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Integrating and using soil carbon stocks information from point to continental scale

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Introduction

Interest in quantifying and monitoring the content and stock of organic carbon in soil arises from the beneficial contributions it makes to the productivity, resilience and sustainability of the soil resource (Murphy, 2015; Hoyle *et al.*, 2011; Baldock and Skjemstad, 1999) and because increases in the stock of soil organic carbon can mitigate emissions of greenhouse gases (Baldock *et al.*, 2012). Land use and land use change may induce a sequestration or emission of carbon depending on the balance between carbon additions (C_A) derived from plant growth or the addition of organic amendments and losses associated with the mineralisation of organic materials during decomposition (C_M) or material transfers associated with erosion (C_E) or leaching (C_L) as delineated by Baldock (2007) (Equation [1]). Initiating agricultural production has typically, but not always, resulted in net losses of soil organic carbon accounting for between 20-70% of the carbon stocks originally present (Luo *et al.*, 2010; Lal, 2004). However, the introduction of soil carbon friendly management strategies including soil conservation programs, reduced tillage, residue retention and increased productivity have resulted in reductions in the magnitude of soil carbon loss (avoided emissions) or increases in carbon stock (sequestration) (Hutchinson *et al.*, 2007; Sanderman *et al.*, 2010).

$$\Delta SOC = C_A - C_M - C_E - C_L \qquad [1]$$

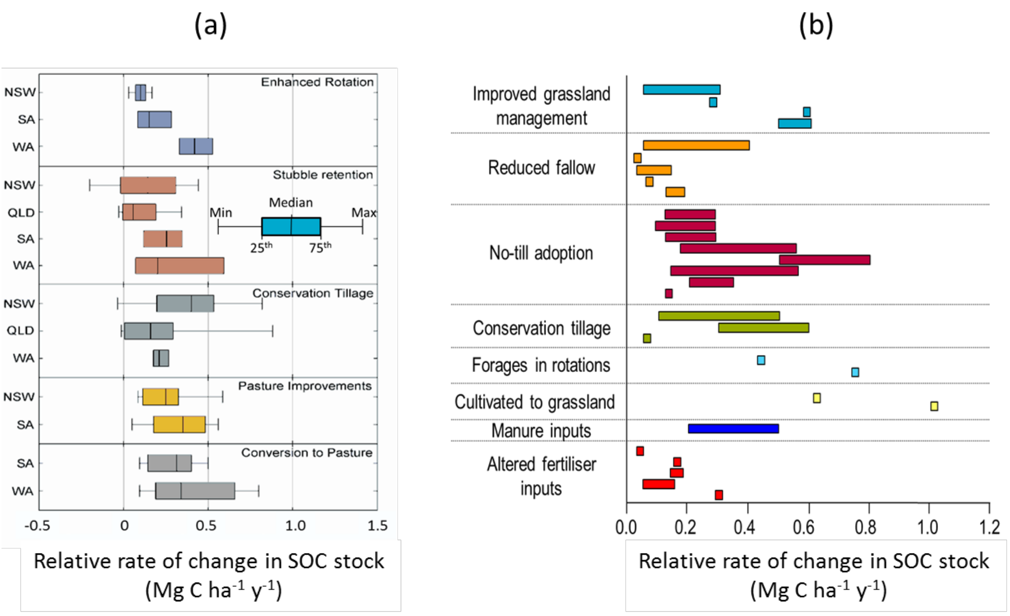

Figure 1. Relative changes in the rate of soil carbon stock change induced by the adoption of carbon friendly management strategies: (a) for Australia (Sanderman *et al.*, 2010) and (b) internationally (Hutchinson *et al.*, 2007) Note that in almost all cases the data presented in these two reviews represent the difference between invoking or not invoking the carbon friendly management practice at a single point in time. Thus the rates of soil carbon stock change are relative and could result from an avoided emission, sequestration or a combination of both.

Soil information that informs carbon management and tracks the carbon stock and change has challenged traditional soil information systems. In this paper, we examine the experience in Australia in integrating information approaches from the point observation to continental estimations and highlight the combined role of measurement, modelling and estimation and monitoring systems. Here we propose that a comprehensive system has components that interlink to provide complete information support for soil carbon management. The components are:

- Sampling and measurement at soil sampling sites chosen to represent environmental and management variability and that allows repeat analysis (the point of truth);
- Modelling of the soil-plant-management system to predict change in soil carbon stocks over time;
- Spatial interpolation of site data (with relevant environmental covariates) to produce the 'baseline' maps of soil carbon stocks;
- Spatial interpolation of soil site data of relevance to soil carbon prediction (with relevant environmental covariates) to produce a soil functions map;
- Integration of the soil maps with modelling to allow prediction and exploration between observation sites and over time; and
- Integration of remote and proximal sensing to allow key dynamics of the production system to be modelled and management systems refined.

It is important to also note that the creation of such a comprehensive information system for soil carbon will have multiple additional uses including predictions of agricultural production outcomes that can then lead on to provide important economic information at scales ranging from individual farm businesses through to continents.

Point source soil carbon data

The point of truth (in space and time) of soil carbon stocks is obtained from individual soil measurements obtained from samples extracted from cores or soil pits (sensing approaches show promise but are not yet operational and will inevitably be calibrated back against measured stocks). Calculating the stock of organic carbon at a soil sampling site requires measurement of the following soil properties according to Equation [2]:

- organic carbon content of air dried <2mm sieved soil ($C_{org, AD}$; g OC/kg air dry <2mm soil),
- gravimetric water content of air dried <2mm sieved soil ($\theta_{m, AD}$; kg air dry <2mm soil/kg oven dry <2mm soil),
- dry soil bulk density (BD; Mg OD soil/m^3 soil),
- thickness of the soil layer sampled (T; cm), and
- gravimetric proportion of soil mass present as >2mm gravel (P_{grav}) to calculate the proportion of soil <2mm (1-P_{grav}, kg oven dry <2mm/kg oven dry soil).

A conversion factor of 0.10 allows expression of the value of organic carbon stock in Mg C/ha.

$$OC_{stock} = OC_{org,AD} \times \left(1 + \theta_{m,AD}\right) \times BD \times T \times \left(1 - P_{grav}\right) \times 0.10 \qquad [2]$$

On examination of the Australian National Soils Database in 2012, of the 55,342 soil samples included, only 12,418 (22%) had measured values for organic carbon contents. When the data requirement was extended to include all parameters identified in Equation [2], only 1045 (2%) had the required values and of those a significant proportion were from unmanaged systems or from agricultural systems prior to the year 2000. In response, the

Australian government established a Soil Carbon Research Program (SCaRP) within its Climate Change Research Program to quantify soil carbon stocks within Australia's managed agricultural lands. The program collected and analysed over 4,500 agricultural soil profiles (Modelling soil carbon change

Within the soil component of Australia's National Greenhouse Gas Inventory (NGGI) soil carbon stock change is estimated within the FullCAM modelling framework (Richards, 2001), using an approach based on the RothC soil carbon simulation model (Jenkinson, 1990; Jenkinson *et al.*, 1987). The NGGI modelling framework differs from the original RothC approach in that the original conceptual pools of soil carbon were replaced by a series of measureable fractions of soil organic carbon referred to as particulate, humus and resistant organic carbon (POC, HOC and ROC, respectively) and the decomposition rate constants were adjusted where required to account for this substitution (Skjemstad *et al.*, 2004) (Figure 3).

In the SCaRP, the fractionation protocol developed by Skjemstad *et al.* (2004) was varied to account for the presence of resistant organic carbon within coarse soil particles (Baldock *et al.*, 2013b) (**Error! Reference source not found.**) and then applied to 312 soils. The fractionation process is both time consuming and requires non-routine specialised equipment (e.g. a solid-state ^{13}C nuclear magnetic resonance spectrometer). To facilitate extension and possible use of the fractions within the agricultural industry, the potential to predict allocations of soil carbon to its component fractions by mid-infrared spectroscopic analysis was developed. Reasonable estimates of the contents of each soil carbon fraction could be obtained from one mid-infrared analysis (Baldock *et al.*, 2013a).

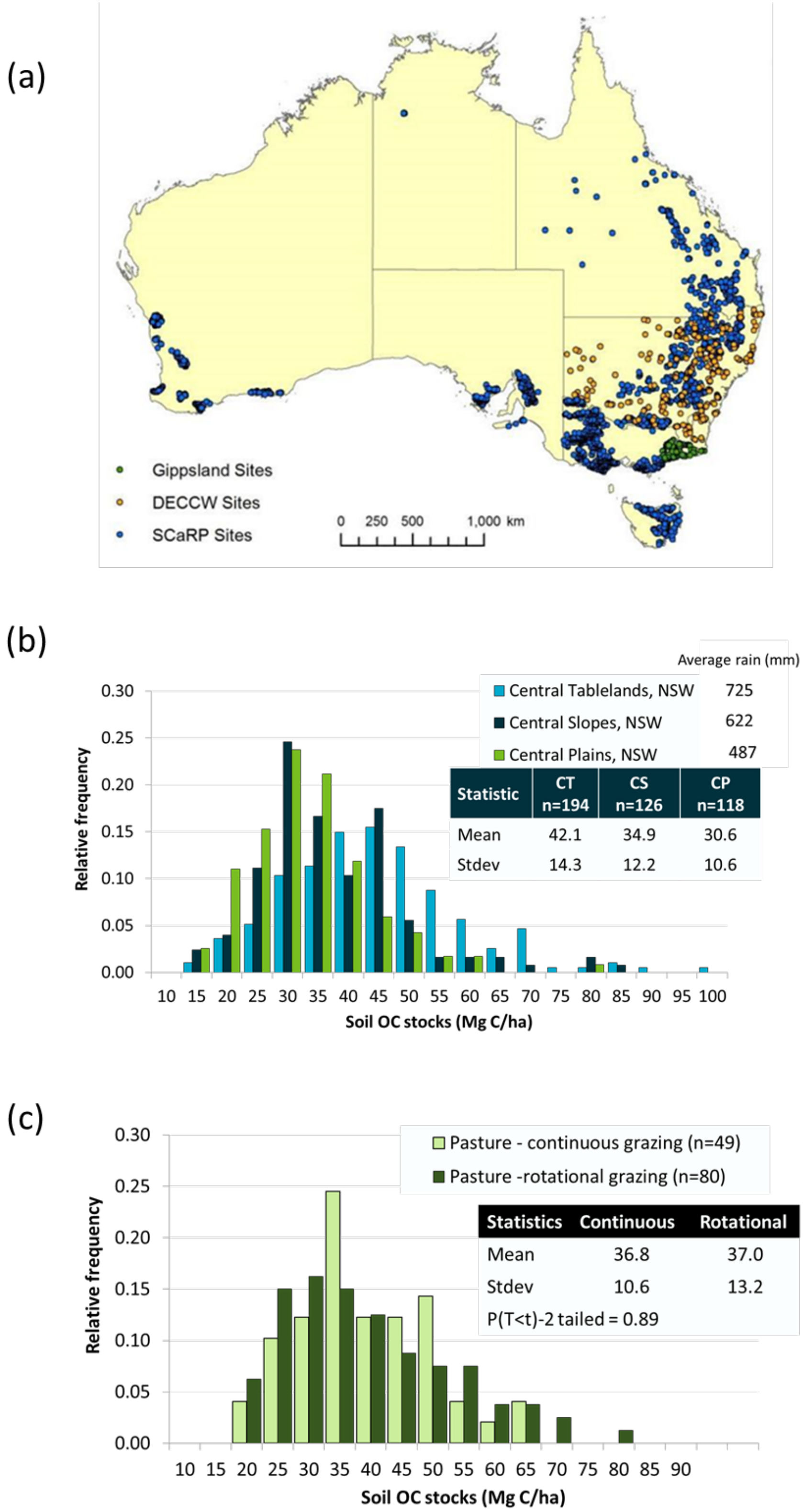

Figure 2a) to a depth of 30cm and calculated the 0-30 cm soil carbon stocks using measured values for all parameters in Equation [2] (Baldock *et al.*, 2013a).

The collection of the SCaRP dataset has established baseline values for soil organic carbon stocks across much of Australia's intensive agricultural zone, at each of the sites sampled and at the time sampled. Second and subsequent sampling is needed begin quantifying changes in soil carbon stocks. However, the distribution of soil organic carbon stocks within regions experiencing variations in environmental conditions (e.g. average annual rainfall, Figure 2b), as well as those between management practices within regions (e.g. grazing strategy applied to pastures, Figure 2c) can provide useful information. Although a wide range of soil organic carbon stocks were obtained for each region in Figure 2b, a shift in the distribution towards higher values within increasing average annual rainfall was evident. In Figure 2c, the two distributions of soil organic carbon stocks obtained under rotational and set stocking grazing regimes could not be differentiated amid the significant variation in stocks existing within each management practice (ranging from approximately 15 – 70 Mg C/ha). Variations in soil type, climate and topographic properties within the region contributed to the range of soil organic carbon stocks measured; however, differences in the way individual landowners implement practices in response to personal preferences or business requirements were also found to contribute.

The SCaRP sampling showed that, even within particular management practices, the dynamics of carbon inputs and losses led to large variations that made general conclusions difficult. There is potential to look for other aggregations that better reflect carbon dynamics, e.g. the net primary productivity achieved by land managers in response to their environment and the particular management options they employ.

While the SCaRP sites do not map carbon stocks, the regional distributions of soil organic carbon stock offer farmers the potential to place their own values in context with those of others. This can be useful in defining the potential for them to enhance soil carbon stocks on their own lands.

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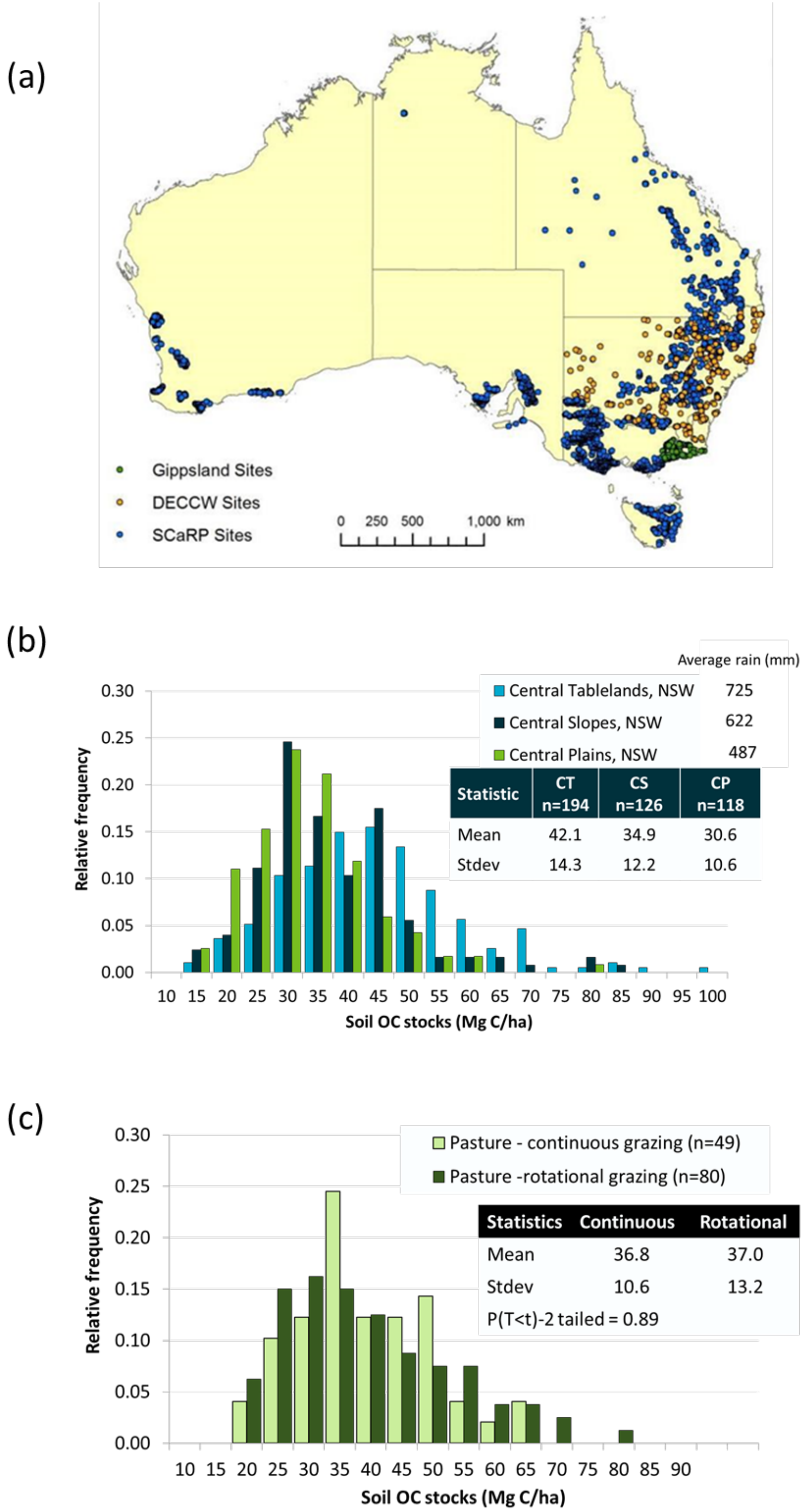


Figure 2. (a) Location of 0-30cm soil profiles included in SCaRP. (b) Frequency distributions of 0-30cm soil carbon stocks within each of three regions across a rainfall gradient in NSW. (c) Frequency distributions of 0-30 cm soil carbon stocks under two different management regimes within a single region of NSW.

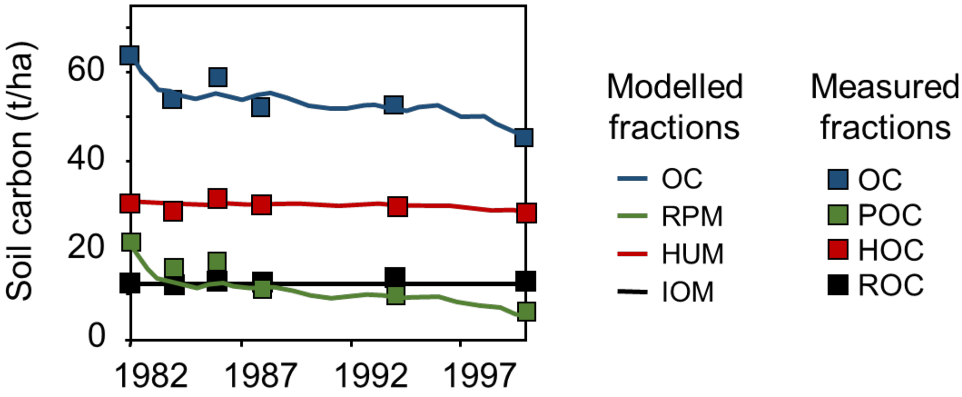


Figure 3. Relationship between measured and predicted stocks of soil carbon fractions (Skjemstad *et al.*, 2004).

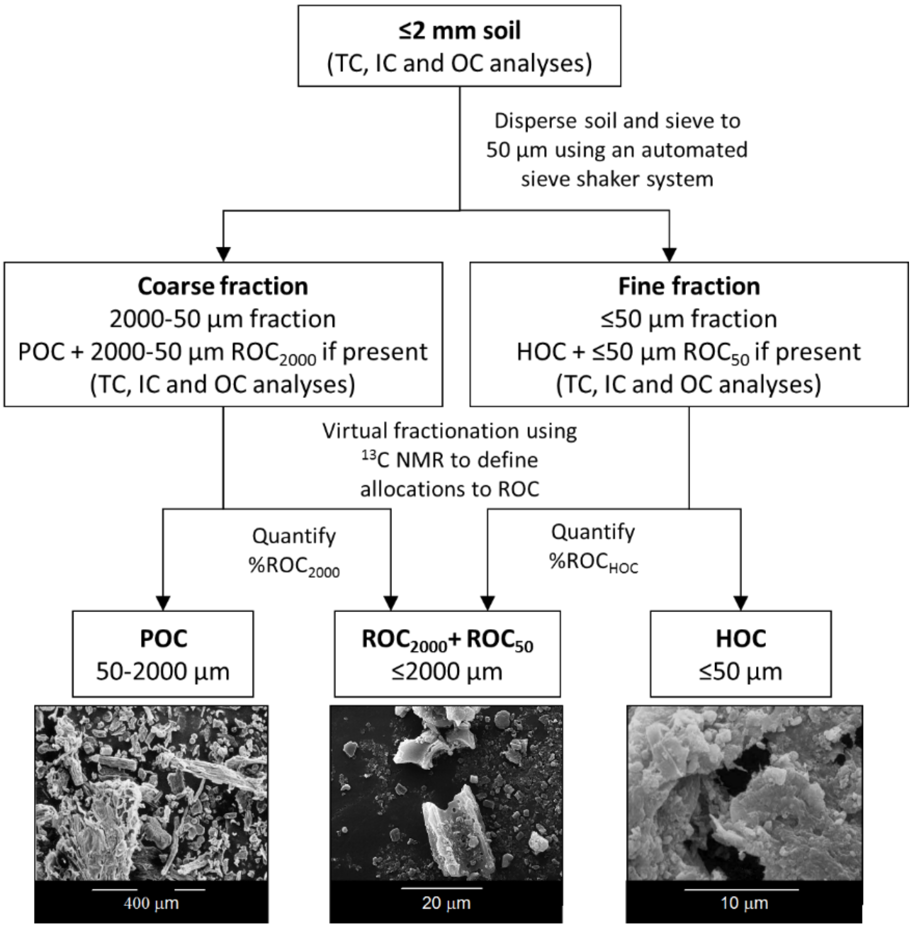


Figure 4. Soil carbon fractionation procedure developed and used within the SCaRP (Baldock *et al.*, 2013b). TC = total carbon, OC = organic carbon, IC = inorganic carbon, POC = particulate organic carbon, HOC = humus organic carbon, ROC = resistant organic carbon.

In response to the development of this prediction capability from acquired MIR spectra, predictions of the allocation of soil carbon to the entire set of SCaRP soils occurred and Viscarra Rossel and Hicks (2015) extended the approach to visible-near infrared spectroscopic analysis. Modelling of change in the fractions of soil carbon is now being integrated into the NGGI.

Given the importance of agricultural practices in the management of soil carbon, particularly the importance of carbon inputs from crops and pastures and its relationship with productivity, a more complete agricultural systems model capable of predicting crop and pasture growth and response to management is required. The APSIM modelling suite (Holzworth *et al.*, 2014) is being modified to use the developments in soil carbon fractions and provides an effective link to agricultural management.

Using point data to derive spatial maps of soil carbon stocks.

The Australian soil carbon stock map is a fine-scaled grid of the continent with estimates of soil carbon in each grid cell with an accompanying estimate of uncertainty. To produce this map using data from a confined time slice, the directly measured soil carbon data from 4125 SCaRP sites (Baldock *et al.*, 2013a) were supplemented with 1101 soils within the National Geochemical Survey of Australia (de Caritat *et al.*, 2008) (values were predicted using visible-near infrared spectroscopy (Viscarra Rossel and Webster, 2012) and 491 soils extracted from the Australian Soil Resource Information System (Johnston *et al.*, 2003) (Figure 5a). After harmonising the three data sources to produce consistent estimates of 0-30cm soil organic carbon stocks, the data mining algorithm CUBIST (Quinlan, 1992) was used to derive models capable of predicting soil organic carbon stocks from a series of 34 covariates with national coverage (Viscarra Rossel *et al.*, 2014). The covariates included were related to soil parent material, climate, topography and vegetation. The optimised solution consisted of 14 different rule sets that used different combinations of the covariates to predict of 0-30cm soil organic carbon stocks at various locations across Australia. These rule sets were then applied to the covariate data to produce a map of 0-30 cm soil organic carbon stocks for Australia (Figure 5b). In addition, a bootstrapping method was used to generate the uncertainty associated with each predicted soil organic carbon stock. The uncertainties were expressed as the range of the 95% confidence intervals divided by their mean (Figure 5c). The largest standardised uncertainty corresponded to the locations with low frequencies of measured data.

The Soil and Landscape Grid of Australia

The application of models and related tools in the use of the soil carbon map requires a broader soil and environmental data set. That has been provided by the generation of the Soil and Landscape Grid of Australia (SLGA) (Grundy *et al.*, 2015). Using similar approaches as well as new methods to disaggregate existing soil maps (Odgers *et al.*, 2015), a fine scale grid (3 arc-seconds or approximately 90 x 90 m pixels) of soil, terrain and solar radiation data has been developed and published and is publicly available in an easily-accessible format (http://www.clw.csiro.au/aclep/soillandlandscapegrid/). In the case of soil data, a minimum data set of functional attributes suitable for pedotransfer functions has been estimated and to depths up to 2m. The Grid is the essential underpinning step in a broader soil information system; its first application in soil carbon inventory has been to allow spatial modelling from the soil carbon baseline.

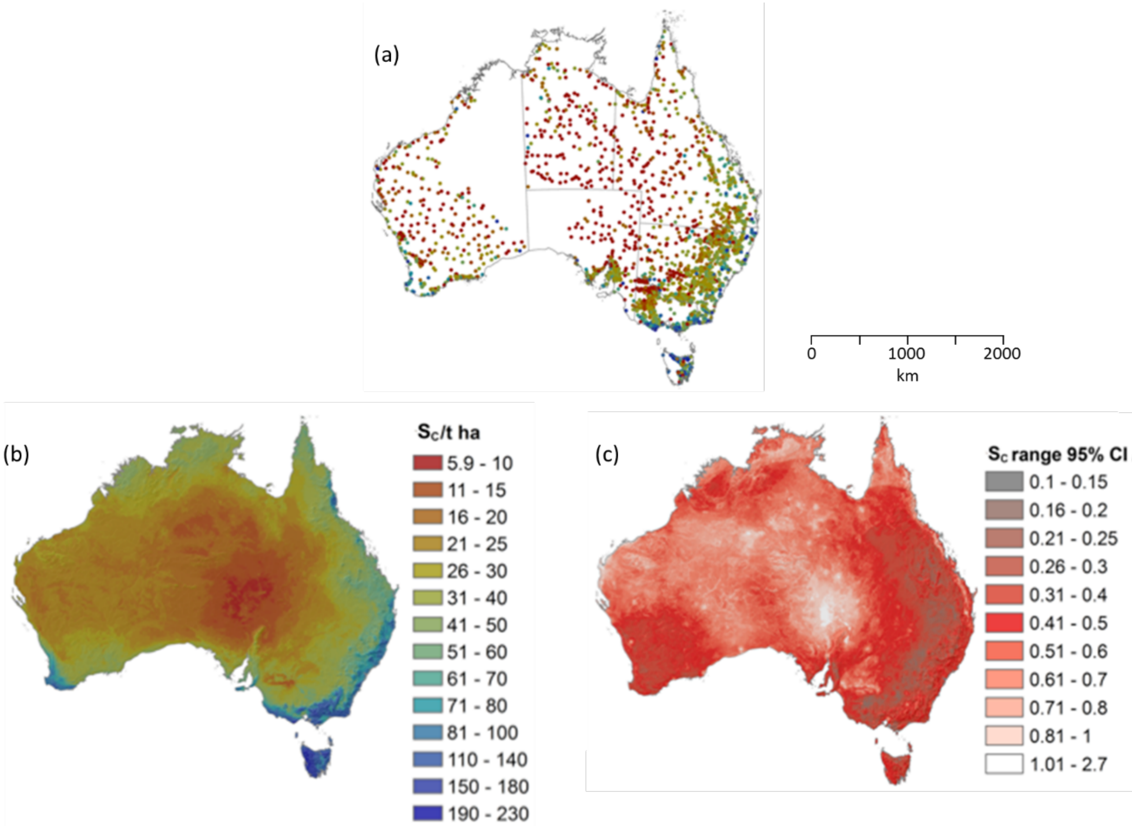


Figure 5. (a) Locations of the soil profile data used in the creation of the Australian 0-30 soil organic carbon stock map. (b) Predicted spatial distribution of Australian 0-30cm soil organic carbon stocks in 2010. (c) Standardised uncertainty estimates expressed as the size of the 95% confidence interval divided by the mean predicted value (Viscarra Rossel *et al.*, 2014).

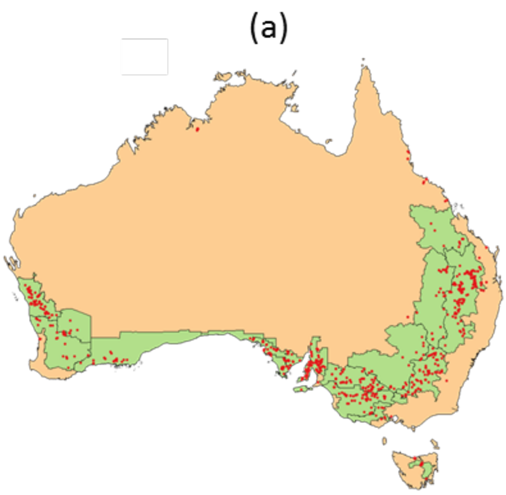
Use of the 0-30 cm soil organic carbon map within Australia's National Greenhouse Gas Inventory.

Together with the modelling capacity embedded in FULLCAM and other soil attributes in the SLGA, the soil carbon map developed by Viscarra Rossel *et al.* (2014) (Figure 5) is now being used in conjunction with the original soil carbon fraction allocations provided to the NGGI in 2003 (Skjemstad and Spouncer, 2003) to predict changes in Australia's soil carbon stocks. In addition, the process of generating separate maps for the stocks of the POC, HOC and ROC fractions has been initiated and it is expected that the next NGGI account will use these new and more detailed and spatially explicit allocations to obtain improved estimates of organic carbon stock changes in Australian soils.

Modelling the full system: combining the soil grid maps with agricultural production models.

Beyond the inventory of soil carbon stocks, land managers and decision makers need to understand and explore options to better manage soil carbon stocks and changes. The SLGA was designed with this potential in mind and the initial integration of the SLGA data with the APSIM model is in place. APSIM requires a range of data defining the soil conditions at a location to be modelled (e.g. soil carbon and nitrogen stocks, bulk density, water holding capacity) expressed in the parameter forms required by the model. Some of the required inputs can be derived directly from the spatial data layers contained within the SLGA (e.g. the soil moisture characteristic), whilst others can be estimated through the construction of pedotransfer functions using data contained within the SLGA (e.g. saturated hydraulic conductivity). The first implementation of this model parameter grid has been developed and is being tested, with promising results (Searle pers comm.).

Figure 6 provides an example of how the SLGA data can be used quantify the wheat yields across the Australian wheat belt. In this example, measured wheat yields were available at all the locations (red dots) indicated within the Australian wheat belt (green shaded region) (Figure 6a). The soil properties required to run APSIM were extracted or calculated from data residing within the SLGA for each location. The wheat yields predicted by APSIM strongly related to the measured values (LCCC=0.85 and R^2=0.79) (Figure 6b). Given the continuous spatial nature of the SLGA soil data, this finding demonstrates the possibility to 1) provide predictions of wheat yields under defined climatic conditions or 2) derive cumulative probability distributions defining the risk associated with obtaining a given yield at any point across Australian wheat belt. Although the example presented describes the ability of SLGA data to inform yield modelling, the soil and landscape attributes contained with the SLGA may be linked in a similar way to provide estimates of other properties. For example, the calculation of net acid addition rates derived from applied agricultural production systems, how this interacts with soil buffer capacity (predicted through a pedotransfer function) to define the rate of acidification of agricultural soils, and the rate of lime addition required to maintain soil pH within acceptable limits. More generally, the capacity of management systems to optimise productivity and therefore soil carbon dynamics can be modelled and options explored.



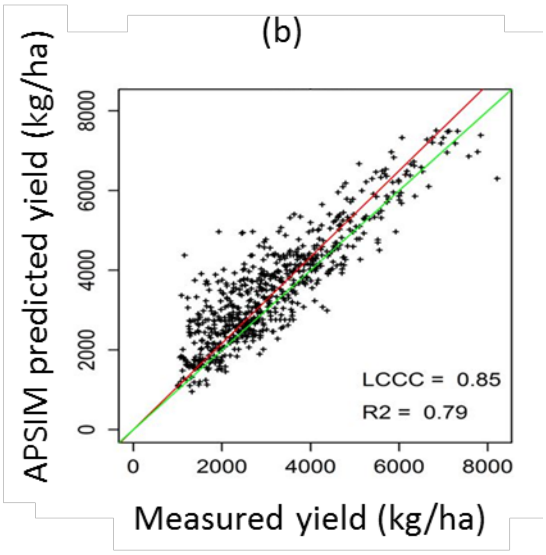


Figure 6. Linking fine scale spatial data to our crop production modelling. (a) Red dots show the locations where measured wheat yields were available within the Australian wheat belt (green shaded area). (b) The correspondence between yields predicted by APSIM using the soil data extracted from the SLGA and actual measured yields for wheat.

Moving to decisions in real time: connecting spatial crop modelling to real time streams of data

While the integration of models with soil carbon and other data provides an increased ability to observe and test the dynamics of management systems, the underlying soil information is essentially static and time bound. The development of model data fusion approaches to soil function (e.g. Barrett, 2010) offers the opportunity to estimate the fluxes in the key soil functions (moisture, carbon, nitrogen) and move to a more immediate management of soil carbon dynamics. Current projects in this space are now focussed on the building the link to real time streams of data (proximal and remote sensing systems) and connecting to the prediction system. Such a capability allows the potential to understand the manage the variance of yield outcomes as a growing season progresses and allow land managers to make more informed management decisions pertaining to potential crop yields and soil carbon dynamics.

Making the capabilities and data available to land managers

While the developments in soil information outlined here promise an increasingly detailed and focussed information support for soil carbon management, the volume and complexity of data also increase. The challenge to ensure that this enables more effective management is at least as important as the development of the information system itself. This is likely to involve the application of new tools in information management and application – locally relevant and simple apps and decision tools. A current example of such a system is the SOILWATER application that can be run off computers, tablets and smart phones so that land managers can access soil water information when and where it is required. It is likely that this decision support element will evolve quickly as the information capacity grows.

Assembling a more complete data/modelling/prediction system that can evolve

Once the linkages between data (e.g. SLGA), models (e.g. APSIM) and real time data sensors (e.g. remotely sensed data) are established, development of a capability that allows continuous improvement of the predicted outcomes can occur. An example of this is provided in Figure 7 using the ability to predict soil carbon stocks and stock change as an example. Component (a) contains the data defining current soil carbon state (e.g. stocks, fractions, etc.) and equates to the information that would be housed within the SLGA. The data from this component is used to define the initial conditions used in subsequent modelling. Component (b) defines the temporal inputs of carbon from plants to the soil and is required to estimate the likely outcomes of management practices on soil carbon stocks. Data pertaining to plant inputs can come from a variety of sources (direct measurement, simple or complex models or sensing). Component (c) is the biophysical model that predicts the likely outcome of an applied management practice given the defined starting conditions and inputs. The model may be simple or complex, but in either case it will contain algorithms with various constants that require calibration. Component (d) represents the model output designed to provide useful information to land managers. For the soil carbon example, useful outputs could take form of the following:

1. a national map of predicted soil carbon stocks and the associated uncertainty at some point in the future for policy makers, particularly those considering the design of an emission trading system and potential volume of emission abatement that may occur,
2. a cumulative probability distribution of the outcome of applying a particular management practice on soil carbon stocks at a particular location to inform the land manager of the potential risks associated with obtaining a specified stock change.
3. a series of trajectories of potential soil carbon changes associated with the application of different management practices.

Component (e) provides a mechanism for using the available data to test and revise the magnitude of the model parameters in a Bayesian Hierarchical Modelling approach as discussed by Clifford *et al.* (2014). Component (f) provides a mechanism to include algorithms to shift plant production in response to increased soil carbon values and thus provide a feedback that is absent from most modelling systems.

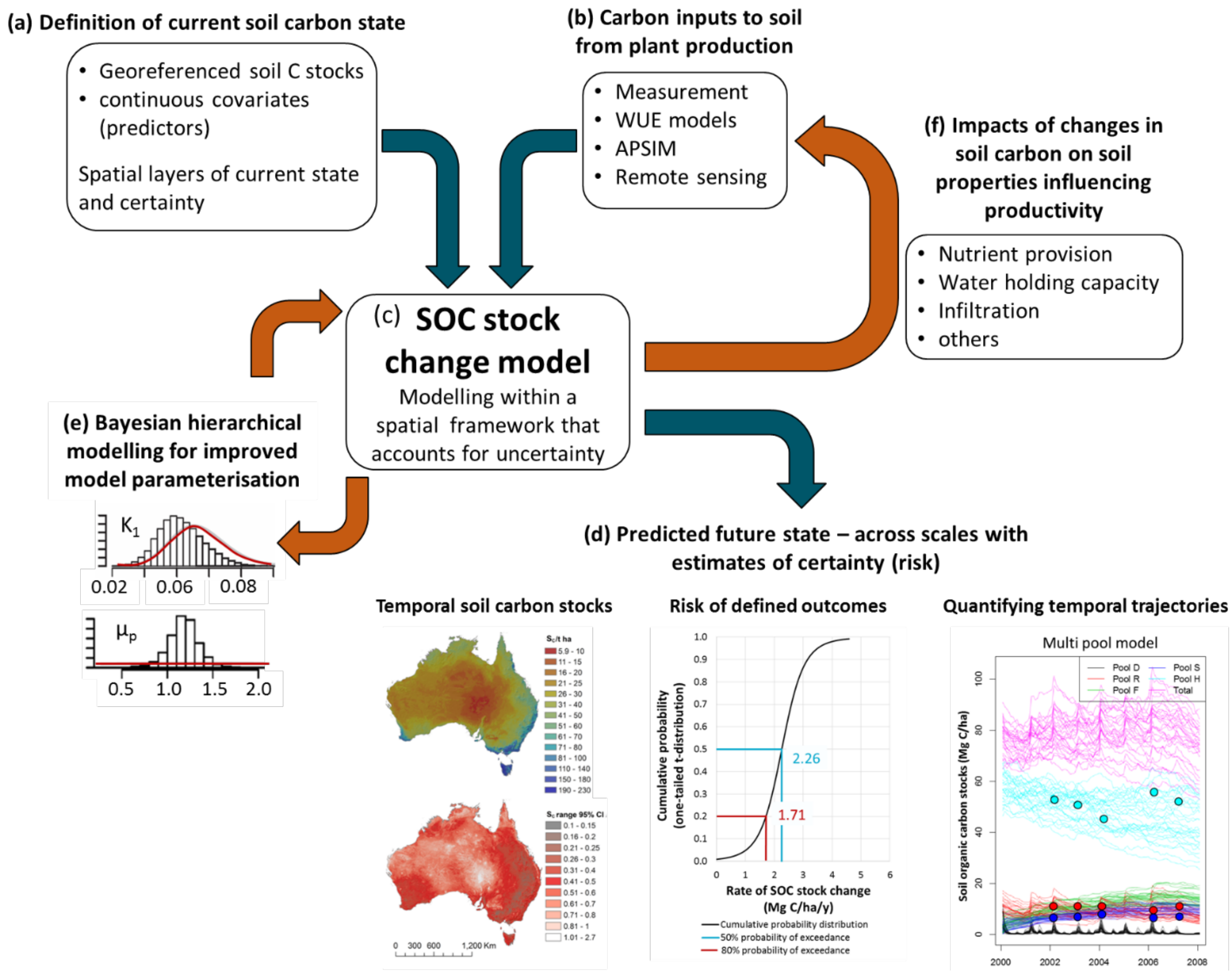


Figure 7. Conceptualisation of a complete data/modelling/prediction system for soil organic carbon stocks with the ability to evolve and provide improved predictions through time as additional data and refinements are made. Blue arrows represent the direction of flow of information. Orange arrows represent feedbacks where 1) model outcomes can be used to improve inputs and 2) tuning of model parameters is possible.

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