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Depth-resolved soil organic carbon estimation: a scalable approach

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Abstract: Soils are a key component of the global carbon (C) cycle and play an important role in climate change mitigation as well as supporting essential ecosystem services. While much research and management attention are focused on topsoils (<30cm), the subsoil can hold a greater share of total C stocks due to its larger volume and potentially less vulnerability to anthropogenic activities. However, subsoil C dynamics are still poorly understood, limiting their representation in both scientific studies and policy frameworks. Many soil organic carbon (SOC) models focus on only the topsoil as a single uniform layer, but differences in soil properties, microbial activity, and the sources and pathways of C inputs at greater depths mean that multi-layer and whole-profile approaches are needed. Land use and management exert strong influences on SOC, with effects mediated by plant morphology, particularly rooting depth and architecture, as well as the presence of nitrogen-fixing species, which are more common in modified pastures than their native counterparts. Management practices in cropping systems, such as fertiliser application, tillage, stubble management and crop rotation, further alter the quantity, quality and depth distribution of C inputs. For example, fertilisation regime affects biomass production which impacts both above and below ground C inputs. Crop rotation impacts the C input quality and depth distribution where deep-rooted species, such as canola, will increase inputs in deeper layers of the soil profile.

Although process-based SOC models have been widely applied at the surface, their use for predicting SOC stocks across the entire soil profile remains limited, and no scalable framework currently exists for continental-scale applications in Australia. This work applies RothPC-1, a layered, whole-profile extension of the RothC model, to predict SOC stocks to depth, extending previous approaches that used readily available data for estimating C inputs. RothPC is a first-order kinetic model that consists of five conceptual C pools with different decomposition rates to represent SOC dynamics. The model was tested on 18 sites in south-eastern New South Wales, grouped into land uses representing cropping, grazing native vegetation and grazing modified pasture. Carbon inputs were estimated from remote evapotranspiration and NDVI derived from remote sensing platforms and scaled for each land use.

The performance of RothPC showed strong agreement between predicted and observed SOC stocks, comparable to other process-based whole-profile models ($R^2 = 0.39$-0.83, RMSE = 7.3-45.3 t C ha^{-1}). Cropping land uses performed the best out of the three land uses, likely due to a larger sample size. The C-input scaling factor between land uses was low and would benefit from a broader range of samples spread over a larger area. RothPC-specific parameters, s, which slows decomposition at depth, and p, which determines the fraction of SOC retained within a layer, differed from values reported in other studies. However, the inconsistencies among those studies themselves indicate a broader uncertainty in these parameters, and our findings reinforce the need for further investigation into their underlying drivers. The results from this work highlight RothPC-1's capability for estimating SOC to depth using easily accessible datasets, and emphasise the need for more extensive and deeper sampling to refine model parameters and improve predictive accuracy. Due to the scalability of the developed framework, there is an opportunity to apply it to carbon farming and to national-scale applications for SOC accounting beyond topsoil.

Keywords: *Soil organic carbon, subsoil organic carbon, process-based whole-profile modelling, RothPC-1, land use management*

1. INTRODUCTION

Soil is a major component of the global carbon (C) cycle and is important for climate change mitigation and several ecosystem services. Soil organic carbon (SOC) is a fundamental driver of soil function and agroecosystem sustainability. It facilitates nutrient cycling and water retention, thereby enhancing soil fertility, supporting sustained crop productivity, and contributing to drought resistance and landscape resilience (Bossio et al. 2020). In addition, SOC promotes microbial diversity, which underpins essential biological processes and strengthens overall ecosystem resilience (Rodrigues et al. 2023). Structurally, SOC contributes to the formation and stabilisation of soil aggregates, improving resistance to erosion and mitigating physical degradation (Rodrigues et al. 2023).

SOC plays a dual role in climate regulation: while its loss contributes to land degradation that increases atmospheric greenhouse gas concentrations, its accumulation represents a major opportunity for long-term carbon sequestration. It has been estimated that SOC accounts for 47% of the mitigation potential in agricultural lands (Bossio et al. 2020). This has been recognised in global commitments such as the United Nations Framework Convention on Climate Change. This includes annual reporting of land sector SOC dynamics through the national inventories, which in Australia is achieved via the Full Carbon Accounting Model (FullCAM). The belowground SOC dynamics component of FullCAM is modelled using RothC, which simulates the turnover of organic carbon in non-waterlogged topsoils using a few easily obtainable inputs (Coleman and Jenkinson 1996). Process-based models, like RothC, incorporate chemical and biological processes to estimate change over time. By explicitly representing SOC accumulation and decomposition while incorporating environmental controls, process-based models can assess impacts of land-use change or management scenarios (Zhang et al. 2021).

Although often overlooked in management strategies and modelling efforts, subsoils store a significant portion of total SOC due to their larger volume and typically contain older, more stable carbon. Their potential for long-term sequestration stems from reduced disturbance, limited microbial access, and greater mineral surface availability (Button et al. 2022). Most SOC models focus primarily on the topsoil, typically representing it as a single homogeneous layer. However, to account for the difference in subsoil physicochemical properties, microbial activity and C input composition and pathways (Rumpel and Kögel-Knabner, 2011) modelling efforts need to shift to multilayered and whole-profile models. Models such as RothPC-1, an extension of the RothC model, allow for simulation of SOC dynamics throughout the soil profile (Jenkinson and Coleman 2008), providing greater resolution and realism in estimating carbon storage potential at depth.

Land use and management practices exert a strong influence on SOC dynamics. Perennial pasture systems typically contribute greater root-derived carbon inputs, enhancing belowground carbon accumulation. Modified pastures often include nitrogen-fixing legume species and may receive phosphorus fertilisation, further supporting biomass production and C input flow, leading to increased SOC stocks relative to native pastures (Chan et al. 2010). In contrast, cropping systems exhibit greater variability in root architecture and carbon allocation, with different crop types contributing unevenly to subsoil carbon (Janke et al. 2025). Management practices like tillage, stubble retention, and crop rotation design affect the quantity and quality of aboveground carbon inputs (Janke et al. 2025). Cultivation and soil disturbance in cropping systems can accelerate SOC losses, with declines of 30–40% reported after conversion from pasture or native vegetation (Chan et al. 2010).

This work builds on earlier efforts to use readily available data to estimate C inputs in different agricultural settings (Coelli et al. 2021), extending the analysis to include SOC to a deeper soil profile using RothPC-1 (Fig. 1). To our knowledge, this represents the first attempt to apply a process-based SOC model in a scalable, whole-profile context across Australia.

2. METHODS

2.1. Data collection

Soil data was collated for 18 sites from two timepoints in the Muttama catchment near Cootamundra in SE NSW. Soil cores were collected to a depth of 100 cm and divided into layers of 0-10, 10-30, 30-60 and 60-100 cm. Cores collected in 2013 (t_0) were analysed for SOC using dry combustion and clay content using the hydrometer method as described in Orton et al. (2016). Cores collected in 2019 (t_1) were analysed for SOC and clay content by dry combustion or mid-infrared spectroscopy (MIR) combined with partial least squares regression (PLSR), calibrated with a spectral library as described by Coelli et al. (2021). Size fractionation, followed by 13C NMR analysis, characterises ROC-like material, as described by Baldock et al. (2013), and was used to derive ROC. The ROC fraction is needed as an estimate of the IOM conceptual pool in the RothPC-

1 model due to similar characteristics and residence time. Data for layers 0-10 and 10-30 cm were combined into a 0-30 layer using a depth-weighted average. SOC and ROC were converted to t C/ha using a pedo-transfer function developed by Tranter et al. (2007), derived to get bulk density estimates. Monthly climate, vegetation and land use data was collected from remote sensing platforms and databases as outlined in Table 1.

$$C\ inputs = b * NDVI * ET \tag{1}$$

C inputs was estimated using the approach presented by Coelli et al. (2021) which is based on transpiration, water use efficiency (WUE) and harvest index (HI) in cropping systems. Transpiration can be represented by ET scaled by NDVI to remove the evaporation portion. WUE and HI is represented by a parameter, b, which can be optimised to suit different land uses. For example, in a grazing system the plants are harvested by being consumed by livestock and would therefore have a different b compared to a cropping system. The b parameter can also be used to scale the ET and NDVI relationship between vegetation types. Therefore, optimising b for different land uses and vegetation types makes this a scalable approach that can be used across Australia. Therefore, C inputs can be estimated by Eq.1.

Table 1. Input data used in RothPC-1 and the respective source. Temporal variables were aggregated to represent monthly estimates.

Model input	Source	Spatial resolution
Land Use	SEED (NSW DCCEEW)	Polygons
Temperature	SILO (Jeffrey et al. 2001)	5 km
Rainfall	SILO (Jeffrey et al. 2001)	5 km
Pan evaporation	SILO (Jeffrey et al. 2001)	5 km
ET	CMRSET (Guerschman et al. 2022)	30 m
NDVI	Landsat 7 and 8 (USGS)	30 m

2.2. Model structure and initialisation

RothPC-1 is a multilayer version of the topsoil focused RothC model (Coleman and Jenkinson 1996; Jenkinson and Coleman 2008). RothPC includes the same five conceptual C pools as RothC, four active conceptual pools; decomposable plant material (DPM), resistant plant material (RPM), microbial biomass C (BIO) and humus C (HUM) and one inactive pool that represents stable inert organic matter (IOM). Each pool has a designated decomposition rate constant that is modified by soil clay content, moisture (calculated from rainfall and open pan evaporation), temperature and plant cover. RothPC has two additional parameters compared to RothC; p is the fraction of C that remains in the same layer and s slows the decomposition rates with depth. Organic C input flows into the DPM and RPM at a set ratio using that varies with the quality of the incoming C into soil system and monthly time steps. C in these pools is decomposed to form CO_2, BIO, HUM within the same layer or is transported to the respective DPM or RPM pool in the layer below (Fig. 1).

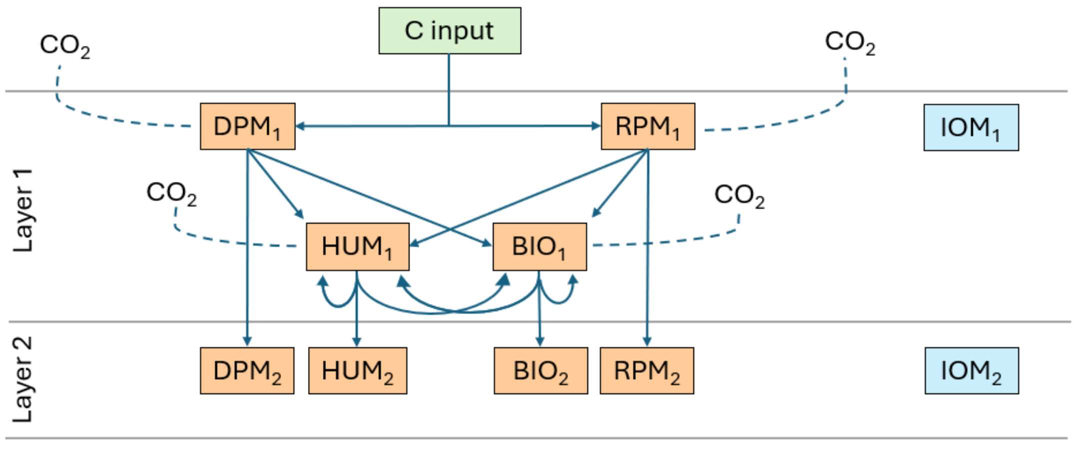

Figure 1. RothPC-1 flow chart adapted from Jenkinson and Coleman (2008). Arrows indicate flows between pools, and dashed lines represent CO_2 flows. The dynamics shown in layer 1 are repeated in each layer below, and the number of layers can be adjusted to any number required, though only two are shown here. Orange squares indicate that the conceptual pool value at t_0 was derived from the equilibrium run (steady-state), and blue squares indicate that the pool value was derived from the MIR/PLSR analysis.

The goal with model initialisation is to get estimated starting values of the conceptual C pools, commonly achieved in process-based carbon models by running it to equilibrium (Jenkinson and Coleman 2008; Wells et al. 2013). In this study, we extracted daily data for rainfall, pan evaporation and temperature between 1983-2000 and calculated monthly long-term averages. The model was then run for 500 years using the RothPC-1 framework scripted in R (R Core Team 2024) with RPM, DPM, HUM and BIO set to zero as a starting point, and IOM set equal to the measured ROC value in 2013. Using the 'optim' function (initialisation run), C input, *s* and *p* were allowed to roam while minimising the root mean squared error (RMSE) between observed SOC for 2013 (t_0) and the sum of the predicted pools (RPM, DPM, HUM, BIO and IOM) for each layer.

2.3. Model calibration and validation

The 18 sites were grouped into land uses: cropping (n=11), grazing modified pasture (n=3) and grazing native vegetation (n=4). Each land use was run separately using real-time monthly input data. Decomposition rate constants for each pool were based on Skjemstad et al. (2004) who calibrated the default RothC constants to Australian agricultural conditions. Using the 'optim' function again (calibration run), the DPM/RPM ratio of the C input, *b*, *s* and *p* were allowed to vary to achieve the lowest RMSE. This resulted in optimised parameter sets for each land use. C inputs were distributed across the three layers in set fractions of 0.7 into the top layer, 0.2 into layer two and 0.1 into layer three. These values were selected based on the literature, where estimates of 80% of C inputs come from below-ground inputs and 60% of root biomass is often found in the top 30 cm, 15-20% in the 30-60 cm range and 5-15% in the 60-100 cm range (Xiao et al. 2023).

The parameter sets were tested on 17 independent sites in the same region. The observed data for these sites was available only for 2019 (t_1), so starting values (t_0) for the C pools were derived from the equilibrium results from the calibration sites using k-nearest neighbour interpolation. The validation sites only included two land uses: cropping (n=13) and grazing modified pasture (n=4).

3. RESULTS AND DISCUSSION

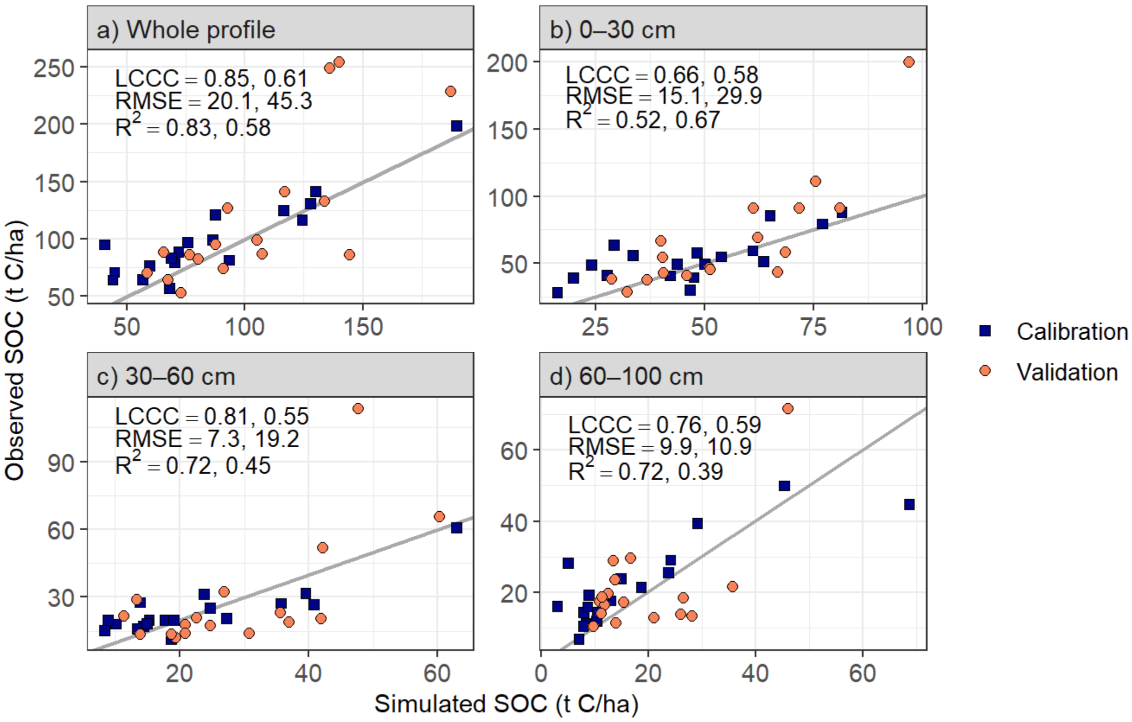

Figure 2. Observed and predicted SOC for all land uses. The first RMSE and Lin's concordance correlation coefficient (LCCC) values listed are for the calibration sites, followed by the values for the validation sites. The grey lines represent the 1:1 line.

The model results show relatively high agreement between observed and simulated SOC for the combined land uses (Fig. 2), with similar R^2 values and lower RMSE compared to other depth-resolved process-based SOC models (Zhang et al. 2021; Wang et al. 2021). As expected, better performance statistics were achieved for calibration sites (Fig. 2). Some of the decreased performance for validation sites is carryover from the interpolation error of the C pools at t_0. Another contributor is likely due to a few validation sites with comparatively high observed SOC, indicating that the parameterisation of the model does not suit sites with higher SOC stocks. This could potentially be mitigated by increasing the number of calibration sites with higher SOC stocks. However, SOC stocks as high as those observed at the validation sites (approximately 250 t C/ha) are unusual in Australian agricultural settings. For example, Wells et al. (2013) reported a maximum of 160 t C/ha across several sites in NSW. Uncertainty propagation was not considered in this work, so any carryover error from MIR and PLSR analysis is unknown. More published studies are needed to better understand if these are real or erroneous values.

Overall, the model tends to underpredict SOC with the highest bias and error from layer one (Fig. 2). This is expected since the range and average SOC values are higher compared to the other layers (Fig. 2). It could also be related to the partitioning of C inputs. The fractions selected here were based on averages from broad studies, but realistically, these fractions vary for different land uses, management and vegetation types (Xiao et al. 2023). The model was also run with all C inputs to the top layer, which improved bias and accuracy for layer one but had the opposite effect for the whole profile and deeper layers (results not shown). The fraction split could likewise have caused the decreased performance in layer two and three for the modified pasture validation sites, where a greater C input allocation to deeper layers may be needed. Future work could include the fraction split into the optimisation process to get more tailored values.

The model for the cropping land use performed the best (Table 2), which can be expected due to the larger sample size. Grazing modified pasture had equal performance as cropping for the calibration data (Table 2), so performance for the validation sites would likely improve with more observations. Similarly, the model for grazing native vegetation, while having slightly lower performance statistics (Table 2), shows potential and would benefit from increased sampling size. Cropping followed by grazing native vegetation had the lowest DPM/RPM ratios (Table 3). This can be explained by the higher lignin content and C:N ratio of cropping species, making these species more resistant to decomposition (Ntonta et al. 2022). Similarly, Australian native pasture species are commonly of lower quality, containing more lignin-like compounds and lower N concentration than modified pasture, especially if introduced legume species are a part of the pasture mix.

Table 2. Model performance metrics by land use and soil layer. Layer one corresponds to 0-30 cm, layer two is 30-60 and layer three is 60-100, while the profile values refer to the combined layers.

		Cropping		**Grazing modified pasture**		**Grazing native vegetation**	
		Calibration	Validation	Calibration	Validation	Calibration	Validation
LCCC	Profile	0.90	0.73	0.84	0.28	0.62	-
	Layer 1	0.67	0.74	0.83	0.43	0.47	-
	Layer 2	0.91	0.56	0.67	0.06	0.57	-
	Layer 3	0.78	0.62	0.85	0.24	0.49	-
RMSE ($t\ C\ ha^{-1}$)	Profile	17.8	36.1	13.5	67	28.5	-
	Layer 1	14.7	15.3	3.6	55.1	20.5	-
	Layer 2	5.6	20.8	9.1	12.2	9.5	-
	Layer 3	11.4	11.4	4.3	9.4	8.4	-
R^2	Profile	0.92	0.76	0.99	0.16	0.54	-
	Layer 1	0.55	0.70	0.84	0.78	0.34	-
	Layer 2	0.86	0.53	0.97	0.01	0.93	-
	Layer 3	0.71	0.49	0.83	0.22	0.84	-

The *s* parameter, which slows decomposition at depth, and the *p* parameter, which determines the fraction of SOC retained within a layer at the end of each month, showed the same trends between land uses (Table 3). Native pasture having the most negative *s* indicates the decomposition at depth is more restricted compared to the other land uses, while the vertical transport is higher. Native pastures are more common in locations that are difficult or ineffective to manage, such as high-sloping areas with inferior soil types, resulting in lower nutrient availability and increased drainage, which limits microbial activity and would appear in this model as a more negative *s*. Overall, the values for *p* were low in this study (0.21-0.29) compared to other studies using RothPC-1 in England (0.49-0.82) and central NSW (0.63-0.81; Jenkinson and Coleman 2008; Wells et al. 2013). This could be related to differences in clay content or pH, as both factors can limit the movement of dissolved organic matter through chemical adsorption (Jenkinson and Coleman 2008). The *s* parameters for cropping and modified pasture align with results from England, but are more negative than results from central NSW. Jenkinson and Coleman (2008) found *s* to be highly sensitive to *p*, generally resulting in a more negative *s* as *p* increases. The logic is straightforward: less downward movement of SOC (higher *p*) result in lower SOC concentrations and reduced microbial activity at depth, leading to more negative *s* values. However, Wells et al. (2013) reported relatively high *p* values alongside much lower *s*, suggesting this relationship is not consistent and warrants further investigation, particularly in the Australian context.

The *b* parameter was quite similar between land use, contrary to Coelli et al. (2021) who found native grazing to have a much larger *b* compared to other land uses. However, their sample size for native pastures was much larger and covered a much larger region in NSW than in this study, so differences in *b* will likely be more prominent with more sites added.

Table 3. Optimised values of model parameters for each land use. The parameters are scalars or fractions, so are unitless and optimisation ranges allowed are indicated in brackets and were based on the literature. The lower range of *p* is determined by site clay content, so an approximate value is indicated here.

Land use	**DPM/RPM ratio** (0.25 – 4)	***b*** (0.01 – 150)	***s*** (-0.14, -0.0025)	***p*** (0.2 – 1)
Cropping	0.51	96.50	-0.06	0.29
Grazing modified pasture	3.01	99.87	-0.08	0.23
Grazing native vegetation	1.92	97.87	-0.14	0.21

4. CONCLUSION

This study demonstrates that RothPC-1 effectively simulates SOC dynamics across land uses, with strong agreement between modelled and measured values. Its capacity to predict SOC to depth supports its suitability as a process-based tool for estimating carbon stocks, and its use of readily available weather, land use, and carbon input data highlights its practical value in data-limited contexts. Its overall performance is on par with other established models, reinforcing its potential utility in carbon accounting frameworks.

A key limitation for this work was the small sample size, particularly for native and modified grazing systems. Expanding the number of sampling sites would likely reduce model error and improve validation metrics. Ongoing efforts to collate datasets and analyse additional soil samples across agricultural and natural environments aim to address this gap. Broader adaption of subsoil sampling should be prioritised across Australia to overcome current data limitations and improve whole-profile SOC modelling.

Increased data availability would also enable future work to optimise several model parameters to improve accuracy. This includes land use-specific carbon input fractions into different soil layers, which are influenced by rooting depth and are critical for representing subsoil carbon dynamics. Further investigation is also needed into the relationship between *p* and *s*. While it is logically consistent that higher *p* (less vertical transport) would correspond to a more negative *s* (slower decomposition at depth), current evidence for this link is inconsistent. Notably, carbon input fractions at depth are likely to influence both *p* and *s*, and should be considered jointly. In addition, the parameter *b* should vary between land uses and deserves further calibration. Optimising these parameters could significantly improve model sensitivity and interpretability across diverse land use contexts.

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