



Catchment scale mapping of measureable soil organic carbon fractions



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ABSTRACT

This study aims to map the measurable fractions of soil organic carbon related to the RothC carbon model at the catchment scale and to assess the model and prediction quality. It also discusses how the outputs can be used to provide initial pool estimates for process modelling of soil carbon in a spatial context. The study was carried out in Cox's Creek catchment in northern New South Wales, Australia. Samples were collected in 2010 using a design-based sampling scheme. The measurable fractions of the RothC soil carbon model considered in this study were resistant organic carbon, humus organic carbon and particulate organic carbon. It has been reported that these measurable fractions of soil organic carbon can successfully substitute for the conceptual pools of carbon in the RothC soil carbon model. All the samples were scanned to create MIR spectra and recently developed spectroscopic models by Commonwealth Scientific and Industrial Research Organisation (CSIRO) under the national soil carbon research programme (2009–2012) were used to carry out the prediction of respective fractions. We used linear mixed models to create a model for mapping the measurable fractions of soil organic carbon across the catchment. The cross validation results revealed that the highest Lin's concordance correlation between measured and predicted values was recorded for resistant organic carbon (0.78), followed by humus organic carbon (0.74) and particulate organic carbon (0.58). Finally, to assess the uncertainty of the predictions we carried out conditional sequential Gaussian simulations. We demonstrated that measurable fractions of carbon related to the RothC model can be mapped at catchment scale with reasonable accuracy. The derived maps could be used in future studies to initialize the RothC model at any location across the landscape with quantified uncertainties.

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1. Introduction

An interest in the content, composition and stocks of soil organic carbon (SOC) has developed resulting from the concomitant positive impacts that SOC can have on soil productivity and sustainability and the potential to reduce the net emission of greenhouse gases by sequestering atmospheric carbon in soil (Guo and Gifford, 2002; Lal, 2004a,b; Post and Kwon, 2000). Global estimates of SOC stock to a depth of 1 m amount to 1550 Pg C (1 Pg = 10¹⁵ g) which represents three times as much carbon as found in the biosphere and twice as much carbon as found in the atmosphere (IPCC, 2000). In Australia, concentrations of SOC have been reduced by 20% to 70% due to the implementation of agricultural production systems (Luo et al., 2010). Lal (2004a) proposed that 50% to 66% of the carbon sequestration potential within soil could be attained. If the amount of carbon globally stored in soil change by 1% of what is currently present, an 8 ppm shift in atmospheric carbon concentration would occur, provided other components of the global carbon cycle remain constant (Baldock et al., 2012). These values demonstrate that small positive or negative changes in global SOC stocks will have a significant impact on atmospheric carbon concentration. Gaining

an understanding and being able to both map and model the implications of land management on SOC stocks are of high importance.

Digital soil mapping methods (DSM) have become more focused on mapping SOC stocks as well as contents. McBratney et al. (2003) formalised the concept of DSM in what is now commonly referred to as the *scorpan* model:

$$S = f(s, c, o, r, p, a, n) + e \quad (1)$$

where S is a soil property such as the stock or concentration of SOC or its component fractions, and f is a prediction method or function which incorporates covariates related to soil (s), climate (c), organisms (o), relief (r), parent material (p), time (a), and space (n) and e is (in some cases) the spatially correlated errors. The SOC (stock or concentration) has been mapped using this approach at the paddock, regional, continental and global scales. Some examples include work by Brodský et al. (2013) and Miklos et al. (2010) at paddock scale; Meersmans et al. (2008) and Minasny et al. (2006) at regional scale and Henderson et al. (2005) and Odgers et al. (2012) at the continental scale.

Even though much attention has been given to mapping total SOC, little research has been completed on mapping compositionally distinct fractions of SOC. One such example is given by Vasques et al. (2010) where they mapped the total carbon and four soil carbon fractions,

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namely recalcitrant carbon, hydrolyzable carbon, hot-water-soluble carbon, and mineralizable carbon, at depths of 0 to 0.3 m across a watershed in north-central Florida, United States. Mapping SOC fractions is as important as mapping total SOC due to the fact that quantitative estimates of the contents of carbon fractions are required as inputs for mechanistic or process models of SOC, to provide important information for land management, for policy decisions and finally to understand the relative contribution of different SOC pools to total carbon across landscapes (Vasques et al., 2010).

In this paper we focus on mapping the spatial distribution of three measurable fractions of SOC that Skjemstad et al. (2004) showed could be simulated by the RothC soil carbon model. The RothC soil carbon model is a process oriented multi-component model (Batlle-Aguilar et al., 2011) developed to simulate the dynamics of SOC in the topsoil (0–0.30 m) layer of non-waterlogged environments (Coleman and Jenkinson, 1999). In the RothC model, SOC is split into five conceptual pools of carbon: four active pools and one inert pool called inert organic matter (IOM). The IOM pool is considered to be resistant to decomposition. The active pools include decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO), and humified organic matter (HUM) (Coleman and Jenkinson, 1999). The RothC model is widely used all over the world. In Australia, the RothC model forms the basis for the FullCAM carbon cycling model used by the Australia national carbon accounting system to estimate the impact of variations in soil carbon on Australian national carbon accounts (Richards, 2001).

Instead of using conceptual pools there have been attempts to substitute these pools with measurable fractions of SOC (Skjemstad et al., 2004; Zimmermann et al., 2007b). Typically the fractions are isolated using physical or chemical methods or a combination of both methods. Due to cost and time consuming nature of determining the content of measurable fractions of SOC, studies have investigated the ability of mid-infrared spectroscopy (MIR) when combined with partial least squares regression (PLSR) to develop predictive algorithms (Baldock et al., 2013a; Janik et al., 2007; Zimmermann et al., 2007a). In Australian soil context, Janik et al. (2007) developed MIR/PLSR models capable of predicting the allocation of SOC to the measurable fractions which Skjemstad et al. (2004) used with RothC model. This approach was modified by Baldock et al. (2013a) and Baldock et al. (2013b) under the Australian national Soil Carbon Research Program (SCaRP). Developing MIR/PLSR models for predicting measurable fractions of SOC offers a rapid and cost effective methodology that can be deployed across many samples using acquired MIR spectra provided adequate calibration algorithms exist for the samples being analysed.

Therefore, the aims of this research were to (a) map measurable fractions of the RothC model using the *scorpan* approach; (b) assess the quality of the developed models and maps; (c) discuss the uncertainties associated with using spectroscopic estimates of fractions as inputs to the mapping process and (d) discuss the possible use of DSM outputs in combination with SOC simulations using the RothC model in a spatial context.

2. Methods

2.1. Study area

The study area was the Cox's Creek catchment situated in northern New South Wales (NSW), Australia (Fig. 1). The spatial extent of the catchment is 1358 km². The catchment had a mixture of land uses including irrigated agriculture (4%), dry land cropping (35%), improved pasture (38%), forest (20%) and other (3%). The elevation of the catchment ranged between 240 m and 635 m above sea level. Soils within the catchment were variable, ranging from heavy textured cracking clays (Vertosols) found along Cox's Creek and its tributaries to sandy soils (Tenosols) located towards the western boundary of the catchment.

2.2. Soil data

2.2.1. Sampling

Soil samples were collected in November 2010 using a stratified random sampling design applied across the catchment. The soil–land use (SLU) complexes created using combinations of both generalised land use/land cover (LULC) and soil type classes were used as strata to determine soil sampling locations. The LULC data were obtained from the Bureau of Rural Sciences (<http://adl.brs.gov.au/landuse/>) which were available at 1:250,000 scale. The LULC data were generalised in to five LULC classes as Forests, Dry land agriculture, Improved pasture, Irrigated agriculture and other in GIS environment. In case of soil class information, soil class map produced by Nelson and Odeh (2009) was used. The soil class map for the study area was produced at 200 m resolution and converted to vector format prior to generalisation in GIS. Two soil type classes were defined (namely Vertosols and All other soils) due to the abundance of Vertosols (55% of the total extent of land) and the limited budget for soil sampling which prevented having a large number of soil categories. The “All other soils” were mainly dominated by Tenosols (21%), Sodosols (9%) and Chromosols (7%). More details of the soil of the study area are given in Nelson and Odeh (2009). Finally, five SLU complexes were created including (i) Forest, (ii) Dry land agriculture, (iii) Improved pasture –Vertosols, (iv) Improved pasture –All other soils and (v) Irrigated agriculture using both generalised LULC and soil maps. In creating the SLU complexes, the forest LULC was considered irrespective of soil as it had only a small amount of Vertosols present. Irrigated agriculture was also considered alone as it encompassed only 4% of the total extent of the study area.

Using SLU complexes as the strata, soil sample collection sites were defined by applying a stratified random sampling approach. A total of forty four sampling sites were identified with the number of sites allocated to each strata being proportional to the area of the strata. At each site, two soil cores were taken approximately 30 m apart. Collection of paired samples at each site was performed to enable modelling of the short-range spatial variation. The second core at each site was taken in a random direction from the first core. Soil samples were collected based on depth intervals of 0–0.1, 0.1–0.3 and 0.3–0.5 m.

2.2.2. Laboratory analysis

A subsample (approximately 10 g) was taken from each sample and finely ground using a Retsch MM400 mixer mill set to an oscillation frequency of 28 Hz for 3 min (Baldock et al., 2013a). Then MIR reflectance spectra (400–8000 cm⁻¹ at a resolution of 8 cm⁻¹) were collected using the Thermo Nicolet 6700 FTIR spectrometer (Thermo Fisher Scientific Inc., MA, USA) equipped with a Pike AutoDiff automated diffuse reflectance accessory (Pike Technologies, WI, USA). Background signal intensity was first quantified by collecting 240 scans on silicon carbide disc prior to analysing each batch of sixty soil samples using the auto sampler. The background signal was used to correct the signal obtained from each sample. Powdered soil samples (100 mg) were placed in stainless steel auto sampler cups and the surface was levelled. A total of 60 scans were accumulated for each sample and averaged to produce a spectrum for each sample.

2.3. Measurement of total SOC

Prior to analysis for total SOC contents, all ground samples were tested for the presence of inorganic carbon. A 0.5 g sub-sample of finely ground soil was placed on a ceramic plate and a few drops of 1 M hydrogen chloride (HCl) were placed directly on to the sample. Any sample that recorded a fizz was considered to contain carbonates. Removal of carbonates was carried out according to the guidelines given by Baldock et al. (2009). The gravimetric carbon content of all samples (untreated and acid treated) was determined using either a LECO CNS2000 or LECO C144 carbon analyser. All carbon contents (g/kg)

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