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Direct soil moisture controls of future global soil carbon changes: An important source of uncertainty

Pete Falloon,¹ Chris D. Jones,¹ Melanie Ades,^{1,2} and Keryn Paul³

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[1] The nature of the climate–carbon cycle feedback depends critically on the response of soil carbon to climate, including changes in moisture. However, soil moisture-carbon feedback responses have not been investigated thoroughly. Uncertainty in the response of soil carbon to soil moisture changes could arise from uncertainty in the relationship between soil moisture and heterotrophic respiration. We used twelve soil moisture-respiration functions (SMRFs) with a soil carbon model (RothC) and data from a coupled climate-carbon cycle general circulation model to investigate the impact of direct heterotrophic respiration dependence on soil moisture on the climate-carbon cycle feedback. Global changes in soil moisture acted to oppose temperature-driven decreases in soil carbon and hence tended to increase soil carbon storage. We found considerable uncertainty in soil carbon changes due to the response of soil respiration to soil moisture. The use of different SMRFs resulted in both large losses and small gains in future global soil carbon stocks, whether considering all climate forcings or only moisture changes. Regionally, the greatest range in soil carbon changes across SMRFs was found where the largest soil carbon changes occurred. Further research is needed to constrain the soil moisture-respiration relationship and thus reduce uncertainty in climate-carbon cycle feedbacks. There may also be considerable uncertainty in the regional responses of soil carbon to soil moisture changes since climate model predictions of regional soil moisture changes are less coherent than temperature changes.

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1. Introduction

[2] Climate change could alter terrestrial carbon storage as changes in temperature, precipitation and atmospheric CO₂ concentration will affect net primary production (NPP), carbon inputs to soil and soil carbon decomposition rates. Due to the large size of terrestrial carbon pools, they have considerable potential to drive large positive climate feedbacks because increased atmospheric CO₂ concentrations will enhance climate change [Cox et al., 2000; Friedlingstein et al., 2001, 2003, 2006; Jones et al., 2003]. Cox et al. [2000] and Jones et al. [2003] assessed the global climate-carbon cycle feedback using a coupled climate-carbon cycle general circulation model (GCM), HadCM3LC, which includes temperature and soil moisture effects on respiration. In those studies, increased heterotrophic respiration (i.e., from soil, not including roots) due to rising temperatures during the 21st century exceeded enhanced biospheric carbon uptake due to elevated atmospheric CO₂ levels. Hence the rate of increase in atmospheric CO₂ and thus the rate of climate change were accelerated. Decreases in soil carbon stocks were predicted across most of the globe, even where vegetation carbon inputs to soil increased [Jones et al., 2003]. Since soil carbon is the largest terrestrial carbon pool, the magnitude, timing and even the sign of the climate-carbon cycle feedback will depend critically on the response of soil carbon to climate [Jenkinson et al., 1991; Schimel et al., 1994; Kirschbaum, 1995; Cox et al., 2000; Friedlingstein et al., 2001, 2003; Jones et al., 2003; Jones and Falloon, 2009]. This soil carbon-climate response is highly uncertain [Kirschbaum, 1995; Giardina and Ryan, 2000; Melillo et al., 2002; Knorr et al., 2005], which is a major contributing factor in the wide range of positive climate-carbon cycle feedback values seen in a recent intercomparison of coupled climate-carbon cycle GCMs [Friedlingstein et al., 2006].

[3] The impact of environmental factors on heterotrophic respiration, including soil temperature and moisture has been investigated both experimentally [e.g., *Moore*, 1986; *Stott et al.*, 1986; *Nyhan*, 1976; *Conant et al.*, 2000; *Coûteaux et al.*, 2001] and in models [e.g., *Lomander et al.*, 1998; *Del Grosso et al.*, 2005]. The short-term relationship between soil temperature and heterotrophic respiration is relatively well established. Most soil temperature–respiration relationships used in soil carbon models are based on the Arrhenius or

¹Met Office Hadley Centre, Exeter, UK.

²Now at Department of Meteorology, University of Reading, Reading, UK.

³CSIRO Ecosystem Sciences, Canberra, Australia.

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Van't Hoff laws [Rodrigo et al., 1997] and are thus relatively similar between soil carbon models. While the impact of soil temperature on soil carbon storage has been the subject of considerable debate in studies using both experimental data [e.g., Giardina and Ryan, 2000; Fang et al., 2005; Knorr et al., 2005; Bond-Lamberty and Thomson, 2010a; Mahecha et al., 2010] and models [e.g., Rodrigo et al., 1997; Jones et al., 2005; Reichstein et al., 2005], and comprehensive review [Davidson and Janssens, 2006], the influence of soil moisture on large-scale soil carbon stocks has received relatively little attention, although it has a key role in regulating soil respiration [Liu et al., 2009]. Figure S1 in the auxiliary material shows the simulated changes in global soil and vegetation carbon stocks from the 11 climatecarbon cycle models in the study by Friedlingstein et al. [2006], and how they are related to the global climatecarbon cycle feedback strength.¹ There is a strong relationship, with models simulating greater sensitivity of soil carbon to climate change exhibiting stronger feedbacks. It is clear that soil carbon response to climate change is one of the most important components of both the climate-carbon cycle feedback, and its uncertainty.

[4] A recent analysis of global soil respiration measurements found respiration rates were strongly linked to annual precipitation amounts and anomalies [Bond-Lamberty and Thomson, 2010a]. There is extensive literature on laboratory experiments examining the impact of moisture on heterotrophic respiration, but the results are hard to compare since the incubation conditions and microbial processes studied are often not the same [Rodrigo et al., 1997]. Previous work has compared soil moisture values at particular sites with the multiplicative factors produced by different models in relation to soil moisture [Rodrigo et al., 1997] and developed statistical relationships between nitrogen mineralization rates and soil moisture [Paul, 2001; Paul et al., 2003], although the impact of different soil moisture-respiration functions (SMRFs) on large scale soil carbon stocks has not been assessed. Uncertainty in the response of soil carbon storage to future changes in soil moisture could result from uncertainty in (1) the relationship between soil moisture and heterotrophic respiration, (2) the size and direction of future soil moisture changes, and (3) the overall response of the carbon cycle to changes in climate. Our aim was to investigate the first of these possible sources of uncertainty.

2. Methods

[5] The relationship between soil moisture and microbial processes in soils is complex since several processes vary with soil water content, particularly water movement, and gas and solute diffusion. Most soil carbon models attempt to estimate heterotrophic respiration, given various parameters including soil moisture. Soil carbon models tend to represent the effect of soil moisture and temperature on decomposition using separate functions, the outputs of which are then multiplied together and applied to calculated decomposition rates. There is, however, evidence that temperature and moisture may exert an interactive effect on heterotro-

phic respiration [Janssens and Pilegaard, 2003; Reichstein et al., 2007; Wan et al., 2007]. Our aim was to isolate the soil moisture–respiration effect. We have therefore not included the interactive effect of temperature and moisture on heterotrophic respiration, instead simply using multiplicative rate modifying functions for temperature and moisture, although this interaction could be a further source of uncertainty in the soil carbon–climate feedback. Each soil carbon model represents the effect of soil moisture on decomposition using different functions (SMRFs: Table S1 and Figure S1).

[6] Among these models, there is a general consensus that heterotrophic respiration has an optimal value when the soil is wet (but not saturated) and decreases at lower values of soil moisture down to a point where respiration is minimal. The reduction in respiration rates in drier soils is mostly attributed to water limitation of microbial activity: as matric suction increases soil water is held in pores inaccessible to microbes. Most soil carbon models represent this relationship in some way, but the precise nature of the SMRFs used varies. The SMRFs have different gradients of descent, assume different soil moisture values as optima, and use different minimum soil moisture values. There is also a weaker consensus that heterotrophic respiration decreases above a certain maximum soil moisture level, particularly concerning the importance of saturation in most mineral soils. Lower respiration rates in very wet soils are attributed to the change in decomposition process from aerobic (producing CO_2) to anaerobic (mostly producing CH_4): anaerobic decomposition rates are around 30-40% of aerobic rates [Bridgham and Richardson, 1992; Moore and Dalva, 1997; DeBusk and Reddy, 1998; Jenkinson, 1988; Wania et al., 2009a]. In organic peat soils where a high water table slows decomposition due to anoxic conditions, moisture is a dominant control on soil carbon storage [Ise et al., 2008]. Many soil carbon models represent the reduction of respiration rates under saturated conditions in various ways, although some models do not represent it at all, including RothC [Paul, 2001].

2.1. RothC Soil Carbon Model

[7] The RothC dynamic soil carbon model is described in detail by Coleman and Jenkinson [1999], and has been extensively validated with laboratory and field data (see Discussion for more information). RothC is the soil carbon model presently used in the Met Office Hadley Centre Global Environmental Model 2-Earth System (HadGEM2ES: a version of the Met Office Unified Model, MetUM). RothC has four active soil organic carbon compartments, decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO) and humified organic matter (HUM) plus a pool of inert organic matter (IOM) that is resistant to decay. Each active pool has an individual decay rate, which is modified according to functions of moisture, temperature and plant cover and soil type. Organic carbon inputs to soil are split between DPM and RPM according to vegetation type: for example, arable crops are assumed to be more readily decomposable than forest litter, and hence contain a greater proportion of DPM than RPM. All active pools decay to release CO_2 to the atmosphere and to form new BIO and HUM. The split between CO2 released and BIO and HUM formed is also a function of soil texture.

¹Auxiliary materials are available with the HTML. doi:10.1029/2010GB003938.

The main input data required to run the model are soil clay content, initial soil organic carbon, soil bulk density, total monthly precipitation, mean monthly temperature, total monthly evaporation, residue quality, soil cover, and plant carbon inputs.

2.2. Soil Moisture-Respiration Functions

[8] In order to assess the impact of heterotrophic respiration dependence on soil moisture on the climate-carbon cycle feedback, we modified RothC to enable the use of twelve different SMRFs (Table S1). Our aim was to capture a representative range of SMRFs but not to use all the available SMRFs since (1) many SMRFs were very similar in form between models and (2) some SMRFs used parameters for their calculations which were not available from our climate model output data. We therefore used the SMRFs from five soil carbon models; RothC, TRIFFID, SOILN, Bethy and Sim-Cycle. There is little comprehensive soil respiration data available across soil types and soil moisture values. However, the strong linear relationship between nitrogen mineralization rates and carbon respiration rates [Schimel, 1986; Hart et al., 1994; Bruun et al., 2006] suggests that the observed nitrogen mineralization rates found at different soil moisture values for 41 soil types (covering a range of soil textures) by *Paul* [2001] and *Paul* et al. [2003] provide a suitable surrogate for soil respiration (see Figure 1). Our chosen SMRFs appear to represent the range of observed data in Figure 1, so should represent the actual range of observed heterotrophic respiration rates at different soil moisture values (with the exception of No Dependence).

[9] We chose these SMRFs since they (1) are currently being used in coupled climate-carbon cycle models. (2) could use either fractional soil moisture values, or parameters readily derived from fractional soil moisture values directly as inputs, and (3) covered a range of SMRF forms (and underlying functions) similar to those used in a variety of current soil carbon models. For instance, the SMRF used in the DNDC model [Li et al., 2000] is similar to the TRIFFID SMRF but is based on water filled pore space, is two-piece linear and allows the rate modifier to reach zero under very dry conditions. The SMRF used in the original version of CENTURY [Parton et al., 1987] is also similar to that used by TRIFFID (but uses the ratio of stored water plus rain to potential evapotranspiration) and is slightly less responsive than the RothC SMRF [Falloon and Smith, 2002], while the "relative water content version" of the CENTURY SMRF is similar in form to the RothC SMRF but is a curve rather than piecewise linear, and uses relative water content values [Paul, 2001]. For detailed comparisons of the characteristics of other SMRFs, see Paul [2001] and Rodrigo et al. [1997]. Variations of four SMRFs were also examined in order to assess the impact of changing internal parameters on soil carbon stocks (Table S1 and Figure S1). For a full description of the SMRFs used, see Text S1 and Table S1. The use of fractional soil moisture-driven SMRFs made direct comparisons more applicable, although we note that functions exist defined on water potential [e.g., Andren and Paustian, 1987]. In addition, our use of RothC as the "parent" soil carbon model only allowed the use of fractional soil moisture values.

[10] We note that the SMRFs may not be fully independent of their soil carbon models (partly because the original models were developed for different environments [Falloon and Smith, 2002]), implying that they could behave differently when used in different models. Nevertheless, some soil carbon models allow the use of different rate modifying functions as an option. For instance, in the CENTURY model (version 5), the temperature effect upon decomposition is calculated differently for monthly and daily versions (CENTURY soil organic matter model, version 5, November 2001. Available from the Natural Resources Ecology Laboratory, Colorado State University, Fort Collins, at http://www.nrel.colostate.edu/projects/century5/), with the monthly version using an exponential function and the daily version using an arctangent function, while the parameters of these equations can also be altered. However, as our aim was to assess how different SMRFs might affect large scale soil carbon changes, using different SMRFs in one soil carbon model was the most practical way to isolate only the impact of the SMRFs. An intercomparison of the original soil models would have been complicated by differences in the soil carbon pool structure and decomposition rates, decomposition-temperature response functions and other factors.

2.3. Climate Forcing Data

[11] We ran RothC with each of these SMRFs using output climate forcing data and plant carbon inputs from simulations using the coupled climate-carbon cycle GCM, HadCM3LC (a version of MetUM) which are described by Jones et al. [2003]. In order to assess the impact of the SMRFs on the soil carbon feedback due to either all climate change factors, or only soil moisture, we ran two sets of simulations: (1) changing all forcings (AF: soil temperature, soil moisture and plant carbon inputs) and (2) changing only soil moisture values relative to equilibrium values (MO). We stress that in the AF simulations, although temperature and plant carbon input forcings vary through the run, the models' sensitivity to temperature is unchanged: only the SMRF is varied. In contrast to the other SMRFs, the two variants of the RothC SMRF were both driven by precipitation and evaporation data since the RothC SMRF does not use soil moisture data directly, but makes its own water balance calculations. For comparability, all simulations applied the TRIFFID soil temperature-respiration relationship used in HadCM3LC [Cox, 2001], which is a Q₁₀-based function with a value of 2: soil respiration rate is assumed to double for every 10 K of warming [Raich and Schlesinger, 1992].

[12] We took driving data from the coupled climate– carbon cycle HadCM3LC simulations of *Jones et al.* [2003] (see Text S1 for full details), following the approach of *Jones et al.* [2005], who also performed offline experiments using the RothC soil carbon model and the soil carbon module of TRIFFID, using simulations of *Jones et al.* [2003]. The offline soil carbon models employed by *Jones et al.* [2005], and in our study were equilibrated at an initial state using the climate from the first decade (1860s) of the climate change simulation. Estimated global totals of soil carbon from *Jones et al.* [2005] were: HadCM3LC, a total of 1180 Gt C (in a single pool); RothC, a total of 950 Gt C of which 220 Gt C is detritus (DPM and RPM) and 730 Gt C is



Figure 1. Variants of the TRIFFID soil moisture respiration function used in this study, and comparison with observed nitrogen mineralization rates [*Paul et al.*, 2003]. Different symbols represent different soil texture classes (see legend). See text and auxiliary material for a full explanation.

BIO and HUM. The global mean NPP was 61 Gt C yr⁻¹: very close to recent best estimates of present-day NPP of about 60 t C yr⁻¹ [e.g., *Prentice et al.*, 2001]. In the original coupled climate–carbon cycle experiments [*Cox et al.*, 2000; *Jones et al.*, 2003] accumulation and release of soil carbon directly affected the atmospheric CO₂ concentration and hence the climate. In this study the climate model output was used to drive RothC in an off-line manner: there was no

feedback between soil carbon changes and climate. The runs used monthly mean output from the GCM averaged over a decade for each month. Hence, there was no interannual variability in our experiments. As *Jones et al.* [2005] demonstrated, this offline approach using 10 year averaged monthly mean input data reproduces the behavior of the fullcoupled approach very closely, implying that aggregation errors are unlikely to significantly affect results. A time step

Table 1. Climate Model Si	mulations Used in This Study						
	Climate Models	Simulation Type	Greenhouse Gas Forcings	Other Climate Forcings	Soil Carbon Model	SMRFs Applied ^a	Experiments Used in Present Study
This study [<i>Jones et al.</i> , 2003, 2005]	HadCM3LC	Transient	IS92a	Natural (solar output, volcanic aerosol) Anthropogenic sulbhate aerosol	RothC (offline)	Twelve variants ^b	AF/M0 ^c
C4MIP [Friedlingstein et al., 2006]	HadCM3LC IPSL-CM2C, IPSL-CM4-LOOP, CSM1, MPI, LLNL, FRCGC,UMD,UVie-2.7, C1.MBFR-I PI, BFRN-CC	Transient Transient	IPCC SRES A2 IPCC SRES A2	-	TRIFFID (online) Native soil carbon models (online)	TRIFFID ^b Native SMRFs	Coupled/uncoupled Coupled/uncoupled
QUMP [Murphy et al., 2004]	HadSM3	Steady state	1xCO ₂ and 2xCO ₂		RothC (offline)	RothC-et1 ^b	AF/MO variants for each of four ensemble members (3, 4, 11, 12) with climate sensitivities 4.1, 2.9, 3.6 and 7.0°C, respectively
^a Soil moisture-respiration fur	iction.						

^aSoil moisture-respiration function. ^bSee Table S1 for details. ^cAF, all climate forcings (temperature, moisture, and litter); MO, only moisture changes applied. of 1 month was also used successfully by *Raich and Potter* [1995] and *Reichstein et al.* [2003]. HadCM3LC simulates naturally occurring changes in vegetation, but disturbance due to agriculture was kept constant at present-day levels and no attempt was made to include the effects of anthropogenic land use changes.

[13] In order to compare our results with those from a wider set of climate models and climate sensitivities, and to assess their robustness, we used two additional sources of data. First, we used soil and vegetation carbon changes from the eleven coupled climate-carbon cycle model (C4MIP) experiments [Friedlingstein et al., 2006], which included HadCM3LC (with the TRIFFID DGVM). C4MIP provides two sets of experiments: one where the carbon cycle and climate interact ("fully coupled") and a second set where the carbon cycle is only affected by changing CO₂ concentrations, and not by the changing climate ("uncoupled"). The TRIFFID simulations from C4MIP differ from the main simulations in our study in two ways. First, the C4MIP simulation used TRIFFID within a fully coupled climatecarbon cycle model, whereas our simulation used the RothC soil carbon model offline, with different versions of the TRIFFID SMRF. Second, the HadCM3LC experimental setup used here [Jones et al., 2003, 2005] differs from the C4MIP design. The former included natural (solar output and volcanic aerosol) and anthropogenic sulphate aerosol forcings, and was based on the IS92a scenario, whereas the latter was based on the IPCC SRES A2 scenario. Note that we have not compared C4MIP simulations driven by AF or MO forcings (which would be complex in coupled climatecarbon cycle GCMs), or different SMRFs as in our present study, but simply the range of results across the fully coupled and uncoupled C4MIP model simulations to put our results into context.

[14] We also used data from four members of the Quantifying Uncertainty in Model Projections climate model ensemble (QUMP [Murphy et al., 2004]) covering a range of climate sensitivities from 2.9 to 7.0°C, following Falloon et al. [2006a] who drove RothC with input data (precipitation, evaporation and litter fall) from QUMP. The QUMP simulations used a single-layer ocean model version of the Met Office Hadley Centre's Third Generation Climate Model HadCM3 (HadSM3: a version of MetUM), and were steady state paired simulations with either present-day or doubled atmospheric CO_2 concentrations. These four simulations were also used by Challinor et al. [2005] and Falloon and Betts [2010] to study uncertainties in climate impacts on crop yields and river flows, respectively. Since the original RothC-QUMP simulations were driven by all climate forcings [Falloon et al., 2006a], we performed additional simulations driven only by moisture forcings (precipitation and evaporation). Table 1 gives an overview of the climate data used in our study.

3. Results

3.1. Global Impacts

[15] The RothC simulations using identical climate driving data, vegetation carbon inputs and temperature response function, but a range of SMRFs showed a large spread in future global soil carbon totals. The AF simulations all showed an increase in global soil carbon stocks until around



Figure 2. Changes in global total soil carbon from 1860 values using the RothC model and different soil moisture–respiration functions driven by HadCM3LC outputs changing (a) all forcings (soil temperature, moisture and plant carbon inputs) and (b) soil moisture only. For comparison, additional simulations are shown: soil C changes using RothC driven by four QUMP ensemble members $(1 \times CO_2 - 2 \times CO_2)$ with all forcings (Figure 2a) and precipitation/evaporation changes only (Figure 2b); fully coupled (Figure 2a) and coupled-uncoupled (Figure 2b) soil carbon changes from the C4MIP experiments; Figure 2a additionally shows the soil carbon responses from RothC of *Jones et al.* [2005] and TRIFFID from C4MIP and *Friedlingstein et al.* [2006].

2060 followed by a rapid loss of global soil carbon thereafter (Figure 2a), mainly caused by an increase in respiration due to higher temperatures. The relative sensitivity of each model to soil moisture differed between simulations with moisture change only or all forcings, showing a nonlinear interaction between the controlling factors of soil carbon decomposition, perhaps due to changes in the initial soil C state of each model. Under the AF scenario, most of the SMRFs resulted in a net loss of soil carbon globally by 2100 although one SMRF, TRIFFID-wp1.7 showed a net gain of global soil carbon by 2100. TRIFFID-sat02 produced the largest loss of global soil carbon. The range of global soil carbon changes from 1860 to 2100 was 71.8 Pg C (minimum -54.1 Pg C, maximum 17.7 Pg C). Relatively small global soil carbon changes under the MO simulations were found for all SMRFs until around 2010 (Figure 2b). Thereafter a large range of changes in global soil carbon stocks was found spanning both large negative and positive values (minimum -17.8 Pg C, maximum 43.1 Pg C, range 60.9 Pg C). As found in the AF simulations, the largest gain and loss in global total soil carbon under the MO simulations were found for TRIFFID-wp1.7 and TRIFFID-sat02, respectively. Thus the impact of uncertainty in SMRFs on uncertainty in the global soil carbon–climate feedback is large when considering both changes in soil moisture values only, and changes in all climate forcings.

[16] The range in global soil carbon changes from the "fully coupled" C4MIP experiments is also shown in Figure 2a (though note that changes are calculated from 1901 to 2099 due to data availability), which indicates the range of responses across coupled climate-carbon cycle models using their native SMRFs. The range of soil carbon changes across the coupled C4MIP experiments is large, though most C4MIP models suggest an increase in global carbon stocks, and the range of changes from our AF experiments is approximately one quarter of the C4MIP range. In the C4MIP simulations, the range in overall "climate impact" on soil carbon storage (difference between coupled and uncoupled simulations, showing the effect of climate-carbon cycle feedbacks; Figure 2b) was also considerable, with all models showing a negative impact on soil carbon. The RothC simulations using input data from the four QUMP ensemble members showed a wide range in global soil carbon changes under doubled CO₂ concentrations (compared to present-day CO_2 concentrations) when driven by all forcings, covering small increases and large decreases: from +39 to -317 Pg C (Figure 2a) [Falloon et al., 2006a]. Note that we have plotted the RothC-QUMP results at the end of the axis because they represent the equilibrium impact of doubled CO₂ concentrations (579 ppmv), in contrast to the dynamic C4MIP and RothC simulations. The time of CO₂ doubling varies widely across models and emissions scenarios: for example, 579 ppmv is reached between 2050 and 2100 in the prescribed IPCC SRES scenarios, between the 2040s and 2070s in the C4MIP simulations, and around 2050 in the HadCM3LC simulations used here. RothC-QUMP simulations using only moisture forcings (precipitation and evaporation; Figure 2b) all showed increases in global total soil carbon, and a smaller range than the equivalent simulations driven by all forcings. Despite the difference in model structure, the TRIFFID C4MIP simulation (using a different experimental setup and TRIFFID soil carbon model) showed a similar response to the RothC simulation using the TRIFFID SMRF (Figure 2a). The RothC simulation of Jones et al. [2005], which used air temperature data and the RothC temperature-respiration relationship, showed a greater loss of soil carbon than our RothC simulations (Figure 2a), which used soil temperature data and the TRIFFID temperature-respiration relationship.

[17] Our simulations using RothC with different SMRFs produced a wide range of initial global soil carbon totals. Comparing initial total global soil carbon values across the models with estimates from global soils databases could be one potential method further constraining the responses. However, there are several issues to consider in any such



Figure 3. Changes in global total soil carbon from 1860 values (as a % of 1860 values) using the RothC model and different soil moisture–respiration functions driven by HadCM3LC outputs changing (a) all forcings (soil temperature, moisture and plant carbon inputs) and (b) soil moisture only.

comparison, including the lack of representation of organic soils in most current soil carbon models. Second, there are difficulties comparing estimates across different sampling depths (see Discussion). In our study, nonlinear interactions between controlling factors led to different initial soil carbon totals across the SMRFs. In order to overcome this discrepancy, it would be possible to artificially alter the underlying decomposition rates (or carbon inputs to soil) to achieve the same stable starting condition, but the former would introduce a fundamental change to the model structure, and likely alter the response to different SMRFs. As an alternative approach, we have scaled the simulated responses postsimulation by the difference in initial soil carbon values (Figure 3). Changes in global total soil carbon for the different SMRFs, scaled as a percentage of initial total soil carbon values, are shown in Figures 3a (AF) and 3b (MO). Interestingly, similar trends to the raw data (Figure 2) were seen, with the largest positive and negative responses from TRIFFID-wp1.7 and TRIFFID-sat02 in both the AF and MO scenarios respectively (Figures 3a and 3b). On the other hand, with the exception of TRIFFID-wp1.7, TRIFFIDsat02 and SOILN, the scaled responses across the different SMRFs under the AF scenario were remarkably similar (Figure 3b), although more scatter between SMRFs was found under the MO scenario (Figure 3b).

[18] The sensitivity of the soil carbon feedback to SMRFs was also nonlinear (Figure S2). There was no pronounced trend between the % change in global soil carbon and the initial global soil carbon amount under the AF simulations (Figure S2a), although mostly decreases in global soil carbon totals were found. However, for most SMRFs (with the exception of RothC-et1 and TRIFFID-sat02) a greater % change in global soil carbon was found with a greater initial global soil carbon total under the MO simulations, and mostly increases in global soil carbon totals were found (Figure S2b).

3.2. Regional Impacts

[19] Zonal mean plots of changes in total global carbon values are shown in Figure 4. Under the AF scenario, soil carbon increases were generally found in midlatitudes to high latitudes, while decreases were found in the tropics. The largest range in soil carbon changes was found in northern midlatitudes to high latitudes, with most SMRFs indicating increases in high latitudes (though some suggested decreases), and most SMRFs showing decreases around 45°N. Under the MO scenario, a much wider range of responses was found, including both increases and decreases in northern mid-to-high latitudes, and a wide range of (mostly) increases in the tropics. The greatest range (and thus uncertainty) in soil carbon changes under the AF scenario was found where the largest changes in soil carbon occurred (Figure S3c): namely, the Amazon, northern Eurasia, northern Canada and Alaska, southern Africa and eastern United States. The range of soil carbon changes under the AF scenario were often as large as, or greater than $(>4 \text{ kg C m}^{-2})$ the mean soil carbon changes. The minimum regional soil carbon changes under the AF simulations were generally similar in sign to the mean changes (Figure S3e) although in contrast the maximum changes were mostly increases in soil carbon (Figure S3g). The majority of SMRFs agreed in the sign of regional soil carbon changes under the AF scenario, although some SMRFs predicted soil carbon losses for southern Europe and large parts of central and northern Asia (Figure S3e) while others predicted gains (Figure S3g).

[20] Generally smaller regional mean soil carbon changes were found when only soil moisture conditions were varied compared to the all forcings simulations (Figure S3b). Mean MO soil carbon changes were not always in the same direction as AF soil carbon changes (Figure S3a): indeed, the MO simulations showed mostly increases in soil carbon, especially where the soil was drier (Figure S4). In the Amazon, southern Africa and central Russia the increases in soil carbon under the MO simulations (1–3 kg C m⁻²) opposed the decreases found under the AF simulations. Here the MO forcing acts to reduce the overall AF soil carbon changes. The change in soil moisture (Figure S4a) may therefore explain the soil carbon gains found for these regions under the MO simulations (Figure S3b).

[21] Increases in soil carbon were found under both the MO and AF simulations for northern Canada and China.



Figure 4. Zonal mean changes in total soil carbon from 1860 values using the RothC model and different soil moisture–respiration functions driven by HadCM3LC outputs changing (a) all forcings (soil temperature, moisture, and plant carbon inputs) and (b) soil moisture only.

Here the MO forcing contributes to the overall soil carbon changes found in the AF simulations. The range of soil carbon changes found under the MO simulations (Figure S3d) was generally similar to, but smaller than those from the AF simulations, with the exception of the Amazon region. The largest range in soil carbon changes was found in regions where the change in soil moisture was greatest (Figure S4a). The greatest range in soil carbon changes (>4 kg C m^{-2}) was also found for the Amazon, northern Eurasia, northern Canada and Alaska, southern Africa and eastern United States, often exceeding the mean change found under the MO simulations. The minimum regional soil carbon changes under the MO simulations were mostly losses in contrast to the mean changes (Figure S3f), while the maximum changes were all increases, the same sign as the mean changes and the maximum AF changes (Figure S3h). There was some disagreement between SMRFs in the sign of regional MO soil carbon changes almost everywhere (Figures S3f and S3h) with some SMRFs predicting gains and others losses. It also appears that much of the range in both AF and MO soil carbon changes (Figures S3c and

S3d) may be explained by the 1860 total soil moisture amount (Figure S4b). In other words, areas which were wetter to begin with were predicted to undergo greater soil carbon changes, perhaps because they may have higher initial soil carbon values, or were more vulnerable to changes in soil moisture.

4. Discussion

[22] The relationship between initial total global soil carbon storage and % change in soil carbon storage from the MO simulations appears to be nonadditive. This is perhaps not surprising: Falloon et al. [2004] also found the impacts of single climate variables (including temperature and rainfall) on future soil carbon changes in the UK to be highly nonadditive. Our runs using data from four simulations from a multimember ensemble of GCM runs (Quantifying Uncertainty in Model Predictions (QUMP) [Murphy et al., 2004]) with RothC indicates that large uncertainties in the global soil carbon feedback and its response to soil moisture changes are also associated with climate model internal parameters [Falloon et al., 2006a]. Global soil carbon changes were also found to cover both small gains and large losses depending on the climate sensitivity (global equilibrium temperature response to doubling CO_2) of the ensemble member, in agreement with the findings of Andreae et al. [2005].

[23] In agreement with our findings, and using data from the same HadCM3LC climate change simulations as this study, with all climate forcings included, Falloon et al. [2007] suggested that regionally, precipitation controlled the sign of soil carbon changes with wetter conditions resulting in higher soil carbon stocks and drier conditions in lower soil carbon stocks, since increased NPP in wetter conditions could override any increase in respiration. In contrast, globally, temperature seemed to control changes in total soil and vegetation carbon, probably because while temperature increases were predicted everywhere, the nature of precipitation changes varied greatly between regions. Although the overall carbon-cycle feedback in coupled climate-carbon cycle models is highly sensitive to the response of NPP to climate change [Matthews et al., 2005; Friedlingstein et al., 2006], RothC simulations parallel to those used here and driven by individual forcings [Jones et al., 2005] showed that carbon inputs increased almost everywhere (with the exception of the Amazon region, where carbon inputs decreased and both temperature and litter contributed to soil carbon decreases). This implies that changes in NPP and litter inputs were not responsible for the global soil carbon losses found in our study, which were based on the simulations of Jones et al. [2005]. The experimental studies of Liu et al. [2009] also suggest that in arid and semiarid regions, increased precipitation may lead to net soil C gains since gross ecosystem productivity was stimulated more than soil respiration. In the RothC-QUMP simulations which covered a wider range of climate forcings than our HadCM3LC-based simulations, litter inputs (NPP) appear to have played a larger role in global soil carbon responses [Falloon et al., 2006a]. Since our RothC simulations here (and those of Falloon et al. [2006a]) used the simple "bucket" water balance model included in RothC (and not soil moisture values from the climate model), the difference between changes in precipitation and evaporation (P-E) give a broad indication of the role of changes in soil moisture status in the soil carbon changes. All of the RothC-QUMP ensemble members studied here showed drying over some parts of the Amazon basin and some increases in P-E at high latitudes and in tropical Africa [Falloon et al., 2006a]. Since the nature of global soil carbon changes varied greatly between the four QUMP ensemble members investigated, it therefore seems likely that moisture played a smaller role in determining global soil carbon changes than changes in litter (NPP) or temperature in these simulations. In the C4MIP experiments, Friedlingstein et al. [2006] also suggest that carbon cycle feedbacks are strongly dependent on NPP responses to climate change. Similarly, the DGVM studies of Sitch et al. [2008] suggest that the differing model responses of vegetation productivity to climate modify the future behavior of soil carbon beyond just the direct climate impact [Jones and Falloon, 2009]. Jones and Falloon [2009] provide a more in-depth discussion of the implications of future climate uncertainty in determining future global soil carbon storage.

[24] The regional patterns of changes in soil carbon from the AF simulations averaged across all SMRFs (Figure S3a) were generally similar to those of Jones et al. [2005] using either the RothC or HadCM3 soil carbon models. The AF simulations showed large decreases in soil carbon for the Amazon region (over 4 kg C m⁻²), southern Africa $(2-4 \text{ kg C m}^{-2})$ and eastern United States $(2-4 \text{ kg C m}^{-2})$ and increases in soil carbon for Siberia, Alaska, northern Canada and much of Eurasia $(1-3 \text{ kg C m}^{-2})$. Compared to the simulations of Jones et al. [2005], generally smaller average changes in soil carbon were found under the AF simulations, although the AF simulations also showed widespread increases in soil carbon for Australia not found in the Jones et al. [2005] simulations. Regionally, soil moisture changes alone appear to have acted to increase soil carbon storage (Figures S3 and S4). This was presumably because drying generally acts to increase soil carbon storage by reducing the respiration rate, while wetter soils experience enhanced decomposition and soil carbon losses. This is illustrated by Figure 1: when soils are at or below the "optimal value" of soil moisture for respiration, a decrease in soil moisture reduces the respiration rate modifier and hence the decomposition rate. However, some SMRFs assume optimal soil moisture content for decomposition with reduced rates for saturated soils, representing inhibition of decomposition under anaerobic conditions. In some regions, therefore, drying of soils could lead to increased respiration and soil carbon loss. This is particularly the case for high latitude wetlands, where melting of permafrost may alter the water table depth and lead to large scale drying [Smith et al., 2005]. All RothC-QUMP simulations showed losses of soil carbon in the high latitudes and over Europe. In tropical regions soil carbon losses were found for simulations with larger climate sensitivities while gains in soil carbon were found for simulations with lower climate sensitivities, with litter inputs being the major driver of soil carbon changes [Falloon et al., 2006a]. However, across parts of Europe and North America, losses in soil carbon

occurred despite increases in litter inputs. Here, the increases in soil respiration due to increases in temperature appear to have outweighed the increases in soil carbon due to increased litter inputs, as found by *Jones et al.* [2005].

[25] Much of the tropical soil carbon response (Figure 4) in our simulations was from the Amazon region (Figure S3), where HadCM3LC projects large decreases in soil moisture. The majority of C4MIP models simulated a reduction in land carbon uptake in the tropics [*Friedlingstein et al.*, 2006], although there was no consensus whether changes in NPP or respiration dominated global land uptake sensitivity. Scholze et al. [2006] drove the LPJ DGVM with outputs from 16 GCMs (and four emissions scenarios) in order to assess climate change impacts on world ecosystems. In their study, losses of at least 5% of current forest vegetation over the Amazon region occurred in all model simulations. Greater global mean temperature changes increased both the risk of forest loss occurring, and the extent of loss. Sitch et al. [2008] ran five different DGVMs with outputs based on HadCM3LC simulations and four different emissions scenarios. They found that while all DGVMs showed results which were consistent with the contemporary global land carbon budget, their responses to projections of future environmental change varied widely, with the largest uncertainties arising from the response of tropical vegetation to drought and of boreal ecosystems to increasing temperatures and changing soil moisture status. However, all DGVMs simulated increased soil carbon turnover in the tropics and extratropics in response to climate change, with varying losses of soil carbon from the Amazon region.

[26] The response of DGVMs to climate change is strongly linked to GCM climatology [Sitch et al., 2008]. In the HadCM3LC C4MIP simulations [Friedlingstein et al., 2006], drying of the Amazon Basin as a result of climate change resulted in a dieback of the Amazon forest and a strong reduction in the C input to soil also resulting in soil C losses in this region, with the Amazon dieback accounting for around 11% of the global climate-driven C losses [Cox et al., 2004]. Biogeophysical effects of the forest dieback were also important locally, acting to further reduce rainfall [Betts et al., 2004]. However, in many GCMs, the moisture balance increases in the tropics [e.g., Held and Soden, 2006]. Malhi et al. [2009] note that not all GCMs can be considered as equivalent, and extreme outcomes cannot be discarded as outliers. For instance, in their study, Malhi et al. [2009] found that HadCM3 produced the strongest drying signal over the Amazon, but the model captures many key aspects of coupling between Atlantic sea surface temperatures and Amazonian drought. The changes in precipitation minus evaporation in the four QUMP ensemble members studied here were broadly similar in direction (but with varying magnitudes) to those across the GCMs studied by Held and Soden [2006]; e.g., showing wetting in Northern Hemisphere high latitudes, tropical Africa and drying over southern Europe and North Africa [Falloon et al., 2006a]. In contrast to the increases in moisture balance over the Amazon found by Held and Soden [2006], most of the OUMP HadSM3 models (and the HadCM3LC simulations used here) showed decreases, even though HadSM3 does not include a dynamic vegetation model or carbon cycle, and is thus unable to capture vegetation-carbon-climate feedbacks. However, *Malhi et al.* [2009] found that most GCMs (not including carbon cycle feedbacks, and including many of those studied by *Held and Soden* [2006]) tend to underestimate current rainfall over Amazonia, and vary greatly in their projections of future climate change in Amazonia. Taking the differences between GCM-simulated and observed rainfall regimes in the 20th century into account, *Malhi et al.* [2009] suggest that dry season water stress is likely to increase in eastern Amazonia over the 21st century, but the region tends toward a climate more appropriate to seasonal forest than to savannah.

[27] Although some of the soil carbon models studied here have been extensively validated using short-term experiments following the decomposition of labeled plant materials [e.g., Jenkinson, 1990; Jenkinson et al., 1987, 1991], changes in total soil carbon from long-term experiments [e.g., Smith et al., 1997; Falloon and Smith, 2002], soil radiocarbon signatures [Coleman et al., 1994, 1997; Jenkinson and Coleman, 1994; Jenkinson et al.. 1992, 1994], and measurements of soil microbial biomass [Jenkinson, 1990; Falloon and Smith, 2009], there have been very few assessments of SMRF performance using observed data. Although our aim is not to assess the validity of the different SMRFs, comparing initial total global soil carbon values across the models with estimates from global soils databases could be one potential method of doing so. There is a large range in contemporary global soil carbon estimates: from approximately 1400-2300 Pg C [Batjes, 1996; Gruber et al., 2004; Denman et al., 2007; Fischlin et al., 2007]. However, since most of the soil carbon models in the present study do not explicitly represent organic soils [Falloon et al., 1998, 2006b] or include inert soil carbon this should be considered carefully in any comparison.

[28] Currently, very few dynamic soil carbon models have been developed to deal with organic soils explicitly (e.g., ECOSSE [Smith et al., 2010a, 2010b]), or fully implemented in coupled climate-carbon cycle GCMs [Limpens et al., 2008]. However, the LPJ DGVM has recently been developed to simulate peatland hydrology, vegetation and decomposition processes [Wania et al., 2009a, 2009b], and a peatland carbon/wetland model has been developed for the Canadian Terrestrial Ecosystem Model [St-Hilaire et al., 2008]. The physical characteristics of organic soils have recently been adopted in GCMs [Lawrence and Slater, 2008] and regional climate models [Rinke et al., 2008] although these models do not include interactive carbon cycles. Globally, organic soils contain around 300-400 Pg C [Batjes, 1996; Limpens et al., 2008], with approximately 270-370 Pg C in boreal and subarctic peatlands [Turunen et al., 2002], and around 52 Pg in tropical peatlands with large uncertainties in the latter [Hooijer et al., 2006]. Globally, approximately 140-150 Pg C is stored as inert soil carbon [Falloon et al., 1998; Intergovernmental Panel on Climate Change (IPCC), 2001]. Thus excluding carbon stored in organic soils and inert soil carbon, simulated values of global total soil carbon of around 850-2100 Pg C seem reasonable. On this basis, the range of AF global soil carbon totals across the SMRFs studied here is large (708 to 1449 Pg C), but similar to the range from observational estimates (excluding organic soils and inert soils

in a very simple manner). It should also be noted that this is a purely illustrative assessment of the likely discrepancy between modeled and observed soil carbon stocks. Since the models considered here do not simulate organic soils explicitly and organic soils are present in several biomes (and the primary soil carbon reservoir in boreal forests), excluding them from our analysis more realistically would be complex. The validity of these modeled estimates also depend on the assumptions that (1) the HadCM3LC plant carbon input values, (2) HadCM3LC soil temperature and moisture, and (3) the decomposition rates calculated by RothC (including temperature dependence of respiration) are realistic. A further potential source of discrepancy is soil depth: HadCM3LC and RothC currently only simulate soil carbon processes in the topsoil (as a single soil carbon pool, and 23cm depth respectively) while most observational estimates include much deeper layers. The discrepancy in initial global soil carbon totals potentially confounds our results due to nonlinear interactions between controlling factors.

[29] Rodrigo et al. [1997], Paul [2001] and Paul et al. [2003] found large differences in SMRF behavior under drier conditions. As noted above, most soil C models, including RothC, have not been explicitly developed to simulate very arid conditions, and may require developments to both the representation of the water balance, and to the SMRFs [Al-Adamat et al., 2007]: in particular, RothC may not allow soils to dry out adequately [Jenkinson et al., 1999]. Grunzweig et al. [2009] found that RothC overestimated dry season respiration in semiarid ecosystems, which may contribute to such uncertainties. Similarly, few soil carbon models have been explicitly developed for organic or waterlogged soils, and many global scale studies do not consider inert soil carbon storage. Soil carbon models also should therefore be developed to include organic and waterlogged soils [Falloon et al., 2006b], inert soil carbon [Falloon et al., 1998, 2000], and very dry soils to allow more meaningful validation.

[30] Soil respiration could also be indirectly affected by the impact of soil moisture changes on temperature (via changes in sensible and latent heat fluxes, driven by moisture availability). Soil moisture strongly influences soil carbon storage, but soil organic matter also significantly alters soil thermal and hydraulic properties, and is not routinely included in the land surface schemes of GCMs [Lawrence and Slater, 2008]. The inclusion of an organic soil layer in RCMs [Rinke et al., 2008] and GCMs [Lawrence and Slater, 2008] can have differing impacts (e.g., overall cooling and warming, respectively), potentially related to differences in evaporation trends, driven by the soil scheme and/or the atmospheric models themselves [*Rinke et al.*, 2008]. These studies used static soil properties (relating carbon content to physical parameters) in uncoupled GCMs or RCMs, not including the carbon cycle itself. Most coupled climate-carbon cycle models [e.g., Friedlingstein et al., 2006] do not simulate changes in soil physical parameters as a result of changing soil carbon contents. Using a simple equation [Huntington, 2006], Falloon and Betts [2010] found changes in soil available water content followed the direction of the soil carbon changes from the HadCM3LC coupled climate-carbon cycle simulations of Jones et al. [2005] used here. The impact of heterotrophic respiration covariance with temperature and moisture [Janssens and Pilegaard, 2003; Reichstein et al., 2007; Wan et al., 2007] could be a further source of uncertainty in the soil carbon-climate feedback. Warming itself may also increase evapotranspiration and thus decrease soil moisture, reducing soil respiration indirectly [Liu et al., 2009]. If the temperature and moisture dependence of different soil carbon pools differ, then this could also influence soil carbon response to climate change [Zeng et al., 2004]. Changes in the nitrogen cycle [Lamarque et al., 2005; Thornton et al., 2009] and ozone concentrations [Sitch et al., 2007] could alter vegetation productivity, carbon inputs and hence soil carbon storage, and change or even reverse the sign of the climate-carbon cycle feedback [Bonan, 2008; Sokolov et al., 2008], although our study has not considered the potential impact of these, or other indirect effects of climate change.

5. Conclusions

[31] Our study has highlighted considerable uncertainty in the magnitude and direction of the future soil carbon feedback, attributable to differences in the SMRFs currently used in carbon cycle models. A better understanding of the relationship between soil moisture and respiration is needed in order to reduce this uncertainty and improve our confidence in climate change predictions. This is also important since soil carbon models are currently being used for Kyoto Protocol and United Nations Framework Convention on Climate Change (UNFCC) reporting of national greenhouse gas emissions [e.g., Falloon and Smith, 2003; Falloon et al., 2006b]. In particular, understanding of heterotrophic respiration under drought and anaerobic conditions is lacking. Research is also needed to assess which SMRF best represents the relationship between soil moisture and heterotrophic respiration. A detailed comparison of modeled and observed respiration rates for different soil types and under different environmental conditions (particularly soil moisture values) would therefore be of great use in assessing the SMRFs, and databases such as those of Bond-Lamberty and Thomson [2010a, 2010b] may provide a useful opportunity for such analyses.

[32] While we have shown that soil moisture control of soil carbon is uncertain, future changes in soil moisture are also less certain than future changes in temperature. Most GCMs agree that much of the globe is likely to experience considerable warming over the next century, but there is much less agreement regarding which regions will experience increases or decreases in precipitation and soil moisture. The GCMs generally agree on the sign of soil moisture changes in many regions, although the magnitudes of change are much more uncertain. Annual mean decreases of up to 20% in soil moisture are predicted in the subtropics, the Mediterranean region and in high latitudes, where snow cover diminishes, while increases of over 20% in soil moisture are predicted in East Africa, central Asia, and some other regions [IPCC, 2007]. The regions where there is least agreement between GCM projections of changes in precipitation are the United States, Russia, South Asia, Australia, tropical Africa in summer, and southern Africa, Australia, South Asia, middle United States and South America in winter [IPCC, 2007]. Interestingly some of these regions

coincide with regions where our range of predicted soil carbon changes across SMRFs was greatest.

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- M. Ades, Department of Meteorology, University of Reading, Earley Gate, PO Box 243, Reading RG6 6BB, UK.
- P. Falloon and C. D. Jones, Met Office Hadley Centre, Fitzroy Road, Exeter EX1 3PB, UK. (pete.falloon@metoffice.gov.uk)
- K. Paul, CSIRO Ecosystem Sciences, GPO Box 284, Canberra ACT 2601, Australia.