

Sensitivity study on the assumptions for soil processes in the Community Land Model 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 stocks (SOC) to estimates from a global data set. We also modify the assumptions about SOC 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 SOC increases in response to a supply of fresh organic matter. The standard model predicted the global distribution of SOC reasonably well in most areas, but it failed to predict the very high stocks of SOC at high latitudes. It also predicted 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 until 2100 for the standard and modified versions. Future simulations showed that differences between the standard and modified versions were maintained

1 in a future with climate change (4-6 Pg and 23-47 Pg difference in soil carbon
2 between standard simulation and the modified with temperature sensitivity and
3 priming respectively). Although the relative changes are small, they are likely to be
4 larger in a fully coupled simulation, and thus warrant future work.

6 **1. Introduction**

7 Soil organic matter (SOM) is the largest store of organic carbon (C) in the biosphere
8 (Batjes, 1996). Even relatively small percentage changes in this store can lead to large
9 changes in atmospheric CO₂ concentrations. However, there is still large uncertainty
10 associated with the response of SOM dynamics to perturbations such as changes in
11 temperature, moisture and plant-derived inputs to soils that are predicted under
12 environmental change (Billings et al., 2010; Heimann and Reichstein, 2008; Conant et
13 al., 2011; Ostle et al., 2009; Zhu and Cheng, 2011). In large part, this uncertainty is a
14 result of incomplete understanding of the complex chemical, physical and biological
15 processes (and interactions) that govern SOM decomposition, and the influence of
16 environmental factors on these processes (Dungait et al., 2012; Subke and Bahn,
17 2010; Paterson et al., 2009). This has limited the extent to which the processes
18 mediating SOM decomposition have been represented explicitly in models,
19 potentially limiting their accuracy in predicting impacts of environmental change
20 across ecosystems.

21 Terrestrial models predict fluxes of C and water and more recently also nitrogen (N)
22 and fire in the earth system. Several terrestrial models exist, such as Lund-Potsdam-
23 Jena (LPJ), the Joint UK Land Environment Simulator (JULES) and the Community
24 Land Model (CLM) (Sitch et al., 2003; Best et al., 2005; Oleson et al, 2010). These
25 models can be integrated into Earth System Models (ESMs) to predict the biotic
26 feedback to climate change. ESM studies have demonstrated that climate-carbon-
27 cycle feedbacks over the next century may have a large impact on future CO₂ levels
28 and climate (Cox et al., 2000; Friedlingstein et al., 2001), although this is not true in
29 all simulations (Thornton, 2009). As well as being a tool in climate prediction, ESMs
30 also provide tools for integration of knowledge about the land surface. A comparison
31 of earth system models included in the Intergovernmental Panel on Climate Change
32 (IPCC) showed that one of the largest uncertainties in predicting biotic feedback to

1 climate change is how the soil will respond (Friedlingstein et al., 2006). The soil
2 response to global warming is a critical parameter in determining future CO₂
3 concentrations and therefore the magnitude of feedbacks to the rate of future climate
4 change (Jones et al., 2003) and represent a large uncertainty in future climate
5 prediction overall, including physical climate effects (Huntingford et al., 2009).
6 Improving the soil part of the model is therefore a priority for earth system modellers.

7 Soils receive inputs of organic matter from plants via living roots (rhizodeposition)
8 and senescent tissue (litter), whereas the dominant loss is as CO₂ from microbial
9 decomposition of these inputs and of native SOM (Paterson et al., 2008; 2009; Yuste
10 et al., 2007; Metcalfe et al., 2011). A large proportion of plant-derived inputs is
11 rapidly mineralised to CO₂ (supporting the activities of diverse microbial
12 communities) with the remainder contributing to the stock of SOM, and for soils in
13 equilibrium, balancing the decay of SOM pools. In simulation models, SOM is
14 usually represented as 2-6 pools defined by their respective rates of turnover. In
15 almost all models the temperature sensitivity of SOC turnover is assumed to be
16 constant for all pools, irrespective of their mineralization rate, or other factors
17 controlling relative turnover rates (e.g. Jenkinson et al., 1987; Parton et al., 1987;
18 1988; 1994; Williams, 1990; Li et al., 2000). In addition, SOC content is modelled to
19 increase as a direct function of increasing rates of plant inputs, which makes the
20 implicit assumption that the decomposition rates of individual pools do not affect each
21 other, i.e. that there is no priming (Kuzyakov, 2010). However, in recent years,
22 evidence derived from mechanistic studies of soil processes has challenged the
23 validity of these assumptions. Firstly, some studies have now reported that SOC pools
24 exhibit distinct temperature sensitivities, although this is still debated (Davidson and
25 Janssens, 2006; Fang et al., 2005; Knorr et al., 2005; Reichstein et al., 2005; Waldrop
26 and Firestone, 2004). Differential temperature sensitivity of SOC pools has been
27 interpreted as being consistent with kinetic theory, where reactions with high
28 activation energy (e.g decomposition of relatively recalcitrant SOC) have greater
29 temperature sensitivity (Conant et al., 2011). Therefore, it has been suggested that
30 incorporation of pool-specific temperature sensitivity into models could be
31 approached through inclusion of an Arrhenius-form equation to modify pool turnover
32 rates (Knorr et al., 2005). Secondly, increased decomposition of native SOM pools in
33 response to fresh inputs from plants (priming effects) has now been demonstrated in

1 many laboratory and field-based experiments (e.g. Fontaine et al., 2003; 2007; 2011;
2 Zhu and Cheng, 2011; Kuzyakov 2010; Paterson et al., 2008, 2011; 2013). It is
3 increasingly recognised that such priming effects are general phenomena intrinsic to
4 plant-soil interactions, but have only recently become reliably quantifiable (Paterson
5 et al., 2009; Kuzyakov, 2010). Plant-mediated decomposition of native SOM is an
6 important means of sustaining plant biomass production, through mobilisation of
7 limiting nutrients from organic forms and may be a key process mediating the balance
8 of ecosystem C-exchange (Paterson, 2003). Therefore, particularly under future
9 environmental conditions where plant growth may be enhanced (e.g. in response to
10 increased atmospheric CO₂ concentration) and result in increased inputs of plant-
11 derived organic matter to soil, consideration of priming effects may be necessary for
12 prediction of soil C-dynamics.

13 Here we carry out a sensitivity study using the Community Land Model (CLM) with
14 both a carbon and a nitrogen cycle (CN) (Oleson et al., 2010; Thornton et al., 2007) to
15 assess the potential global effects of changing the assumptions about temperature
16 sensitivities of SOM pools and the effect of organic matter input on SOC
17 mineralization rate. We assess the effects on a global scale and compare model output
18 to available observational data at the global scale, and conduct simulations using both
19 the standard and the modified versions with predicted climate change.

20

21 **2. Materials and methods**

22 **2.1 Model**

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

29 The SOC sub-model in CLM is described in detail by Thornton and Rosenbloom
30 (2005), structured as a converging cascade. The model has three litter pools and four
31 SOC pools with different turnover time, similar to most SOM models. The fraction of
32 plant litter allocated to each of the three litter pools depends on which plant functional

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

13 2.2 Modifications

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

17 2.2.1 Temperature sensitivity of pools

18 In the standard version of the model, decomposition rates of all soil and litter organic
19 C pools are equally sensitive to temperature, using a Q10 formulae ($Q_{10}=1.5$). Knorr
20 et al. (2005) suggested how decomposition rates of pools could be calculated based on
21 Arrhenius kinetics:

$$22 \quad k = Ae^{\frac{-Ea}{RT}} \quad (1)$$

23 Where k is the decomposition rate, Ea is activation energy, R is the universal gas
24 constant, T is temperature in Kelvin, and A is the theoretical decomposition rate at 0
25 K. This therefore provides a methodology for how to calculate pool decomposition
26 rates based on theoretical considerations from thermodynamics. Here we wanted to
27 modify the temperature sensitivity, but keep the shape of the temperature response.
28 We wanted to modify decomposition of pools so that the temperature response of the
29 standard model is kept at 15°C which is close to the global average temperature. We
30 therefore wanted to produce a conversion factor $c_1=k_{15}/k$ where k_{15} is k at 15°C (T_{15}):

1

$$2 \quad c1 = \frac{k_{15}}{k} = e^{\frac{Ea(T-T_{15})}{RTT_{15}}} \quad (2)$$

3 To make temperature sensitivity increase with pool turnover time, the fast
4 decomposing pools should have unchanged or decreased temperature sensitivity,
5 whilst the opposite should be true for the slowly decomposing pools. Knorr et al.
6 (2005) also developed an empirical formula for how activation energy can be
7 calculated from turnover time. We therefore further modify the conversion factor so
8 that the modified activation energy depending on pool turnover time is included:

$$9 \quad c2 = c1_{modified}/c1 = e^{\frac{(Ea-Ea_{mod})*(T-T_{15})}{R*T*T_{15}}} \quad (3)$$

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

12 2.2.2 Priming effect

13 Plants add C to the soil, broadly in proportion to their growth rate. In the standard
14 model, this means that everything else being equal, C contents of soils will increase
15 with increasing plant biomass production. However, there is evidence that input of
16 fresh C can increase the decomposition rate of the C that is already there, through the
17 priming effect (Kuzyakov, 2010). To account for priming of native SOM, we used
18 data from a laboratory incubation experiment (Garcia-Pausas and Paterson, 2011).
19 This experiment used ¹³C-enriched glucose as a surrogate for plant-derived inputs
20 allowing the mineralisation of native SOM to be quantified by isotopic mass balance
21 (partitioning SOM-derived CO₂ efflux from that derived from the added glucose).

22 The model contains distinct SOM and litter pools, and it calculates a potential flux
23 from each pool which is then reduced if nitrogen is limiting. We expressed priming as
24 a fractional increase in decomposition of all SOM (but not litter) pools as a function
25 of the ratio between potential litter flux and potential SOM flux. If we further assume
26 that the effect of increasing the amount of added substrate levels off at just above the
27 highest sugar concentration in this experiment, we can fit a function to describe it: A
28 continuous function that increases asymptotically to a maximum was fitted to the
29 data:

$$30 \quad \text{increase in SOC flux} = a * (1 - e^{-b * \text{litter}/\text{SOC}}) \quad (4)$$

1 where a and b are constants, here $a = 0.5$ and $b = 0.1291$ (Figure 2). These parameters
2 were fitted directly from the experimental data. The assumption is that higher
3 substrate addition rates than those used in this experiment would not increase the
4 effect further. Further experiments have shown that the priming effect does saturate at
5 high substrate addition rates, but sometimes at rates much higher than the maximum
6 used here (Paterson and Sim, 2013). Therefore, the representation of the magnitude of
7 priming effects can be considered conservative. These coefficients are only for an
8 initial assessment of the global effects of including priming. If priming is to be
9 permanently included in the model, a more thorough calibration using more data
10 collected under different conditions would be required.

11 2.3 Simulation protocol

12 CLM simulations were conducted for long enough to reach equilibrium for the
13 unmodified SOM model and for each of the modified versions. For these equilibrium
14 simulations we used present-day land cover (Hurtt et al., 2006), atmospheric CO₂
15 concentration, and N and aerosol deposition. The terrestrial biosphere was forced
16 from the atmosphere by prescribed temperature, precipitation, solar radiation, wind,
17 specific humidity and air pressure, and data for this analysis were taken from the re-
18 analysis by Qian et al. (2006). A 25-year period (1972-2004) from the re-analysis
19 was cycled throughout the CLM equilibrium simulations. The cycling was continued
20 until the total global drift in net ecosystem C exchange was less than 0.05 PgC/y
21 averaged over a 25-year atmospheric forcing cycle. This “spin-up” procedure required
22 approximately 1000 model years for all cases. The model was simulated at 1.9 degree
23 latitude by 2.5 degree longitude horizontal grid spacing and a time step of 30 minutes.

24 Additional simulations were carried out with the modified and unmodified SOC
25 model versions to explore how the different models predict future changes in SOC.
26 These simulations were initialized from the final state of the corresponding
27 equilibrium runs, but used transient atmospheric CO₂ and meteorological forcing.
28 Output from the ECHAM5/MPI-OM CMIP3 runs (Roeckner et al., 2006) based on
29 the SRES A1B greenhouse gas projection (Nakicenovic et al., 2000) was used to
30 define future climate anomalies (for the period 2000-2100, relative to the 1948-1972
31 mean) for the quantities used in the atmospheric forcing (listed above). The climate
32 anomalies are applied to a repeating, 25-year cycle of atmospheric reanalysis (from
33 the years 1948-1972) to create the atmospheric forcing datasets. With this method we

1 retain observed diurnal, seasonal and interannual climate variability into the future
2 even as it is scaled to the predicted future climate trends (Kloster et al., 2012; Ward et
3 al., 2012). Transient atmospheric CO₂ concentrations also follow the SRES A1B
4 scenario for the year 2000 through 2100. In this scenario, CO₂ concentrations
5 increase through the 21st century, exceeding 700ppm by the year 2100. Global N
6 deposition distributions from the year 2000 (Lamarque et al. 2005) were used
7 throughout for all simulations.

8 2.4 Soil data

9 Soil data from ISRIC-WISE 05 degree (Batjes, 2005) were used to compare against
10 output from the simulations. As the model generates SOC as a stock in each grid cell,
11 whilst the data set gives SOC as percentage in each map unit within a grid cell, it was
12 necessary to convert the map data set into SOC stocks. SOC stock in each map unit in
13 each grid cell was calculated as follows:

$$14 \quad C_s = d * 10000 * \left(1 - \frac{g}{100}\right) * b * C_p / 100 \quad (5)$$

15 Where C_s are SOC stocks (g/m²), d is thickness of soil layer (cm), g is gravel content
16 (%) b is bulk density (g/cm³) and C_p is SOC content (%). These data are all in the
17 ISRIC-WISE database. The calculation was done separately for the two soil layers
18 that the WISE data set has data for (0-0.3 m and 0.3-1 m) The SOC content of both
19 layers were summed, and a weighted average of C_s over the map units was calculated
20 based on fractional area covered by each map unit.

21

22 3. Results and discussion

23 The unmodified CLM predicted about 26% less SOC than estimated from the WISE
24 data set (Table 1). It should be noted that the data set only has SOC in the top 1 m, so
25 that real SOC storage and underprediction is even higher. The main reason for the
26 underprediction is that the model is unable to predict the very high SOC contents in
27 northern latitudes (Figure 3). This is to be expected, as the model does not include
28 effects of waterlogging, low pH and permafrost on SOC dynamics. However, the
29 model also underpredicts slightly in many other areas. Exceptions are tropical rain
30 forests in Amazonia and Africa and temperate forests in Asia and eastern United
31 States where the model overpredicts SOC (Figure 3). This suggests that the model

1 underpredicts turnover, at least in high productivity areas. Plant productivity will
2 therefore appear as a stronger determinant of SOC in the model than in reality (overall
3 r^2 between net primary productivity (NPP) and the magnitude of the model
4 overprediction of SOC compared to the observed was 0.56). It is also important to
5 note that the standard model does not account for influences of soil texture and
6 structure, which are strong determinants of stabilisation of SOC through constraining
7 the access of decomposers to SOM (von Lutzow et al., 2006; Dungait et al., 2012).
8 This could account for some of the unexplained variability in the distribution of SOC.

9 Inclusion of temperature and priming modifications did not dramatically alter
10 predictions of total global SOC, but did affect the predicted distribution (Table 1;
11 Figure 4). The results do not include litter pools, but the difference in litter pools
12 between the various versions of the model was negligible (data not shown) as is to be
13 expected as the modifications introduced act on SOC pools but not (directly) on litter
14 pools. While the standard model has been calibrated to reproduce global SOC stocks,
15 the lack of explicit representation of soil processes may limit their capacity to capture
16 spatial variability in these stocks. That is, setting standard model functions to
17 represent global means can reproduce global SOC stocks, but without further
18 modification may be poor in the prediction of geographical variation. Such spatial
19 variability would be expected where soil and environmental factors affect the relative
20 importance of SOC-accrual and SOC-loss processes, causing deviation from mean
21 responses on a global scale. In addition, analogously to predicting geographic
22 variation in SOC, modelling impacts of environmental change on global SOC stocks
23 may require more explicit representation of soil processes, as factors such as CO₂
24 fertilisation, nitrogen addition through deposition and/or fertilisation and temperature
25 rise may directly affect the balance of these soil processes.

26 The change in temperature sensitivity of SOC pools decreased SOC slightly in most
27 areas (Table 1). In a few small areas, particularly on mountains the decrease was quite
28 pronounced (Figure 4), and these are also areas where the standard model
29 overpredicted, so that this modification improved prediction of SOM distribution
30 somewhat. The attempt here was to make the temperature sensitivity of slowly and
31 fast turning over pools different, without changing overall sensitivity. However, it is
32 inherently difficult to achieve this. Here it was done by standardizing the response so
33 that it did not change at 15°C.

1 The inclusion of a simple priming effect also reduced global carbon stocks (Table 1,
2 Figure 4), however, this is to be expected as this modification was such that carbon
3 turnover could only decrease or remain unchanged. Importantly the land areas where
4 the priming had the greatest effect on SOC were those with high NPP (tropical and
5 temperate forest). These were the same regions where the standard model over-
6 predicted SOC relative to measured data to the greatest extent. Inclusion of a priming
7 effect therefore improved predictions in these areas (by 20-25%), but predictions got
8 worse in other, lower productivity ecosystems (by 1-9%) (Figure 5). This suggests
9 that inclusion of priming effects in ESMs may be useful in refining model predictions,
10 particularly in resolving relationships between plant productivity, turnover and
11 equilibrium SOC stocks. Whilst underprediction in lower productivity regions can be
12 explained by water-logging and perma-frost, overpredictions in high productivity
13 regions can only be resolved by better mechanistic predictions turnover and how it
14 depends on productivity, and including a priming effect is a plausible way of doing
15 that.

16 The conservative assumption used here was that the maximum change in C turnover
17 from input of plant-derived C is 25%. However, although our results indicate where
18 priming effects may be expected to have the greatest impact, the magnitude and
19 geographic variation in these effects may be greater, as changes in SOC turnover of
20 up to 300% have been reported (Zhu and Cheng, 2011). Further work should focus on
21 parameterizing how various factors affect the strength of SOC turnover, and evaluate
22 if this further improves predictions of SOC. For example, empirical data are emerging
23 indicating that priming responses can be quantified as soil-specific functions of C-
24 input rate (Paterson and Sim, 2013), are affected by composition of inputs (Ohm et
25 al., 2007), are modified by nutrient availability (Fontaine et al., 2003; Garcia-Pausas
26 and Paterson, 2011), change with soil depth (Salome et al., 2010; Fontaine et al.,
27 2007) and may vary in response to direct and indirect effects of environmental
28 conditions on the biological processes involved (Dijkstra et al., 2010; Thiessen et al.,
29 2013; Ghee et al., 2013). These effects are potentially complex due to interactions
30 between environmental factors and the biological processes mediating element fluxes.
31 For example, plant-derived C enters soil from both aboveground litter and
32 rhizodeposition, supplying organic material of differing quality, affecting retention in
33 soil, microbial activity and processes mediated by microbial communities (including

1 priming). The magnitude and relative contribution of above- and below-ground plant-
2 C is affected by a host of factors, including interactions between plant type,
3 temperature and nutrient availability (Metcalf et al., 2011). Under conditions of high
4 nutrient availability, relative allocation of plant C to roots and mycorrhizal symbionts
5 is reduced (Yuan and Chen, 2010; Grman and Robinson, 2013). However, whether
6 this results in an absolute reduction in C-transfer to soil is dependent on whether the
7 reduction in relative belowground allocation outweighs the impact of increased gross
8 plant productivity (Henry et al., 2005). These interactions, across ecosystem types,
9 require further quantitative study to refine the representation of plant-mediated
10 priming effects in models.

11 The difference in pool size between the standard and the modified runs was to a large
12 extent maintained into the future (Figure 6, Table 2), although the vegetation pool
13 with priming effect was reduced early in the future simulation. It is not certain why
14 this happened, but it could be because carbon stocks in the soil were smaller at
15 equilibrium with this modification. That means that there was less nitrogen available
16 for mineralisation, and the effect of warming nitrogen mineralisation and availability
17 was therefore less. The difference in pool sizes would potentially have a large effect
18 in a fully coupled simulation, and could therefore mean a different biotic feedback to
19 climate change than current models predict. The predictions of changes to the C cycle
20 under global change appear to be relatively robust towards the assumptions made
21 about SOC sensitivity to temperature, as differences in pool sizes at equilibrium were
22 maintained (Figure 6, Table 2). This should be reassuring as these assumptions remain
23 uncertain.

24

25 **4. Conclusions**

26 Comparison of CLM model simulations to observations suggest an overprediction of
27 soil carbon in the high productivity regions of mid-latitudes and the tropics, with too
28 little soil carbon in other regions, especially the high latitudes, as noted elsewhere
29 (e.g. Thornton et al., 2009; Randerson et al., 2009). This differential in the soil C bias
30 in the model can be due to multiple causes, and we explore two of these effects in this
31 paper, temperature dependence and soil priming. We did not explore some potentially

1 important effects specific to high latitudes such as a representation of the inhibition of
2 biological processes in soils subject to permafrost and waterlogging.

3 The overprediction of carbon in the high productivity areas indicated that the model
4 underpredicts C turnover when plant input is high, and one way of improving that is
5 to include a priming effect, which does improve the predictions of SOC distribution
6 by 20-25%. Further work should focus on better quantification of priming, and how it
7 depends on external factors, and may also improve our ability to predict biotic
8 feedback to climate change. In this paper we also explored the impact of different
9 temperature sensitivity of carbon pools, but this mechanism had less effect in most
10 areas.

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

15

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19

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1 Table 1: Total SOC storage estimated from the ISRIC-WISE data set in top 1 m in
 2 comparison to those calculated with CLM at equilibrium (unmodified) and with each
 3 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

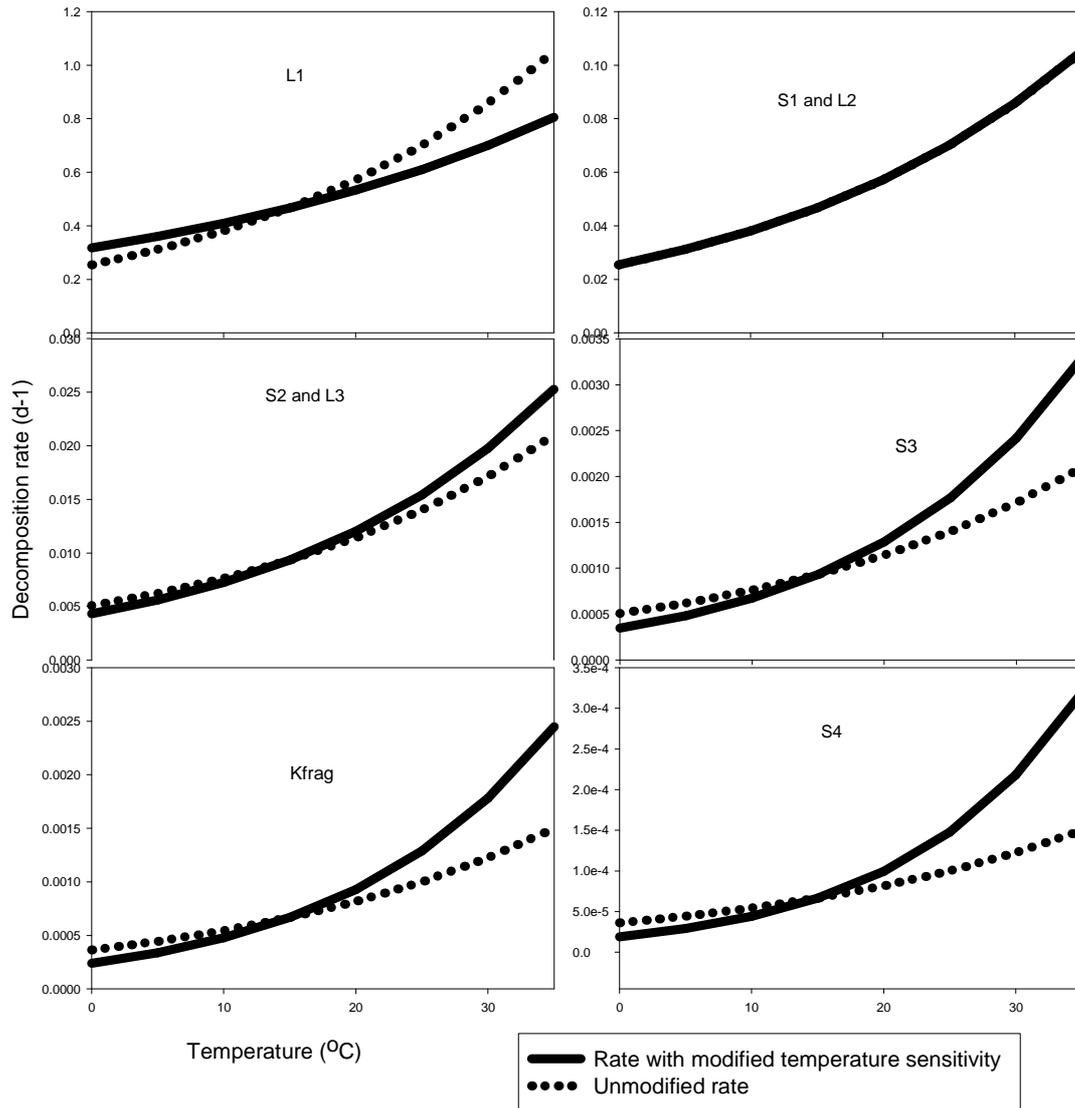
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1 Table 2: Predicted total carbon in pools at the end of the future simulation
 2 (year 2100) and percentage increase in each carbon pool over the simulation
 3 period.

	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%

4



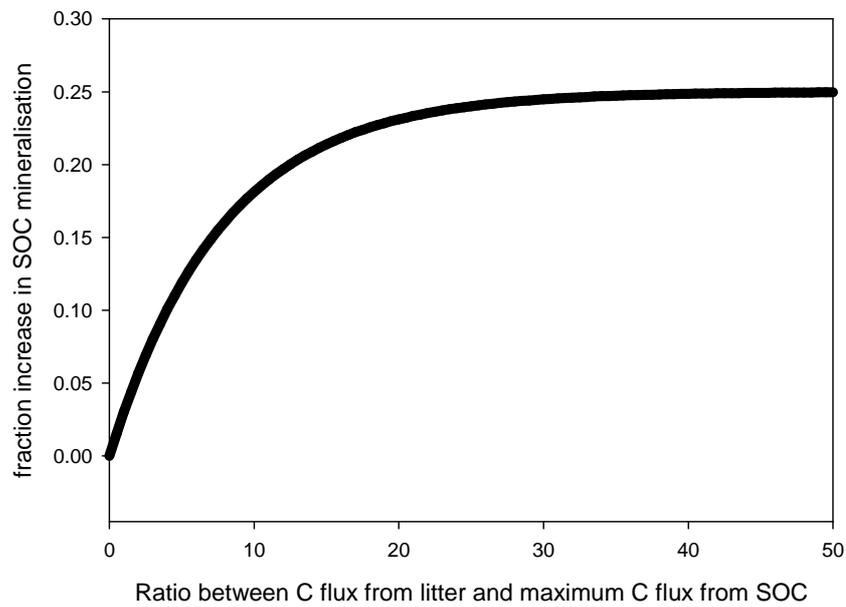
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2 Figure 1: Decomposition rate (k) as a function of temperature in the standard version
 3 and after decomposition rate was changed. The changes make slowly turning over
 4 pools more sensitive to temperature than fast turning over pools (Knorr et al. 2005).

5

6

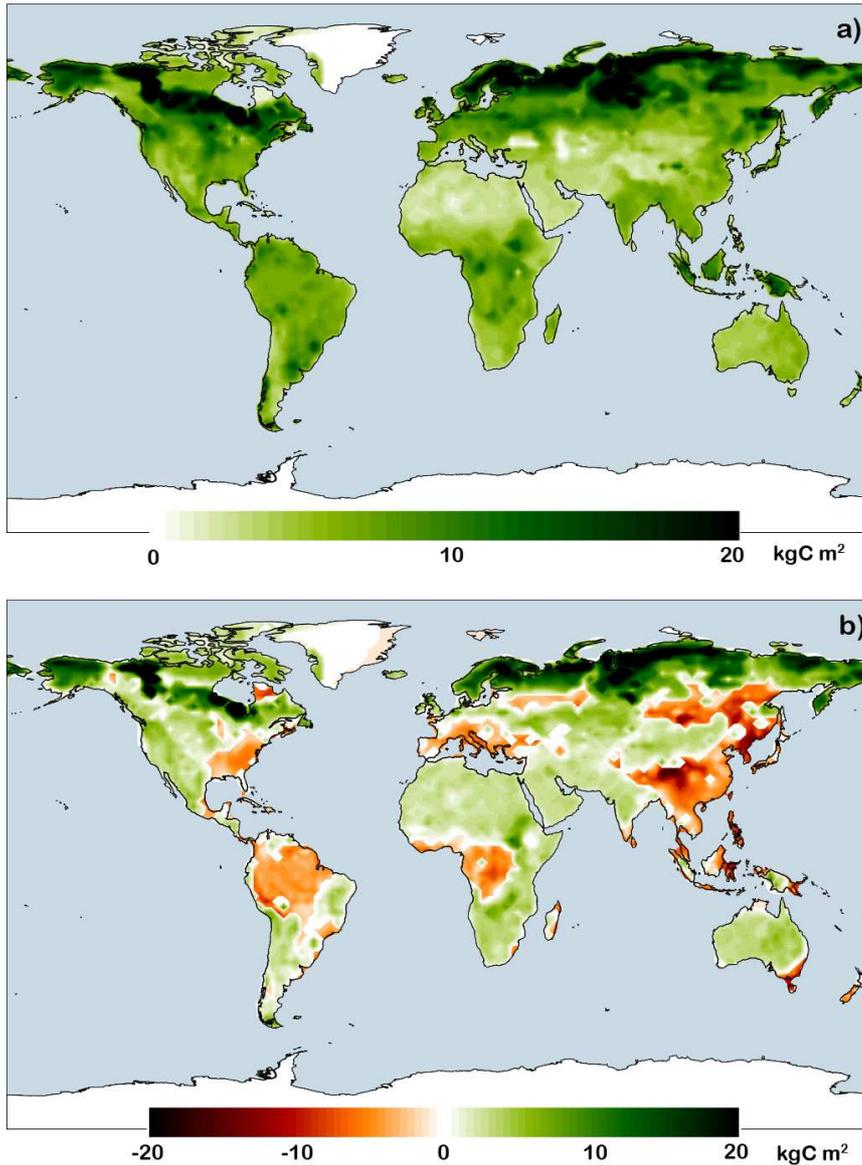
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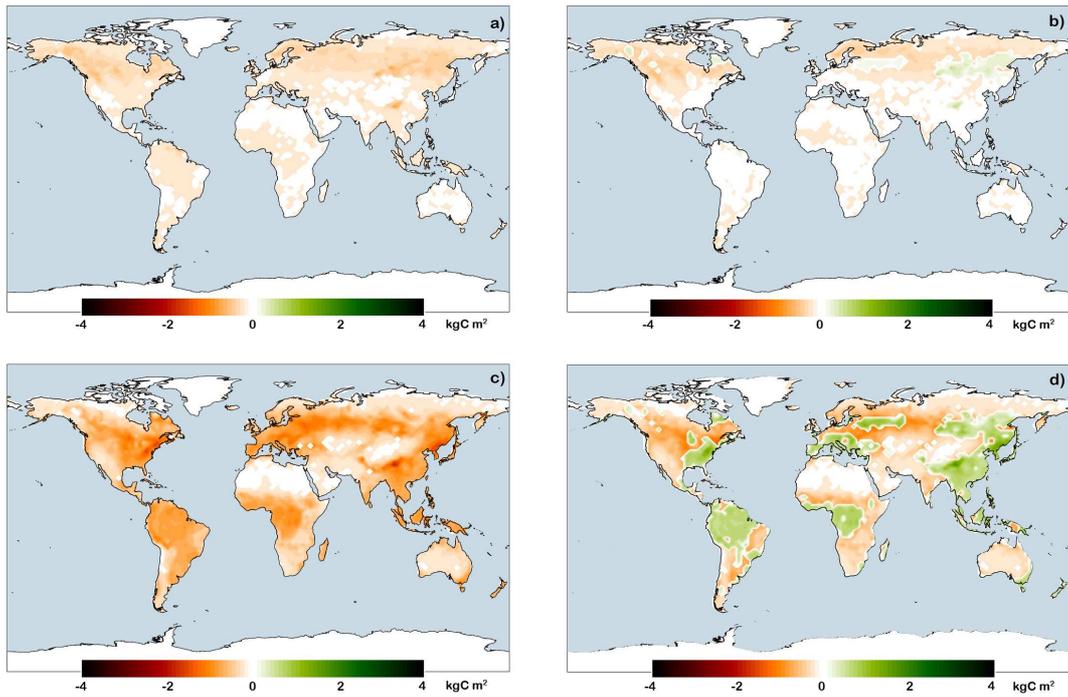
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4 Figure 2: Parameterization of the priming effect. The priming effect was implemented
5 as a fractional increase in the mineralisation of all SOC pools. The fractional increase
6 in SOC mineralisation was set to be in proportion to the relative contribution of total
7 plant-derived C to the total soil respiration in each time step.



1

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

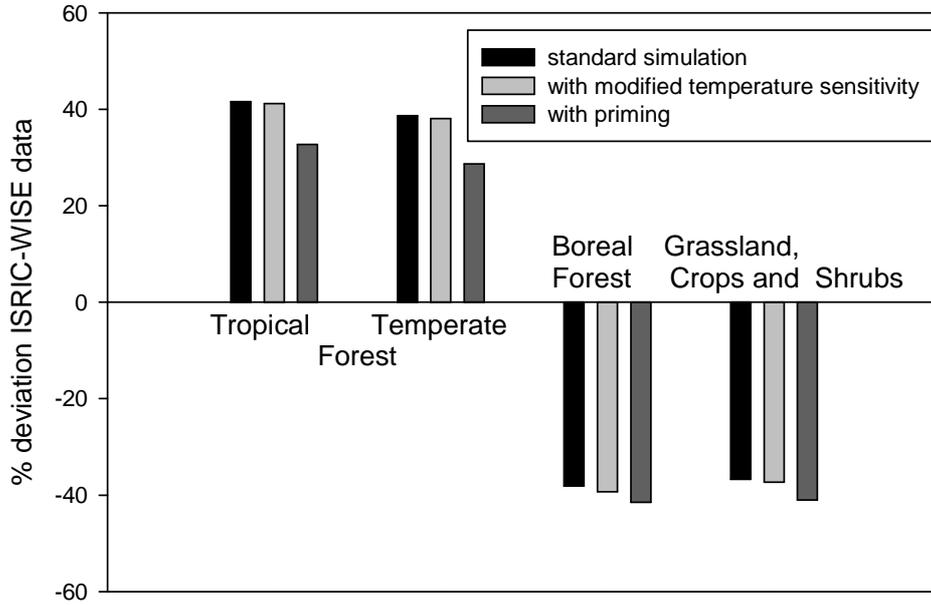


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2 Figure 4: Difference in SOC at equilibrium between the standard model and the
 3 model with modified differential temperature sensitivity of pools (a), with added
 4 priming effect (c), and the change in error in SOC predictions with respect to the
 5 observations due to the modified temperature sensitivity (b) and due to adding
 6 priming (d). Positive values in (b) and (d) indicate the modification to the model
 7 improved prediction of SOC compared to the observations.

8

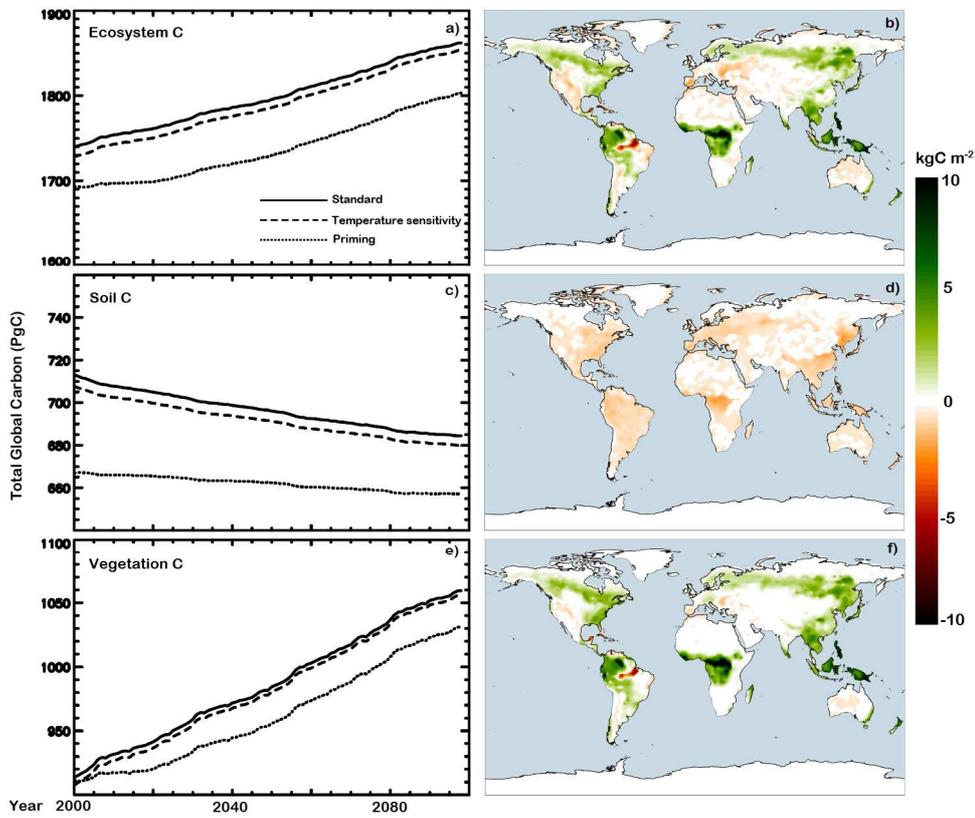
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2

3 Figure 5: Deviation from ISRIC-WISE data for the standard model and the two
4 modifications grouped on eco-regions.

5



6

1 Figure 6: Predicted total global organic carbon in the entire ecosystem (a), soil (c) and
2 vegetation (e) starting from equilibrium year 2000 under predicted climate change
3 with the standard CLM and with the two modified versions of the model. The spatial
4 maps show the changes between the average of the last 25 years of the equilibrium
5 run and the average of the last 25 years of the future run (i.e. the period 2075-2099)
6 for total ecosystem C (b), soil C (d), and vegetation C (f) using the standard model.