with high NPP (tropical and temperate forest) the same regions where the standard model over-predicted SOC relative to measured data to the greatest extent. Inclusion of a priming effect therefore improved predictions in these areas (by 20–25 %), but predictions got worse in other, lower productivity ecosystems (by 1–9 %) (Fig. 5). This suggests that inclusion of priming effects in ESMs may be useful in refining model predictions, particularly in resolving relationships between NPP and equilibrium SOC stocks. Whilst underprediction in lower productivity regions can be explained by waterlogging and perma-frost, overpredictions in high productivity regions can only be resolved by decreasing the effect of plant input on soil carbon, and including a priming effect is a mechanistically plausible way of doing that.

The conservative assumption used here was that the maximum change in C turnover from input of plant-derived C is 25 %. However, although our results indicate where priming effects may be expected to have the greatest impact, the magnitude and geographic variation in these effects may be greater, as changes in SOC turnover of up to 300 % have been reported (Zhu and Cheng, 2011). Further work should focus on parameterizing how various factors affect the strength of SOC turnover, and evaluate

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if this further improves predictions of SOC. For example, empirical data are emerging indicating that priming responses can be quantified as soil-specific functions of C-input rate (Paterson and Sim, 2013), are affected by composition of inputs (Ohm et al., 2007), are modified by nutrient availability (Fontaine et al., 2003; Garcia-Pausas and Paterson, 2011), change with soil depth (Salome et al., 2010; Fontaine et al., 2007) and may vary in response to direct effects of environmental conditions on the biological processes involved (Dijkstra et al., 2010; Thiessen et al., 2013; Ghee et al., 2013).

The difference in pool size between the standard and the modified runs was to a large extent maintained into the future (Fig. 6, Table 2), although the vegetation pool with priming effect was reduced early in the future simulation. The difference in pool sizes would potentially have a large effect in a fully coupled simulation, and could therefore mean a different biotic feedback to climate change than current models predict. The predictions of changes to the C cycle under global change appear to be relatively robust towards the assumptions made about SOC sensitivity to temperature, as differences in pool sizes at equilibrium were maintained (Fig. 6, Table 2). This should be reassuring as these assumptions remain uncertain.

4 Conclusions

Comparison of CLM model simulations to observations suggest an overprediction of soil carbon in the high productivity regions of mid-latitudes and the tropics, with too little soil carbon in other regions, especially the high latitudes, as noted elsewhere (e.g. Thornton et al., 2009; Randerson et al., 2009). This differential in the soil C bias in the model can be due to multiple causes, and we explore two of these effects in this paper, temperature dependence and soil priming. We did not explore some potentially important effects specific to high latitudes such as a representation of the inhibition of biological processes in soils subject to permafrost and waterlogging.

The overprediction of carbon in the high productivity areas could be due to a too large sensitivity to plant input as a determinant of SOC, and one way of improving that

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is to include a priming effect, which does improve the predictions of SOC distribution by 20–25 %. Further work should focus on better quantification of the process, and how it depends on external factors, and may also improve our ability to predict biotic feedback to climate change. In this paper we also explored the impact of different temperature sensitivity of carbon pools, but this mechanism had less effect in most areas.

As soil carbon feedbacks in earth system models is one of the most important uncertainties in future climate predictions (Huntingford et al., 2009), further work should focus on better quantification of the priming effect and how it depends on other factors and how this can improve predictions of SOC distribution even further.

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Table 1. Total SOC storage estimated from the ISRIC-WISE data set in top 1 m in comparison to those calculated with CLM at equilibrium (unmodified) and with each of the modifications described in the text.

	Data (from ISRIC-WISE)	Unmodified CLM	Modified temperature sensitivity of pools	Modified with priming effect
Total soil organic carbon (Pg)	967.9	712.7	707.1	666.0
Proportion (% of ISRIC-WISE data)	100	74	73	69

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Table 2. Predicted total carbon in pools at the end of the future simulation (year 2100) and percentage increase in each carbon pool over the simulation period.

	Unmodified CLM	Modified temperature sensitivity of pools	Modified with priming effect
Ecosystem carbon (Pg)	1862.3 7.4 %	1853.7 7.5 %	1803.6 6.7 %
Vegetation carbon (Pg)	1058.9 16.9 %	1055.5 17.0 %	1030.9 13.4 %
Soil organic carbon (Pg)	684.6 −3.9 %	680.2 −3.8 %	657.5 −1.3 %

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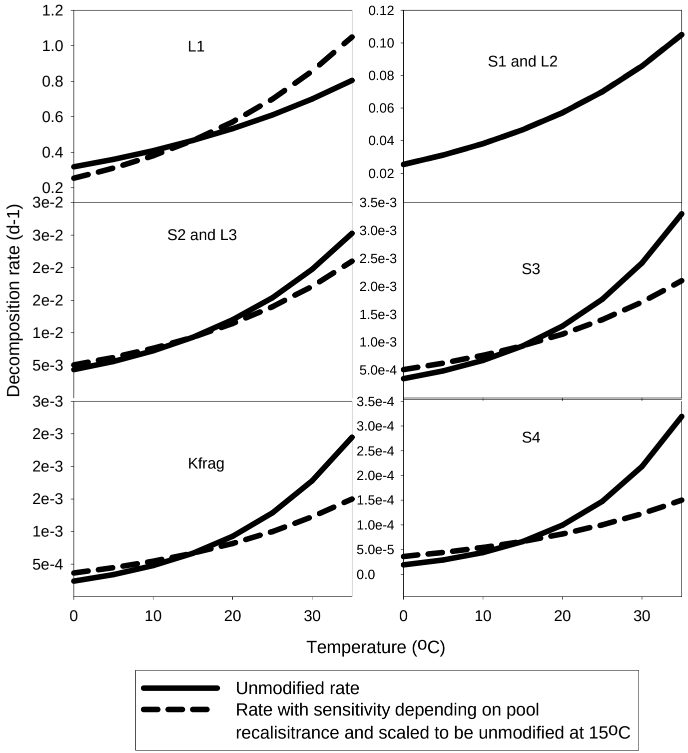

Fig. 1. Decomposition rate (k) as a function of temperature in the standard version and after decomposition rate was changed to make slowly turning over pools more sensitive to temperature than fast turning over pools (Knorr et al., 2005).

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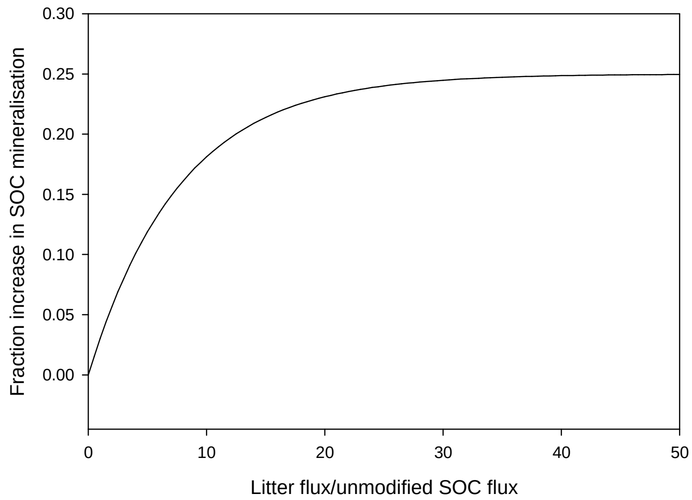

Fig. 2. Parameterization of the priming effect. The priming effect was implemented as a fractional increase in the mineralisation of all SOC pools as a response to the ratio between the CO_2 flux from all litter pools and all SOC pools.

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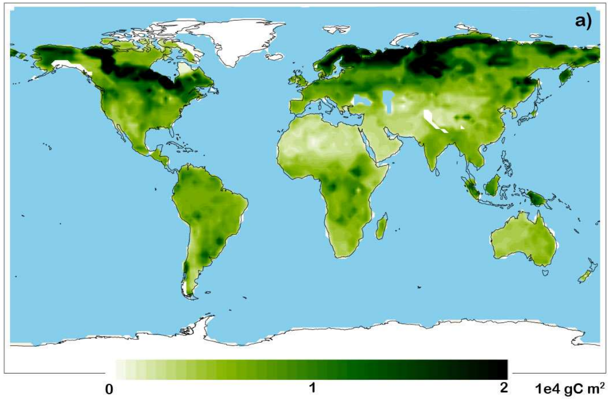

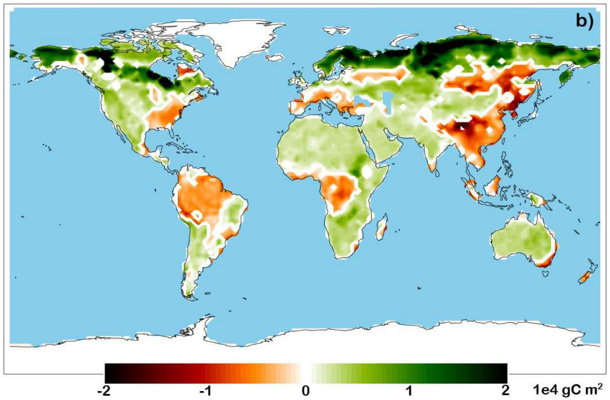

Fig. 3. Soil carbon from the ISRIC-WISE data set (top panel) and the difference between this and simulated SOC with the standard (unmodified) CLM at equilibrium (bottom panel). Data from the ISRIC-WISE data set were recalculated for stocks in the top 1 m and a weighted average over map units was produced. A full description of the calculation method is given in the text.

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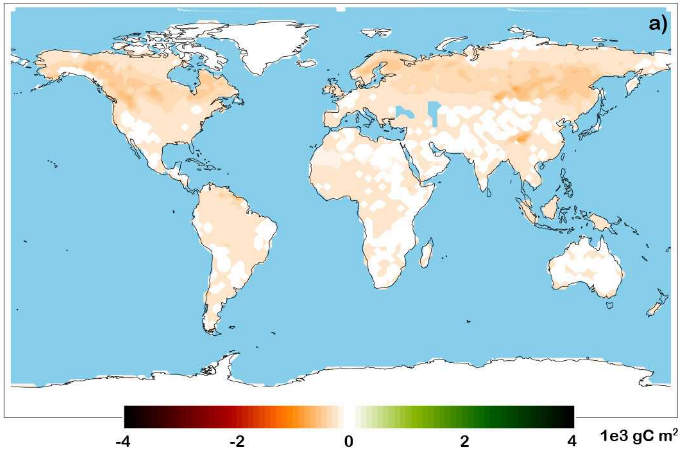

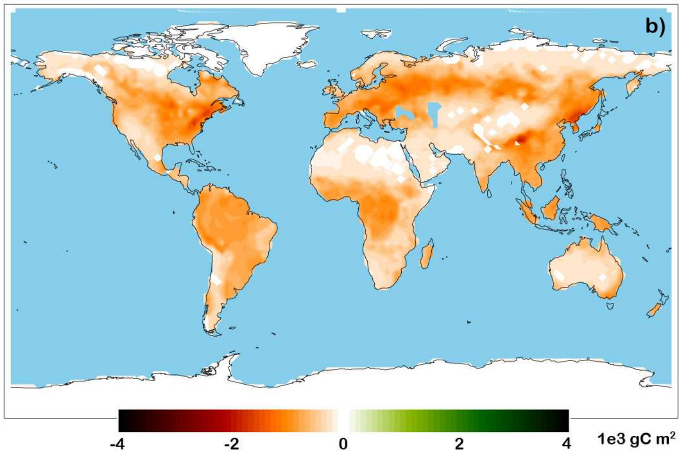

Fig. 4. Difference in model result for SOC at equilibrium between standard and differential temperature sensitivity of pools (top panel) and added priming effect (bottom panel).

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Effects of model assumptions for soil processes on carbon turnover

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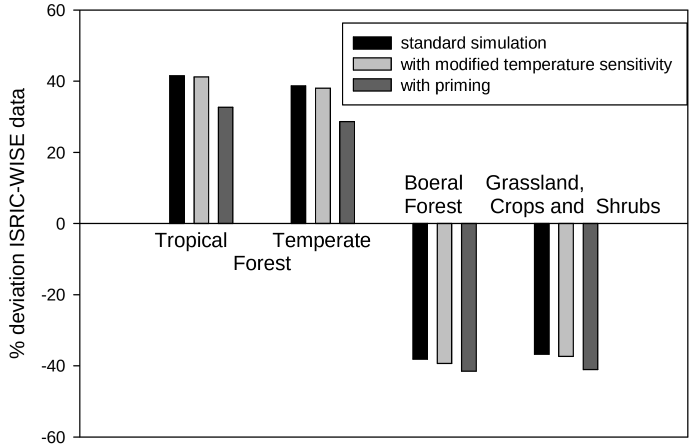

Fig. 5. Deviation from ISRIC-WISE data for the standard model and the two modifications grouped on eco-regions.

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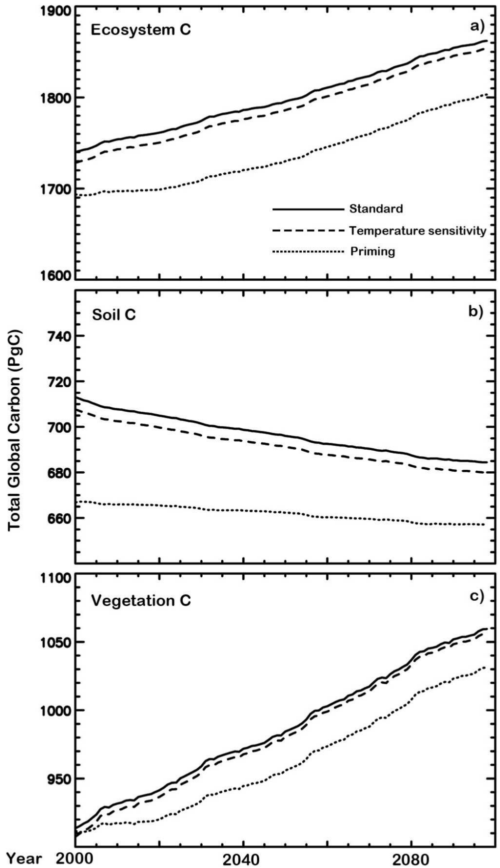

Fig. 6. Predicted total global organic carbon in the entire ecosystem (top panel), soil (middle panel) and vegetation (bottom panel) starting from equilibrium year 2000 under predicted climate change with the standard CLM and with the two modified versions of the model.