

1 **The sensitivity of carbon turnover in the Community**
2 **Land Model to modified assumptions about soil**
3 **processes**

4
5 **B. Foereid^{1*}, D. S. Ward¹, N. Mahowald¹, E. Paterson² and J. Lehmann¹**

6 [1]{Cornell University, Ithaca, New York}

7 [2]{The James Hutton Institute, Aberdeen, United Kingdom}

8 [*]{now at: University of Abertay Dundee, United Kingdom}

9 Correspondence to: B. Foereid (1307280@live.abertay.ac.uk)

10

11 **Abstract**

12 Soil organic matter (SOM) is the largest store of organic carbon (C) in the biosphere,
13 but the turnover of SOM is still incompletely understood and not well described in
14 global C cycle models. Here we use the Community Land Model (CLM) and compare
15 the output for soil organic C stocks (SOC) to estimates from a global data set. We also
16 modify the assumptions about SOC turnover in two ways: 1) We assume distinct
17 temperature sensitivities of SOC pools with different turnover time and 2) We assume
18 a priming effect, such that the decomposition rate of native SOC increases in response
19 to a supply of fresh organic matter. The standard model predicted the global
20 distribution of SOC reasonably well in most areas, but it failed to predict the very
21 high stocks of SOC at high latitudes. It also predicted too much SOC in areas with
22 high plant productivity, such as tropical rain forests and some mid-latitude areas.
23 Assuming that the temperature sensitivity of SOC decomposition is dependent on the
24 turnover rate of component pools reduced total SOC at equilibrium by a relatively
25 small amount (<1% globally). Including a priming effect reduced total global SOC
26 more (6.6% globally) and led to decreased SOC in areas with high plant input
27 (tropical and temperate forests), which were also the areas where the unmodified
28 model overpredicted SOC (by about 40%). The model was then run with climate
29 change prediction until 2100 for the standard and modified versions. Future
30 simulations showed that differences between the standard and modified versions were

1 maintained in a future with climate change (4-6 Pg and 23-47 Pg difference in soil
2 carbon 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.

5

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 (Heimann and Reichstein, 2008; Ostle et al., 2009; Billings et
13 al., 2010; Conant et al., 2011; Zhu and Cheng, 2011). In large part, this uncertainty is
14 a 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 (Paterson et al., 2009; Subke and Bahn,
17 2010; Dungait et al., 2012). 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 (N) and fire in
22 the earth system. Several terrestrial models exist, such as Lund-Potsdam-Jena (LPJ),
23 the Joint UK Land Environment Simulator (JULES) and the Community Land Model
24 (CLM) (Sitch et al., 2003; Best et al., 2005; Oleson et al, 2010). These models can be
25 integrated into Earth System Models (ESMs) to predict the biotic feedback to climate
26 change. ESM studies have demonstrated that climate-carbon-cycle feedbacks over the
27 next century may have a large impact on future CO₂ levels and climate (Cox et al.,
28 2000; Friedlingstein et al., 2001), although this is not true in all simulations
29 (Thornton, 2009). As well as being a tool in climate prediction, ESMs also provide
30 tools for integration of knowledge about the land surface. A comparison of earth
31 system models included in the Intergovernmental Panel on Climate Change (IPCC)
32 showed that one of the largest uncertainties in predicting biotic feedback to climate

1 change is how the soil will respond (Friedlingstein et al., 2006). The soil response to
2 global warming is a critical parameter in determining future CO₂ concentrations and
3 therefore the magnitude of feedbacks to the rate of future climate change (Jones et al.,
4 2003) and represents a large uncertainty in future climate prediction overall, including
5 physical climate effects (Huntingford et al., 2009). Improving the soil part of the
6 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 (Yuste et al., 2007; Paterson et al.,
10 2008; 2009; 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 C turnover. In
15 almost all models the temperature sensitivity of soil organic C (SOC) turnover is
16 assumed to be constant for all pools, irrespective of their mineralization rate, or other
17 factors controlling relative turnover rates (e.g. Jenkinson et al., 1987; Parton et al.,
18 1987; 1988; 1994; Williams, 1990; Li et al., 2000). In addition, SOC content is
19 modelled to increase as a direct function of increasing rates of plant inputs, which
20 makes the implicit assumption that the decomposition rates of individual pools do not
21 affect each other, i.e. that there is no priming (Kuzyakov, 2010). However, in recent
22 years, 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 (Waldrop and
25 Firestone, 2004; Fang et al., 2005; Knorr et al., 2005; Reichstein et al., 2005;
26 Davidson and Janssens, 2006). Differential temperature sensitivity of SOC pools has
27 been 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 Paterson et al., 2008, 2011; 2013; Kuzyakov 2010; Zhu and Cheng, 2011;). 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) (Thornton et al., 2007; Oleson et al., 2010) 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, and conduct simulations using both standard and
19 modified SOM models 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 (Thornton et al., 2007; Thornton, 2009; Oleson et al., 2010).

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

1 material is assumed to fractionate before it enters any litter pool, using a fractionation
2 constant (K_{frag}). As the litter pools decompose, a fraction of the C is released as CO_2
3 and a fraction is transformed into the corresponding SOC pool. The SOC pools either
4 mineralize to CO_2 or decompose to enter another pool except the last (and slowest
5 turning over SOC pool) that only mineralizes to CO_2 . The response of the model to
6 climate change in offline and fully coupled simulations has been explored (Thornton
7 et al., 2007; 2009), and comparisons to detailed observations has been examined
8 (Randerson et al., 2009). A version of this model was included in the Coupled Model
9 Intercomparison Project (CMIP5) analysis prepared in part for the 5th Assessment
10 report of Intergovernmental Panel on Climate Change (IPCC) (Lindsay et al., 2013).
11 The model has also been compared to other fully coupled models (e.g. Arora et al.,
12 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 Q_{10} formulae ($Q_{10}=1.5$). Knorr et
20 al. (2005) suggested how decomposition rates of pools could be calculated based on
21 Arrhenius kinetics:

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

23 Where k is the decomposition rate, E_a is activation energy, R is the universal gas
24 constant, T is temperature in Kelvin, and A is the theoretical decomposition rate at
25 $E_a=0$. This therefore provides a methodology for how to calculate pool decomposition
26 rates based on theoretical considerations from thermodynamics. We used this
27 methodology to modify the standard Q_{10} model temperature sensitivity (k_{mod}) while
28 retaining the shape of the temperature response:

$$29 \quad k_{\text{mod}} = k_{Q_{10}} e^{\frac{-E_a}{RT}} \quad (2)$$

30 Standard model approximations of $k(T)$ are based on data from experiments on

1 quickly decomposing SOC pools. However, Knorr et al. (2005) argued that the
 2 decomposition of slowly decaying SOC is more sensitive to temperature than
 3 decomposition in the quickly decaying pools common to most experiments.
 4 Therefore, we modified the Arrhenius model term in Eq. 2 to be dependent on the
 5 turnover time characteristic of each soil and litter pool, expressed as the difference
 6 between the activation energy of the pool and a standard activation energy (E_{astd}). The
 7 sign convention was chosen such that the temperature sensitivity of k increases with
 8 pool turnover time, as used by Knorr et al. (2005):

$$9 \quad k_{mod} = k_{Q10} e^{\frac{(E_a - E_{astd})}{RT}} \quad (3)$$

10 To be consistent with the conclusions of Knorr et al. (2005) as mentioned above, we
 11 use the activation energy of the fastest decomposing soil pool as the standard in this
 12 expression. Activation energy was calculated for each C pool using the turnover times
 13 from Thornton and Rosenbloom (2005), also used in CLM4, and a linear fit to
 14 empirical activation energy data given by Knorr et al. (2005) (Table 1).

15 In addition, we modified the term in the exponent from Eq. 3 to equal zero when the
 16 pool temperature equals 15°C, or roughly the global average temperature, by
 17 multiplying by the factor $(T - T_{15})/T_{15}$ where T_{15} is $T = 15^\circ\text{C}$. This ensured that the
 18 temperature response of the model was the same for k_{mod} and k_{Q10} at this temperature.

$$19 \quad k_{mod} = k_{Q10} e^{\frac{(E_a - E_{astd})(T - T_{15})}{RT_{15}}} \quad (4)$$

20 We computed new decomposition rates for all C pools and temperatures using Eq. 4
 21 and fitted a new Q_{10} coefficient to the temperature sensitivity of k_{mod} for each pool
 22 (Table 1, Figure 1). The quickly decomposing soil 1 pool was used as the standard
 23 and was kept unchanged. The values of Q_{10} increase up to 2.27 in the more slowly
 24 decomposing pools (Table 1).

25 2.2.2 Priming effect

26 Plants add C to the soil, broadly in proportion to their growth rate. In the standard
 27 model, this means that everything else being equal, C contents of soils will increase
 28 with increasing plant biomass production. However, there is evidence that input of
 29 fresh C can increase the decomposition rate of the C that is already there, through the
 30 priming effect (Kuzyakov, 2010). To account for priming of native SOM, we used

1 data from a laboratory incubation experiment (Garcia-Pausas and Paterson, 2011).
 2 This experiment used ^{13}C -enriched glucose as a surrogate for plant-derived inputs
 3 allowing the mineralisation of native SOM to be quantified by isotopic mass balance
 4 (partitioning SOM-derived CO_2 efflux from that derived from the added glucose).
 5 They found that the SOM-derived CO_2 -C efflux from soils increased by roughly 25%
 6 with the addition of the glucose. Here we modified the SOM decomposition scheme
 7 in CLM to account for up to a 25% increase in decomposition rate from an input of C
 8 from the litter pools.

9 CLM calculates a potential C flux from each soil and litter pool that occurs if N is not
 10 limiting. We expressed priming as a function of the ratio between the potential C loss
 11 flux from all litter pools (F_{litter}) and potential C loss flux from all soil pools (F_{soil})
 12 before priming had been introduced. Priming can then be represented as a
 13 proportional increase in the decomposition rate of each soil pool that grows with an
 14 increase in the ratio of F_{litter} to F_{soil} and reaches a maximum at a proportional increase
 15 in soil decomposition rate of 25%, following the results of Garcia-Pausas and
 16 Paterson (2011). This relation was described with a continuous function that
 17 asymptotes to the maximum proportional increase in decomposition rate (25%) and is
 18 added to the potential C flux from decomposition of SOM (C_p):

$$19 \quad C_{p-mod} = C_p * \left[1 + a * \left(1 - e^{(-b * F_{litter} / F_{soil})} \right) \right] \quad (5)$$

20 where a and b are constants, here a=0.25 (maximum proportional increase) and
 21 b=0.1291, and C_{p-mod} is the modified potential C flux from decomposition. The
 22 parameter b was fitted such that the function nears the maximum proportional
 23 increase, a=0.25, for a ratio of F_{litter} to F_{soil} that corresponds roughly to the ratio of C
 24 added through the glucose treatments to the soil C efflux in the experiments of
 25 Garcia-Pausas and Paterson (2011). Here we assume that the effect of increasing the
 26 amount of added substrate levels off near the highest glucose concentration added in
 27 their experiments. The behaviour of this function for a range of $F_{litter}:F_{soil}$ values is
 28 shown in Figure 2. Further experiments have shown that the priming effect does
 29 saturate at high substrate addition rates, but sometimes at rates much higher than the
 30 maximum used here (Paterson and Sim, 2013). Therefore, the representation of the
 31 magnitude of priming effects can be considered conservative. These coefficients are
 32 only valid for an initial assessment of the global effects of including priming. If

1 priming were to be permanently included in the model, a more thorough calibration
2 including interactions with environmental variables, would be required.

3 2.3 Simulation protocol

4 We tested the sensitivity of global C stocks to these changes in the decomposition
5 rates in CLM experiments using the standard, unmodified model (referred to as ES),
6 the model including the modified temperature sensitivity of decomposition (referred
7 to as ET), and the model including the modified priming effect on decomposition
8 (referred to as EP). Initially, equilibrium simulations were performed with CLM for
9 ES, ET, and EP, to assess the impacts of the modified decomposition treatments on
10 steady-state model C stocks. For these equilibrium simulations we used present-day
11 land cover (Hurt et al., 2006), atmospheric CO₂ concentration, and N and aerosol
12 deposition. The terrestrial biosphere was forced from the atmosphere by prescribed
13 temperature, precipitation, solar radiation, wind, specific humidity and air pressure,
14 and data for this analysis were taken from the re-analysis by Qian et al. (2006). A 25-
15 year period (1972-2004) from the re-analysis was cycled throughout the CLM
16 equilibrium simulations. The cycling was continued until the total global drift in net
17 ecosystem C exchange was less than 0.05 PgC/y averaged over a 25-year atmospheric
18 forcing cycle. This “spin-up” procedure required approximately 1000 model years for
19 all cases. The model was simulated at 1.9 degree latitude by 2.5 degree longitude
20 horizontal grid spacing and a time step of 30 minutes.

21 Additional simulations were carried out with the modified and unmodified SOC
22 model versions to explore how the different models predict future changes in SOC.
23 These simulations were initialized from the final state of the corresponding
24 equilibrium runs, but used transient atmospheric CO₂ and meteorological forcing.
25 Output from the ECHAM5/MPI-OM CMIP3 runs (Roeckner et al., 2006) based on
26 the SRES A1B greenhouse gas projection (Nakicenovic et al., 2000) was used to
27 define future climate anomalies (for the period 2000-2100, relative to the 1948-1972
28 mean) for the quantities used in the atmospheric forcing (listed above). The climate
29 anomalies are applied to a repeating, 25-year cycle of atmospheric reanalysis (from
30 the years 1948-1972) to create the atmospheric forcing datasets. With this method we
31 retain observed diurnal, seasonal and interannual climate variability into the future
32 even as it is scaled to the predicted future climate trends (Kloster et al., 2012; Ward et
33 al., 2012). Transient atmospheric CO₂ concentrations also follow the SRES A1B

1 scenario for the year 2000 through 2100. In this scenario, CO₂ concentrations
2 increase through the 21st century, exceeding 700ppm by the year 2100. Global N
3 deposition distributions from the year 2000 (Lamarque et al. 2005) were used
4 throughout for all simulations.

5 2.4 Soil data

6 Soil data from ISRIC-WISE 05 degree (Batjes, 2005) were used to compare against
7 output from the simulations. The model generates SOC as a stock in each grid cell,
8 while the ISRIC-WISE dataset gives SOC as a percentage of soil mass in each map
9 unit within a grid cell. Therefore we converted the observed data to SOC stocks with
10 the following expression:

$$11 \quad C_s = d * 10 * \left(1 - \frac{g}{100}\right) * b * \frac{C_p}{100} \quad (6)$$

12 Where C_s are SOC stocks (kg/m²), d is thickness of soil layer (cm), g is gravel content
13 (%) b is bulk density (g/cm³) and C_p is SOC content (%) from the ISRIC-WISE
14 dataset. The calculation was done separately for the two soil layers in the ISRIC-
15 WISE dataset (0-0.3 m and 0.3-1 m). The SOC content of both layers is summed, and
16 a weighted average of C_s over the map units was calculated based on fractional area
17 covered by each map unit.

18

19 3. Results and discussion

20 The unmodified CLM predicts about 26% less SOC than estimated from the ISRIC-
21 WISE data set (the ISRIC-WISE dataset is abbreviated as “OBS” in the tables and
22 figures) (Table 2). It should be noted that the data set only has SOC in the top 1 m, so
23 that real SOC storage and underprediction is even higher. The main reason for the
24 underprediction is that the model is unable to predict the very high SOC contents in
25 northern latitudes (Figure 3). This is unsurprising as the model does not include
26 effects of waterlogging, low pH and permafrost on SOC dynamics. However, the
27 model also underpredicts slightly in many other areas. Exceptions are tropical rain
28 forests in Amazonia and Africa and temperate forests in Asia and eastern United
29 States where the model overpredicts SOC (Figure 3). These are all high productivity
30 regions, which suggests that plant productivity is a stronger determinant of SOC in the
31 model than in reality (overall r^2 between net primary productivity (NPP) and the

1 magnitude of the model overprediction of SOC compared to the observed is 0.56). It
2 is also important to note that the standard model does not account for influences of
3 soil texture and structure, which are strong determinants of stabilisation of SOC
4 through constraining the access of decomposers to SOM (von Lutzow et al., 2006;
5 Dungait et al., 2012). This will account for some of the unexplained variability in the
6 distribution of SOC.

7 Including temperature and priming modifications did not dramatically alter
8 predictions of total global SOC, but did affect the predicted distribution (Table 2;
9 Figure 4). The results do not include litter pools, but the difference in litter pools
10 between the various versions of the model was negligible (data not shown) as is to be
11 expected as the modifications introduced act on SOC pools but not directly on litter
12 pools. While the standard model has been calibrated to reproduce global SOC stocks,
13 the lack of explicit representation of soil processes may limit their capacity to capture
14 spatial variability in these stocks. That is, setting standard model functions to
15 represent global means can reproduce global SOC stocks, but without further
16 modification may not improve prediction of geographical variation. Such spatial
17 variability would be expected where soil and environmental factors affect the relative
18 importance of SOC-accrual and SOC-loss processes, causing deviation from mean
19 responses on a global scale. In addition, analogously to predicting geographic
20 variation in SOC, modelling impacts of environmental change on global SOC stocks
21 may require more explicit representation of soil processes, as factors such as CO₂
22 fertilisation, N addition through deposition and/or fertilisation and temperature rise
23 may directly affect the balance of these soil processes.

24 SOC decreased at most grid points for ET relative to ES, especially in the high
25 latitudes of the Northern Hemisphere (Figure 4a). However, the magnitude of the
26 decrease was small, never exceeding 1 kgC/m² at any location, compared to the
27 difference in SOC between the ES results and OBS, which falls between 5 and 20
28 kgC/m² at many locations (Figure 3). This comparison is made even clearer in Figure
29 4c, which shows how the difference between the model and observations changes
30 when the modified temperature sensitivity is included in the simulation.

31 Including the simple priming effect also reduced global SOC (Table 2, Figure 4b) and
32 by a higher magnitude compared to the reduction from the modified temperature
33 sensitivity. The global decrease results from the representation of priming in EP for

1 which C turnover could only decrease or remain unchanged. Importantly, the land
2 areas where the priming had the greatest effect on SOC were those with high NPP
3 (tropical and temperate forest). These are the same regions where the standard model
4 over-predicted SOC relative to measured data to the greatest extent (Figures 3 and
5 4d). Including a priming effect improved predictions in these areas by 20-25%, but
6 predictions got worse in lower productivity ecosystems such as grasslands, shrubs,
7 and boreal forests (by 1-9%) (Figure 5). While underprediction in lower productivity
8 regions can be explained by water-logging and perma-frost, overprediction in high
9 productivity regions can be resolved by better mechanistic predictions of turnover and
10 its dependence on productivity. We suggest that including a priming effect is a
11 credible and mechanistically sound way to improve these predictions in high
12 productivity regions.

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

1 availability, relative allocation of plant C to roots and mycorrhizal symbionts is
2 reduced (Yuan and Chen, 2010; Grman and Robinson, 2013). However, whether this
3 results in an absolute reduction in C-transfer to soil is dependent on whether the
4 reduction in relative belowground allocation outweighs the impact of increased gross
5 plant productivity (Henry et al., 2005). These interactions, across ecosystem types,
6 require further quantitative study to refine the representation of plant-mediated
7 priming effects in models.

8 The difference in pool size between the standard and the modified runs is to a large
9 extent maintained into the future (Figure 6, Table 3), although the vegetation pool in
10 EP is reduced early in the future simulation. This may be a result of smaller C stocks
11 in the soil at equilibrium with this modification. That means that there was less N
12 available for mineralisation, and the effect of warming on N mineralisation and
13 availability was therefore less. The difference in pool sizes would potentially have a
14 large effect in a fully coupled simulation, and could therefore mean a different biotic
15 feedback to climate change than current models predict. The predictions of changes to
16 the C cycle under global change appear to be relatively robust towards the
17 assumptions made about SOC sensitivity to temperature, as differences in pool sizes
18 at equilibrium were maintained (Figure 6, Table 3).

19

20 **4. Conclusions**

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

29 The overprediction of C in the high productivity areas indicated that the model
30 underpredicts C turnover when plant input is high, and one way of improving that is
31 to include a priming effect, which does improve the predictions of SOC distribution
32 by 20-25%. Further work should focus on better quantification of priming, and how it

1 depends on external factors, and may also improve our ability to predict biotic
2 feedback to climate change. In this paper we also explored the impact of different
3 temperature sensitivity of C pools, but this mechanism had less of an effect in most
4 areas.

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

9

10 **Acknowledgements**

11 The lead author was supported by a grant from NASA-USDA (No. 2008-35615-
12 18961). The use of computing resources at NCAR is gratefully acknowledged.

13

14 **References**

- 15 Arora, V. K., Boer, G. J., Friedlingstein, P., Eby, M., Jones, C., Christian, J., Bonan,
16 G., Bopp, L., Brovkin, V., Cadule, P., Hajima, T., Ilyina, T., Lindsay, K., Tjiputra, J.
17 F., and Wu, T.: Carbon-Concentration and carbon-climate feedbacks in CMIP5 earth
18 system models, *J. Climate*, 26, 5289-5314, 2013.
- 19 Batjes, N. H.: Total carbon and nitrogen in the soils of the world, *Eur. J. Soil Sci.*, 47,
20 151-163, 1996.
- 21 Batjes, N. H.: ISRIC-WISE global data set of derived soil properties on a 0.5 by 0.5_
22 grid (version 3.0), ISRIC – World Soil Information, Wageningen, 2005.
- 23 Best, M.: JULES Technical Documentation, 16, Hadley Centre, Exeter, 2005.
- 24 Billings, S. A., Lichter, J., Ziegler, S. E., Hungate, B. A., and Richter, D. B.: A call to
25 investigate drivers of soil organic matter retention vs. mineralization in a high CO₂
26 world, *Soil Biol. Biochem.*, 42, 665–668, 2010.
- 27 Conant, R. T., Ryan, M. G., Agren, G. I., Birge, H. E., Davidson, E. A., Eliasson, P.
28 E., Evans, S. E., Frey, S. D., Giardina, C. P., Hopkins, F. M., Hyvonen, R.,
29 Kirschbaum, M. U. F., Lavallee, J. M., Leifeld, J., Parton, W. J., Steinweg, J. M.,
30 Wallenstein, M. D., Wetterstedt, J. A. M., and Bradford, M. A.: Temperature and soil

1 organic matter decomposition rates – synthesis of current knowledge and a way
2 forward, *Global Change Biol.*, 17, 3392–3404, 2011.

3 Cox, P. M., Betts, R. A., Jones, C. D., Spall, S. A., and Totterdell, I. J.: Acceleration
4 of global warming due to carbon-cycle feedbacks in a coupled climate model, *Nature*,
5 408, 184–187, 2000.

6 Davidson, E. A. and Janssens, I. A.: Temperature sensitivity of soil carbon
7 decomposition and feedbacks to climate change, *Nature*, 440, 165–173, 2006.

8 Dijkstra, F. A., Morgan, J. A., Blumenthal, D., and Follett, R. F.: Water limitation and
9 plant interspecific competition reduce rhizosphere-induced C decomposition and plant
10 N uptake, *Soil Biol. Biochem.*, 42, 1073–1082, 2010.

11 Dungait, J. A., Hopkins, D. W., Gregory, A. S., and Whitmore, A. P.: Soil organic
12 matter turnover is governed by accessibility not recalcitrance, *Global Change Biol.*,
13 18, 1781–1796, 2012.

14 Fang, C., Smith, P., Moncrieff, J. B., and Smith, J. U.: Similar response of labile and
15 resistant soil organic matter pools to changes in temperature, *Nature*, 433, 57–59,
16 2005.

17 Fontaine, S., Mariotti, A., and Abbadie, L.: The priming effect of organic matter: a
18 question of microbial competition?, *Soil Biol. Biochem.*, 35, 837–843, 2003.

19 Fontaine, S., Barot, S., Barre, P., Bdioui, N., Mary, B., and Rumpel, C.: Stability of
20 organic carbon in deep soil layers controlled by fresh carbon supply, *Nature*, 450,
21 277–280, 2007.

22 Fontaine, S., Henault, C., Aarmor, A., Bdioui, N., Bloor, J. M. G., Maire, V., Mary,
23 B., Revaillet, S., and Maron, P. A.: Fungi mediate long term sequestration of carbon
24 and nitrogen in soil through their priming effect, *Soil Biol. Biochem.*, 43, 86–96,
25 2011.

26 Friedlingstein, P., Bopp, L., Ciais, P., Dufresne, J. L., Fairhead, L., LeTreut, H.,
27 Monfray, P., and Orr, J.: Positive feedback between future climate change and the
28 carbon cycle, *Geophys. Res. Lett.*, 28, 1543–1546, 2001. Friedlingstein, P., Cox, P.,
29 Betts, R., Bopp, L., von Bloh, W., Brovkin, V., Cadule, P., Doney, S., Eby, M., Fung,
30 I., Bala, G., John, J., Jones, C., Joos, F., Kato, T., Kawamiya, M., Knorr, W., Lindsay,
31 K., Matthews, H. D., Raddatz, T., Rayner, P., Reick, C., Roeckner, E., Schnitzler, K.

1 G., Schnur, R., Strassmann, K., Weaver, A. J., Yoshikawa, C. and Zeng, N.: Climate
2 carbon cycle feedback analysis: results from the C4MIP model intercomparison, J.
3 Climate, 19, 3337–3353, 2006.

4 Garcia-Pausas, J. and Paterson, E.: Microbial community abundance and structure are
5 determinants of soil organic matter mineralisation in the presence of labile carbon,
6 Soil Biol. Biochem., 43, 1705– 1713, 2011.

7 Ghee, C., Neilson, R., Hallett, P. D., Robinson, D., and Paterson, E.: Priming of soil
8 organic matter mineralisation is intrinsically insensitive to temperature, Soil Biol.
9 Biochem., 66, 20– 28, doi:10.1016/j.soilbio.2013.06.020, 2013.

10 Grman E., Robinson, T.M.P.: Resource availability and imbalance affect plant-
11 mycorrhizal interactions: a field test of three hypotheses, Ecology 94, 62-71, 2013.

12 Heimann, M. and Reichstein, M.: Terrestrial ecosystem carbon dynamics and climate
13 feed-backs, Nature, 451, 289–292, 2008.

14 Henry F., Nguyen C., Paterson E., Sim A. and Robin, C.: How does N availability
15 alter rhizodeposition in *Lolium multiflorum* during vegetative growth?, Plant and Soil
16 269, 181-191, 2005.

17 Huntingford, C., Lowe, J., Booth, B., Jones, C., Harris, G., Gohar, L., and Mier, P.:
18 Contributions of carbon cycle uncertainty to future climate projection spread, Tellus
19 B, 61, 355–360, 2009.

20 Hurtt, G. C., Frolking, S., Fearon, M. G., Moore, B., Sheviliakova, E., Malyshev, S.,
21 Pacala, S. W., and Houghton, R. A.: The underpinnings of land-use history: three
22 centuries of global gridded land-use transitions, wood-harvest activity, and resulting
23 secondary lands, Global Change Biol., 12, 1208–1229, 2006.

24 Jones, C., Robertson, E., Arora, V. K., Friedlingstein, P., Sheviliakova, E., Bopp, L.,
25 Brovkin, V., Hajima, T., Kato, E., Kawamiya, M., Liddicoat, S., Lindsay, K., Reick,
26 C., Roelandt, C., Segschneider, J., and Tjiputra, J. F.: 21st century compatible CO2
27 emissions and airborne fraction simulated by CMIP5 Earth System models under 4
28 Representative Concentration Pathways, J. Climate, 26, 4398–4413, 2013.

29 Jones, C. D., Cox, P., and Huntingford, C.: Uncertainty in climate-carbon-cycle
30 projections associated with sensitivity of soil respiration to temperature, Tellus B, 55,
31 642–648, 2003.

1 Kloster, S., Mahowald, N. M., Randerson, J. T., and Lawrence, P. J.: The impacts of
2 climate, land use, and demography on fires during the 21st century simulated by
3 CLM-CN, *Biogeosciences*, 9, 509–525, 2012.

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

6 Kuzyakov, Y.: Priming effects: interactions between living and dead organic matter,
7 *Soil Biol. Biochem.*, 42, 1363–1371, 2010.

8 Lamarque, J.-F., Kiehl, J., Brasseur, G., Butler, T., Cameron-Smith, P., Collins, W.
9 D., Collins, W. J., Granier, C., Hauglustaine, D., Hess, P., Holland, E., Horowitz, L.,
10 Lawrence, M., McKenna, D., Merilees, P., Prather, M., Rasch, P., Rotman, D.,
11 Shindell, D., and Thornton, P.: Assessing future nitrogen deposition and carbon cycle
12 feedbacks using a multi-model approach: Analysis of nitrogen deposition, *J. Geophys.*
13 *Res.*, 110, D19303, 2005.

14 Li, C. S.: Modeling trace gas emissions from agricultural ecosystems, *Nutr. Cycl.*
15 *Agroecosys.*, 58, 259–276, 2000.

16 Lindsay, K., Bonan, G., Doney, S., Hoffman, F., Lawrence, D., Long, M. C.,
17 Mahowald, N., Moore, J. K., Randerson, J. T., and Thornton, P.: Preindustrial control
18 and 20th century carbon cycle experiments with the earth system model CESM1-
19 (BGC) *J. Climate*, in review, 2013.

20 Metcalfe, D. B., Fisher, R. A., and Wardle, D. A.: Plant communities as drivers of soil
21 respiration: pathways, mechanisms, and significance for global change,
22 *Biogeosciences*, 8, 2047–2061, 2011.

23 Nakicenovic, N., Davidson, O., Davis, G., Gruebler, A., Kram, T., La Rovere, E. L.,
24 Metz, B., Morita, T., Pepper, W., Pitcher, H., Sankovski, A., Shukla, P., Swart, R.,
25 Watson, R., and Dadi, Z.: Special report on emissions scenarios, in: *Contribution to*
26 *the Intergovernmental Panel on Climate Change*, Cambridge University Press,
27 Cambridge, UK, 2000.

28 Ohm, H., Hamer, U., and Marschner, B.: Priming effects in soil size fractions of a
29 podzol Bs horizon after addition of fructose and alanine, *J. Plant Nutr. Soil Sci.*, 170,
30 551–559, 2007.

1 Oleson, K. W., Lawrence, D. M., Bonan, G. B., Flanner, M. G., Kluzek, E.,
2 Lawrence, P. J., Levin, S., Swenson, S. C., and Thornton, B.: Technical Description
3 of Version 4.0 of the Community Land Model, National Center for Atmospheric
4 Research, Boulder, Colorado, 2010.

5 Ostle, N. J., Smith, P., Fisher, R., Woodward, F. I., Fisher, J. B., Smith, J. U.,
6 Galbraith, D., Levy, P., Meir, P., McNamara, N. P., and Bardgett, R. D.: Integrating
7 plant-soil interactions into global carbon cycle models, *J. Ecol.*, 97, 851–863, 2009.

8 Parton, W. J., Schimel, D. S., Cole, C. V., and Ojima, D. S.: Analysis of factors
9 controlling soil organic matter levels in Great Plains grasslands, *Soil Sci. Soc. Am. J.*,
10 51, 1173–1179, 1987.

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

13 Parton, W. J., Schimel, D. S., Ojima, D. S., Cole, C. V., Bryant, R. B., and Arnold, R.
14 W.: A general model for soil organic matter dynamics: sensitivity to litter chemistry,
15 texture and management, in: *Quantitative modeling of soil forming processes:*
16 *proceedings of a symposium sponsored by Divisions S-5 and S-9 of the Soil Science*
17 *Society of America in Minneapolis, 2 November 1992, Minnesota, USA, Soil Science*
18 *Society of America Inc.*, 147–167, 1994.

19 Paterson, E.: Importance of rhizodeposition in the coupling of plant and microbial
20 productivity, *Eur. J. Soil Sci.*, 54, 741–750, 2003.

21 Paterson, E. and Sim, A.: Soil-specific response functions of organic matter
22 mineralisation to the availability of labile carbon, *Global Change Biol.*, 19, 1562–
23 1571, 2013.

24 Paterson, E., Thornton, B., Midwood, A. J., Osborne, S. M., Sim, A., and Millard, P.:
25 Atmospheric CO₂ enrichment and nutrient additions to planted soil increase
26 mineralisation of soil organic matter, but do not alter microbial utilization of plant-
27 and soil C-sources, *Soil Biol. Biochem.*, 40, 2434–2440, 2008.

28 Paterson, E., Midwood, A. J., and Millard, P.: Through the eye of the needle: a review
29 of isotope approaches to quantify microbial processes mediating soil carbon balance,
30 *New Phytol.*, 184, 19–33, 2009.

1 Paterson, E., Neilson, R., Midwood, A. J., Osborne, S. M., Sim, A., Thornton, B., and
2 Millard, P.: Altered food web structure and C-flux pathways associated with
3 mineralisation of organic amendments to agricultural soil, *Appl. Soil Ecol.*, 48, 107–
4 116, 2011.

5 Qian, T., Dai, A., Trenberth, K. E., and Oleson, K. W.: Simulation of global land
6 surface conditions from 1948 to 2004, Part I: Forcing data and evaluations, *J.*
7 *Hydrometeorol.*, 7, 953–975, doi:10.1175/JHM540.1, 2006.

8 Randerson, J., Hoffman, F., Thornton, P., Mahowald, N., Lindsay, K., Lee, Y.-H.,
9 Nevison, C. D., Doney, S., Bonan, G., Stockli, R., Covey, C., Running, S., and Fung,
10 I.: Systematic assessment of terrestrial biogeochemistry in coupled climate-carbon
11 models, *Global Change Biol.*, 15, 2462–2484, 2009.

12 Reichstein, M., Subke, J. A., Angeli, A. C., and Tenhunen, J. D.: Does the
13 temperature sensitivity of decomposition of soil organic matter depend upon water
14 content, soil horizon, or incubation time?, *Global Change Biol.*, 11, 1754–1767, 2005.

15 Roeckner, E., Brasseur, G., Giorgetta, M., Jacob, D., Jungclaus, J., Reick, C., and
16 Sillmann, J.: Climate projections for the 21st century, in: Internal Report, Max Planck
17 Institut fuer Meteorologie, Hamburg, 2006.

18 Salomé, C., Nunan, N., Pouteau, V., Lerch, T. Z., and Chenu, C.: Carbon dynamics in
19 topsoil and in subsoil may be controlled by different regulatory mechanisms, *Global*
20 *Change Biol.*, 16, 416–426. 2010.

21 Sitch, S., Smith, B., Prentice, C., Arneth, A., Bondau, A., Cramer, W., Kaplans, J. O.,
22 Levis, S., Lucht, W., Sykes, M. T., Thonicke, K., and Venevsky, S.: Evaluation of
23 ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ
24 dynamic global vegetation model, *Global Change Biol.*, 9, 161–185, 2003.

25 Subke, J. A. and Bahn, M.: On the “temperature sensitivity” of soil respiration: can
26 we use the immeasurable to predict the unknown?, *Soil Biol. Biochem.*, 42, 1653–
27 1656, 2010.

28 Thiessen, S., Gleixner, G., Wutzler, T., and Reichstein, M.: Both priming and
29 temperature sensitivity of soil organic matter decomposition depend on microbial
30 biomass – an incubation study, *Soil Biol. Biochem.*, 57, 739–748, 2013.

1 Thornton, P. E. and Rosenbloom, N. A.: Ecosystem model spin-up: estimating steady
2 state conditions in a coupled terrestrial carbon and nitrogen cycle model, *Ecol.*
3 *Model.*, 189, 25–48, 2005.

4 Thornton, P. E., Lamarque, J. F., Rosenbloom, N. A., and Mahowald, N. M.:
5 Influence of carbon-nitrogen cycle coupling on land model response to fertilization
6 and climate variability, *Global Biogeochem. Cy.*, 15, 2462–2484, 2007.

7 Thornton, P. E., Doney, S. C., Lindsay, K., Moore, J. K., Mahowald, N., Randerson,
8 J. T., Fung, I., Lamarque, J.-F., Feddema, J. J., and Lee, Y.-H.: Carbon-nitrogen
9 interactions regulate climate-carbon cycle feedbacks: results from an atmosphere-
10 ocean general circulation model, *Biogeosciences*, 6, 2099–2120, 2009.

11 Waldrop, M. P. and Firestone, M. K.: Altered utilization patterns of young and old
12 soil C by microorganisms caused by temperature shifts and N additions,
13 *Biogeochemistry*, 67, 235–248, 2004.

14 Ward, D. S., Kloster, S., Mahowald, N. M., Rogers, B. M., Randerson, J. T., and
15 Hess, P. G.: The changing radiative forcing of fires: global model estimates for past,
16 present and future, *Atmos. Chem. Phys.*, 12, 10857–10886, 2012.

17 Williams, J. R.: The erosion productivity impact calculator (EPIC) model: a case
18 history, *Philos. T. Roy. Soc. Lond.*, 329, 421–428, 1990.

19 Yuste, J. C., Baldocchi, D. D., Gershenson, A., Goldstein, A., Misson, L., and Wong,
20 S.: Microbial soil respiration and its dependency on carbon inputs, soil temperature
21 and moisture, *Global Change Biol.*, 13, 2018–2035, 2007.

22 Yuan, Z.Y. and Chen, H. Y. H.: Fine root biomass, production, turnover rates, and
23 nutrient contents in boreal forest ecosystems in relation to species, climate, fertility,
24 and stand age: Literature review and meta-analyses, *Critical Rev. Plant Sci.*, 29, 204-
25 221, 2010.

26 Zhu, B. and Cheng, W.: Rhizosphere priming effect increases the temperature
27 sensitivity of soil organic matter decomposition, *Global Change Biol.*, 17, 2172–2183,
28 2011.

29

1 Table 1: Values for the parameters used in the calculation of the temperature
 2 sensitivity of decomposition rates for this study (Eq.4). Turnover times for all carbon
 3 pools are from Thornton and Rosenbloom (2005) and are the same as those used in
 4 CLM4. Activation energies are computed using the linear fit given by Knorr et al.
 5 (2005) in their Figure 2. A least-squares, best-fit Q_{10} coefficient is given for each of
 6 the modified decomposition rates, $k_{\text{mod}}(T)$.

7

Carbon Pool	Turnover Time (T=25°C) [days]	Activation Energy [J mol ⁻¹]	Q_{10} coefficient for K_{mod}
Soil 1	21.4	39882	1.50
Soil 2	107.1	46736	1.66
Soil 3	1071.4	56543	1.93
Soil 4	15000.0	67783	2.27
Litter 1	2.1	30075	1.29
Litter 2	21.4	39882	1.50
Litter 3	107.1	46736	1.66
K-frag	1500.0	57976.0	1.97

8

9

10

11

12

13

14

15

16

17

18

19

20

21

1 Table 2: Total SOC storage estimated from the ISRIC-WISE data set in top 1 m, using
2 the Eq. 6 unit conversion, in comparison to those calculated with CLM at equilibrium
3 (unmodified) and with each of the modifications described in the text.

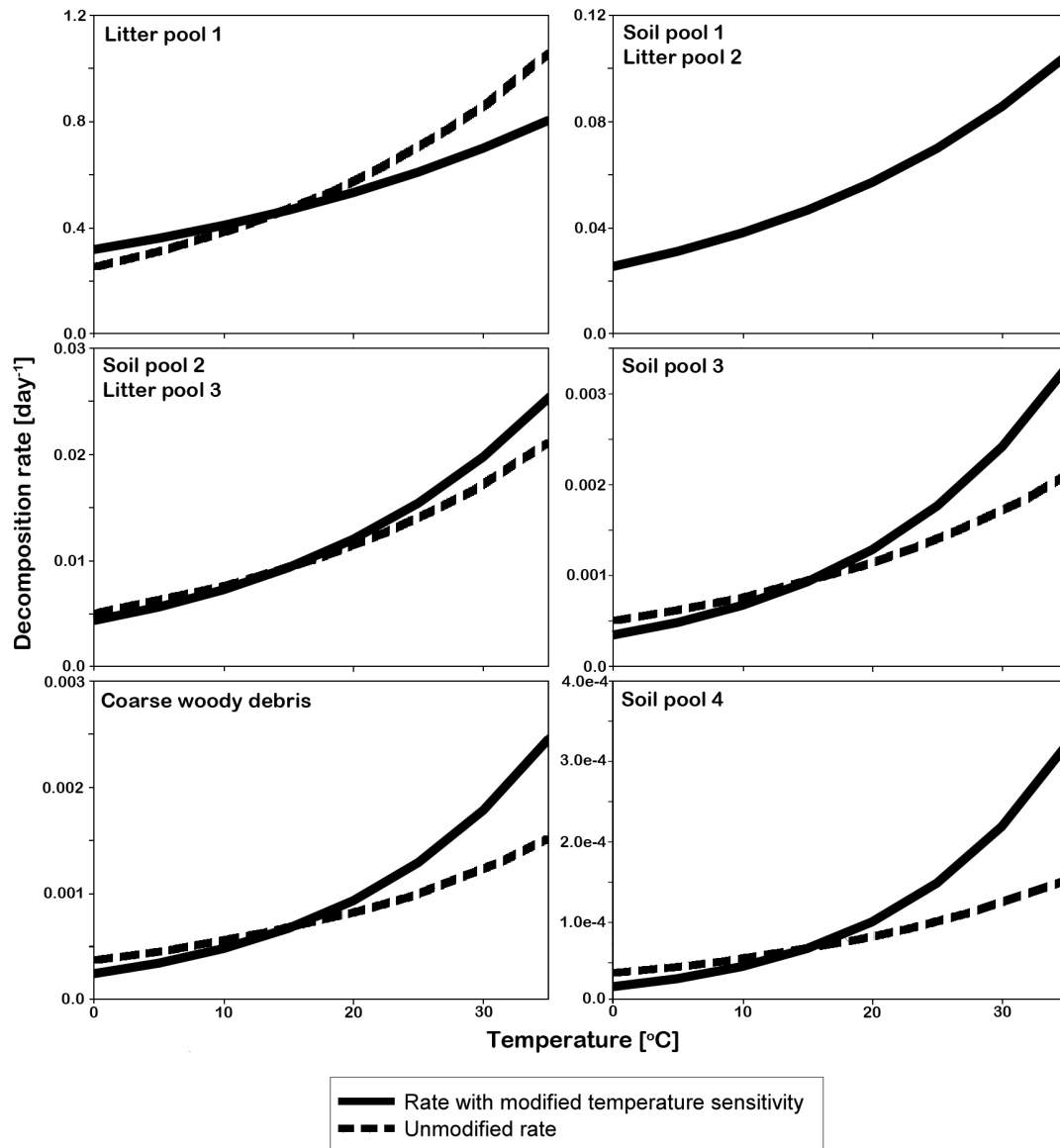
	OBS	ES	ET	EP
Total soil organic carbon (Pg)	967.9	712.7	707.1	666.0
Proportion (% of OBS)	100	74	73	69

4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34

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

	ES	ET	EP
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%

3



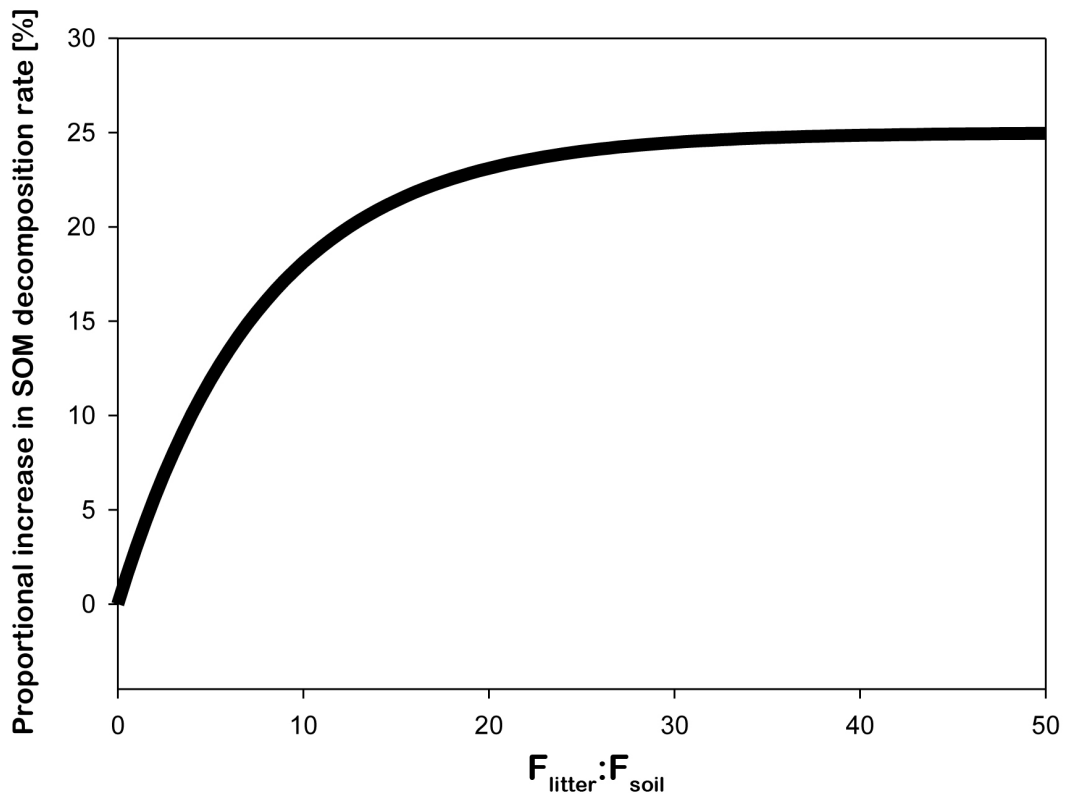
1

2 Figure 1: Decomposition rate (k) as a function of temperature in the standard Q_{10}
 3 model (unmodified rate) and the modified model given by Equation 4. The rates are
 4 plotted for all model carbon pools, indicated in the top left of each panel.

5

6

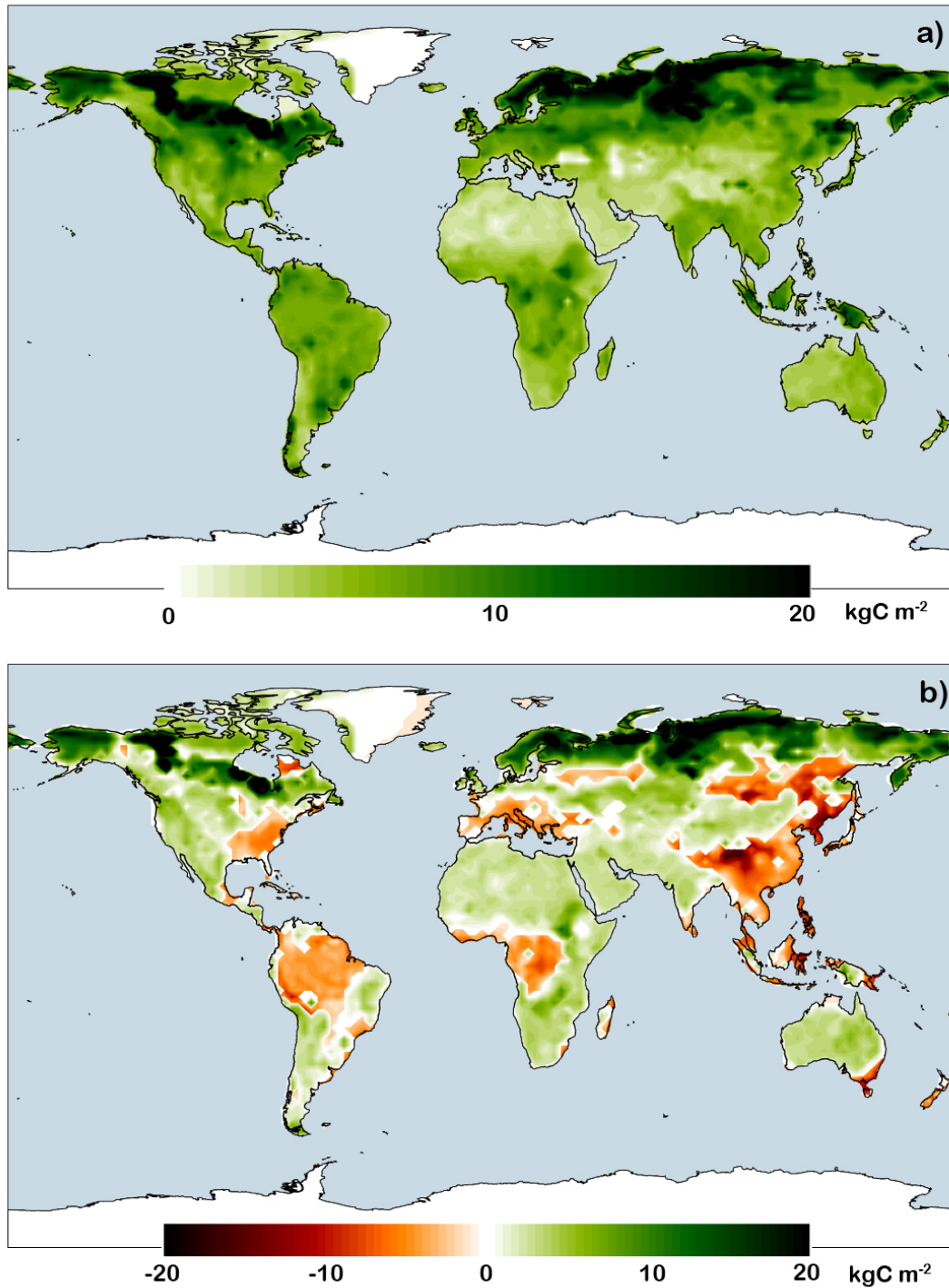
1



2

3

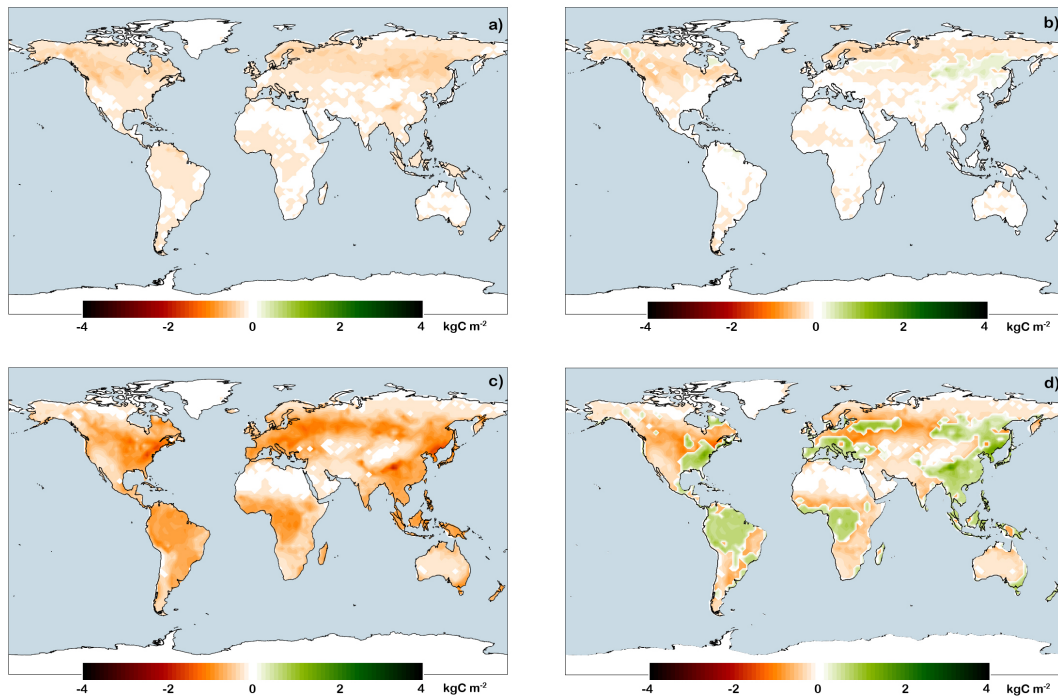
4 Figure 2: Plot of the proportional increase in decomposition rate of all soil pools,
5 given as percentages, due to priming from an influx of C from the litter pools,
6 computed from Eq. 5. The changes in rates are plotted as a function of the
7 sum of the unmodified potential C loss fluxes from all litter pools, F_{litter} , to the sum of
8 the unmodified potential C loss fluxes from all soil pools, F_{soil} .



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 {OBS –
 4 ES}(b). Data from the ISRIC-WISE data set were recalculated for stocks in the top 1
 5 m and a weighted average over map units was produced. A full description of the
 6 calculation method is given in the text.

7

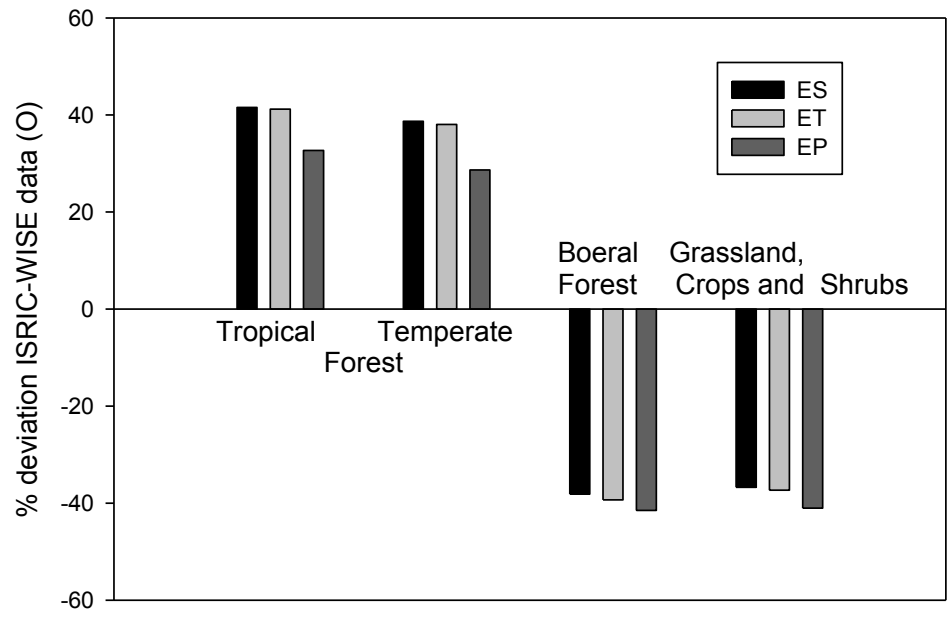


1

2 Figure 4: Difference in SOC at equilibrium between ET and ES { $ET - ES$ } (a),
 3 between EP and ES { $EP - ES$ } (c), and the change in error in SOC predictions with
 4 respect to the observations due to the modified temperature sensitivity { $|OBS - ES| -$
 5 $|OBS - ET|$ } (b), and due to adding priming { $|OBS - ES| - |OBS - EP|$ } (d).
 6 Positive values in (b) and (d) indicate the modification to the model improved
 7 prediction of SOC compared to the observations.

8

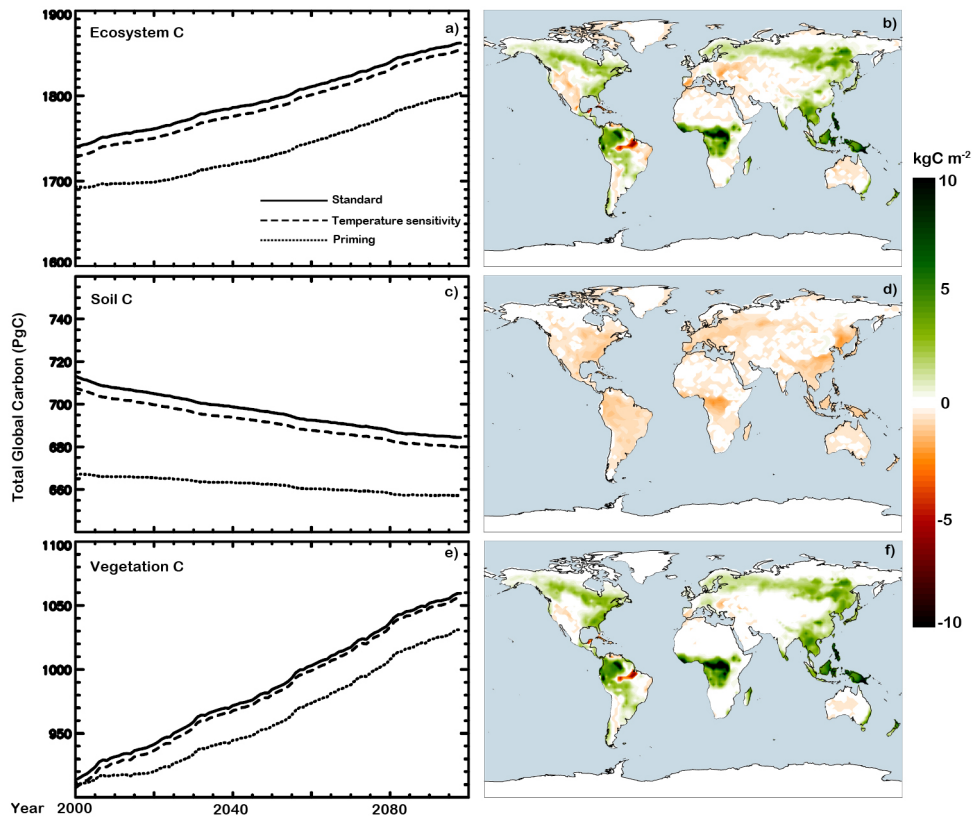
1



2

3 Figure 5: Deviation from ISRIC-WISE data (OBS) for the ES and the two
4 modifications, ET and EP grouped on eco-regions.

5



2

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