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Measuring and monitoring the impact of agricultural management on soil carbon stocks from point to continental scale in Australia

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Abstract

Soil organic carbon (SOC) content and stock contribute positively to soil productivity, resilience and stainability and provide a potential mechanism for mitigating greenhouse gas emissions. Australia has completed projects examining how to measure SOC stocks and monitor temporal changes. A method exists to allow landowners to receive financial rewards for accumulating additional carbon in their soils. The main features of the method are presented. A significant soil sampling project was completed to quantify the impact of management practice on SOC stocks across Australia's intensive agricultural zone. Significant variations in SOC stocks within management practices limited the ability to make conclusive statements about practice impacts. The SOC stock data generated, when combined with other data, has enabled maps of SOC stocks and certainty to be created which now underpin the soil component of Australia's National Inventory Report. A framework integrating measurement, monitoring and prediction of the magnitude and certainty of the outcomes of management practices on SOC stock that can evolve and improve over time will be presented.

Introduction, scope and main objectives

Interest in quantifying and monitoring the content and stock of soil organic carbon (SOC) arises from the contributions it makes to soil productivity, resilience and sustainability and because increases in SOC stocks can mitigate emissions of greenhouse gases. Land use and land use change may induce sequestration or emission of carbon depending on the balance between carbon additions (C_A) derived from plant growth or organic amendments and carbon losses associated with decomposition induced mineralisation (C_M) or material transfers associated with erosion (C_E) or leaching (C_L) (Equation [1]).

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

Initiating agricultural production typically, but not always, results in net losses of SOC amounting to 20-70% of the original SOC stocks. However, the introduction of SOC friendly management practices (e.g. reduced tillage, residue retention and increased productivity) can result in sequestration or reductions in the magnitude of SOC loss (avoided emissions).

The objectives of this paper are to report results from recent Australian research programs that have: 1) developed approaches for quantifying and monitoring SOC stocks, 2) assessed the potential impact of management practises on SOC stocks, and 3) used point based SOC stock data to produce national SOC surfaces that underpin the SOC component of Australia's National Inventory Report (NIR). The paper will conclude by presenting a measurement/modelling/prediction framework that can evolve over time.

Quantifying SOC stocks and temporal change

Various methods exist for quantifying and monitoring SOC stocks (Figure 1). Direct measurement methods provide the most accurate assessment at a defined location, and indeed, provide the SOC stock data required to calibrate other methods. In progressing from direct measurement, through proximal sensing to remote sensing and computer simulation, the accuracy of estimates of SOC stock at a particular location and time

declines. However, the ability to take many more measurements and obtain more complete spatial coverage increases. Developing a range of methods for quantifying SOC stocks over space and time and selection of the most appropriate method for a particular SOC project will be important.

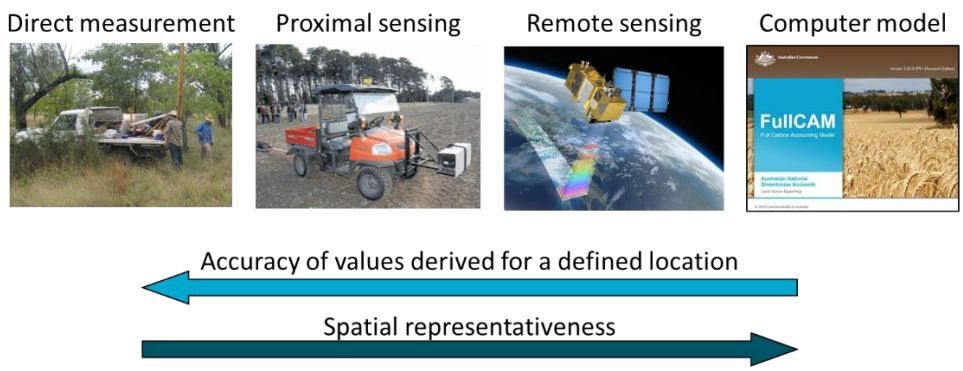


Figure 1. Potential methods for quantifying and monitoring soil carbon stocks.

In the Australian government's Emission Reduction Fund (ERF), the first SOC method developed (Sequestering carbon in soils in grazing systems) used a direct measurement approach. It was designed to be broadly applicable and assumed no prior information on SOC stock variation within a carbon estimation area (CEA). Under this method, baseline SOC stocks are measured, new management activities are implemented and future SOC stocks are monitored over time.

The method uses a stratified simple random sampling design (Figure 2) in which a CEA is divided into equal area strata (n=9 for Figure 2). Soil samples randomly located within the strata are combined to form composite samples (n=3 for Figure 2). Each composite sample comprises one soil sample from each stratum. The CEA is repeatedly sampled through time (t_0, t_1, …,t_n). To be consistent with the Australian NIR and IPCC recommendations, the collection of soil to a minimum depth of 30 cm was adopted; however, proponents may nominate to collect additional soil to depths >30cm.

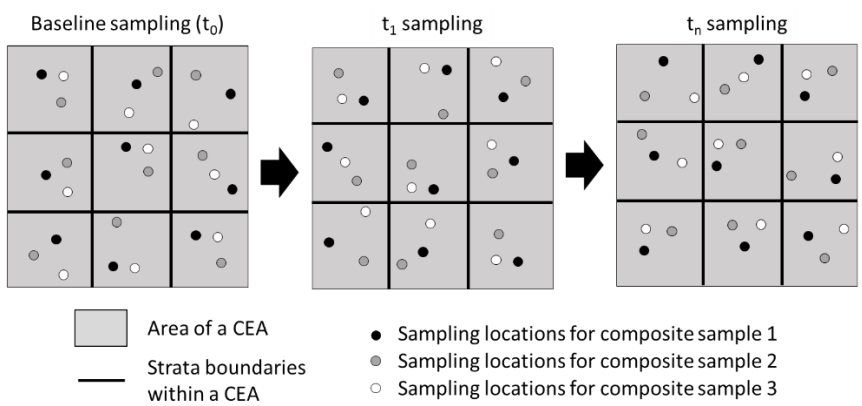


Figure 2. Sampling design defined for the "Sequestering carbon in soils in grazing systems" methodology.

The mass of soil collected (Equation[2]) and SOC stock (Equation [3]) are calculated. An equivalent soil mass corresponding to the 10th decile of all soil masses obtained during the baseline sampling is defined. All SOC stock values (baseline and subsequent values) are adjusted to provide the mass of SOC associated with the equivalent soil mass (Equation [4]). The equivalent mass approach accounts for variations that may occur in soil bulk density due to altered management practices and to reduce the impact of error that may occur during sample collection.

$$\underset{(\text{Mg/ha})}{\text{Soil mass}} = \underset{(\text{Mg/m}^3)}{\text{Dry bulk density}} \times \underset{(\text{cm})}{\text{Soil layer thickness}} \times 100 \qquad [2]$$

$$\underset{(\text{Mg C/ha})}{\text{Soil organic carbon stock}} = \left[\underset{(\text{mg C/g})}{\text{Soil organic carbon content}} \times \left(1 + \underset{(\text{g/g})}{\text{Water content}}\right)\right] \times \underset{(\text{Mg/m}^3)}{\text{Dry bulk density}} \times \underset{(\text{cm})}{\text{Soil layer thickness}} \times \left(1 - \text{Proportional mass of gravel}\right) \times 0.10 \qquad [3]$$

$$\underset{(\text{Mg C/ha})}{\text{Equivalent soil mass organic carbon stock}} = \underset{(\text{Mg C/ha})}{\text{Soil organic carbon stock in the entrie soil layer}} \times \frac{\text{Equivalent soil mass for the layer sampled } (\text{Mg/ha})}{\text{Soil mass for the layer sampled } (\text{Mg/ha})} \qquad [4]$$

After the baseline and t_1 sampling, a one tailed t-test assuming unequal variance across time is used to define the SOC stock change associated with a 60% probability of exceedance. Since it is difficult to be confident that the temporal change in SOC is discounted to 50% of the calculated change.

Once three or more temporal measurements of equivalent mass SOC stocks are completed, a regression approach is used (Figure 3). In this approach, the magnitude and standard error of the slope of the regression line obtained for equivalent mass SOC stock expressed as a function of the duration of the project is calculated. These values are used to define the slope (annual change in equivalent mass SOC stock) associated with a 60% probability of exceedance, which is then multiplied by the duration of the project and the CEA area, to define the amount of SOC sequestered.

From the onset of its development, it was identified that this sampling design may not provide the most efficient approach, and additional components are being incorporated to allow stratification based on prior information and other improvements.

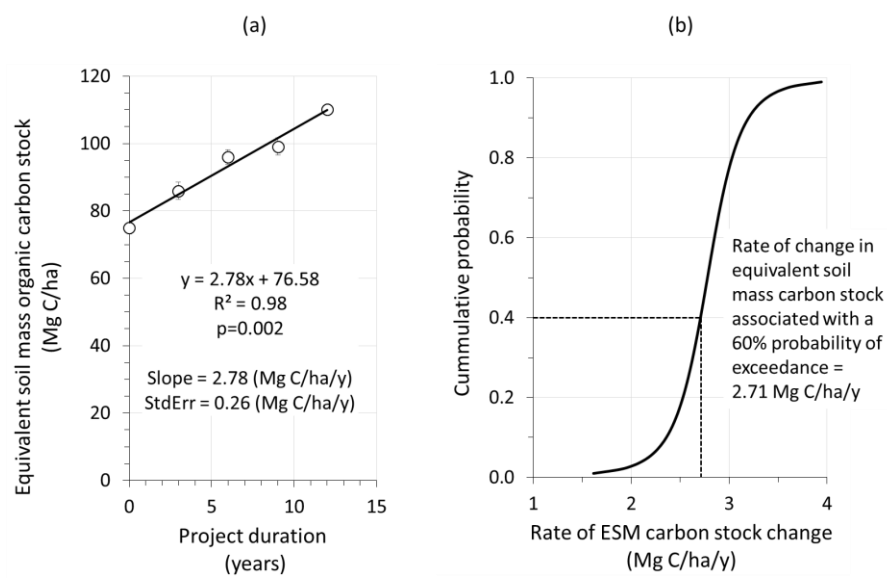


Figure 3. (a) Temporal measurements of equivalent mass SOC stocks within a CEA and the required regression statistics. (b) The probability of exceeding a particular rate of change of equivalent mass SOC stock defined from the slope and standard error of the regression equation.

Potential impacts of agricultural management on SOC stock

As part of a Soil Carbon Research Program over 4,500 agricultural soils (Figure 4a) were sampled and analysed to calculate 0-30 cm SOC stocks using measured values for all parameters in Equation [3]. Second and subsequent sampling is now needed to begin quantifying SOC stock change and sequestration rates. Although a wide range of soil organic carbon stocks were obtained (Figure 4b), a shift towards higher SOC stocks with increasing average annual rainfall was evident. In Figure 4c, the two distributions of SOC stocks obtained under rotational and set stocking grazing regimes could not be differentiated given the significant variation in SOC stocks within each management practice.

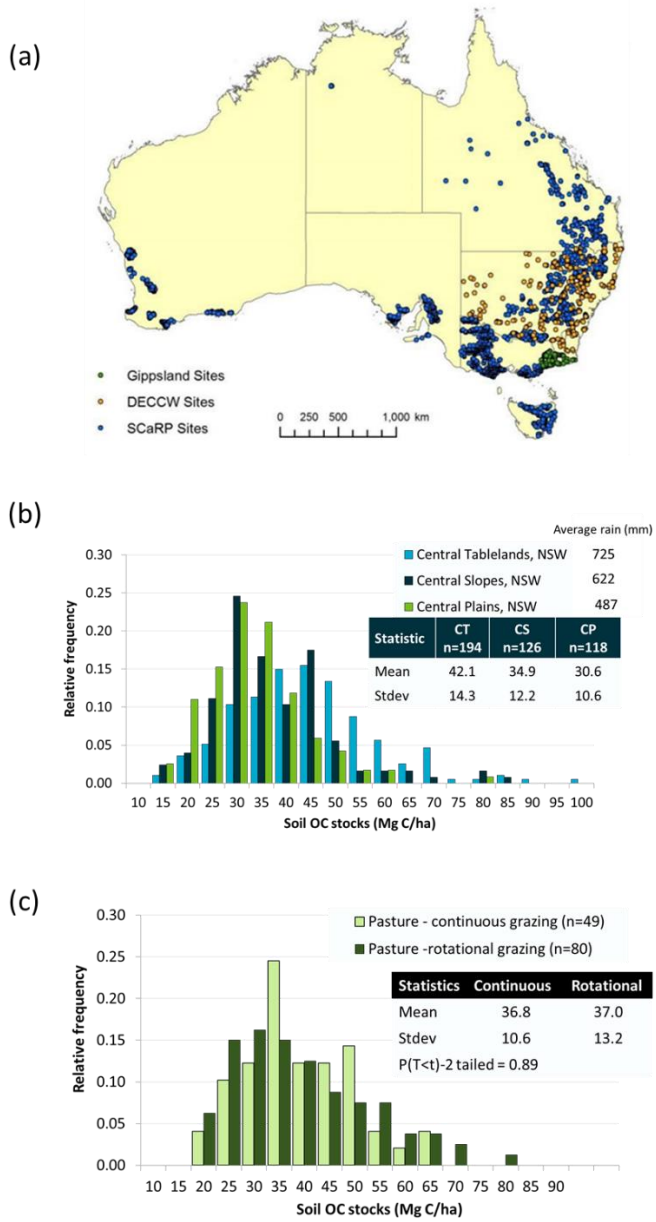


Figure 4. (a) Location of soil profiles sampled in SCaRP. (b) Frequency distributions of 0-30cm soil carbon stocks within each of three regions across a rainfall gradient in NSW. (c) Frequency distributions of 0-30 cm soil carbon stocks under two different grazing regimes within a single region of NSW (Baldock et al. 2013).

Variations in soil type, climate and topographic properties within the region contributed to the range of SOC stocks; however, differences in the way individual landowners implement practices in response to personal preferences or business requirements also contributed. Within particular management practices, the dynamics of carbon inputs and losses led to large variations in SOC stock that made general conclusions difficult. There is potential to use other aggregations that better reflect carbon dynamics, e.g. the net primary productivity achieved in response to environment and management options employed.

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

The point data acquired by the SCaRP program has been combined with additional datasets (Figure 5a) and used to derive a continental 90m grid map of 0-30 cm SOC stocks with an accompanying estimate of uncertainty (Figure 5b and c). After harmonising the data sources, the data mining algorithm CUBIST was used to derive models capable of predicting SOC stocks from a series of 34 covariates with national coverage. The covariates included were related to soil parent material, climate, topography and vegetation. The optimised solution consisted of 14 different rule sets using different combinations of covariates to predict of 0-30cm SOC stocks at locations across Australia. These rule sets were then applied to the covariate data to produce the 0-30 cm SOC stock map for Australia.

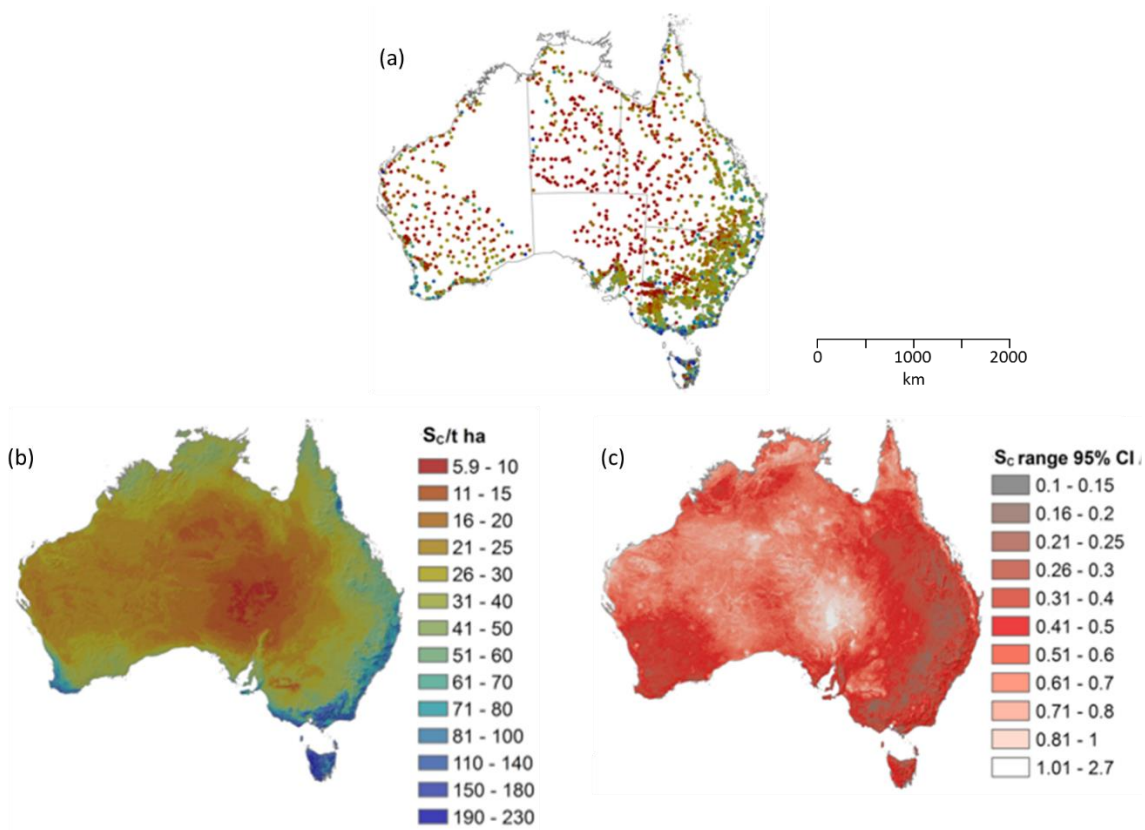


Figure 5. (a) Locations of the soil profile data. (b) Predicted spatial distribution of Australian 0-30cm SOC stocks in 2010. (c) Standardised uncertainty estimates expressed as the size of the 95% confidence interval divided by the mean predicted value (Viscarra Rossel et al. 2014).

Linking SOC stock measurements and composition to simulation models

The soil component of Australia's NIR uses a computer model to simulate dynamics of a series of measureable fractions of SOC referred to as particulate, humus and resistant organic carbon (POC, HOC

and ROC, respectively). The decomposition rate constants of the fractions were defined through a calibration process using field trial data (Figure 6). The analytical process of quantifying the allocation of SOC to its component fractions is time consuming and expensive. To facilitate extension and possible use of the SOC fractions within the agricultural industry, a capability of predicting contents of SOC and its component fractions by mid-infrared spectroscopic analysis was developed (Figure 7). Reasonable estimates of the contents of each SOC fraction can be obtained from one mid-infrared analysis.

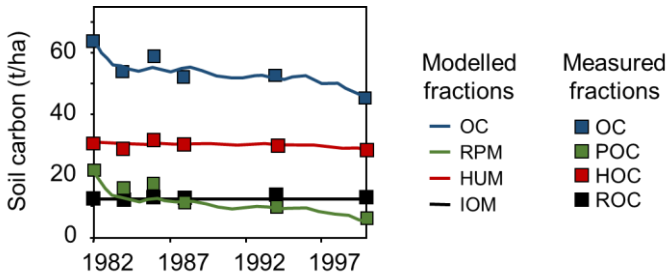
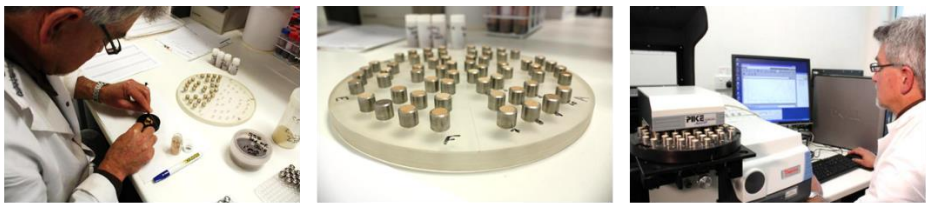


Figure 6. Relationship between measured and predicted stocks of soil carbon fractions (Skjemstad et al. 2004).



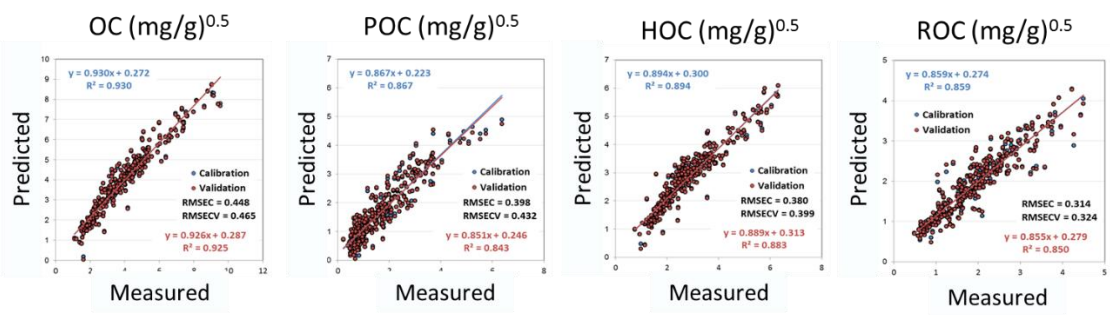


Figure 7. The process of scanning soil samples by MIR and the MIR/PLSR prediction algorithms developed for SOC, POC, HOC and ROC contents (Baldock et al. 2013).

Assembling a more complete measurement/modelling/prediction system for SOC stocks that can evolve over time

Once the linkages between point measurements of SOC stock and composition, data layers, and models are established, development of a capability to continuously improve predicted SOC stock outcomes can occur (Figure 8). Component (a) contains data defining current SOC state used to initialise and validate subsequent modelling. Component (b) defines the temporal carbon inputs from plants and is required to estimate likely outcomes of management practices on SOC stocks. Plant input data can come from direct measurement, simple or complex models or sensing. Component (c) is the SOC model predicting the likely outcome of applied management practices. Component (d) represents the model output designed to provide useful information that could take the form of:

1. a national map of predicted SOC stocks and the associated uncertainty at some point in time,

2. a cumulative probability distribution of the SOC stock outcome associated with applying a particular management practice at a particular location.
3. a series of trajectories of potential SOC stock 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. 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 many modelling systems.

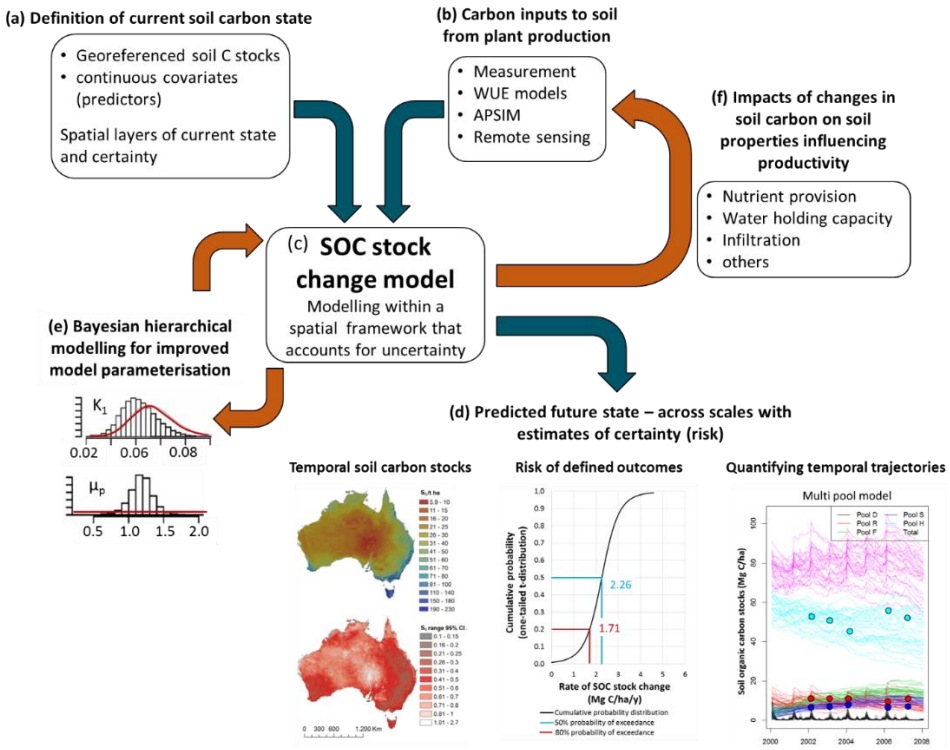


Figure 8. Conceptualisation of a complete data/modelling/prediction system for SOC stocks.

References

Baldock, J., B. Hawke, J. Sanderman, and L. Macdonald. 2013. Predicting contents of carbon and its component fractions in Australian soils from diffuse reflectance mid-infrared spectra. Soil Research **51**:577-595.

Skjemstad, J. O., L. R. Spouncer, B. Cowie, and R. S. Swift. 2004. Calibration of the Rothamsted organic carbon turnover model (RothC ver. 26.3), using measurable soil organic carbon pools. Australian Journal of Soil Research **42**:79 - 88.

Viscarra Rossel, R. A., R. Webster, E. N. Bui, and J. A. Baldock. 2014. Baseline map of organic carbon in Australian soil to support national carbon accounting and monitoring under climate change. Global Change Biology **20**:2953-2970.