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Predicted consequences of increased rainfall variability on soil carbon stocks in a semiarid environment

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ABSTRACT: Research on the impacts of climate change on soil organic carbon (SOC) stocks has focused on the effects of changes in average climate, but the potential effects of increased climate variability, including more frequent extreme events, remain under-examined. In this study, set in a semiarid agricultural landscape in southeastern Australia, we used the Rothamsted carbon (RothC) model to isolate the effects of interannual rainfall variability on SOC stocks over a 50 yr period. We modelled SOC trends in response to 3 scenarios that had the same 50 yr average climate but different interannual rainfall distributions: non-changing average climate, historic variability (H), and increased variability due to more frequent extreme rainfall years (XH). Relative to the non-changing average climate, RothC simulations predicted net decreases in mean SOC stocks to 50 yr of 11% under the H scenario and 13% under the XH scenario. These decreases were the result of predicted SOC decreases (and increased CO_2 emissions) in extreme wet years (ca. 0.26 Mg ha^{-1} yr^{-1}) that were not counterbalanced by SOC increases in extreme dry years (ca. 0.11 Mg ha^{-1} yr^{-1}). No significant difference in mean SOC stocks at 50 yr between the H and XH scenarios was likely due to an increase in both extreme wet and counterbalancing extreme dry years in the latter. Strong negative correlations were found between annual changes in SOC stocks and rainfall. Our modelled predictions indicate the potential for extreme rainfall years to influence SOC gains and losses in semiarid environments and highlight the importance of maintaining plant inputs in these environments, particularly during extreme wet years.

KEY WORDS: Soil organic carbon · Rothamsted carbon model · RothC · Climate variability · Interannual rainfall variability

1. INTRODUCTION

The carbon stored in soils comprises two-thirds of that stored in terrestrial systems and is 2 to 3 times more than that present in the atmosphere as CO_2 (Trumbore et al. 1996). Losses of carbon from soil organic carbon (SOC) stocks have adversely affected soil and water quality and sustainable food production and have been associated with declining air quality and global warming (Lal 2004). Our ability to predict future trends of SOC stocks and to develop carbon sequestration strategies is highly dependent on our understanding of SOC dynamics, particularly as they are affected by soil type, long-

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term climate, and long-term land use (Jobbagy & Jackson 2000).

SOC stocks are the result of a dynamic balance between carbon inputs and outputs (Lal 2004). Carbon inputs occur through additions of plant material to soil, whereas outputs are primarily as CO_2 emissions that result from microbial decomposition of SOC (Davidson & Janssens 2006). Changes in environmental conditions (land use and climate change) can shift the SOC balance towards either net gains (plant inputs > decomposition losses) or losses (decomposition losses > plant inputs) in SOC stocks.

Many studies indicate the importance of climate as a driver of SOC decomposition (Jobbagy & Jackson 2000, Goidts et al. 2009, Ostle et al. 2009, Zhao et al. 2013). There are strong established ties between the biogeochemical processes that regulate soil CO_2 emissions and climate variables, although there remains a high degree of uncertainty around SOC and climate relationships, particularly the scale and direction of SOC changes under climate change (Baldock et al. 2012). Previous studies have indicated the importance of temperature and rainfall in regulating soil heterotrophic respiration (Cox et al. 2000, Jones et al. 2003). Annual precipitation is the dominant factor in determining regional distributions of SOC stocks (Jobbagy & Jackson 2000, Saiz et al. 2012) and short-term SOC dynamics (Shen et al. 2009).

Many climates are characterised by high variability, including interannual rainfall variability and extreme rainfall events such as droughts and floods (Katz & Brown 1992). Increased rainfall variability, including increased frequency of extreme rainfall events, is predicted for many arid and semiarid regions, including southeastern Australia, under future climate change (IPCC 2012). However, while isolated studies have examined the effects of increased temperature variability on SOC stocks (Sierra et al. 2011), most climate change research on SOC stocks has focused on the effects of changes in annual climate (e.g. Jenkinson et al. 1991, Potter 2004, Davidson & Janssens 2006, Lugato & Berti 2008, Pan et al. 2010) and has largely ignored the potentially substantive effects of increasing rainfall variability.

This study addresses an outstanding question posed by Trumbore et al. (1996), namely, to what extent does interannual climate variability, particularly rainfall availability, affect transient SOC release and sequestration? We use the Rothamsted carbon (RothC) model to compare changes in SOC stocks over 50 yr under 3 scenarios of rainfall variability in a semiarid agricultural landscape of southeastern Australia. We consider such landscapes to be particularly important in interpreting changes in the global carbon cycle, since semiarid and arid climates characterise 30% of the world's, and 78% of Australia's, land mass (Peel et al. 2007) and are likely to expand under predictions of warmer and drier future climates (Timbal & Jones 2008). Our principal aims were to isolate and quantify the effects of interannual rainfall variability on SOC trends and thereby highlight any potential risks posed by climate variability to a significant terrestrial carbon stock.

2. MATERIALS AND METHODS

2.1. Study area and soil data

The study area is a semiarid agricultural landscape of 30 200 ha (302 km^2) in southeastern Australia (35° 24.53′ to 35° 41.23′ S, 143° 37.72′ to 143° 54.22′ E; Forouzangohar et al. 2014). The landscape has been extensively cleared for agriculture, and small patches of native perennial vegetation are highly fragmented and limited to riparian zones. Many land parcels in the study area have recently come under management by a single entity and are part of a land-use reconfiguration plan to promote ecosystem complexity and services, including soil services like carbon sequestration. However, climate change and variability are acknowledged as potential sources of uncertainty in future service provision.

To provide an empirical basis for the modelling (see Section 2.3), soils were sampled from 60 points on a ca. 2 km grid across the landscape. Composite soil samples were collected from each of 3 soil depths (0–10, 10–20, and 20–30 cm) at each point. Separate intact cores from each depth were also collected for bulk density determination (i.e. used in the calculation of SOC stocks from total organic carbon concentration). The 180 composite samples were air dried and passed through a 2 mm sieve for further analyses. A subset of 60 soil samples was analysed using established methods for total organic carbon concentration (dry combustion of a finely ground subsample using a LECO CHN 2000 analyser) and for clay content (hydrometer method; Gee & Bauder 1996). Mid-infrared spectroscopy was used to estimate total organic carbon concentration and clay content of the remaining 120 samples, following the methodology described in detail by Forouzangohar et al. (2009). The data were then combined across depths at each point to provide 60 sets of soil data to 30 cm depth as a basis for each of the three 50 yr modelling scenarios (see Section 2.2).

2.2. Rainfall variability scenarios

The study area has a semiarid climate (Noy-Meir 1973), classified as cold steppe arid, BSk, in the Köppen-Geiger climate classification system (Noy-Meir 1973, Peel et al. 2007). It is characterised by hot summers and cold winters and by mean annual precipitation (399 mm; 1962–2011, Kerang weather station) that is markedly less than mean annual potential open-pan evaporation (1638 mm). Most rain falls in winter (mean 112 mm) and spring (mean 114 mm), although rain can fall at any time of the year, and seasonal rainfall variability is high. For example, mean monthly rainfall in the summer months (23 to 31 mm, December to February) is typically lower than the standard deviations of the means (27 to 33 mm). Mean monthly minimum temperatures range from 4.1 (July) to 15.5°C (February), and mean monthly maximum temperatures range from 14.2 (July) to 31.5°C (January).

The area is characterised by considerable interannual variability in both rainfall and temperature (Fig. 1), which is predicted to increase under climate change (IPCC 2012). This inherent variability was utilised to define climate scenarios used in modelling. First, given that rainfall is the dominant controlling factor for biological processes in arid environments (Noy-Meir 1973), extreme climate years were identified from historical weather data (1962–2011, Kerang weather station) as those having both annual rainfall and open-pan evaporation in the 10th or 90th percentile (i.e. consistent with IPCC 2012 definition of extreme). Of the 50 years, 2 years were identified as being extreme for both rainfall and open-pan evaporation while also having the same annual average temperature (16.1°C). That is, 1974 (year 13 of scenario H in Fig. 2) was identified as the extreme wet year (annual rainfall 656 mm) with a low annual open-pan evaporation (1432 mm), and 1967 (year 6 of scenario H in Fig. 2) was identified as the extreme dry year (annual rainfall 172 mm) with a high annual open-pan evaporation (1769 mm). As explained below (this subsection), these 2 years were used in combination with the historical climate data to simulate the extreme historical rainfall scenario.

Three climate variability scenarios were applied in this study to examine the net impacts of rainfall variability and extremes on SOC stock changes. In these scenarios, the 50 yr average climate (i.e. average rainfall, open-pan evaporation, and temperature) was kept constant, and only the degree of rainfall variability was changed, as follows.

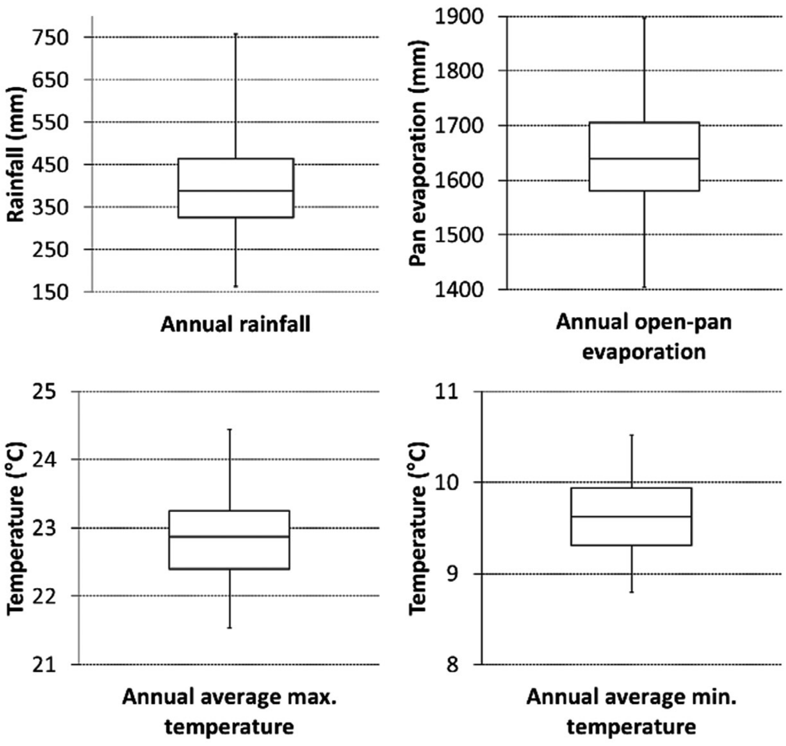

Fig. 1. Box plots of annual averages of selected climate variables (minimum air temperature, maximum air temperature, rainfall, open-pan evaporation) in the study area over the past 50 yr (1962–2011), based on data from the nearby Kerang weather station. Each box plot indicates the median (middle line), first and third quartiles (bottom and top of the box), and the minimum and maximum (ends of the whiskers)

(1) Average historical (AH): This scenario assumed no interannual variability in climate and thus used 50 yr of average non-changing monthly data as input to the RothC model (Fig. 2). This AH scenario was also used to run the model to equilibrium (i.e. for estimating SOC fractions at year 1) and for producing land management information (i.e. monthly plant inputs required to maintain a constant SOC content under average climate [see Section 2.3]).

(2) Historical (H): This scenario used the recorded monthly climate data of the past 50 yr (1962–2011) as input to the RothC model. This scenario included 4 extreme wet years and 5 extreme dry years defined, respectively, as having annual rainfall in the 90th or 10th percentile of records (Fig. 2).

(3) Extreme historical (XH): This scenario, designed to isolate the effects of rainfall variability, involved an increase in annual rainfall variability and in the

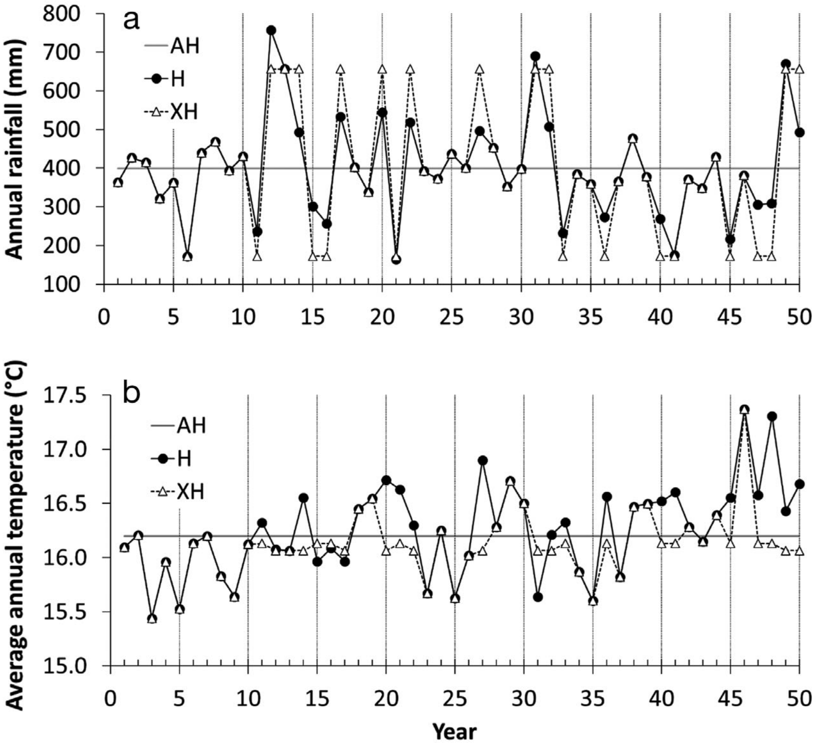

Fig. 2. Distributions of (a) annual rainfall and (b) average annual temperature over 50 yr in the 3 climate variability scenarios. AH: average historical; H: historical; XH: extreme historical. Note that the 50 yr average climate is constant among the scenarios

frequency of extreme rainfall years without shifting the mean annual rainfall. Here, climate data in those years from 1962 to 2011 that had annual rainfall below the 25th percentile and above the 75th percentile were respectively replaced with climate data from the extreme dry year (year 6, as above, this subsection) and the extreme wet year (year 13). Those years having annual rainfall between the 25th and 75th percentiles retained their climate as per the H scenario (Fig. 2). The XH scenario thus involved more extreme wet years (11 versus 4) and more extreme dry years (12 versus 5) than the H scenario (Fig. 2) but with a flatter rainfall distribution that was truncated at the dry end by the annual rainfall of year 6 and at the wet end by year 13 (Fig. 3).

2.3. RothC for estimating SOC dynamics

Among various models developed for estimating the dynamics of SOC, one that has gained considerable attention is RothC, which is a simple and transparent model that has been widely tested in Australia for carbon accounting (Skjemstad & Spouncer 2003, Skjemstad et al. 2004). RothC can be initialised with fewer inputs than many other models and is known for its accuracy across a range of conditions (Kirschbaum et al. 2001, Davidson & Janssens 2006, Ostle et al. 2009), including semiarid environments (Skjemstad et al. 2004, Liu et al. 2011). RothC simulates the turnover of SOC in non-waterlogged surface soils, accounting for the effects of plant cover, plant litter quality and quantity, clay content, rainfall, pan evaporation, and soil temperature (Coleman & Jenkinson 1996). The model separates SOC into 4 active fractions and a small passive fraction called inert organic matter (IOM). The active fractions are (1) easily decomposable plant material (DPM), (2) resistant plant material (RPM), (3) microbial biomass (BIO), and (4) humified organic matter (HUM). Carbon from the added plant residue supplies the DPM and RPM fractions to different degrees based on the DPM/RPM ratio of the particular incoming material (i.e. an estimate of decomposability of the incoming plant material). Both DPM and RPM fractions decompose to form BIO and HUM as well as CO_2, which is lost from the system (Coleman & Jenkinson 1996).

RothC input data were of 3 types: (1) climate variables: monthly precipitation (mm), open-pan evaporation (mm), and average air temperature (°C);

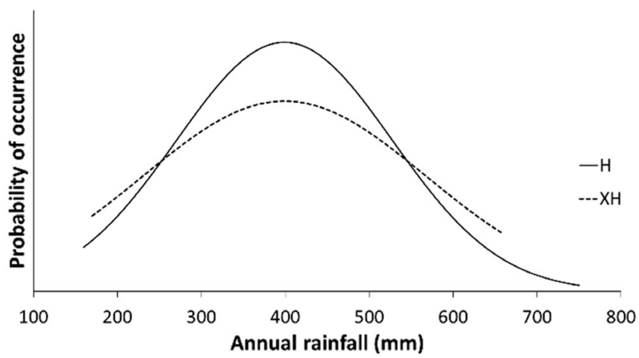

Fig. 3. Probability distribution of annual rainfall in historical (H) and extreme historical (XH) climate scenarios. Scenario H was based on 50 yr of recorded rainfall (1962–2011, Kerang weather station). Scenario XH was derived from scenario H but involved an increase in rainfall variability (i.e. an increase in the frequency of extreme rainfall years from 20 to 50 %) with no shift in mean annual rainfall

(2) soil variables: topsoil depth (cm), clay content (%), and SOC fractions (DPM, RPM, BIO, HUM, and IOM); and (3) land use and management variables: monthly input of carbon as plant material (Mg C ha^{-1}), input material DPM/RPM ratio, and soil cover. As is common elsewhere, monthly plant inputs and the initial active SOC fractions were unknown. Thus, monthly plant inputs were estimated by running RothC in inverse mode, using measured total SOC content, monthly climate data from the AH scenario (see Section 2.2), DPM/RPM ratios based on the predominant land use, and an assigned proportional monthly input distribution. An additional output of this step was an estimation of the IOM fraction based on the Falloon equation (Falloon et al. 1998). To estimate active SOC fractions at year 1, RothC was run for 1000 yr to reach equilibrium, using climate data from the AH scenario, estimated monthly plant inputs and DPM/RPM ratios, and the estimated size of the IOM fraction. A similar approach for running RothC for Australian soils was also used by Setia et al. (2011).

As indicated in Section 2.2, RothC was run for each of the 3 climate variability scenarios over 50 yr. This involved predictions of SOC content and CO_2 emissions for each of the 60 sample points per year per scenario (i.e. 60 points × 50 yr × 3 scenarios = 9000 model runs).

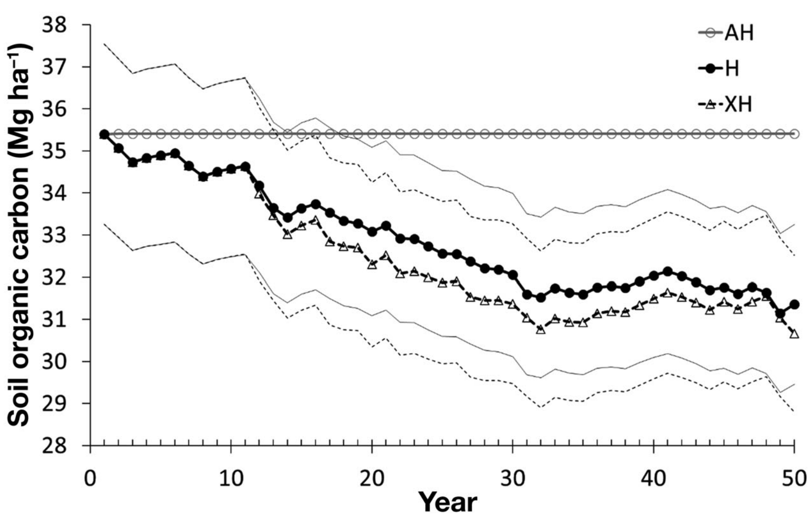

Fig. 4. Predicted trends of soil organic carbon (SOC) stocks (Mg C ha^{-1}) under 3 climate variability scenarios over 50 yr of simulation using the Rothamsted carbon model. AH: average historical; H: historical; XH: extreme historical. Each data point is the mean of 60 sampling points over the study area. A repeated-measures ANOVA indicated a significant effect of climate scenario on SOC stocks ($p < 0.001$), with Tukey's post hoc tests indicating significant differences between AH and H and between AH and XH scenarios ($p < 0.05$). Standard errors of the means were constant for the AH scenario (±2.1 Mg ha^{-1}) and are indicated by solid lines for the H scenario and dashed lines for the XH scenario

2.4. Statistical analysis

Since SOC stocks were repeatedly predicted for the same 60 points over the 50 yr modelling period, repeated-measures ANOVA (Kabacoff 2011) was used to test climate variability effects, with scenario (AH, H, XH) as the between-groups factor and year as the within-groups factor using R (R version 3.0.2; R Core Team 2013). Differences in SOC stocks between each pair of climate scenarios were tested using Tukey's post hoc test. In addition, Pearson's product-moment correlation coefficients were used to examine relationships between annual rainfall variability and changes in SOC stocks and CO_2 emissions.

3. RESULTS AND DISCUSSION

Mean measured SOC stocks to 30 cm depth were 35.4 Mg C ha^{-1} but varied within a range of 12.8 to 102.1 Mg C ha^{-1}. As established by our model parameterisation, mean SOC stocks were invariant for the 50 yr modelling period under the AH scenario. In contrast, predicted SOC stocks to 50 yr decreased significantly under both the H and XH scenarios ($p < 0.001$ for scenario in repeated-measures ANOVA; AH > H, AH > XH Tukey's post hoc test, $p < 0.05$). Pairwise tests indicated no significant differences in SOC stocks between the H and XH scenarios at the end of the 50 yr modelling period ($p = 0.16$), despite divergent trends leading to lower mean stocks in the XH scenario from years 12 to 47 (Fig. 4). Differences at the end of the 50 yr modelling period equated to mean decreases (relative to the AH scenario) of 4.0 Mg C ha^{-1} under the H scenario (i.e. to 31.4 Mg C ha^{-1}) and 4.7 Mg C ha^{-1} under the XH scenario (to 30.7 Mg C ha^{-1}; Fig. 4).

Predicted changes in SOC stocks were strongly associated with patterns in annual rainfall over the simulation years but not with annual temperature (data not shown). Mean annual changes in SOC stocks were negatively correlated with the difference between that year's rainfall and average annual rainfall in both the H scenario ($r = -0.77$) and the XH sce-

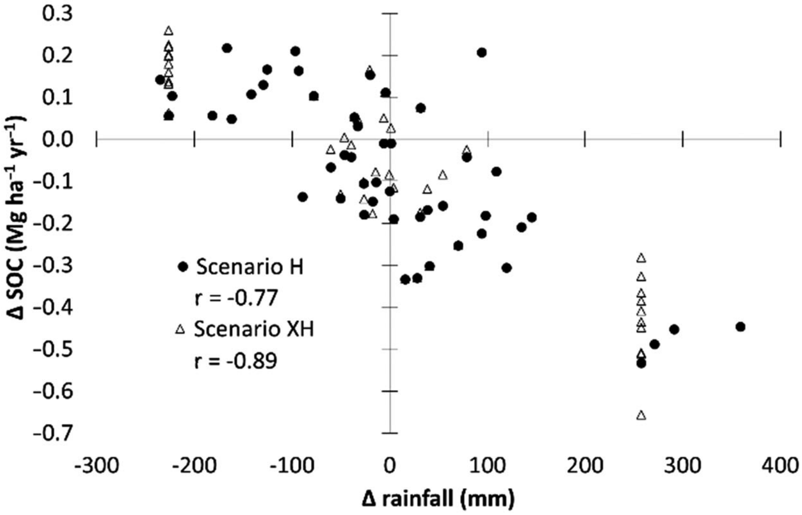

Fig. 5. Relationships between Δrainfall and Δsoil organic carbon (SOC) for 2 climate variability scenarios, where Δrainfall = rainfall$_t$ – average annual rainfall, ΔSOC = SOC$_t$ – SOC$_{t-1}$, and t is any particular year in the simulation period. ΔSOC values are the means of 60 points for each of the 50 yr periods. H: historical; XH: extreme historical

nario (r = –0.89; Fig. 5). That is, above-average annual rainfall was predicted to lead to decreases in SOC stocks, whereas below-average annual rainfall was predicted to lead to increases (Fig. 5). Extreme rainfall years in the XH scenario formed 2 clusters, with extreme wet years leading to predicted losses of SOC in the range of 0.28 to 0.66 Mg C ha^{-1} yr^{-1} and extreme dry years leading to gains of 0.06 to 0.26 Mg C ha^{-1} yr^{-1} (Fig. 5). Similarly, under the H scenario, mean decreases in SOC stocks associated with above-average rainfall years (0.26 Mg C ha^{-1} yr^{-1}; Fig. 5) were not counterbalanced by mean increases associated with below-average rainfall years (0.11 Mg C ha^{-1}), thus producing the above-mentioned (this section) net decreases in SOC stocks to 50 yr under both the H and XH scenarios.

As indicated by the changes in SOC stocks, predicted mean annual emissions of CO_2 (an indication of microbial decomposition) over the 50 yr period were significantly less under the AH scenario (0.86 Mg C ha^{-1} yr^{-1}) than under the H (0.94 Mg C ha^{-1} yr^{-1}) and XH scenarios (0.96 Mg C ha^{-1} yr^{-1}). Predicted mean releases of CO_2 were 1.25 Mg C ha^{-1} yr^{-1} for the 4 extreme wet years of scenario H and 1.30 Mg C ha^{-1} yr^{-1} for the 11 extreme wet years of scenario XH (Fig. 6). In comparison, mean CO_2 releases during extreme dry years were 0.75 Mg C ha^{-1} yr^{-1} for the 5 yr of scenario H and 0.70 Mg C ha^{-1} yr^{-1} for the 12 years of scenario XH (Fig. 6).

Our modelling results clearly indicate the potential importance of interannual rainfall variability and extremes on predicted annual gains and losses in SOC. In general, wet years were predicted to decrease SOC stocks due to increased microbial decomposition, as indicated by increased annual CO_2 emissions from soils. Mean losses in extreme wet years were greater than mean gains during extreme dry years, leading to net decreases in SOC stocks in both the H and XH scenarios over the 50 yr modelling period. Nonetheless, net decreases were not significantly greater under the XH than under the H scenario despite nearly 3-fold more extreme wet years during the 50 yr period (11 versus 4). This was likely due to both the greater number of counteracting extreme dry years in the XH scenario (12 versus 5) and the cumulative effects of an extended 16 yr dry period from years 33 to 48 (Fig. 2a; accentuated by more extreme dry years during that period in the XH scenario), leading to a convergence of SOC stocks in the XH and H scenarios at the end of the modelling period (Fig. 4).

The key to understanding why RothC predicted greater losses in extreme wet years than gains in extreme dry years lies in the model's decomposition

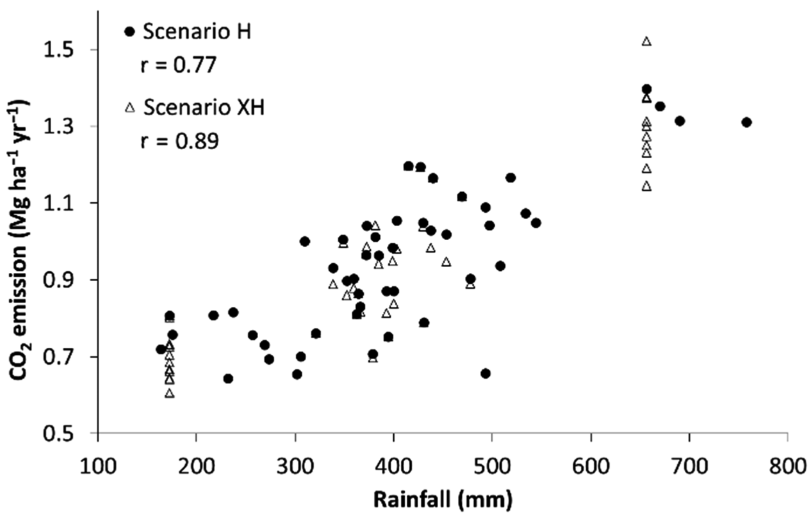

Fig. 6. Relationships between predicted annual CO_2 emissions and annual rainfall for 2 climate variability scenarios. Each data point is the mean of 60 sampling points over the study area. H: historical; XH: extreme historical

function. In RothC, if Y is the carbon content of the active compartment of SOC, then $Y \times e^{-abckt}$ will be the carbon content at the end of a given month, where a is the monthly rate-modifying factor for temperature, b is the monthly rate-modifying factor for moisture, c is the monthly soil cover rate-modifying factor, k is the yearly decomposition rate constant for that compartment, and t is 1/12, since k is based on a yearly decomposition rate (Coleman & Jenkinson 1996). Our aim was to keep all variables other than b constant in our scenarios to isolate the effects of changes in b (i.e. the effects of rainfall variability). This did not involve artificially changing all climate variables but instead only increasing the frequency of selected extreme dry and wet years (each retaining the average annual temperature) throughout the XH scenario. As such, inherent variations in monthly temperatures occurred throughout the simulation period, but monthly values of the rate-modifying factor a for temperature did not markedly differ from the 50 yr average in extreme dry and extreme wet years (Fig. 7a). In contrast, the rate-modifying factor b for moisture varied markedly among the average, extreme dry, and extreme wet years (Fig. 7b). Throughout the extreme dry year (annual rainfall = 172 mm), b was invariant at the lowest possible value of 0.2. Similarly, b remained at 0.2 for much of the 50 yr average year (annual rainfall = 399 mm), increasing to a maximum of 0.34 only during the wetter winter months. In contrast, b remained at the highest possible value of 1.0 for 7 mo of the extreme wet year (annual rainfall = 656 mm; Fig. 7b). These greater differences in b rather than a indicate that moisture rather than temperature was the driving force behind the RothC predictions of greater carbon losses in extreme wet years than carbon gains in extreme dry years.

Existing research provides strong mechanistic support for the increased CO_2 emissions during extreme wet years predicted by the RothC model in our study. SOC decomposition is known to be primarily controlled by microbial activity, which is strongly controlled by climate (Sanderman et al. 2010). Microcalorimetry experiments have shown that microbial activity is positively correlated with soil moisture (Barros et al. 1995, Prado & Airoldi 1999) and is optimised at field capacity (Barros et al. 1995). Indeed, climate variables that regulate the microbial activity in soil explained up to 90% of the variance in SOC decomposition rates in various geographic regions (Sanderman et al. 2010).

We held many variables constant, including monthly plant inputs, to examine the effects of rainfall variability on SOC stocks. We acknowledge that this probably accentuated the predicted rainfall effects, since plant productivity and associated inputs could reasonably be expected to increase in wet years, thereby counteracting, albeit with some lags, decomposition losses due to increased soil microbial activity. Nonetheless, our approach highlighted the potential for SOC stock decreases in extremely wet years and the importance of maintaining rather than removing plant inputs under these conditions, particularly in agricultural landscapes where SOC stocks are expected to decrease due to regular harvesting of organic material (Pan et al. 2010)

Our simulations indicated a strong influence of rainfall on SOC stocks

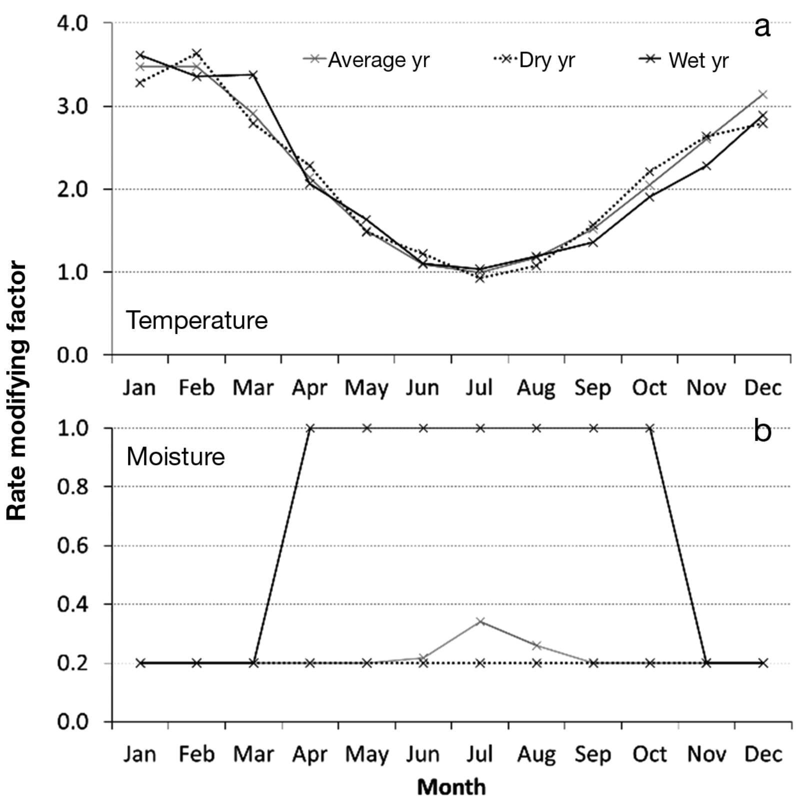

Fig. 7. Monthly variation in Rothamsted carbon model rate-modifying factors for (a) temperature and (b) moisture in the extreme dry years (172 mm rainfall) and the extreme wet years (656 mm rainfall) compared with the 50 yr average (399 mm rainfall)

and CO_2 emissions (Figs. 5 & 6) but no clear effects of annual temperature (no significant correlations with SOC stocks, data not shown). While we note that our study was not designed to examine extreme temperature effects, the clear influence of rainfall on SOC stocks in this semiarid environment is consistent with findings elsewhere. For example, observations by Giardina & Ryan (2000) and predictions by Shen et al. (2009) indicated a greater effect of moisture content/precipitation than temperature in controlling SOC decomposition rates in arid climates. Similarly, Saiz et al. (2012) found that mean annual precipitation/evapotranspiration and sand content together explained 84% of the variability in SOC stocks in their study area, which involved a climate transect from arid and semiarid regions (annual rainfall 200 to 400 mm) to tropical forest (>1200 mm annual rain). Nonetheless, regional patterns of SOC have been shown to be negatively correlated with mean annual temperature (Jobbagy & Jackson 2000), and SOC turnover times have been predicted to decrease with increasing temperature (albeit assuming no change in carbon inputs and precipitation), particularly in a tropical rainforest but also in temperate and boreal forest soils (Trumbore et al. 1996). Davidson & Janssens (2006) argue that while SOC decomposition processes, by nature, are expected to respond to temperature changes, it must be acknowledged that temperature is only one of many environmental variables that influence decomposition, one that could be largely obscured by other environmental constraints, such as drought and flooding. Indeed, research has confirmed that in arid and semiarid soils, changes in water balance may have significant consequences for SOC balance (Sponseller 2007) and that precipitation under water scarcity conditions appears to override the role of temperature in controlling SOC decomposition (Conant et al. 2004).

4. CONCLUSIONS

Our study indicates that, considered in isolation, extreme wet years will promote microbial decomposition, leading to decreases in SOC stocks in semiarid environments. This finding highlights the importance of maintaining counterbalancing plant inputs during wet periods. This, in turn, highlights the importance of management practices designed to maintain SOC (e.g. conservation tillage practices) and perhaps lends support to establishing perennial systems rather than more intensive harvesting systems in these environments.

Our RothC simulations did not indicate a significant impact of increased rainfall variability alone (i.e. no shift in 50 yr mean climate variables) on SOC stock balance over 50 yr. That was likely due to the increased number of both dry and wet years in our extreme rainfall variability scenario, so that a greater number of decreases in wet years was counterbalanced by a greater number of gains in dry years. There are no guarantees that such counterbalancing effects will play out under future climates. Currently, most studies of climate change effects focus on changes in average climate variables. Given the likelihood of more frequent climate extreme events (IPCC 2012, Fischer & Knutti 2015) and the potentially large impact on SOC processes indicated in this study, we emphasise the importance of more explicit consideration of the magnitude, direction, and frequency of interannual rainfall variability in future predictions of SOC.

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