Global Change Biology

Global Change Biology (2013) **19**, 1585–1597, doi: 10.1111/gcb.12145

Impact of agricultural management practices on soil organic carbon: simulation of Australian wheat systems

GANG ZHAO*†, BRETT A. BRYAN†, DARRAN KING†, ZHONGKUI LUO‡, ENLI WANG‡, XIAODONG SONG†§ and QIANG YU*¶

Key Laboratory of Water Cycle and Related Land Surface Processes, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A Datun Road, Anwai, Beijing 100101, China, †CSIRO Ecosystem Sciences, Waite Campus, Urrbrae, SA 5064, Australia, ‡CSIRO Land and Water, Black Mountain, Canberra, ACT 2601, Australia, §College of Environment and Natural Resources, Zhejiang University, Hangzhou 310058, China, ¶Plant Functional Biology and Climate Change Cluster, School of the Environment, University of Technology, PO Box 123, Broadway, Sydney, NSW 2007, Australia

Abstract

Quantifying soil organic carbon (SOC) dynamics at a high spatial and temporal resolution in response to different agricultural management practices and environmental conditions can help identify practices that both sequester carbon in the soil and sustain agricultural productivity. Using an agricultural systems model (the Agricultural Production Systems sIMulator), we conducted a high spatial resolution and long-term (122 years) simulation study to identify the key management practices and environmental variables influencing SOC dynamics in a continuous wheat cropping system in Australia's 96 million ha cereal-growing regions. Agricultural practices included five nitrogen application rates (0–200 kg N ha^{-1} in 50 kg N ha^{-1} increments), five residue removal rates (0–100% in 25% increments), and five residue incorporation rates (0–100% in 25% increments). We found that the change in SOC during the 122-year simulation was influenced by the management practices of residue removal (linearly negative) and fertilization (nonlinearly positive) – and the environmental variables of initial SOC content (linearly negative) and temperature (nonlinearly negative). The effects of fertilization were strongest at rates up to 50 kg N ha^{-1}, and the effects of temperature were strongest where mean annual temperatures exceeded 19 °C. Reducing residue removal and increasing fertilization increased SOC in most areas except Queensland where high rates of SOC decomposition caused by high temperature and soil moisture negated these benefits. Management practices were particularly effective in increasing SOC in south-west Western Australia – an area with low initial SOC. The results can help target agricultural management practices for increasing SOC in the context of local environmental conditions, enabling farmers to contribute to climate change mitigation and sustaining agricultural production.

Keywords: agricultural management practice, APSIM, Australia, carbon sequestration, climate change, crop model, soil organic carbon, wheat

Received 3 September 2012 and accepted 26 December 2012

Introduction

The terrestrial carbon pool stores more carbon than the vegetation and atmosphere pools combined (Post *et al.*, 1982; Davidson & Janssens, 2006). Around 75% of the carbon in the terrestrial pool is stored as soil organic carbon (SOC) (Batjes, 1996). Agricultural land occupies 38% of the earth's land surface and its SOC stock is strongly influenced by human activities (The World Bank, 2012). Agricultural and degraded soils can potentially sequester up to 78 Gt of carbon – equal to 66% of the historic carbon emissions from SOC loss in pre- and postindustrial eras (Lal, 1999). Changes in SOC in agricultural land over time are characterized by dynamic exchange processes which are controlled by environmental conditions such as soil texture, temperature, and rainfall; and management practices such as cropping systems, fertilization, residue removal, and tillage regimes (Lal, 2004; Dolan *et al.*, 2006; Alston *et al.*, 2009; Van Wesemael *et al.*, 2010; De Gryze *et al.*, 2011).

Although the effects of environmental variables and agricultural management practices on SOC have been widely studied, the results remain inconclusive. For example, some studies have found that higher temperatures increased SOC content in croplands (Trumbore *et al.*, 1996; Kätterer *et al.*, 1998; Dalias *et al.*, 2001), whereas other studies have found that higher temperatures decreased it (Peterjohn *et al.*, 1994; Oechel *et al.*, 2000). Davidson & Janssens (2006) pointed out that the inherently diverse nature of SOC and environmental constraints obscured the responses of SOC dynamics to warmer temperatures. On the management side,

Correspondence: Gang Zhao, tel. + 61 08 8303 8679, fax + 61 08 8303 8582, e-mail: gang.zhao@csiro.au

adopting conservation agriculture practices such as changing from monoculture to diverse rotation cropping, reducing soil disturbance by no-tillage practices, and increasing primary production by fertilization, are generally considered ways to increase SOC content (West & Post, 2002; Deen & Kataki, 2003). These practices increase SOC either by reducing decomposition, increasing sequestration, or both. The benefits from these agricultural practices are highly dependent upon the climate and soil conditions for specific cropping systems (Smith *et al*., 1997; Luo *et al*., 2010). As environmental conditions vary spatially (Giardina & Ryan, 2000), investigating the spatially explicit relationships between SOC, climate, soil, and agricultural practices is essential for prescribing agricultural management practices for carbon sequestration and promoting crop productivity according to local environmental conditions (Trumbore *et al*., 1996; Falloon *et al*., 2007).

Regional- and continental-scale assessments of SOC have typically been supported by data from soil inventories and soil profile maps (Batjes, 1996; Davidson & Janssens, 2006). However, these data sources often tell us little about changes in SOC over time and it is impractical to implement long-term field experiments with multiple agricultural management practices over a large geographic extent. While monitoring networks can provide reliable, spatially referenced data on SOC over time (Meersmans *et al*., 2008), they are currently established only in a few countries and network densities are typically not sufficient to detect changes in soil properties over large areas at a high spatial resolution (Giardina & Ryan, 2000). The lack of spatiotemporal continuity in SOC monitoring data over meaningfully large areas limits its ability to support consistent conclusions about the factors that control SOC dynamics (Meersmans *et al*., 2008, 2011). Alternatively, process-based models can be used to simulate the biogeochemical processes influencing changes in SOC (Van Wesemael *et al*., 2010). A distinct advantage of process-based models is that they can analyze the impacts of management practices and environmental variables on SOC dynamics separately (Ciais *et al*., 2011).

A number of process-based terrestrial carbon models such as CENTURY, DNDC, and Rothamsted carbon model (RothC) (Schimel *et al*., 1994; Li *et al*., 1997; Bellamy *et al*., 2005; Jones *et al*., 2005; Smith *et al*., 2005; Bonan, 2008) have been equipped with crop growth modules to simulate SOC in agricultural systems. Conversely, a number of agricultural systems models such as ORCHIDEE-STICS (Gervois *et al*., 2008), EPIC (Izaurralde *et al*., 2006), and Agricultural Production Systems sIMulator (APSIM) (Keating *et al*., 2003) have been equipped with soil carbon modules. These models have been extensively validated against measured SOC data (Ranatunga *et al*., 2001; Thomson *et al*., 2006; Huth *et al*., 2010; Luo *et al*., 2011; Meersmans *et al*., 2011). A few studies have used these models to simulate the effects of management practices and environmental variables on SOC at regional and continental scales. For example, Falloon *et al.* (2007) found that precipitation controlled the sign of SOC changes in Kenya, Jordan, Brazil, and India. Using RothC to simulate SOC in European cropland and grassland, Smith *et al.* (2005) found that warmer soil temperature and higher soil moisture affected SOC both through accelerating decomposition (negative effect), but also through promoting net primary production (NPP) (positive effect). They also found that using advanced technologies led to an increase in NPP and thereby increased SOC. Smith *et al.* (2007) predicted that SOC would decrease in Russian and Ukrainian croplands under a range of climate change scenarios, but conservative management was able to mitigate these losses by up to 44% compared with the baseline management practice. These studies suggest that using process-based simulation models to assess the influence of agricultural management practices on SOC dynamics given local environmental conditions can provide useful information to address increasing concerns about carbon emissions, climate change, and the sustainability of agricultural systems.

In this study, we quantified the influence of management practices and environmental variables on SOC across Australia's cereal-growing regions. The SOC was simulated under 125 fertilization and residue management scenarios at a daily time step, over 122 years, and at a high spatial resolution, using the APSIM process-based agricultural systems model. We chose APSIM over other biophysical models because APSIM has been more extensively validated in simulating long-term SOC dynamics in Australian croplands than other models (Ranatunga *et al*., 2001; Van Antwerpen *et al*., 2002; Micheni *et al*., 2004; Huth *et al*., 2010; Luo *et al*., 2011). The influence of management practices and environmental variables on SOC was quantified using Spearman's rank correlation coefficient with bootstrapping. Effects from combinations of the two most influential management practices on SOC were assessed and mapped across the study area. Changes in SOC over time were assessed under a range of management practices for three illustrative climate-soil (CS) units. We discuss the implications and uncertainties of the results in the context of developing farm management strategies that enhance carbon sequestration in agricultural soils, and contribute to climate change mitigation and the sustainability of agricultural production.

Materials and methods

Study area

The study area covered the potential cropping area of Australia (Fig. 1) defined using the Australian Land Use and Management Classification (ABARE, 2010). The different types of land use include dryland croplands (2.52×10^7 ha), grazing modified pastures (6.91×10^7 ha), irrigated croplands (1.14×10^6 ha), and irrigated modified pastures (8.75×10^5 ha) (Fig. 1). Climate in the study area ranges from subtropical in Queensland (QLD) to temperate and semiarid in parts, but the majority of the cropping areas in south-west Western Australia (WA), South Australia (SA), Victoria (VIC), and New South Wales (NSW) are of Mediterranean climate.

Climate-soil units

We used CS units – zones with homogeneous soil types and climate attributes – as our basic modeling units. A series of spatial analyses were undertaken to divide the study area into CS units. We first extracted broad soil type data from Digital Soil Atlas of Australia. The database mapped 13 soil types in the study area including: calcarosol, chromosol, dermosol, ferrosol, hydrosol, kaurosol, kurosol, organosol, podosol, rudosol, sodosol, tenosol, and vertosol [Australian Soil Classification, Izaurralde *et al.* (2006)]. An iterative *k*-means cluster analysis on historical mean annual climate layers (maximum temperature, minimum temperature, rainfall, solar radiation) (Hartigan & Wong, 1979), obtained from the Australian Bureau of Meteorology (BOM), was then used to divide the study area into 38 climate clusters. Lastly, the climate clusters layer was overlaid with the soil type layer and remnant vegetation areas were removed, thereby creating 9432 CS units (average size 10 178 ha), which were irregular polygons with the same soil type and similar climate (Fig. 1, left).

APSIM

Agricultural Production Systems sIMulator is a point-based agricultural systems model (Keating *et al.*, 2003) that can simulate crop growth and enables the implementation of management rules governing sowing, irrigation, fertilization, and tillage. In APSIM, the SoilN module simulates SOC dynamics on a daily time step – coupling with modules of soil water (SoilWat), surface organic matter (SurfaceOM), and plant modules (Cai *et al.*, 1997). Soil organic matter (SOM) is divided into three pools: fresh organic matter pool (FOM), microbial biomass pool (BIOM), and humic matter pool (HUM) (Keating *et al.*, 2003; Probert *et al.*, 2005). The FOM pool includes the fresh organic matter including roots and crop residues and is further separated into three subpools: carbohydrate-like (CH), cellulose-like (CL), and lignin-like (LIG). The BIOM pool contains the soil microbial biomass and microbial products. The HUM pool contains the rest of the SOM. A fraction of HUM is considered indecomposable inert carbon (Inert_C). The Nitrogen (N) flux between the three pools is coupled with carbon (C) and calculated based on the C : N ratio of the receiving pool. The C : N ratio of BIOM was specified in the plant parameter file, whereas the C : N ratio of HUM was specified in the soil parameters. The C : N ratio of all the pools was kept constant through time. Each pool has a maximum decomposition rate. Decomposition of each pool is computed as first-order processes modified by soil temperature and moisture. Decomposition of the FOM pool leads to emissions of CO_2 to the atmosphere and the transfer of carbon to the BIOM and HUM pools. The flows are defined in terms

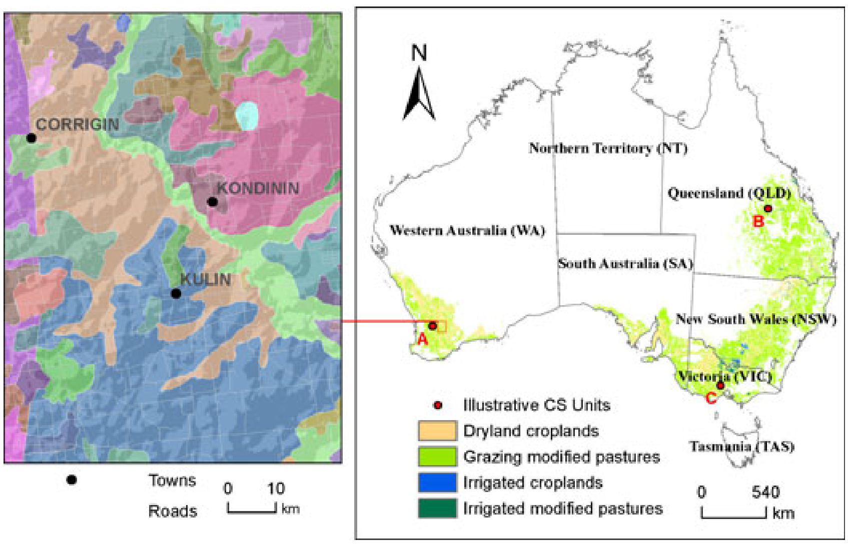

Fig. 1 Location and land use in the study area (right) and an example of the spatial resolution of the climate-soil (CS) units (left). Each CS unit is represented by a unique color or gray scale. The small cropping areas in Tasmania and the Northern Territory were excluded in this study.

of efficiency coefficients which represent the proportion of carbon retained in the system and the fraction of the retained carbon that is synthesized into the BIOM pool.

The SurfaceOM module of APSIM used in this study simulates the fate of surface residues which can be burnt; removed from the system; incorporated into the soil by tillage operations; or decomposed. The decomposition of residue adds N and C to the soil and emits CO_2 to the atmosphere. Different residue components have different C : N ratios and maximum decomposition rates. Tillage and incorporation of residue result in a transfer of surface organic matter into the FOM pool across soil layers to the nominated depth. The FOM was assumed evenly distributed through the soil layers.

Spatial data

Soil parameters in this study were sourced from three soil databases. Bulk density (BD), pH, drained upper limit (DUL), 15 bar lower limit (LL15), and layer depth (LD) were extracted from the Australian Soil Resources Information System [ASRIS, Mckenzie *et al.* (2005)] – a vector format soil database with seven hierarchical levels of generalization. We chose ASRIS level four which had five layers of soil properties. Soil layer depth varies over the study area. The gap in the New South Wales soil data was filled by interpolating data from 613 APSIM reference site data points located in this area, extracted from the APSoil database (Dalgliesh *et al.*, 2006; Fig. S1). As initial SOC content has a significant impact on the change in SOC over time (Goidts *et al.*, 2009), and the layers of SOC content in ASRIS only covered a small area, we obtained initial SOC data from the ISRIC-WISE database [5 arc-minutes ≈ 9 km grid cell resolution, Batjes (2006)]. The area-weighted average initial SOC was then calculated for each CS unit. Other parameters where values were not available in the spatial databases were initialized by default values of APSIM (Zhao *et al.*, 2013).

Continental-scale climate data layers at 0.05° spatial resolution (Jeffrey *et al.*, 2001) were sourced from the BOM, Australia (http://www.bom.gov.au). The daily time-series climate data layers span 122 years from 1889 to 2010 and include maximum and minimum temperature, total solar radiation, rainfall, and evaporation. Climate layers were summarized and mean values for each of the climate variables were calculated for each CS unit (Zhao *et al.*, 2012).

Agricultural management scenarios

Fertilization, crop residue removal, and residue incorporation through tillage are the major management practices that influence SOC sequestration and dynamics in croplands (Chan & Heenan, 2005; Van Wesemael *et al.*, 2010). Farm survey showed that fertilization rates during the past 20 years in the study area varied from 0 to 200 kg ha^{-1} with the most common application rates between 50 and 100 kg ha^{-1} [ABARE-BRS (2003); Fig. S2]. Residue management in 2009–2010 has been characterized as follows: residue retention occurred on 48% of the cropland, ploughing crop residue into the soil occurred on 34% of the cropland, and removal of crop residue by baling or heavy grazing occurred on 23% of the cropland (ABS, 2010). These practices varied widely across space and time depending on many factors such as the previous year's profit and current climate and soil conditions (D'emden *et al.*, 2008). To quantify the effect of agricultural management practices on SOC, we simulated wheat crops under 125 combinations of fertilizer application, residue removal, and residue incorporation.

Management practices included five nitrogen application rates (0–200 kg N ha^{-1} in 50 kg N ha^{-1} increments, i.e., N:0, N:50, N:100, N:150, and N:200). Apart from N:0, we specified that 25 kg N ha^{-1} was applied at sowing, with the rest applied at the stem elongation stage by top-dressing. The nitrogen rate is different from the surveyed fertilizer application rate which is the total weight of fertilizer applied. This was converted to nitrogen rates for specification in APSIM according to the percentage of N in the fertilizer. The term *fertilization* refers specifically to nitrogen application hereafter. We also specified five residue removal rates (0–100% in 25% increments, i.e., R:0, R:25, R:50, R:75, and R:100), and five residue incorporation rates (0–100% in 25% increments, i.e., I:0, I:25, I:50, I:75, and I:100). Residue removal rates denoted the percentage of aboveground straw and leaf biomass removed from the system. Incorporation rates denoted the proportion of remaining residue incorporated into the soil by tillage. Management practice combinations are abbreviated in this study as N:x, R:x, I:x. The N:0, R:0 I:0 denotes the baseline management practice which was no fertilization, no residue removal, and no residue incorporation.

Although crop rotations and mixed cropping/grazing systems occur across the study area, there is scant information quantifying the extent of this. As wheat is the dominant crop for most of the study area, we simulated a continuous wheat system. The sowing window was determined according to the location of the CS unit (Table 1). The sowing date was determined according to cumulative rainfall and soil water content in each CS unit during the sowing window. Cultivars were selected according to the sowing date so that earlier sowing dates will invoke a later maturing cultivar, and vice versa (Table 1).

In total, we ran 1 179 000 (125 scenarios × 9432 CS units) APSIM simulations. Each simulation quantified SOC content in the top 30 cm of soil over the 122-year simulation period. Change in SOC (ΔSOC) in the top 30 cm was calculated as the difference in SOC between 2010 and 1889: $\Delta SOC = SOC_{2010} - SOC_{1889}$. Each simulation took about 4 min which presented a significant computing challenge. To overcome this challenge, we developed a hybrid, high performance computing approach combining grid computing and parallel programming (Zhao *et al.*, 2013).

Identifying variables that control the SOC dynamics

We assessed the influence of management practices and selected environmental variables on SOC using Spearman's rank correlation coefficient (*rho*). In the assessment, the ways that climate, soil and management options varied were different. Climate data varied both spatially and temporally, soil parameters only varied spatially across the CS units, and each CS unit was simulated under the 125 management scenarios.

Table 1 Sowing windows and cultivars in different states

Location	Sowing windows	Consecutive rainfall	Cultivars
QLD	10 May–31 July	25 mm in 10 days	Janz (10 May–30 June), Hartog (1 July–31 July)
NSW	20 April–31 July	25 mm in 10 days	Batavia (20 April–30 April), Sunco (1 May–31 May), Buckly (1 June–30 June), Hartog (1 July–31 July)
VIC	1 May–31 July	16 mm in 6 days	Sunco (1 May–31 April), Buckly (1 June–30 June), Hartog (1 July–31 July)
SA	20 April–15 July	25 mm in 10 days	Batavia (20 April–30 April), Sunco (1 May–31 May), Buckly (1 June–30 June), Hartog (1 July–15 July)
WA	20 April–15 July	25 mm in 10 days	Spear (20 April–31 May), Kulin (1 June–15 July)

Selected climate variables included mean annual temperature (hereafter simply *temperature*) and mean annual rainfall (hereafter simply *rainfall*) as these have been found to be uncorrelated and capture a large proportion of the spatial variation in a range of climatic parameters (Linacre, 1977; Bryan, 2003). In preparing the data for correlation analysis, we summarized the long-term daily climate variables to mean annual values. Selected soil parameters included soil water holding capacity (SWHC, DUL-LL15), pH, and initial SOC content (initialized from BD and OC).

The potential effect of spatial autocorrelation on the Spearman's rank correlation coefficient was minimized using bootstrap sampling based on separation distances informed by semivariogram analysis (Goodchild, 1986; Bryan *et al.*, 2011b). The aim of the bootstrap sampling strategy was to reduce the degree of spatial autocorrelation while still providing a sample which is large enough for robust correlation analyses. The spatial autocorrelation in the climate and soil variables was first calculated and graphed as semivariograms (Figs. S3–S6). On the basis of the semivariance (γ) of these variables, we chose 0.5 degrees ($\approx$55 km) as the separation distance (or *range* in the semivariogram) beyond which spatial autocorrelation was greatly reduced (reflected by an increase in γ). The number of CS units sampled for the correlation analysis was then calculated to equal 317 [960 000 km^2/(55 km $\times$ 55 km) = 317]. This provides a sample of CS units separated by 0.5 degrees on average, and containing a relatively low degree of spatial autocorrelation.

Spearman's rank correlation coefficient was calculated between ΔSOC and the selected climate and soil variables across the full set of agricultural management practices and CS units, for 1000 bootstrapped random samples of 317 CS units. The nonparametric Spearman's rank correlation coefficient was preferred as it is robust to departures from the normal distribution (Lehmann & D'abrera, 2006) commonly found in our samples. The sign of *rho*, positive or negative, indicates the direction of association between the independent variables (management and environmental variables) and the dependent variable (ΔSOC). The absolute magnitude of *rho*, between 0 and 1, indicates the strength of correlation between the two variables. The bootstrap distribution of *rho* was graphed for each management practice and environmental variable as the median and the 5th and 95th percentile values calculated from the bootstrap samples.

We investigated the effects of each of the four most influential variables on ΔSOC by producing boxplots characterizing the influence of each variable on ΔSOC including the variance calculated across agricultural management practices, CS units, and the three other influential variables. Similarly, we assessed the combined effects of the four most influential variables on ΔSOC using bivariate contour plots of the median and the 5th and 95th percentile ΔSOC values calculated across agricultural management practices, CS units, and the two other influential variables.

Spatial and temporal impacts of management on SOC

We mapped the spatial distribution of the impacts on SOC of the two most influential agricultural management practices – residue removal and fertilization – with incorporation set at 0% because it had the least effect on ΔSOC. The ΔSOC was mapped for each CS unit, for each combination of three residue removal rates (0%, 50%, and 100%) and three nitrogen application rates (0, 50, and 100 kg N ha^{-1}).

Guided by the maps of ΔSOC, three CS units (A, B, C) (Fig. 1) – each illustrating a distinct response of SOC to the management practices of fertilization and residue removal typical of their broader cropping regions (south-western Australia, Queensland, and south-eastern Australia) – were selected to illustrate SOC change over time. The soil and climatic characteristics of the three illustrative CS units are presented in Table 2. We assessed six management practices – combinations of two fertilization rates (N:0, N:100), two residue removal rates (R:0, R:100), and two residue incorporation rates (I:0, I:100), but omitting the two combinations containing R:100 and I:100 (Fig. 6), as no residue can be incorporated when all residue is removed.

Table 2 Description of the soils and climate of the illustrative climate-soil (CS) units

	Soil properties				Climate factors*				
CS units	BD (g/cc)	pH	SWHC†	Initial SOC content‡	Tmax	Tmin	Rad	Prec	Evap
A	1.425, 1.439, 1.533, 1.545, 1.508§	4.956, 5.477, 5.950, 6.084, 5.95	0.070, 0.073, 0.093, 0.108, 0.104	18.26	23.73	9.87	18.20	358	1698
B	1.593, 1.447, 1.557, 1.467, 1.036	5.791, 7.126, 6.240, 7.114, 7.468	0.067, 0.122, 0.083, 0.146, 0.151	27.05	29.04	14.32	20.30	580	2088
C	1.039, 1.569, 1.360, 1.689, 1.689	4.527, 5.800, 4.889, 7.700, 7.700	0.198, 0.145, 0.136, 0.062, 0.062	56.02	15.98	5.92	15.29	908	1111

*Values of the climate factors are mean daily maximum temperature (Tmax, °C), mean daily minimum temperature (Tmin, °C), mean daily radiation (Rad, MJ m^{-2}), mean annual precipitation (Prec, mm), and mean annual potential evaporation (Evap, mm).
†SWHC is the abbreviation of soil water-holding capacity which equals to DUL-LL15 (mm).
‡The initial SOC content is the soil organic carbon in top 30 cm layer (t ha^{-1}).
§Five numbers in soil texture grid represent texture values for layers from 1 to 5, respectively.

Results

Correlations between management practices, environmental variables, and ΔSOC

Initial SOC content was strongly but negatively correlated (median *rho* = −0.61) with ΔSOC (Fig. 2). Residue removal (median *rho* = −0.40) and temperature (median *rho* = −0.34) both displayed a moderate negative correlation, whereas fertilization displayed a moderate positive correlation (median *rho* = 0.26) with ΔSOC. Variation in *rho* values calculated across the 1000 bootstrap samples was relatively small (Fig. 2).

The impacts of the four most influential variables – initial SOC content, residue removal, temperature, and fertilization – on ΔSOC are presented in Fig. 3. Initial SOC content and residue removal had a relatively linear negative effect on ΔSOC. The negative effect of temperature on ΔSOC increased at mean annual temperatures over 19 °C. Fertilization increased ΔSOC most strongly at nitrogen application rates between 0 and 50 kg N ha^{-1}, with a limited influence at higher application rates. Variation in the influence of these parameters on ΔSOC across the full set of simulations (CS units and management scenarios) is relatively large (Fig. 3).

Figure 4 presents the effects of interactions between initial SOC content, residue removal, temperature, and fertilization on ΔSOC. The initial SOC content and residue removal had a negative effect on median ΔSOC which decreased linearly with increases in these variables. Initial SOC content and temperature had a similar negative effect on ΔSOC, but the effect of temperature was nonlinear, having a strong effect at mean annual temperatures exceeding 19 °C. The combined effects of fertilization and initial SOC content were nonlinear with strong positive effects of fertilization on ΔSOC up to 50 kg N ha^{-1}, but with initial SOC content dominating at greater fertilization rates. The impact of fertilization rates and residue removal, and of fertilization rates and temperature, on ΔSOC were very similar. Fertilization effects were strongest up to 50 kg N ha^{-1}. At fertilization rates above 50 kg N ha^{-1}, the effect of residue removal and temperature (especially at temperatures >19 °C) dominated ΔSOC. The

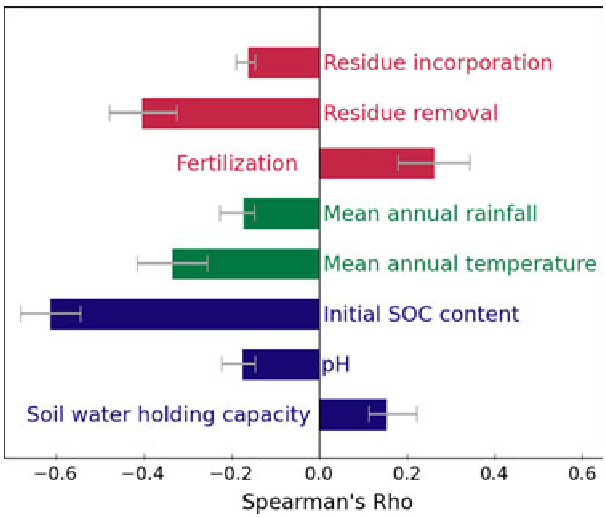

Fig. 2 Spearman's rank correlation coefficients between ΔSOC (1889–2010, t ha^{-1}) and climate (green or light gray), soil (blue or medium gray), and management (red or dark gray) variables. All the tests were significant ($P < 0.001$).

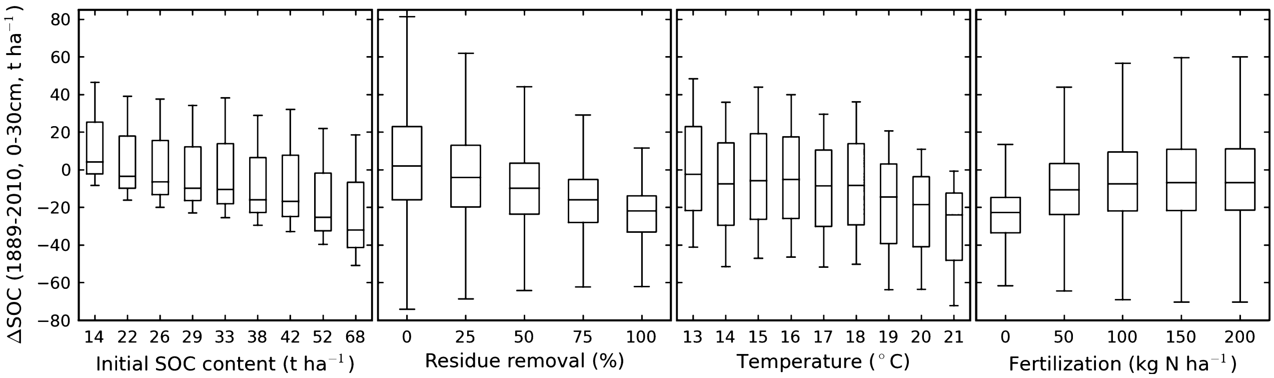

Fig. 3 Response of ΔSOC (1889–2010, t ha^{-1}) to the four most influential variables – initial soil organic carbon (SOC) content, residue removal, temperature, and fertilization. For the continuous variables initial SOC content and temperature, *x*-axis values are the decile interval midpoints. Boxplots show the median and interquartile range, with whiskers extending to the most extreme data point within 1.5 × (75–25%) data range.

strong effect of higher temperature on ΔSOC was also evident when comparing its combined effect with residue removal. Substantial differences occurred in the magnitude but similarities occurred in patterns of ΔSOC at the median, 5th and 95th percentile levels in response to covariation in variables (Fig. 4).

Spatial effects of agricultural practices on SOC

The response of ΔSOC to fertilization and residue removal varied over the study area (Fig. 5). With no fertilization and no residue removal or incorporation (i.e., N:0, R:0, I:0), the SOC content decreased over most (87%) of the study area except the cropping districts of south-west Western Australia (WA). The SOC in WA began to decline when residue removal rate was greater than 50%. Nearly all (99.2%) of the study area showed a decrease in SOC under N:0, R:50, I:0 and 100% of the study area under N:0, R:100, I:0. Fertilization arrested the declining SOC trend. For example, SOC increased in most (71%) of the study area under N:100, R:0, I:0 except for the warmer climates (e.g., QLD).

Temporal effects of agricultural practices on SOC

For all three illustrative CS units – A (WA), B (QLD), and C (VIC), fertilization had positive effects on SOC even when all residue was removed (Fig. 6). The impact of residue incorporation on SOC fluctuated over time. With no management intervention (N:0, R:0, I:0), the baseline scenario, the SOC content in CS unit A (WA) increased from 20 t ha^{-1} in 1889 to about 38 t ha^{-1} in 1940 and remained relatively stable after that. In CS units B (QLD) and C (VIC), SOC decreased significantly before stabilizing. CS unit A showed a potential for increasing SOC. Fertilization had a positive effect on SOC content which increased by 80 t ha^{-1} over 122 years under N:100, R:0, I:0. CS unit B showed a strong declining trend in SOC over time under all management options. Residue incorporation had a negligible effect on SOC, while fertilization of 100 kg N ha^{-1} with 0% residue removal (N:100, R:0, I:0) reduced the decline. Residue incorporation promoted SOC sequestration in CS unit C. Compared with N:100, R:0, I:0, around 30 t ha^{-1} more SOC was sequestered under N:100, R:0, I:100. The effect of residue incorporation on SOC sequestration was fairly small at lower fertilization rates and higher residue removal rates.

Discussion

Interpretation and implication of the results

Many SOC models have been used at a local and/or point scale (Schimel *et al*., 1994; Coleman *et al*., 1997; Li *et al*., 1997; Luo *et al*., 2011), despite the driving factors varying dramatically over the landscape (Knorr *et al*., 2005; Ogle *et al*., 2010). Consideration of the spatially explicit impact of environmental covariates is essential for quantifying the contribution of changes in agricultural management practices on SOC. Without considering these nuances, uniform agricultural management recommendations could lead to very different outcomes for SOC in different locations and environments. These results can be used to guide agricultural management practices toward effective carbon sequestration in agricultural soil which is sensitive to local environmental conditions. This can also help sustain agricultural production and provide an opportunity for the agricultural sector to contribute to carbon sequestration and climate change mitigation.

Initial SOC content was identified as the predominant environmental variable that negatively influenced SOC. Essentially, under otherwise similar environmental

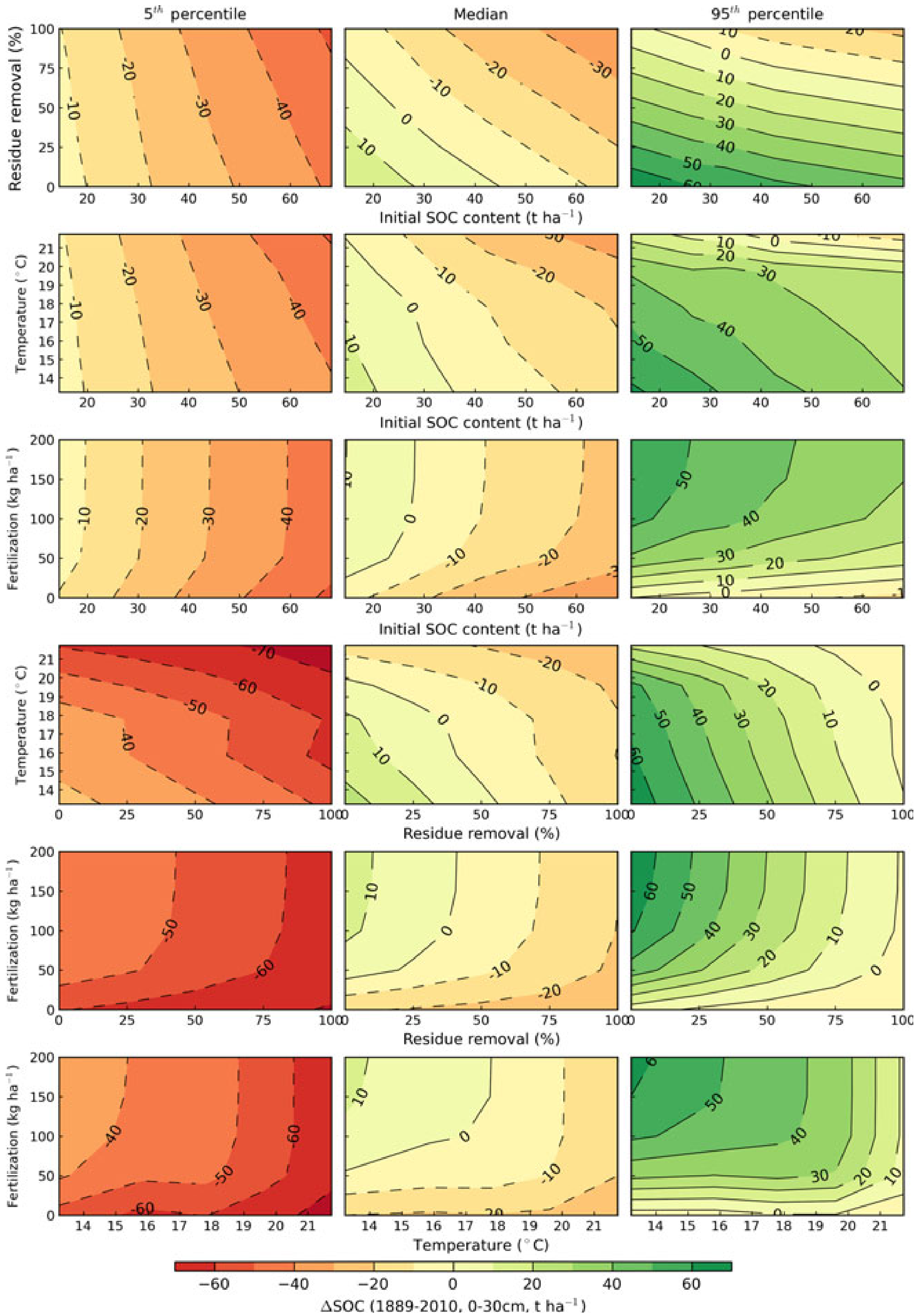

Fig. 4 ΔSOC (1889–2010, t ha^{-1}) resulting from interactions between the four most influential variables – initial soil organic carbon (SOC) content, residue removal, temperature, and fertilization.

conditions, soils with greater initial SOC displayed greater SOC loss in the early stages following cultivation, and vice versa. The negative correlation between ΔSOC and initial SOC content – the *baseline effect* – also has been documented in other studies (Bellamy *et al.*, 2005; Saby *et al.*, 2008; Goidts *et al.*, 2009).

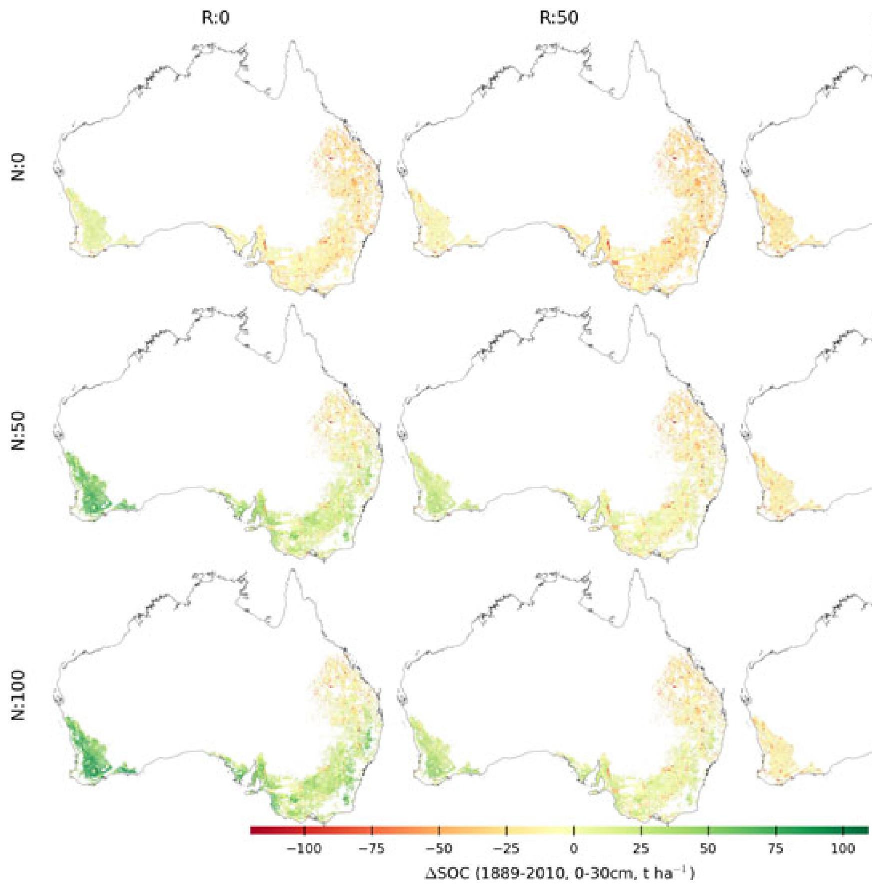

Fig. 5 Spatial pattern of the effects of nitrogen application (N) and residue removal (R) rates on ΔSOC (1889–2010, 0–30 cm, t ha^{-1}). The maps assume no residue incorporation (I:0).

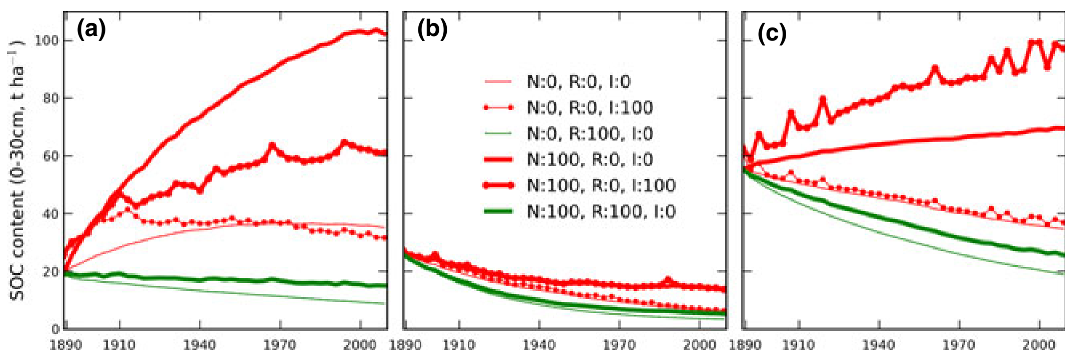

Fig. 6 Soil organic carbon (SOC) content evolution of three illustrative climate-soil (CS) units under two nitrogen application rates (N:0, N:100), two residue harvest rates (R:0, R:100), and two incorporation rates (I:0, I:100) over 122-year simulation from 1889 to 2010. To assist with interpretation – color indicates residue removal (red R:0, green R:100 or dark gray R:0, light gray R:100), line thickness indicates fertilization (thin N:0, thick N:100), dots indicate residue incorporation (no dots I:0, dots I:100). The location of these CS units can be found in Fig. 1.

Our finding that mean annual temperature and, to a lesser extent, mean annual rainfall were the next most influential environmental variables, and were negatively correlated with ΔSOC, is consistent with the findings of Meersmans *et al*. (2011) and the findings of Goidts *et al.* (2009) for croplands. In APSIM, high soil temperature and soil water content increase the decomposition rate of SOC which underpins the negative relationship of SOC sequestration with both temperature and rainfall (Keating *et al.*, 2003). However, high temperature and rainfall may increase the productivity of crop residue under specific soil types and agricultural management practices. This is in agreement with findings of Goidts *et al.* (2009) for SOC under grassland in Belgium over the past 50 years. Thus, the influence of temperature and rainfall on SOC depends on other factors such as soil and management practices (Giardina & Ryan, 2000). For Australia's cereal-growing regions, the negative effects of higher rainfall on SOC resulted in increased rates of decomposition, which overshadowed the positive effects of enhanced plant growth on SOC. The negative effect is significantly stronger where mean annual temperatures exceed 19 °C.

A related and increasingly relevant question that needs to be addressed is the effect of elevated CO_2 and climate change on SOC. The increased SOC decomposition rates induced by climatic warming and the degree to which it could be compensated for by increased higher NPP need to be assessed (Callesen *et al.*, 2003; Smith *et al.*, 2005; Yang *et al.*, 2009). Debate about the temperature sensitivity of SOC content is also ongoing (Giardina & Ryan, 2000; Fang *et al.*, 2005). As initial conclusions have been reached at different sites, temperature sensitivity could be obscured by other environmental factors (Davidson & Janssens, 2006). Effects of interactions between residue management and microbial activity on the permanence of SOC may also need greater consideration in modeling studies (Cheng *et al.*, 2012).

Residue removal was identified as the predominant agricultural management practice driving SOC. The negative linear effect of residue removal (Fig. 3) occurred because in APSIM a specific rate of residue removal relates to a specific proportion of the SOC pool that cannot be replenished. Removing 50% of crop residue from the system can seriously deplete the SOC pool for all CS units (Fig. 5). This negative effect should be considered a trade-off when assessing the potential benefits of crop-based bioenergy (Bryan *et al.*, 2010), especially second-generation biofuels (Lal, 2005). To sustain soil productivity, residue harvest should be considered only when the SOC content of a particular soil and cropping system can be maintained with management practices such as addition of organic amendments or fertilization (Gollany *et al.*, 2011).

Fertilization had a positive effect on SOC, especially within the range of 0–50 kg N ha^{-1}. As irrigation of cereal crops does not occur over most of the study area, water and soil fertility are generally the limiting factors in crop productivity (Hochman *et al.*, 2009). Positive effects of fertilization on SOC can result from enhanced net primary productivity and decreased decomposition rate, including aboveground biomass and underground roots. The effect from underground roots is evident in Fig. 6 where SOC content with 100 kg N ha^{-1} fertilization was higher than with no fertilization when all residue was removed. Ignoring the role of nitrogen in carbon cycling and carbon–nitrogen interactions could overestimate the negative effect of climatic warming on terrestrial carbon storage, or even lead to a wrong conclusion about the feedback between climate and the terrestrial carbon cycle (Bonan, 2008; Sokolov *et al.*, 2008). However, these processes only partially capture the impacts of fertilization on atmospheric greenhouse gas mitigation, as the benefit of fertilization on SOC sequestration can be offset by N_2O emissions from the soil and greenhouse gas emissions from fossil fuel combustion during fertilizer production, transport, and application (Knorr *et al.*, 2005). Future studies need to focus on adjusting the nitrogen application rates and timing according to environmental conditions to improve nitrogen use efficiency.

Although overall residue incorporation was weakly correlated with SOC, it had a clear impact on SOC in the illustrative areas assessed (Fig. 6). For these areas, residue incorporation had either positive (A early stage, C) or negative effects (A later stage, B) on SOC. One possible cause is the difference in the decomposition rate of surface and incorporated residue within APSIM as tillage results in a transfer of surface organic matter into the soil FOM pool at specific tillage depths.

Maps of ΔSOC illustrated that most of the study area could increase or maintain SOC content by retaining crop residues (i.e., R:0) and through fertilization of 50 kg N ha^{-1} (i.e., N:50). Higher fertilization rates (e.g., 100 kg N ha^{-1}) provided little further increase in SOC. The declining trend of SOC across much of Queensland reflected the higher temperature and, to a lesser extent, humid climate (Table 2, CS unit B). The negative impact of temperature and rainfall on SOC overshadowed the positive effects from fertilization in these areas (Fig. 5). These declining trends of SOC are consistent with the results of a long-term field experiment conducted in Queensland by Ranatunga *et al.* (2001). In high rainfall areas, high temperature promoted both production and decomposition, but the promotion of decomposition was greater (Jobbágy & Jackson, 2000). The SOC sequestration rates in CS unit A (WA) are likely to result from the low initial SOC content of the well-drained sandy soils (Kragt *et al.*, 2012), characteristic of the area in addition to the region's moderate temperature and rainfall (Henderson *et al.*, 1988). A rapid increase in measured and simulated SOC for a well-drained sandy soil with low initial SOC has been reported by Gollany *et al.* (2010).

Through the simulation of Australian wheat systems, we found that the management practices of residue removal and fertilization were strongly correlated with

SOC. The impact of fertilization occurred at low application rates, with fertilization rates above 50 kg N ha^{-1} having little additional benefit (Figs 3 and 4). We also found that the initial SOC content of the soil and mean annual temperature were strongly correlated with SOC. Little change in SOC was predicted for soils with high initial SOC content and a significant decrease in SOC was predicted for soils in climates with mean annual temperatures >19 °C. The impact of high temperatures (>19 °C) in increasing SOC decomposition negated the influence of all beneficial agricultural management practices (e.g., Queensland). The influence of these environmental variables indicated that the impact of agricultural management practices on SOC varied over the study area. In the cooler climates of southern Australia, the combined effects of fertilizer application (up to 50 kg N ha^{-1}) and retaining stubble residue (either incorporated into the soil or not) led to a substantial increase in SOC. These benefits were especially evident in areas of low initial SOC content such as south-west Western Australia. These simulated results can guide targeted agricultural management practices to increase SOC in croplands which can simultaneously enhance the sustainability of agricultural production and contribute to climate change mitigation.

Uncertainties and limitations

Uncertainties in the simulation results for this study were due to three main limitations: (i) the reliability of the soil data, especially the initial SOC data; (ii) model parameterization, and; (iii) a lack of validation of APSIM's SurfaceOM module. First, there is no consistent and comprehensive soil dataset for parameterizing APSIM across the entire study area. Interpolation techniques were implemented to fill data gaps for some input parameters. Furthermore, the initial SOC content data were sourced from ISRIC-WISE – a relatively low-resolution soil database. Further research into refining the initial SOC data for Australia is required to increase the reliability of this parameter which has a strong influence on ΔSOC. An initialization of SOC content for modeling, such as by simulating previous management history (Bruun & Jensen, 2002), may be viable in future studies where information about past management is available. Global sensitivity analysis (Song *et al.*, 2012) would also help quantify the uncertainty in SOC estimates derived from initial SOC content. Second, actual agricultural management practices such as cultivars used and sowing rules are not known precisely over the study area (Goidts & Van Wesemael, 2007). Here, we specified these based on best practice guidelines from agricultural extension handbooks. Misspecified sowing rules would increase uncertainty in biomass production and SOC replenishment. Also, actual farming systems involve rotations such that cereal cropping is interspersed with break crops and fallow periods (Bryan *et al.*, 2011a). The continuous wheat cropping system simulated here does not consider the effects of farming system rotations which can influence nutrient and water carryover from 1 year to the next. Third, although the main SOC module in SoilN has been well validated, the SurfaceOM module has not been individually validated as done for other modules. This leads to uncertainty in the impact of residue incorporation on SOC. For example, Luo *et al.* (2011) reported that APSIM could not predict the decomposition rate of SOC after tillage due to its simplification in simulating the effect of tillage on soil properties such as water, porosity, and aeration. Further efforts are needed to validate the SurfaceOM module against observational data. This will enable a better understanding of the influence of the incorporation of residue on SOC.

Acknowledgments

This work was jointly supported by the National Basic Research Program of China (2012CB955304), the National Science Foundation of China (31270588), CSIRO Integrated Carbon Pathways (ICP) initiative, CSIRO's Sustainable Agriculture Flagship, and the Chinese Scholarship Council. We thank David Jacquier of CSIRO Land and Water, Canberra for providing soil texture data. We appreciate the constructive comments from three anonymous reviewers.

References

ABARE (2010) *Catchment Scale Land Use Mapping for Australia*. Bureau of Rural Sciences, Canberra.

ABARE-BRS(2003) *Australian Farm Survey Report*. Australian Bureau of Agriculture and Resource Economics, Canberra.

ABS (2010) *Land management and farming in Australia, 2009-10*. Australian Bureau of Statistics, Canberra.

Alston JM, Beddow JM, Pardey PG (2009) Agricultural research, productivity, and food prices in the long run. *Science*, **325**, 1209–1210.

Batjes NH (1996) Total carbon and nitrogen in the soils of the world. *European Journal of Soil Science*, **47**, 151–163.

Batjes NH (2006) ISRIC-WISE derived soil properties on a 5 by 5 arc-minutes global grid. Report 2006/ISRIC–World Soil Information.

Bellamy PH, Loveland PJ, Bradley RI, Lark RM, Kirk GJD (2005) Carbon losses from all soils across England and Wales 1978–2003. *Nature*, **437**, 245–248.

Bonan G (2008) Carbon cycle: fertilizing change. *Nature Geoscience*, **1**, 645–646.

Bruun S, Jensen LS (2002) Initialisation of the soil organic matter pools of the Daisy model. *Ecological Modelling*, **153**, 291–295.

Bryan BA (2003) Physical environmental modeling, visualization and query for supporting landscape planning decisions. *Landscape and Urban Planning*, **65**, 237–259.

Bryan BA, King D, Wang E (2010) Biofuels agriculture: landscape-scale trade-offs between fuel, economics, carbon, energy, food, and fiber. *GCB Bioenergy*, **2**, 330–345.

Bryan BA, King D, Ward JR (2011a) Modelling and mapping agricultural opportunity costs to guide landscape planning for natural resource management. *Ecological Indicators*, **11**, 199–208.

Bryan BA, Raymond CM, Crossman ND, King D (2011b) Comparing spatially explicit ecological and social values for natural areas to identify effective conservation strategies. *Conservation Biology*, **25**, 172–181.

Cai Z, Xing G, Yan X, Xu H, Tsuruta H, Yagi K, Minami K (1997) Methane and nitrous oxide emissions from rice paddy fields as affected by nitrogen fertilisers and water management. *Plant and Soil*, **196**, 7–14.

Callesen I, Liski J, Raulund-Rasmussen K, Olsson MT, Tau-Strand L, Vesterdal L, Westman CJ (2003) Soil carbon stores in Nordic well-drained forest soils—relationships with climate and texture class. *Global Change Biology*, **9**, 358–370.

Chan KY, Heenan DP (2005) The effects of stubble burning and tillage on soil carbon sequestration and crop productivity in southeastern Australia. *Soil Use and Management*, **21**, 427–431.

Cheng L, Booker FL, Tu C *et al.* (2012) Arbuscular mycorrhizal fungi increase organic carbon decomposition under elevated CO_2. *Science*, **337**, 1084–1087.

Ciais P, Gervois S, Vuichard N, Piao SL, Viovy N (2011) Effects of land use change and management on the European cropland carbon balance. *Global Change Biology*, **17**, 320–338.

Coleman K, Jenkinson DS, Crocker GJ *et al.* (1997) Simulating trends in soil organic carbon in long-term experiments using RothC-26.3. *Geoderma*, **81**, 29–44.

Dalgliesh N, Wockner G, Peake A (2006) Delivering soil water information to growers and consultants. *Proceedings of the 13th Australian Agronomy Conference*, pp. 10–14, September 2006, Perth, Western Australia, Australian Society of Agronomy. Available at: http://www.regional.org.au/au/asa/2006/poster/water/4552_dalglieshn.html (accessed 4 February 2013).

Dalias P, Anderson JM, Bottner P, Coûteaux MM (2001) Long-term effects of temperature on carbon mineralisation processes. *Soil biology and Biochemistry*, **33**, 1049–1057.

Davidson EA, Janssens IA (2006) Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. *Nature*, **440**, 165–173.

De Gryze S, Lee J, Ogle S, Paustian K, Six J (2011) Assessing the potential for greenhouse gas mitigation in intensively managed annual cropping systems at the regional scale. *Agriculture, Ecosystems & Environment*, **144**, 150–158.

Deen W, Kataki PK (2003) Carbon sequestration in a long-term conventional versus conservation tillage experiment. *Soil and Tillage Research*, **74**, 143–150.

D'emden FH, Llewellyn RS, Burton MP (2008) Factors influencing adoption of conservation tillage in Australian cropping regions. *Australian Journal of Agricultural and Resource Economics*, **52**, 169–182.

Dolan MS, Clapp CE, Allmaras RR, Baker JM, Molina JaE (2006) Soil organic carbon and nitrogen in a Minnesota soil as related to tillage, residue and nitrogen management. *Soil and Tillage Research*, **89**, 221–231.

Falloon P, Jones CD, Cerri CE *et al.* (2007) Climate change and its impact on soil and vegetation carbon storage in Kenya, Jordan, India and Brazil. *Agriculture, Ecosystems & Environment*, **122**, 114–124.

Fang C, Smith P, Moncrieff JB, Smith JU (2005) Similar response of labile and resistant soil organic matter pools to changes in temperature. *Nature*, **433**, 57–59.

Gervois S, Ciais P, De Noblet-Ducoudré N, Brisson N, Vuichard N, Viovy N (2008) Carbon and water balance of European croplands throughout the 20th century. *Global Biogeochemical Cycles*, **22**, 13–19.

Giardina CP, Ryan MG (2000) Evidence that decomposition rates of organic carbon in mineral soil do not vary with temperature. *Nature*, **404**, 858–861.

Goidts E, Van Wesemael B (2007) Regional assessment of soil organic carbon changes under agriculture in Southern Belgium (1955–2005). *Geoderma*, **141**, 341–354.

Goidts E, Wesemael BaSV, Van Oost K (2009) Driving forces of soil organic carbon evolution at the landscape and regional scale using data from a stratified soil monitoring. *Global Change Biology*, **15**, 2981–3000.

Gollany HT, Novak JM, Liang Y *et al.* (2010) Simulating soil organic carbon dynamics with residue removal using the CQESTR. *Soil Science Society of America Journal*, **74**, 372–383.

Gollany H, Rickman R, Machado S, Albrecht S, Liang Y, Kang S (2011) Predicting agricultural management influence on long-term soil organic carbon dynamics: implications for biofuel production. *Agronomy Journal*, **103**, 234–246.

Goodchild M (1986) *Spatial Autocorrelation*. Geo Books, Norwich.

Hartigan JA, Wong MA (1979) A k-means clustering algorithm. *Applied statistics*, **28**, 100–108.

Henderson C, Levett A, Lisle D (1988) The effects of soil water content and bulk density on the compactibility and soil penetration resistance of some Western Australian sandy soils. *Soil Research*, **26**, 391–400.

Hochman Z, Holzworth D, Hunt JR (2009) Potential to improve on-farm wheat yield and WUE in Australia. *Crop and Pasture Science*, **60**, 708–716.

Huth NI, Thorburn PJ, Radford BJ, Thornton CM (2010) Impacts of fertilisers and legumes on N_2O and CO_2 emissions from soils in subtropical agricultural systems: a simulation study. *Agriculture, Ecosystems & Environment*, **136**, 351–357.

Izaurralde RC, Williams JR, Mcgill WB, Rosenberg NJ, Jakas MCQ (2006) Simulating soil C dynamics with EPIC: model description and testing against long-term data. *Ecological Modelling*, **192**, 362–384.

Jeffrey SJ, Carter JO, Moodie KB, Beswick AR (2001) Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environmental Modelling & Software*, **16**, 309–330.

Jobbágy EG, Jackson RB (2000) The vertical distribution of soil organic carbon and its relation to climate and vegetation. *Ecological applications*, **10**, 423–436.

Jones C, Mcconnell C, Coleman K, Cox P, Falloon P, Jenkinson D, Powlson D (2005) Global climate change and soil carbon stocks; predictions from two contrasting models for the turnover of organic carbon in soil. *Global Change Biology*, **11**, 154–166.

Kätterer T, Reichstein M, Andrén O, Lomander A (1998) Temperature dependence of organic matter decomposition: a critical review using literature data analyzed with different models. *Biology and Fertility of Soils*, **27**, 258–262.

Keating BA, Carberry PS, Hammer GL *et al.* (2003) An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy*, **18**, 267–288.

Knorr W, Prentice IC, House JI, Holland EA (2005) Long-term sensitivity of soil carbon turnover to warming. *Nature*, **433**, 298–301.

Kragt ME, Pannell DJ, Robertson MJ, Thamo T (2012) Assessing costs of soil carbon sequestration by crop-livestock farmers in Western Australia. *Agricultural Systems*, **112**, 27–37.

Lal R (1999) Soil management and restoration for C sequestration to mitigate the accelerated greenhouse effect. *Progress in Environmental Science*, **1**, 307–326.

Lal R (2004) Soil carbon sequestration impacts on global climate change and food security. *Science*, **304**, 1623–1627.

Lal R (2005) World crop residues production and implications of its use as a biofuel. *Environment International*, **31**, 575–584.

Lehmann EL, D'abrera HJM (2006) *Nonparametrics: Statistical Methods Based on Ranks*. Springer, New York.

Li C, Frolking S, Crocker GJ, Grace PR, Klír J, Körchens M, Poulton PR (1997) Simulating trends in soil organic carbon in long-term experiments using the DNDC model. *Geoderma*, **81**, 45–60.

Linacre ET (1977) A simple formula for estimating evaporation rates in various climates, using temperature data alone. *Agricultural meteorology*, **18**, 409–424.

Luo Z, Wang E, Sun OJ (2010) Soil carbon change and its responses to agricultural practices in Australian agro-ecosystems: a review and synthesis. *Geoderma*, **155**, 211–223.

Luo Z, Wang E, Sun OJ, Smith CJ, Probert ME (2011) Modeling long-term soil carbon dynamics and sequestration potential in semi-arid agro-ecosystems. *Agricultural and Forest Meteorology*, **151**, 1529–1544.

Mckenzie N, Jacquier D, Maschmedt D, Griffin E, Brough D (2005) Australian Soil Resource Information System (ASRIS): Technical Specifications–Version 1.5. 67–68.

Meersmans J, De Ridder F, Canters F, De Baets S, Van Molle M (2008) A multiple regression approach to assess the spatial distribution of soil organic carbon (SOC) at the regional scale (Flanders, Belgium). *Geoderma*, **143**, 1–13.

Meersmans J, Van Wesemael B, Goidts E, Van Molle M, De Baets S, De Ridder F (2011) Spatial analysis of soil organic carbon evolution in Belgian croplands and grasslands, 1960–2006. *Global Change Biology*, **17**, 466–479.

Micheni A, Kihanda F, Warren G, Probert M (2004) Testing the APSIM model with experimental data from the long-term manure experiment at Machang's (Embu), Kenya. In: *Modeling Nutrient Management in Tropical Cropping Systems*, Vol 114 (eds Delve RJ, Probert ME), pp. 110–117. Australian Centre for International Agricultural Research, Canberra, Australia.

Oechel WC, Vourlitis GL, Hastings SJ, Zulueta RC, Hinzman L, Kane D (2000) Acclimation of ecosystem CO_2 exchange in the Alaskan Arctic in response to decadal climate warming. *Nature*, **406**, 978–981.

Ogle SM, Breidt F, Easter M, Willianms S, Killian K, Paustian K (2010) Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. *Global Change Biology*, **16**, 810–822.

Peterjohn WT, Melillo JM, Steudler PA, Newkirk KM, Bowles FP, Aber JD (1994) Responses of trace gas fluxes and N availability to experimentally elevated soil temperatures. *Ecological applications*, **4**, 617–625.

Post WM, Emanuel WR, Zinke PJ, Stangenberger AG (1982) Soil carbon pools and world life zones. *Nature*, **298**, 156–159.

Probert ME, Delve RJ, Kimani SK, Dimes JP (2005) Modelling nitrogen mineralization from manures: representing quality aspects by varying C:N ratio of sub-pools. *Soil biology and Biochemistry*, **37**, 279–287.

Ranatunga K, Hill M, Probert M, Dalal R (2001) Comparative application of APSIM, RothC and Century to predict soil carbon dynamics. *MODSIM 2001: International Congress on Modelling and Simulation Modelling and Simulation Society of Australia and New Zealand Inc*, **2**, 733–738.

Saby NPA, Arrouays D, Antoni V, Lemercier B, Follain S, Walter C, Schvartz C (2008) Changes in soil organic carbon in a mountainous French region, 1990–2004. *Soil Use and Management*, **24**, 254–262.

Schimel DS, Braswell B, Holland EA *et al*. (1994) Climatic, edaphic, and biotic controls over storage and turnover of carbon in soils. *Global Biogeochemical Cycles*, **8**, 279–293.

Smith P, Smith JU, Powlson DS *et al*. (1997) A comparison of the performance of nine soil organic matter models using datasets from seven long-term experiments. *Geoderma*, **81**, 153–225.

Smith JO, Smith P, Wattenbach M *et al*. (2005) Projected changes in mineral soil carbon of European croplands and grasslands, 1990–2080. *Global Change Biology*, **11**, 2141–2152.

Smith JO, Smith P, Wattenbach M *et al*. (2007) Projected changes in the organic carbon stocks of cropland mineral soils of European Russia and the Ukraine, 1990–2070. *Global Change Biology*, **13**, 342–356.

Sokolov AP, Kicklighter DW, Melillo JM, Felzer BS, Schlosser CA, Cronin TW (2008) Consequences of considering carbon–nitrogen interactions on the feedbacks between climate and the terrestrial carbon cycle. *Journal of Climate*, **21**, 3776–3796.

Song X, Bryan BA, Paul KI, Zhao G (2012) Variance-based sensitivity analysis of a forest growth model. *Ecological Modelling*, **247**, 135–143.

The World Bank (2012) *World Development Indicators*. The World Bank, Washington, DC.

Thomson AM, Izaurralde RC, Rosenberg NJ, He X (2006) Climate change impacts on agriculture and soil carbon sequestration potential in the Huang-Hai Plain of China. *Agriculture, Ecosystems & Environment*, **114**, 195–209.

Trumbore SE, Chadwick OA, Amundson R (1996) Rapid exchange between soil carbon and atmospheric carbon dioxide driven by temperature change. *Science*, **272**, 393–396.

Van Antwerpen R, Thorburn P, Horan H, Meyer J, Bezuidenhout C (2002) The impact of trashing on soil carbon and nitrogen: ii: implications for sugarcane production in South Africa. *Proceedings of the South African Sugar Technologists' Association*, **76**, 269–280.

Van Wesemael B, Paustian K, Meersmans J, Goidts E, Barancikova G, Easter M (2010) Agricultural management explains historic changes in regional soil carbon stocks. *Proceedings of the National Academy of Sciences*, **107**, 14926–14930.

West TO, Post WM (2002) Soil organic carbon sequestration rates by tillage and crop rotation. *Soil Science Society of America Journal*, **66**, 1930–1946.

Yang Y, Fang J, Smith P *et al*. (2009) Changes in topsoil carbon stock in the Tibetan grasslands between the 1980s and 2004. *Global Change Biology*, **15**, 2723–2729.

Zhao G, Bryan BA, King D, Song X, Yu Q (2012) Parallelization and optimization of spatial analysis for large scale environmental model data assembly. *Computers and Electronics in Agriculture*, **89**, 94–99.

Zhao G, Bryan BA, King D *et al*. (2013) Large-scale, high-resolution agricultural systems modeling using a hybrid approach combining grid computing and parallel processing. *Environmental Modelling & Software*, **41**, 231–238.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Spatial distribution of APSRU soil reference sites (APSoil).
Figure S2. The range and density of fertilization rate in Australian croplands. The dataset was obtained from Australian Agricultural and Grazing Industries Survey (AAGIS). The surveys were conducted by Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) based on the ABARES zones. The total records of this dataset were 849.
Figure S3. Semivariograms of annual mean temperature according to the centroid of the CS units.
Figure S4. Semivariograms of annual mean rainfall according to the centroid of the CS units.
Figure S5. Semivariograms of pH according to the centroid of the CS units.
Figure S6. Semivariograms of soil water-holding capacity according to the centroid of the CS units.