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Mapping future soil carbon change and its uncertainty in croplands using simple surrogates of a complex farming system model

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ABSTRACT

Soil organic carbon (SOC) in agricultural soils is vital for soil fertility for sustainable agricultural production and climate change resilience. Process-based farming system models are widely used to predict SOC dynamics in agricultural soils, but their application at regional scales is largely limited by computational requirements, data availability, and uncertainties in model predictions. Here we present an approach of combining a farming system model and a simplified surrogate model that emulates and mimics the behaviour of complex process-based models to predict SOC change (ΔSOC) and its uncertainty in Australian dryland cropping regions under anticipated climate change. We first calibrated and validated the farming system model APSIM for simulating ΔSOC (0–30 cm soil) using data from 90 farming-system trials at 28 sites across the study regions. Next we conducted a comprehensive simulation across the region using the validated APSIM model to predict ΔSOC over the period 2009–2070. Then simple surrogate models were developed based on the APSIM outputs. The surrogate models were able to explain > 96% of the variation in APSIM-predicted ΔSOC. Last the surrogate models were applied across the regions at the resolution of 1 km. In our simulations, Australian dryland cropping soils under farmers' common management practices and future climate conditions were a net carbon source (0.66 Mg C ha^{-1} with the 95% confidence interval ranging from −5.79 to 8.38 Mg C ha^{-1}) during the 62-year period. Across the regions, simulated ΔSOC exhibited great spatial variability ranging from −108.8 to 9.89 Mg C ha^{-1} at the resolution of 1 km, showing significant ($P < 0.05$) negative correlation with baseline SOC level, temperature and rainfall, and positive correlation with pasture frequency (the duration of pasture in the rotation divided by the whole duration of the rotation) and nitrogen application rate. The uncertainty in ΔSOC and the underlying drivers were also assessed. This study presented a novel approach to efficiently predict future SOC dynamics and their uncertainty at fine resolutions, facilitating the development of site-specific management strategies for soil carbon sequestration.

1. Introduction

Conservation of soil organic carbon (SOC) in agricultural soils is vital for sustainable agricultural production and mitigating climate change (Bradford et al., 2016; Kahiluoto et al., 2014; Lal, 2004). SOC usually declines after land use change to cropping (Sanderman et al., 2017) until a lower steady state is reached. Synthesising global data sets, Guo and Gifford (2002) estimated the decline in SOC to be in the order of 42–59% when natural systems were converted to cropland. Similarly, Luo et al. (2010) estimated that Australian cropping soils

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have lost 50–60% of the initial SOC stocks in top 30 cm that were present before land clearing. However, detailed SOC dynamics in different regions depend on agricultural management practices, and vary with soil and climate conditions. Conservation agriculture practices such as stubble retention, no-tillage, organic amendments, avoidance of long fallow periods, and increased crop rotation complexity (e.g., the introduction of legumes and cover crops) have been recommended to reduce SOC declines or to enhance carbon sequestration (Gan et al., 2014; Luo et al., 2010; Smith, 2016; West and Post, 2002). More recently, the international initiative "4 per 1000" aims at a yearly 4‰ increase of SOC in global agricultural soils to ensure food security and mitigate climate change (Minasny et al., 2017). However, this ambitious target has been challenged by the soil carbon research community because of uncertainties surrounding carbon predictions across spatio-temporal scales and resource requirements such as financial support for farmers to change agricultural practices to sequester carbon (Baveye et al., 2018; Vandenbygaart, 2018; White et al., 2018). It is vital to elucidate SOC dynamics across space and time under various cropping systems and management practices, particularly under climate change, to enable a realistic assessment of the likelihood of being able to improve SOC stocks (or minimise losses).

Numerous experimental studies have been conducted to assess the response of SOC to various agricultural management practices, and it has been widely accepted that practices that increase organic matter input into the soil can reduce SOC losses or sequester more carbon (Freibauer et al., 2004; Luo et al., 2010; West and Post, 2002). In addition, the quality of organic matter inputs, local climate and soil conditions may regulate the trend of SOC change after adopting those practices due to their effects on SOC losses via microbial decomposition (Kong et al., 2005; Luo et al., 2017a). Nevertheless, manipulated field experiments can only consider limited variations in crop rotations and associated management practices such as residue removal and fertilizer application, making it difficult to extrapolate experimental findings to field conditions across a number of regions with different soils and climate. In Australia's grain-cropping regions, for example, farmers' choices of crop rotations and management practices depend on local climate, soil and market conditions, resulting in diverse cropping systems. To account for > 99% of the cropped area in Australia, it has been suggested that 22 crops should be included in the national carbon accounting system (Unkovich et al., 2009). Considering the many possible crop sequences and their varying impact on SOC, it is impractical, if not impossible, to use field experiments to investigate the SOC dynamics influenced by this large number of crop species grown under different rotations and management across regions that contain a range of soils and climates. A modelling approach is best suited for such purposes.

Agricultural system models with well-tested crop and soil modules enable the investigation of the impact of alternative management scenarios, climate variability and future climate change on the productivity of agricultural systems and SOC dynamics. A large number of studies have used such strengths of agricultural system models to simulate SOC dynamics under various conditions in terms of soil, climate and agricultural management (Kucharik et al., 2001; Liu et al., 2009; Luo et al., 2011; Qiu et al., 2009). In general, modelling results suggest that carbon inputs are the predominant factor influencing the SOC balance in agricultural soils (Wang et al., 2016; Zhao et al., 2013). However, most modelling studies have focused on the verification of models for simulating SOC dynamics under specific cropping systems (including rotations) at the plot scale. When applying the model to larger spatial scales, model predictions may suffer from large uncertainties induced by model structure, parameter equifinality, and limited data availability for model initialization/parameterization (Luo et al., 2015; Ogle et al., 2010b; Saby et al., 2008). Thus, extending plot-scale modelling to analyse SOC dynamics over space and time relies not only on the availability of information required for the modelling, but also on the capability of the models to simulate the growth of various crops and their interaction with management practices, and SOC decomposition processes across environments.

In this study, we combined the Agricultural Production Systems sIMulator (APSIM) (Holzworth et al., 2014) and surrogate modelling to predict future SOC dynamics over 62 years in Australian dryland cropping regions. The APSIM model allows flexible specification of management options such as crop and rotation type, tillage, residue management, and fertilizer application, and has the capacity to simulate the interaction of crop growth and soil processes with soil, climate and management practices. In the present study, the APSIM model was first constrained for simulating SOC dynamics using observational data sets collected from the major dryland cropping regions across Australia. Then the constrained model was applied to simulate SOC dynamics during the period 2009–2070 under farmers' current common management practices (i.e., business-as-usual) at 1869 sites across the study region. The uncertainty in model predictions was also assessed. Based on the APSIM simulation results, we developed surrogate models of the APSIM model to predict the spatial pattern of SOC change across large regions at fine resolution. Surrogate modelling derives simple relationships driven by easily obtainable information to mimic results of complex process-based models (Luo et al., 2013; Marie and Simioni, 2014). Surrogate models have the advantage of requiring much less information than complex models like APSIM, facilitating the application of the model across large spatial scales in terms of both lower computational cost and data requirements. Specifically, the objectives of the study were to: 1) predict SOC dynamics from 2009 to 2070 under various management practices under future climate change conditions using the constrained APSIM model; 2) quantify whether and how future SOC changes correlate to local soil and climate conditions and management practices; and 3) present and assess a surrogate modelling approach to represent the complex APSIM model, and 4) implement the surrogate model to assess the spatial pattern of SOC change in Australia's cereal-growing regions at 1 km resolution.

2. Materials and methods

2.1. Study region and representative cropping systems

This study focuses on Australian rainfed cropping areas identified from the map of Land Use of Australia 2010–11 at the resolution of 1 × 1 km (Fig. 1). This cropping area includes a total of ~260,000 grid cells (1 × 1 km), accounts for ~3% of the total area of Australia, and is spread across 23 different Agro-Ecological Regions (AERs) (Williams et al., 2002) (Fig. 1), and cover a wide range of climatic and soil conditions. Specifically, the annual average temperature across the region ranges from 6.5 to 28.2 °C, precipitation from 124.7 to 4291.0 mm, and SOC in the top 0.3 m soil from 11.8 to 264.1 Mg C ha^{-1}. For each AER with cropping, a crop rotation (Table S1) was derived based on data from Australian Bureau of Statistics for the period from 2010 to 11 to 2014–15. Along with the crop rotations, the relevant fertilizer use and crop residue management were calculated using the Yield and Nitrogen Calculator (Baldock, 2012) and from the Australian crop and pasture management database (Unkovich & Baldock 2017, unpublished data), respectively. In brief, these crop rotations and the relevant management represent current common agricultural management in each AER. The details on compiling this information are provided in Supplementary Material and Methods S1.

2.2. Soil and climate data

Soil data (0–2 m) was obtained from the database of the Soil and Landscape Grid of Australia (SLGA, http://www.clw.csiro.au/aclep/soillandscapegrid/). The SLGA is derived based on digital soil mapping methods and integrates historical soil data, new measurements with spectroscopic sensors, and novel spatial modelling (Grundy et al., 2015). The SLGA provides detailed soil attributes at the