



Using measured stocks of biomass and litter carbon to constrain modelled estimates of sequestration of soil organic carbon under contrasting mixed-species environmental plantings

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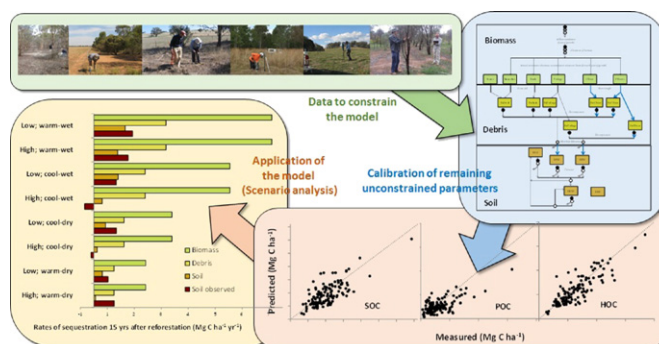
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HIGHLIGHTS

- A mechanistic model predicted sequestration of soil organic C following reforestation.
- Measures of growth, allocation, litterfall and decomposition constrained the model.
- Calibrations of the constrained model maximised efficiency of prediction of soil C.
- High capacity to sequester soil carbon on high rainfall agricultural land depleted in soil carbon
- Planting width, tree density, and proportion of eucalypts influenced sequestration rate.

GRAPHICAL ABSTRACT



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ABSTRACT

Reforestation of agricultural land with mixed-species environmental plantings of native trees and shrubs contributes to abatement of greenhouse gas emissions through sequestration of carbon, and to landscape remediation and biodiversity enhancement. Although accumulation of carbon in biomass is relatively well understood, less is known about associated changes in soil organic carbon (SOC) following different types of reforestation. Direct measurement of SOC may not be cost effective where rates of SOC sequestration are relatively small and/or highly

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spatially-variable, thereby requiring intensive sampling. Hence, our objective was to develop a verified modelling approach for determining changes in SOC to facilitate the inclusion of SOC in the carbon accounts of reforestation projects. We measured carbon stocks of biomass, litter and SOC (0–30 cm) in 125 environmental plantings (often paired to adjacent agricultural sites), representing sites of varying productivity across the Australian continent. After constraining a carbon accounting model to observed measures of growth, allocation of biomass, and rates of litterfall and litter decomposition, the model was calibrated to maximise the efficiency of prediction of SOC and its fractions. Uncertainties in both measured and modelled results meant that efficiencies of prediction of SOC across the 125 contrasting plantings were only moderate, at 39–68%. Data-informed modelling nonetheless improved confidence in outputs from scenario analyses, confirming that: (i) reforestation on agricultural land highly depleted in SOC (i.e. previously under cropping) had the highest capacity to sequester SOC, particularly where rainfall was relatively high ($>600 \text{ mm year}^{-1}$), and; (ii) decreased planting width and increased stand density and the proportion of eucalypts enhanced rates of SOC sequestration. These results improve confidence in predictions of SOC following environmental reforestation under varying conditions. The calibrated model will be a useful tool for informing land managers and policy makers seeking to understand the dynamics of SOC following such reforestation.

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1. Introduction

Reforestation is one of the most cost-effective ways to sequester carbon in agricultural landscapes (e.g. [Nabuurs et al., 2007](#)), and provides valuable opportunities for landscape remediation and positive environmental outcomes in degraded agricultural regions (e.g. [Rhoades et al., 1998](#); [Nair, 2008](#); [Cunningham et al., 2015b](#)). While most studies of carbon sequestration following reforestation estimate rates of accumulation in biomass and litter, there is relatively little validated information on associated changes in soil organic carbon (SOC; e.g. [Cunningham et al., 2015a](#)), as it is highly spatially variable and hence difficult to measure accurately ([Allen et al., 2010](#)). However, soil is the largest terrestrial pool of organic carbon, so small proportional changes could significantly affect atmospheric carbon concentration ([Stockmann et al., 2013](#)).

Recent studies suggest that high sampling intensities are needed at the plot scale to accurately estimate change in SOC following reforestation due to high spatial variability (e.g. [Cunningham et al., 2017](#)). Minimising SOC sampling errors by ensuring appropriate sample designs with adequate sampling intensity is particularly important if the relatively small changes in SOC following reforestation are to be detected. A new equilibrium in 0–30 cm SOC may take hundreds of years to reach, especially when considering inputs from decomposition of coarse tree roots (e.g. [Hibbard et al., 2003](#); [Poeplau et al., 2011](#); [Bárcena et al., 2014](#)). Observed trends in SOC changes following reforestation tend to be weak and imprecise (e.g. [Prior et al., 2015](#); [England et al., 2016](#)). Because most reforestation of agricultural land is in lower productivity regions (where the opportunity costs of land use change are relatively small) the amounts of carbon sequestration are relatively low (e.g. [Paul et al., 2016](#)). Consequently, conventional direct measurement approaches may be cost-prohibitive even under relatively high carbon prices. Thus, a modelling approach to SOC accounting may provide a practical alternative ([Paul and Polglase, 2004b](#); [Paul et al., 2013a](#)).

SOC is a diverse mix of organic materials with different susceptibilities to biological decomposition ([Baldock et al., 2013a](#)). Conceptual pools of C that turnover at different rates are required to model complex SOC dynamics (e.g. RothC, CENTURY; [Jenkinson, 1990](#); [Parton et al., 1993](#)), including following reforestation (e.g. [Del Galdo et al., 2003](#); [Cunningham et al., 2015a](#)). Recent advances in mid-infrared reflectance spectroscopy (MIRS) have allowed accurate and cost-effective measurement of SOC fractions (particulate, humic, resistant) across a large range of agricultural soils ([Baldock et al., 2013a, 2013b](#)) and following reforestation ([Madhavan et al., 2017](#)). These methodologically-defined fractions can be used as surrogates for the conceptual pools of the RothC soil carbon model ([Skjemstad et al., 2004](#)).

Simulating SOC dynamics requires estimation of the transfer of carbon from above- and below-ground biomass to the debris pool (litter, coarse woody debris and dead roots) and then to SOC. This has been achieved through integration of RothC into the Full Carbon Accounting Model, FullCAM ([Richards and Brack, 2004](#)). FullCAM is currently applied in Australia for both national greenhouse gas accounting, and for project-scale accounting in the regulated carbon market ([Australian Government, 2014, 2017](#)). Simulations of reforestation have shown that sequestration in the 0–30 cm soil and debris contribute ca 5–20% of the total carbon sequestered ([Paul et al., 2013a](#)). However, to date, carbon market regulators in Australia have considered uncertainty in estimations of change in SOC to be too high to enable proponents of reforestation projects to gain carbon credits for sequestration of carbon in soil in addition to that sequestered in biomass and debris ([Australian Government, 2014](#)).

In Australia, mixed-species environmental plantings of native trees and shrubs are increasingly being established on agricultural land for both sequestration of carbon and other ecosystem services (e.g. [Mitchell et al., 2012](#)). Accurate estimates of biomass accumulation by a representative range of environmental plantings are now possible through recent calibration of FullCAM biomass yield functions ([Paul et al., 2015](#)). Previous work has measured litter and SOC (including its fractions) under environmental plantings compared with agricultural land (paired sites or with baseline sampling, [England et al., 2016](#); [Madhavan et al., 2017](#)) representing much of the temperate and Mediterranean-type, and part of the tropical and sub-tropical, climates across the continent. Further, typical rates of litterfall and decomposition of litter in eucalypt-dominated forest ecosystems, the dominant genus in environmental plantings, have been previously reviewed ([Paul and Polglase, 2004a](#)). Assuming that the reforested sites were originally like the current pasture or cropping sites at the time of reforestation, these data sets facilitated calibration of FullCAM ([Fig. 1](#)) to extend confidence in estimation of carbon sequestration following reforestation to include the SOC pool in addition to the biomass and debris pools.

If well-calibrated, a wide range of scenarios of climate and soil conditions may be applied to simulate the short- and long-term impacts on SOC in environmental plantings under alternative designs known to impact biomass yields (e.g. planting width, stand density, and the proportion of eucalypts). This will improve our understanding of the dynamics of SOC following reforestation, including the longer-term resilience of SOC under a changing climate. To achieve this, our objectives were to: (i) constrain FullCAM with measured data on biomass and litter carbon, (ii) maximise the efficiency of prediction of SOC by calibrating FullCAM parameters that cannot be estimated from measured values or the literature, and (iii) apply this calibrated model to undertake scenario analyses.

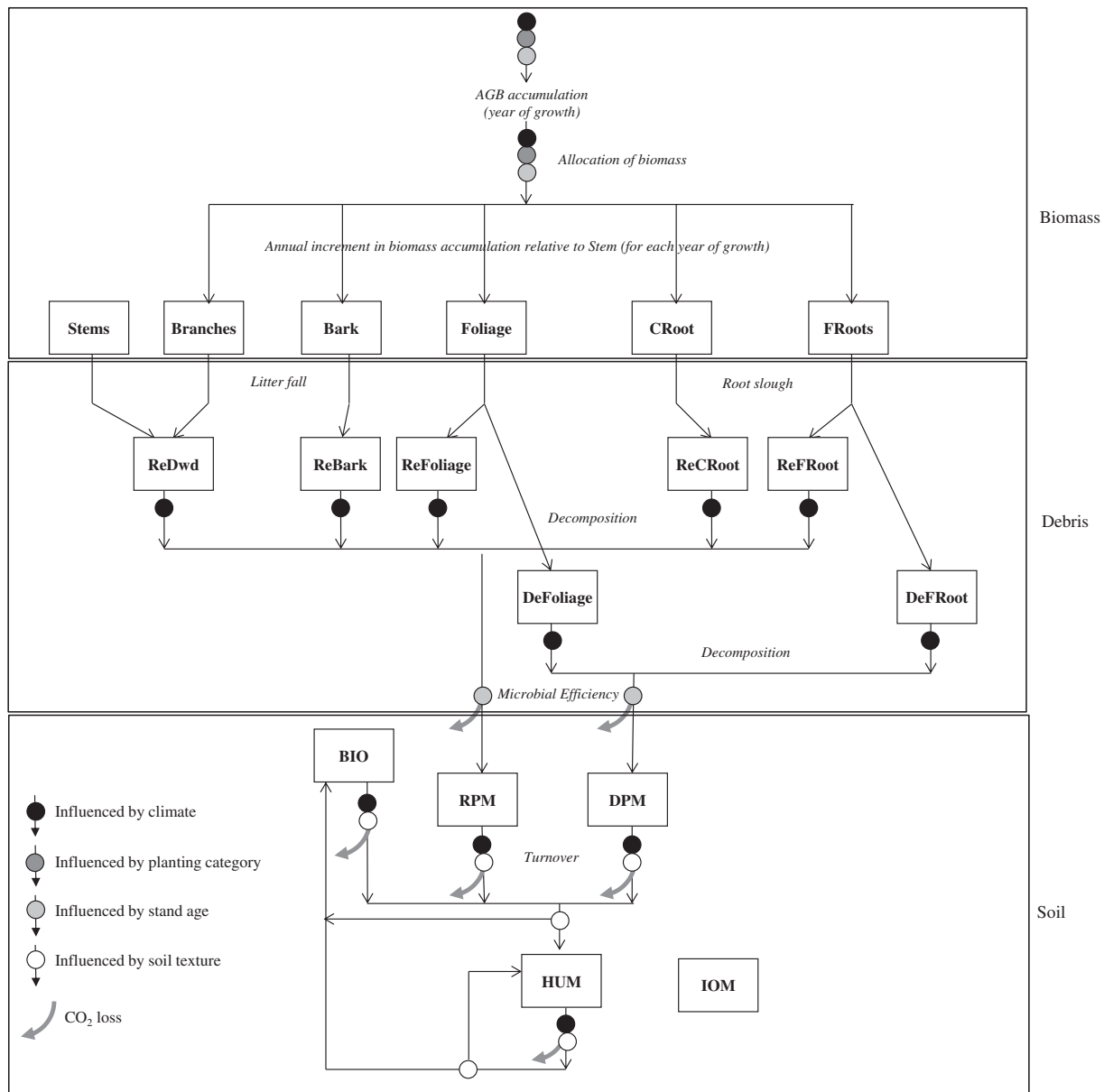


Fig. 1. Overview of the FullCAM model configuration using RothC v 263 including Biomass, Debris and RothC Soil sub-models. In the Debris sub-model of litter decomposition, tree components (Dwd = dead wood, and CRoots and FRoots = coarse and fine roots, respectively) and pools of debris (Res = resistant pools of debris, and De = decomposable pools of debris) are represented in the boxes. In the Soil sub-model of soil carbon, the pools are RPM = resistant plant material (0.17 year^{-1} , Chappell and Baldock, 2013), DPM = decomposable plant material (10 year^{-1}), BIO = microbial biomass (0.66 year^{-1}), HUM = humified organic matter (0.02 year^{-1}) and IOM = inert organic matter (0 year^{-1}).

2. Methods

2.1. Model description

The carbon accounting model FullCAM (Fig. 1) calculates carbon sequestration in biomass, debris and soil pools following reforestation in Australia's national greenhouse gas accounts (e.g. Richards and Brack, 2004, Fig. 1). In FullCAM, growth of above-ground biomass (AG biomass) is predicted by the empirical Tree Yield Formula (TYF), with the CAMFor sub-model tracking the flow of carbon turnover to the soil via pools of debris (Paul and Polglase, 2004a), and the RothC sub-model tracking the turnover of the fractions of SOC (Paul and Polglase, 2004b). Values for weights of biomass and necromass listed in this work refer to dry matter (DM).

Details of the steps to calculate biomass accumulation via the TYF have been previously documented (Paul et al., 2015). Here, we provide

a brief description of subsequent model calculations to predict SOC change, with more detail in Richards and Brack (2004) and Australian Government (2017). Based on the age of the stand, the annual increment in growth is allocated to the various stand components; wood, branches, bark, foliage and coarse- and fine-root biomass. Once biomass has been allocated, rates of litterfall and root turnover are calculated from default turnover constants. Foliage and fine root debris are allocated to both decomposable and resistant pools, while wood, bark and coarse root components of debris only have a resistant pool (Fig. 1). The model assumes decomposition rates of debris pools are modified by climate only. During the decomposition of debris, some carbon enters the soil, with the remainder emitted as a range of gaseous carbon compounds, with an end product assumed to be mainly CO₂. 'Microbial efficiency' is defined by the ratio of carbon respired during decomposition of debris to carbon transformed to dead organic matter of a form that is subsequently transferred to soil, e.g. microbial biomass (Cotrufo

et al., 2013). Microbial efficiency parameters were assumed to differ between decomposable (DeDebris) and resistant (ReDebris) pools of debris (Paul and Polglase, 2004b, Fig. 1).

Five pools of carbon are simulated by the RothC sub-model (Fig. 1, Jenkinson, 1990): (i) decomposable plant material (DPM); (ii) resistant plant material (RPM); (iii) microbial biomass (BIO); (iv) humified organic matter (HUM), and (v) inert organic matter resistant to biological decomposition (IOM). All of the carbon entering the soil through decomposition of the decomposable debris pools (DeFoliage and DeFineRoot) is assumed to enter the fast-turnover DPM soil pool (Jenkinson, 1990). All other carbon from debris decomposition enters the slow-turnover RPM pool. The DPM and RPM pools decompose to, in effect, produce CO₂, and pools of BIO and HUM, with these pools decomposing to yield more CO₂. All pools (except IOM) in RothC decompose at defined rates modified by temperature, soil moisture deficit and the plant cover factor.

2.2. Data set collated

Data were collated from 125 environmental planting sites (England et al., 2016); 104 of these were paired with adjacent agricultural land, and the remaining 21 had baseline sampling with repeated measurements at different stand ages (Table 1). Methods of planting establishment varied and included use of tube-stock (68%), direct seeding (22%), a combination of tube-stock and direct seeding (8%), and broadcast seeding/natural regeneration (2%). The sites were distributed predominantly across temperate southern Australia (Fig. 2). Mean planting age was 13.6 ± 6.9 years old. Plantings were generally sampled from regions where the mean annual rainfall (MAR) ranged from 352 to 1474 mm year⁻¹, with a mean of 670 ± 204 mm year⁻¹. Note, average values are reported with their standard deviation (SD) unless otherwise stated.

The data set included measurements of AG biomass, litter and SOC and its fractions, with details of the methodology described previously (England et al., 2016; Madhavan et al., 2017). In brief, biomass was determined from measurements of stem diameters and species at each site, with the application of allometric equations to predict above-ground (Paul et al., 2013b) and below-ground (Paul et al., 2014) biomass of trees and shrubs. Between 26 and 2487 (mean 428 ± 489) trees (or shrubs) per site were measured from plots ($N = 1$ –51 per planting, area = 0.01 – 3.37 ha) or transects ($N = 2$ –8 per planting, area = 0.001 – 0.010 ha).

Generally, litter (ca 0.1 m² quadrats) and soil (from ca. 42 mm diameter cores) were sampled from 0.4 ha plots (located within the larger biomass inventory plots) divided into 40 sampling units (each 10 m × 10 m). For both litter and soil, one sample was taken from a random location within each of the 40 sampling units. From among the 40 samples, sets of five were randomly selected for bulking to make eight large composite samples for each litter component (<2 mm and >2 mm) and soil layer, generally 0–10 cm (or 0–5 and 5–10 cm) and 10–30 cm. Each soil sample was air-dried, crushed and sieved (<2 mm), and the proportion of gravel (>2 mm) measured. SOC was generally measured with a CNS analyser (LECO Corporation, St. Joseph, MI, USA). Fractions of SOC were particulate (POC or RPM), humus (HOC or HUM), and resistant (ROC or IOM) organic carbon. These fractions were measured using calibrated mid-infrared spectroscopy (MIRS) Partial Least Squares Regression (PLSR) models (Madhavan et al., 2017). Litter and SOC results were subsequently reported on an oven-dry basis (i.e. 70 °C for litter and 105 °C for <2 mm soil). SOC stocks in the fast-turnover DMP and BIO pools were assumed to be negligible. To estimate SOC contents from SOC concentrations, bulk density (g cm⁻³) of the 0–10, 10–30 and 0–30 cm soil depths was calculated from the mass of the fine (<2 mm) fraction adjusted for oven-dry (105 °C) moisture content and volume of the bulked samples. The carbon concentration in biomass was 46.1–52.9% (or g kg⁻¹), while the carbon concentration in litter (and hence, assumed for coarse woody debris) was $46.3 \pm 1.99\%$ (mean \pm SD, $N = 43$, from 15 different sites).

Stocks of SOC and their fractions were calculated based on fixed depths of soil rather than on equivalent soil mass, as RothC was developed for simulation of fixed depths, not equivalent soil mass (Jenkinson, 1990). Further, it was found that for this data set, statistical analysis of the drivers of SOC stocks estimated using equivalent soil mass gave similar results, albeit with lower explained variation, when compared with those using SOC stocks based on fixed depths (England et al., 2016).

2.3. General approach used to predict soil carbon

FULLCAM simulations were run for each of the 125 sites (Table 1), each with specific inputs of planting attributes (i.e. planting width, stand density and species-mix; Table 1), climate (i.e. monthly rainfall, temperature and evaporation observed during the years of simulation, BoM, 2015) and 0–30 cm soil clay contents (Paul and Polglase, 2004b;

Table 1

Details of the data sets collated, including region of Australia from which sites were located (SE = south east; NE = north-east, and; SW = south-west of Australia), number of sites (N), and the between-site range in stand age, previous land use (PLU; G = grazing, C = cropping or rotational cropping/grazing), mean annual rainfall (MAR), planting width (Belt ≤ 40 m wide, Block > 40 m wide), stand density (number of trees or shrubs per hectare, ha⁻¹), the proportion of trees that were eucalypts (PropEuc), measures of AG tree and shrub biomass dry matter (AGB, Mg ha⁻¹), litter mass, and sampling intensity (N , where first, second and third numbers are the number of: 0–30 cm soil cores sampled from the agricultural pairs (A), 0–30 cm soil cores sampled from the environmental plantings (EP), and litter (L) quadrats sampled from the environmental plantings, respectively).

Region of Australia	N	Age (years)	PLU	MAR (mm year ⁻¹)	Planting width	Stand density (ha ⁻¹)	PropEuc	AGB (Mg ha ⁻¹)	Litter (Mg ha ⁻¹)	Sampling intensity (N ; A, EP, L)
Existing studies										
SE ^a	36	5–46	G	448–794	Block, Belt	241–1122	0.34–1.00	14–211	0.9–23.3	5–10, 5–10, 10
SE ^b	20	1–19	G	550–884	Belt	1438–20,768	0.05–1.00	1–166	6.0–15.0	9–24, 18–24, 3
SE ^c	7	8–16	G, C	352–1112	Block, Belt	838–6344	0.06–0.82	15–130	5.5–26.7	6, 12, 6–12
This study										
SE, intensive	3	5	G	427–965	Block	255–1231	0.18–0.87	18–114	4.5–24.5	56, 120, 120
SE, repeat ^d	21	5–20	G, C	509–696	Block	124–1268	0.08–0.62	6–66	5.7–19.1	NA, 9–40, 3–40
SE, riparian	10	9–23	G, C	407–774	Block, Belt	299–8741	0.00–0.94	28–260	3.8–14.4	40, 40, 40
SE	19	9–20	G, C	365–1423	Block, Belt	152–1604	0.19–0.79	4–110	2.4–15.5	40, 40, 40
SE	4	6–29	C	372–652	Block	200–1490	0.38–1.00	17–67	11.6–13.0	10–40, 40, 0–40
NE	3	5–19	G	852–1474	Block	281–1583	0.02–0.97	7–185	4.5–16.1	40, 40, 40
SW	2	15–16	C	370–422	Belt	567–768	0.72–0.86	66–82	19.5–26.9	40, 40, 40
Range		1–46		352–1423		124–20,768	0.00–1.00	1–260	0.9–30.6	

^a Cunningham et al. (2015a).

^b Read (2016); using weighted mean of inter-trees and between row sampling, and with SOC measured using Heanes (1984) method.

^c Baker, T., unpublished data.

^d Sites were measured two or three times.

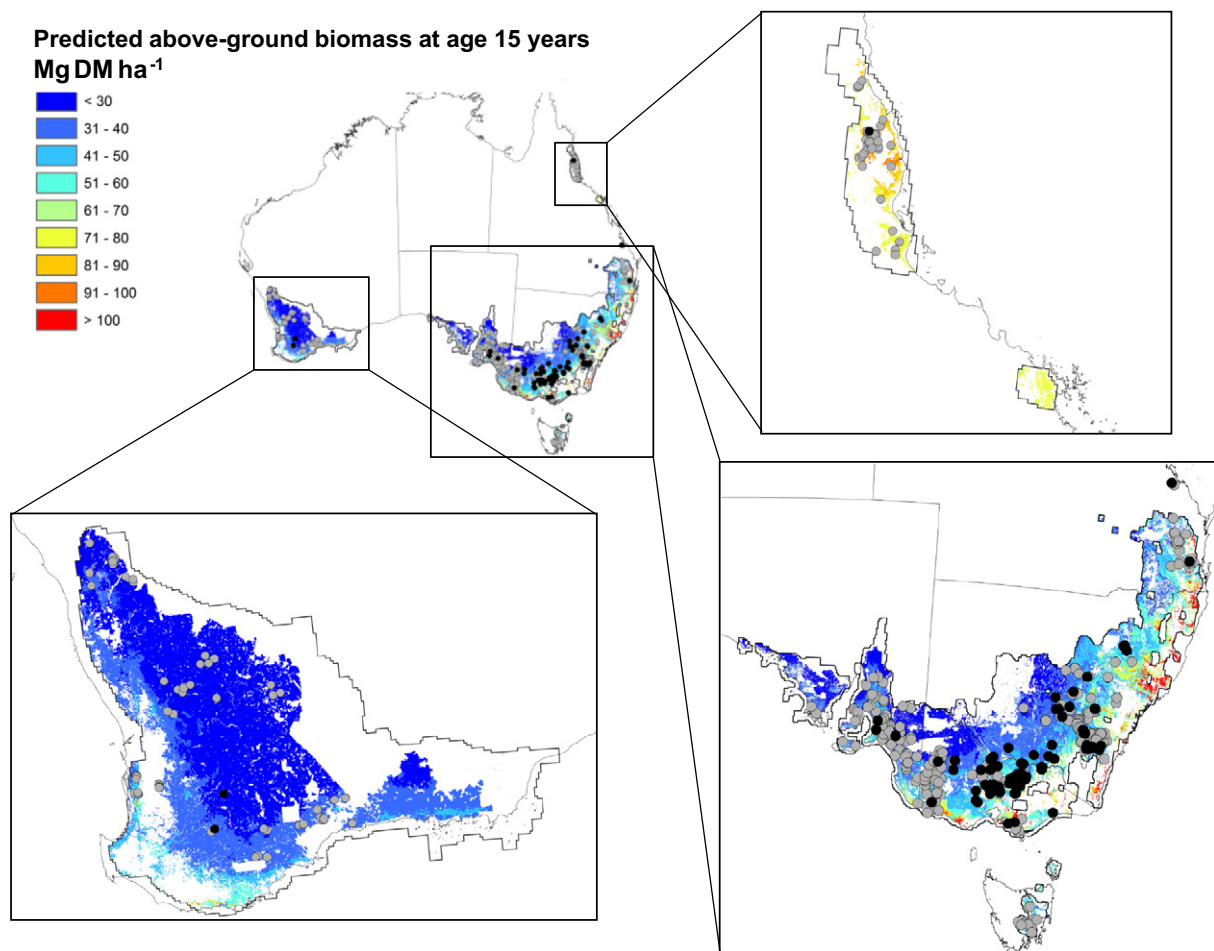


Fig. 2. Location of environmental planting sites: (i) from which data on AG biomass were previously collated for calibration of yields in AG biomass (Paul et al., 2015) (●), and; (ii) from which soils were collected (●). Coloured regions indicate the regions of application of calibrations for yields in AG biomass, with colours providing an indication of spatial variation in prediction of AG biomass 15 years after environmental planting reforestation under the scenario of belt plantings (<40 m wide).

Paul et al., 2015). Monthly time-steps were simulated between plantings until the time of measurement.

Initial pools of carbon in biomass and debris were assumed to be zero prior to reforestation, while initial pools of POC and HOC were those measured either at the baseline (for re-measured sites), or from the paired agricultural site. In contrast, initial pools of ROC prior to reforestation were taken as the mean measured among the paired sites (or among the repeat measures). We assumed that ROC was stable within the <50 year timeframe of the simulations as there was no statistical difference in ROC among the different land uses across all paired-measurement plots ($N = 252$).

RothC was originally developed and parameterised to model turnover of organic carbon in arable soils (0–30 cm, Jenkinson, 1990) and later applied to soils under forests (e.g. Romanyà et al., 2000; Paul and Polglase, 2004b; Paul et al., 2013b). Predictions of change in SOC are very sensitive to pool turnover rates, particularly for the RPM (or POC) pool (Janik et al., 2002; Paul and Polglase, 2004b). We used values for POC turnover of 0.17 year^{-1} from a recent comprehensive calibration (Chappell and Baldock, 2013). All other RothC parameters were maintained as per Jenkinson (1990). Inputs of climate, soil clay content, and initial pools of carbon varied among sites. Most inputs and parameters in FullCAM were modelled based on observed data. The only parameters that remained to be calibrated in this study were turnover and decomposition of dead roots, and microbial efficiency during decomposition of debris pools (Fig. 1). These parameters are highly uncertain due to a lack of constraining data (Paul and Polglase, 2004b).

2.4. Constraining the model with observations

2.4.1. Growth rates

Environmental plantings can be grouped into different planting types according to planting width, stand density, and species mix, each categorised with different biomass yield formula (TYF) calibrations in FullCAM (Paul et al., 2015). To allow application of these calibrations, plantings sampled here were in similar categories. Planting width was categorised as block (>40 m width), wide belt (20–40 m width) or narrow belt (<20 m width). Stand density (number of trees and shrubs per hectare) was categorised as either low (<500 ha^{-1}), medium (500–1500 ha^{-1}), or high (>1500 ha^{-1}). Species mix was defined as the proportion of individuals in the planting that were *Eucalyptus* species (PropEuc); the dominant tree genus in these plantings. Plantings were categorised as either eucalypt dominant (PropEuc ≥ 0.75) or mixed (PropEuc < 0.75 i.e. having a more diverse mix of trees and shrubs). These categories were used to classify each of the 125 sites (Table 2) and the TYF for this planting type was selected to predict default rates of accumulation of AG biomass. As found by Paul et al. (2015), this enabled predictions of enhanced rates of growth with narrower planting widths, higher tree densities, and an increased proportion of over-storey trees (PropEuc).

Prior to any fitting of AG biomass to observed values, we compared observed AG biomass with that predicted using default values for TYF calibrations for the different planting types (Paul et al., 2015). To test the assumption that the default TYF calibrations for environmental

Table 2

Types of environmental plantings with statistically different ($P < 0.05$) rates of accumulation of AG biomass (Paul et al., 2015, Table 1). Initial rates of growth are inversely related to the parameter G (years, or age of maximum rates of accumulation of AG biomass). The parameter y represents the multiplier defining the maximum potential accumulation in AG biomass, given site-based productivity constraints (e.g. climate and soil fertility). NA, found by Paul et al., 2015 not to be statistically important variables for these planting types.

Region	Planting width (m)	Stand density (trees ha ⁻¹)	PropEuc	% of data set	G (years)	y
Temperate & Mediterranean	<20	<1500	<0.75	15	5.504	1.4
			≥0.75	3	3.627	1.5
		>1500	<0.75	14	3.380	1.4
			≥0.75	2	2.667	1.5
	20–40	<1500	<0.75	10	6.063	1.2
			≥0.75	4	3.893	1.3
		>1500	<0.75	2	4.633	1.2
			≥0.75	1	2.746	1.3
	>40	<500	<0.75	16	8.534	1.2
			≥0.75	8	7.365	1.3
		500–1500	<0.75	14	5.460	1.2
			≥0.75	3	4.828	1.3
Tropical and sub-tropical		>1500	NA	6	5.187	1.3
			NA	2	8.489	0.9

plantings can be applied to plantings with access to more water (than rainfall alone), AG biomass estimates from 90 dryland plantings were compared to that estimated from: (i) 10 sites selected from riparian or floodplain landscape positions, and; (ii) 25 plantings with greater access to surface or ground water, e.g. sites located near dams, in gullies, or with access to urban or road run-off.

There were then two further steps to model biomass production. For the 35 plantings that were likely to have had access to water other than rainfall, AG biomass was significantly under-predicted based on rainfall alone. Therefore, the TYF growth parameter for the maximum possible AG biomass was increased to 300 Mg ha⁻¹ for these plantings, to replace the much lower default value based on an empirical relationship using climate and soil properties for any given location across Australia (Kesteven et al., 2004). Then, for all 125 sites, parameter rates for accumulation of AG biomass were varied until predicted AG biomass matched that observed. Predicted biomass was adjusted on a site-by-site basis by applying a multiplier to modelled annual yield. These multipliers were required to obtain accurate site-based estimates of AG biomass accumulation because, although existing growth TYF defaults are unbiased on regional or national-scales, they are imprecise for a specific site (Paul et al., 2015).

2.4.2. Allocation of biomass

Parameters defining the allocation of biomass were based on recently revised defaults for environmental plantings (Paul and Waterworth, 2015), whereby allocation was based on stand age, MAR, and the initial rates of growth (G parameter value in the TYF, Table 2). In brief, the stand AG biomass could be divided into crown (foliage, twigs < 5 cm diameter) and bole. The proportion of AG biomass that was crown decreased with stand age and the initial rates of yield, and was particularly low for tree-dominant plantings (PropEuc > 0.75) growing in regions of relatively low rainfall (MAR < 500 mm year⁻¹). The ratio of coarse roots to AG biomass decreased with initial rates of growth, and with increasing stand age for tree-dominant plantings. Biomass of fine roots was estimated using an empirical relationship based on total AG biomass (Mokany et al., 2006).

2.4.3. Litterfall

Two factors were used to constrain the model parameters for litterfall rates. Default rates of turnover (% of biomass year⁻¹) for branches, bark and foliage were fine-tuned to ensure that; (i) predicted rates of litterfall in each stand were similar to those reported in reviews of litterfall rates for branches, bark and foliage of eucalypt-dominated forest ecosystems (Paul and Polglase, 2004b; Paul et al., 2017), and; (ii) predicted rates of litterfall of woody and non-woody

components matched those measured at four contrasting 13–20 year old environmental planting sites in the present study.

The four litterfall sites included: (i) Wyoming Springs (35.11° S, 149.10° E), high density (>1500 ha⁻¹), block planting with PropEuc < 0.75; (ii) Castlesteads (34.50° S, 148.74° E), low density (<1500 ha⁻¹) wide belt planting, with PropEuc ≥ 0.75, (iii) Hawk Hill (34.53° S, 148.65° E), moderate density (500–1500 ha⁻¹), block planting with PropEuc < 0.75, and; (iv) Allendale (34.38° S, 148.71° E), high density (>1500 ha⁻¹) block planting with PropEuc < 0.75. At each of these sites litterfall was sampled every 23–73 days over a 12-month period using six randomly-placed litterfall traps (0.18 m²) located in each of two plots (approx. 0.04 ha), avoiding edge rows and large gaps in the stand. Woody and non-woody components collected from the traps were separated and oven-dried (70 °C).

2.4.4. Decomposition of litter

Decomposition rates of foliage debris in eucalypts are well predicted by a double exponential relationship (representing both decomposable and resistant components), whereas a single exponential relationship describes decomposition rates of dead wood and bark debris (Paul and Polglase, 2004b). The decomposable fraction, together with assumed rates of decomposition of each pool of debris, was modelled to match those reported from reviews of eucalypt-dominant forest ecosystems (Paul and Polglase, 2004b).

To test the assumed, generic, defaults of rates of litterfall and litter decomposition, we compared the predicted and measured mass of litter with measurements available at 109 of the 125 sites (Table 1). At a subset ($N = 21$ sites) of these sites, litter mass was further divided into components (twig, bark and foliage debris pools), thereby providing a more refined verification of predicted litter mass.

Although there were measurements of litter mass, coarse woody debris (CWD, >25 mm diameter) was not measured. In mixed-species plantings with comparable AG biomass to those measured here (i.e. <250 Mg ha⁻¹), CWD averaged 24 Mg ha⁻¹, which represented approximately 70% of the mass of dead wood (Prior et al., 2015). Therefore, in the absence of any other information, it was assumed that the dead wood and bark litter measured in the litter quadrats represented only about 30% of the total debris of these components.

2.5. Calibrating the model for maximum prediction efficiency of SOC

Parameters of turnover and decomposition of dead roots, and microbial efficiency during decomposition of debris pools (Fig. 1), required calibration because of their high uncertainty arising from a lack of constraining data (Paul and Polglase, 2004b). Across all 125 sites, each of these calibration parameters was adjusted to maximise the

efficiency of prediction of SOC and each of its pools (Table 1). This index of model performance, model efficiency (Soares et al., 1995) is expressed as;

$$EF = \left[1 - \frac{\overline{e^2}}{\overline{o^2}} \right] \quad (1)$$

where $\overline{o^2}$ is the mean square deviation of each observation from the mean of the observations and $\overline{e^2}$ is the mean squared residual. When expressed as a percentage, an EF of 100% indicates perfect match between observations and predictions; 0% indicates the predictions are no better than simply using the mean of the observations; and <0% indicates that residual variation is higher than the variation in the data.

2.6. Scenario analysis

For scenario analyses, the 125 sites were categorised into eight groupings of soil-climate conditions. Across all sites, the median values of SOC stock, mean annual temperature (MAT) and MAR observed were 45 Mg ha⁻¹, 16 °C and 600 mm year⁻¹, respectively. Using these median values, the eight soil-climatic categories were derived using different combinations of bi-variate (high or low) factors of initial stocks of SOC, MAT and MAR. There were between 8 and 30 sites represented in each category.

We anticipated that much of the observed variability in SOC sequestration rates within soil-climatic categories may be attributable to variation in planting type. This is because we know planting types influence biomass productivity (Paul et al., 2015). To explore this, FullCAM simulations were run for contrasting planting types (Table 2) under scenarios where initial SOC was either low (36 Mg ha⁻¹) or high (62 Mg ha⁻¹), and where there were four different climatic conditions simulated: (i) warm-wet, MAT ca 20 °C, MAR ca 900 mm year⁻¹; (ii) cool-wet, MAT ca 14 °C, MAR ca 700 mm year⁻¹; (iii) cool-dry, MAT ca 15 °C, MAR ca 450 mm year⁻¹; and (iv) warm-dry, MAT ca 20 °C, MAR ca 450 mm year⁻¹. The scenarios for the initial SOC and climate were based on typical ranges of conditions found in our sampling. Clay soils generally have a larger capacity to accumulate SOC than those with lower clay content (Oades, 1988; Solins et al., 1995; Laganière et al., 2010). In all scenarios, soil clay content was assumed to be 20–26%. For each simulation, mean annual rates of carbon sequestration 15 years after reforestation were predicted for each pool – AG biomass, debris and SOC. The mean (and standard deviation) of these predicted sequestration rates were calculated for each of the 13 planting

types simulated for all eight scenarios of soil-climatic conditions (two soil conditions × four climate conditions).

3. Results and discussion

3.1. Constraining the model with observations

3.1.1. Growth rates

For planting sites that were solely rain-fed ($N = 90$), AG biomass was predicted with a model efficiency of 46% (Fig. 3a), which was within the range of efficiencies observed previously for environmental plantings (Paul et al., 2015). Although the precision of prediction was low for a particular site, across a number of sites there was no bias in the predictions. Hence, in national or regional carbon accounting, and in project-level accounting across aggregated sites, estimates will be un-biased on average, despite low precision at the site-scale. These results provide confidence that application of the default TYF parameters is appropriate for national and regional-scale carbon accounting of solely rain-fed environmental plantings.

In contrast to Paul et al. (2015), the new data sets obtained here showed that for plantings accessing additional water to rainfall, default TYF parameters for prediction of AG biomass are inappropriate. Among the 35 plantings assumed to be accessing additional water, AG biomass was underestimated by an average of 47%, with this significant prediction bias resulting in a model efficiency of prediction of only 9% (Fig. 3b). Thus, further work is required to develop TYF modifications for plantings accessing additional water. This was not an issue for this calibration study because modelled biomass yields, where growth multipliers were applied to ensure predicted AG biomass matched that observed, were used (Fig. 3a and b).

3.1.2. Allocation of biomass

Overall, there was no substantial bias in predicted allocation of biomass when compared with that expected based on the empirical modelling of environmental plantings (Paul and Waterworth, 2015; Fig. 4). There were some individual plantings where biomass components were predicted poorly, but overall model efficiencies varied from 66 to 93% among components (Fig. 4).

Total AG biomass was adjusted to fit the measured value. However, due to the imperfect prediction of allocation of this biomass to tree components, some errors will be introduced when simulating inputs of carbon into the SOC pools. Because turnover rates are particularly high for foliage and fine roots, they have a relatively strong influence on SOC. The relative efficiencies of prediction of these pools of biomass were

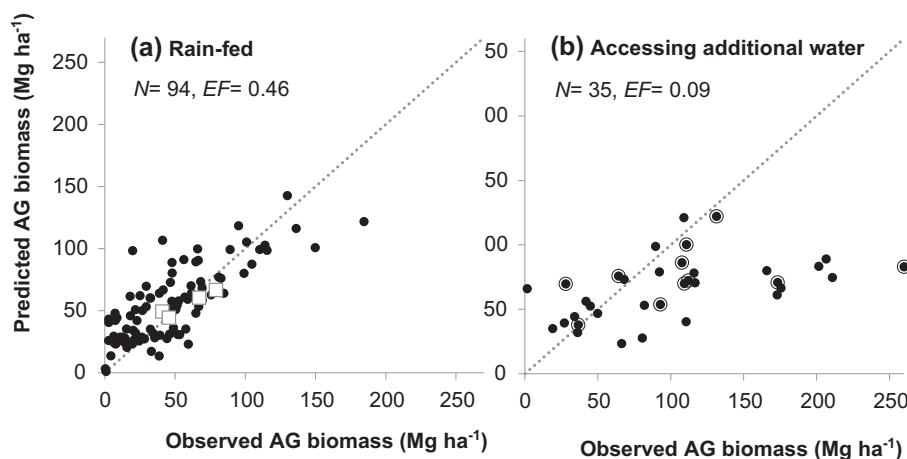


Fig. 3. Relationships between predicted and observed AG biomass (Mg ha⁻¹) for: (a) 90 plantings that were solely rain-fed, and also the four rain-fed plantings where litter fall was monitored (open squares) prior to fitting of AG yields; and (b) 35 plantings that were either plantings along streams and floodplains (circled) or otherwise accessing additional water, prior to fitting of AG yields. Dashed line is 1:1.

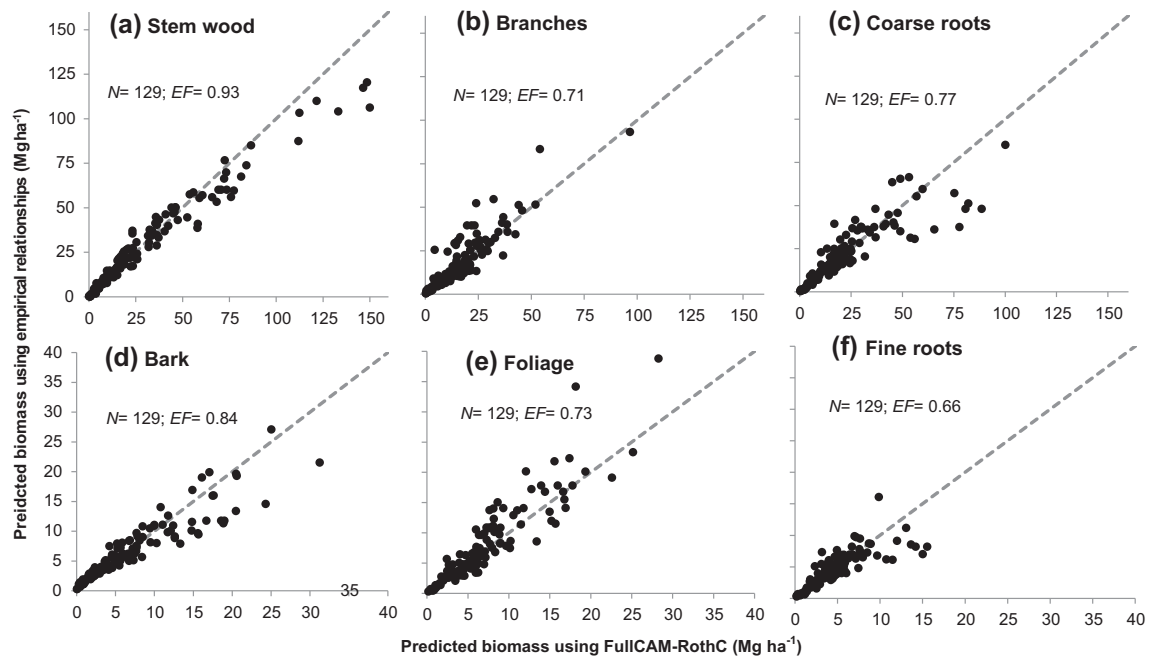


Fig. 4. Relationships between predicted and observed components of biomass (Mg ha^{-1}) in stands of environmental plantings: (a) stem wood; (b) branches; (c) coarse roots; (d) bark; (e) foliage; and (f) fine roots. Dashed line is 1:1. Note: Data from the four litterfall sites were included here together with the 125 sites measured for pools of SOC.

only 73% for foliage and 66% for fine roots. This is likely to introduce uncertainty when calibrating SOC models.

3.1.3. Litterfall

When constraining the model to match data, we found parameters of turnover rates were $8.5\% \text{ year}^{-1}$ for branches, $4.8\% \text{ year}^{-1}$ for bark, and $15.7\% \text{ year}^{-1}$ for foliage. Across all study sites (Table 1), this was equivalent to mean \pm SD rates of turnover of 1.57 ± 1.37 , 0.37 ± 0.51 and $1.24 \pm 1.09 \text{ Mg ha}^{-1} \text{ year}^{-1}$ for branch, bark and foliage, respectively. The large ranges in rates of litterfall for the eucalypt-dominant environmental plantings were consistent with those found in reviews of eucalypt-dominant forests (Paul and Polglase, 2004a; Paul et al., 2017). In these reviews, rates of litterfall for branches, bark and foliage were 0.17 – $2.67 \text{ Mg ha}^{-1} \text{ year}^{-1}$, 0.04 – $1.99 \text{ Mg ha}^{-1} \text{ year}^{-1}$, and 0.30 – $6.34 \text{ Mg ha}^{-1} \text{ year}^{-1}$, respectively.

Comparison of predicted litterfall rates with observations at the four environmental planting sites (Section 2.4.3) indicated that bias averaged only $-0.34 \text{ Mg ha}^{-1} \text{ year}^{-1}$ across all component types (Fig. 5). Given that rates of litterfall are inherently highly variable (e.g. with climate, stand age, tree density, species mix), uncertainties in predicted rates of litterfall are inevitable until these influencing factors are accounted for in the model. Nonetheless, results obtained here provided confidence that predicted rates of litterfall were well within the expected range.

3.1.4. Decomposition of litter

On fitting of the single or double exponential decay models to data obtained from litter bag studies in eucalypt-dominant stands (Paul and Polglase, 2004a), we found that the average observed parameters for resistant fraction of foliage litter was 0.77, while the decay constants for deadwood, bark litter and decomposable and resistant foliage litter were 14, 16, 100 and $28\% \text{ year}^{-1}$, respectively. These parameter values were applied in FullCAM.

Assessment of the amount of litter mass provided further verification of assumed rates of litterfall and litter decomposition. Litter mass varies widely among forest types and species, partly reflecting differences in litter quality and climate (Prescott, 2010). Our results also indicated a wide variation in measured mass of litter among 113 plantings (Fig. 5).

Although we found model predictions of total or components of litter mass to be highly imprecise for any given site, across all plantings, the mean predictions were within ± 1 SD of that observed (Fig. 5). This suggests that although the modelled rates of litterfall and litter decomposition agree with typical rates observed, site-based factors influence these rates, resulting in poor precision of litter mass prediction for an individual site (e.g. Russell et al., 2015). For example, accounting for soil fauna in addition to climatic factors may improve the models performance in predicting decomposition (Filser et al., 2016). Hence, in the absence of site-specific calibrations, this model is most appropriate for application at regional scales given errors will be minimised when applied across multiple sites, with site-level errors largely cancelling each other out.

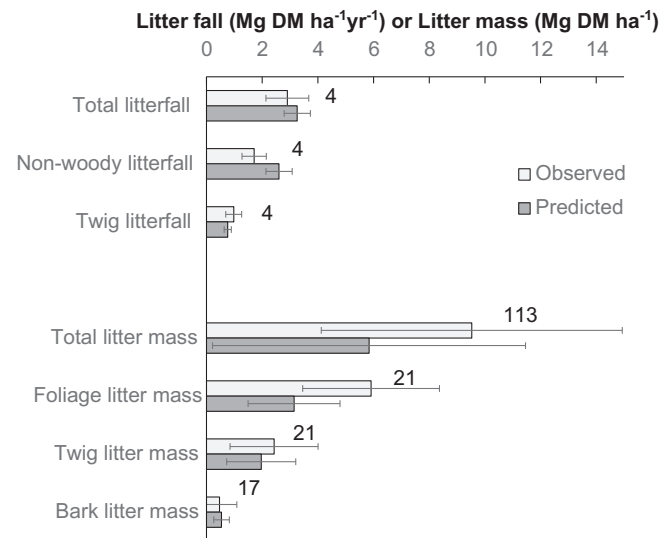


Fig. 5. Relationship between predicted and observed rates of litterfall and litter mass (in DM) of total, and woody and non-woody components, under various environmental plantings across Australia. Numbers represent the N, the number of site-based averages used to calculate the mean observed. Error bars represent the SD of the mean.

Intensive sampling ($N = 120$) of three environmental plantings by Cunningham et al. (2017) showed that litter mass was more variable than SOC due to much larger spatial variability, and consequently much higher sampling intensities were required to confidently measure the litter mass under environmental plantings. Therefore, imprecise predictions of litter mass here were to be expected since ≤ 40 replicates per site were sampled (Table 1). Also assumptions were required to account for CWD components. Further work with higher sampling intensities of litter and CWD is required to improve estimates of wood, bark and foliage debris under environmental plantings. Despite their high sampling errors, observations from the specific calibration sites provided the best available constraint to predictions of litter mass under environmental plantings.

3.2. Calibrating the model for maximum prediction efficiency of SOC

3.2.1. Root turnover, decomposition of dead roots and microbial efficiency

The highest overall model efficiencies for the various pools of SOC were obtained under the following combination of parameter settings: (i) rates of root turnover to 0–30 cm soil of 10 and 80% year⁻¹ for coarse and fine roots respectively; (ii) default decomposition rates of 30 and 100% year⁻¹ for coarse and fine root debris respectively; and (iii) microbial efficiencies that varied with stand age, being 40% and 80% under stands of <12 or ≥ 12 years of age respectively for most debris pools. However, for the relatively small fraction of foliage litter that was relatively 'decomposable', microbial efficiencies were 77% and 90% under stands of <12 or ≥ 12 years of age, respectively.

In general, most carbon inputs to the soil come from the high turnover pool of fine roots (Coleman et al., 2000; Rasse et al., 2005; Lewis et al., 2016). Previous estimates of rates of fine-root turnover under forests range from 20 to 290% year⁻¹ (e.g. Gill and Jackson, 2000; Brunner et al., 2013), with higher rates expected in warmer climates (e.g. McCormack and Guo, 2014). A review of eucalypt-dominant forests by Paul et al. (2017), found that mean rates of fine root (<3 mm) turnover within the surface soil (<30 cm depth) were 109% year⁻¹ (ranging between 58 and 182% year⁻¹; Jourdan et al., 2008; Xu et al., 2013). However, these rates of fine-root turnover would be expected to be higher, on average, than those in the 125 calibration sites because measurements were for eucalypt plantations in tropical or sub-tropical sites with relatively high MAR (1360–1534 mm year⁻¹) compared to those in the present study (Table 1). Hence, our assumed rate of turnover of fine roots of 95% year⁻¹ may be suitable, on average, for application to environmental plantings.

Measurements of rates of coarse root turnover are also rare (Paul and Polglase, 2004b). There are also few data available to guide whether our calibrated rates for decomposition of root debris pools under eucalypt-dominant environmental plantings were justified. A global review of decomposition rates of coarse and fine roots (Zhang and Wang,

2015) included no observations of decomposition from eucalypt-dominant forest ecosystems in Australia.

Microbial efficiency is a critical parameter in modelling SOC (Polglase and Paul, 2011) but is also poorly quantified because it is very difficult to measure directly. Studies have begun to explore this problem (Fröberg et al., 2009; Rubino et al., 2010), but to our knowledge there are no estimates of microbial efficiency for environmental plantings. Moreover, it is possible that the moderation of carbon inputs to the soil via adjusting a 'microbial efficiency' parameter is a simplification of the processes occurring within the soil. It is possible that soils become 'saturated' with respect of carbon inputs due to silt and clay protection, soil structure and/or the biochemical complexity of the organic compounds (Stewart et al., 2007). There is therefore a pressing need to understand how plant debris are decomposed to form SOC, particularly on the soil surface under woody vegetation (Cotrufo et al., 2013; Carnovale et al., 2015).

3.2.2. Efficiency of prediction of pools of SOC

The calibration method used to maximise the prediction efficiency of the various SOC pools had mixed results (Fig. 6). The ROC pool includes highly-carbonised organic material such as charcoal (Baldock and Skjemstad, 2000), surviving for >500 years (Lehmann et al., 2008). We assumed this pool was stable, and therefore remained unchanged over the time of reforestation (data not shown). Because the other pools of SOC were more dynamic, their prediction was more difficult, with prediction efficiencies of 68% for HOC (Fig. 6c), and only 43% for POC (Fig. 6b). The higher efficiency of prediction for the HOC pool relative to the POC pool was consistent with previous findings that fluxes of HOC following land use change can be small relative to POC (e.g. Rabbi et al., 2014). The HOC pool is considered to be more stabilised against microbial decomposition due to formation of organo-mineral complexes (Baldock and Skjemstad, 2000).

Largely because of the imprecision in prediction of the POC pool, the overall prediction efficiency of total SOC was only moderate, at 39% (Fig. 6a). Hence, although predictions were unbiased, they were imprecise given uncertainties in carbon inputs into pools of SOC (allocation of biomass, rates of turnover and decomposition of debris), and in the SOC observations at each site used for calibration. Indeed, SOC is often highly variable and concurrent work on sampling intensity (Cunningham et al., 2017) found that a minimum of 30 cores was required within a hectare to have a 95% probability of estimating SOC within 10% of the population mean. This suggests existing sites ($N = 5$ –24 cores, Table 1) may not have been adequately sampled, potentially reducing the apparent precision of the model.

In addition to possible sampling errors at some measurement sites and, as mentioned above, high uncertainties in data used to constrain models parameters accounting for carbon dynamics in pools of biomass and debris, other key caveats to our findings included inadequate representation of all regions across which environmental plantations are

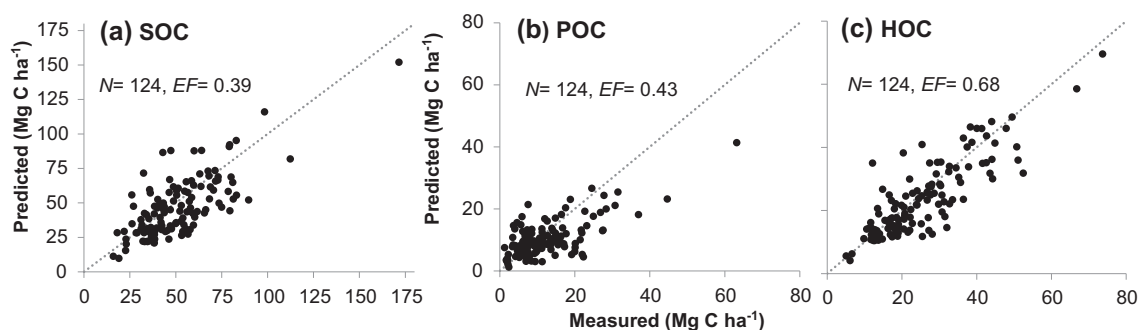


Fig. 6. Relationship between observed and predicted carbon stocks (Mg C ha⁻¹) in surface soil (0–30 cm) for: (a) total soil organic carbon (SOC); (b) particulate organic carbon (POC), representing the RPM pool in RothC; and (c) humus organic carbon (HOC), representing the HUM pool in RothC. The ROC pool was not presented as results were on the 1:1 line given the ROC measurements were used to constrain the model estimates of ROC.

commonly established (Fig. 2), and lack of accounting for changes in SOC in soil deeper than 30 cm, and how inputs of carbon from root turnover vary with soil depth.

3.3. Scenario analyses

As expected, predicted rates of SOC sequestration varied with initial stocks of SOC and climate (Fig. 7). Previous land use can be an important determinant of sequestration of SOC following reforestation, with increases in stocks on ex-cropland, and either small increases, or losses, in stocks on ex-pasture (Paul et al., 2002; Guo and Gifford, 2002; Laganière et al., 2010). SOC stock is generally higher under improved pasture than cropped soils (e.g. Rabbi et al., 2014; England et al., 2016). Climate can also have a strong influence on changes in SOC with reforestation (Fig. 7), with increases in tropical and sub-tropical regions and often small decreases in temperate and Mediterranean-type regions (e.g. Paul et al., 2002).

Although initial stocks of SOC and climate are important factors influencing SOC sequestration following reforestation with environmental plantings in Australia (e.g. England et al., 2016), other factors that may influence SOC include enhanced rates of sequestration with narrower planting widths, higher tree densities, and an increased proportion of over-storey trees. Such factors have been largely overlooked, but could be accounted for in our scenario analyses given previous calibrations of FullCAM's AG biomass yield curves for stands of differing planting width, density and PropEuc (Paul et al., 2015). These scenario analyses suggested that the use of alternative planting designs among sites may partly explain previous findings that variation in changes in SOC among sites, even within a relatively small geographical area, was much higher than observed changes in SOC with land use change (e.g. Cunningham et al., 2015a; Prior et al., 2015; Lewis et al., 2016).

4. Conclusions

Changes in SOC stocks following establishment of environmental plantings on agricultural land were modelled by using field measurements to constrain parameters accounting for carbon dynamics in

pools of biomass and debris. To provide the most accurate modelling of carbon inputs into the soil, microbial efficiencies and rates of turnover and decomposition of roots required calibration to maximise efficiencies of prediction of SOC. Differences in predicted SOC stocks between scenarios of differing initial SOC stocks and climate were relatively small. A novel aspect of this work was the demonstration of how planting designs such as planting width, tree density, and proportion of eucalypts, further influence SOC sequestration following reforestation. Although uncertainties remain in many model parameters (e.g. microbial efficiency), this verified modelling approach provides further improvement to our understanding of the dynamics of SOC following reforestation.

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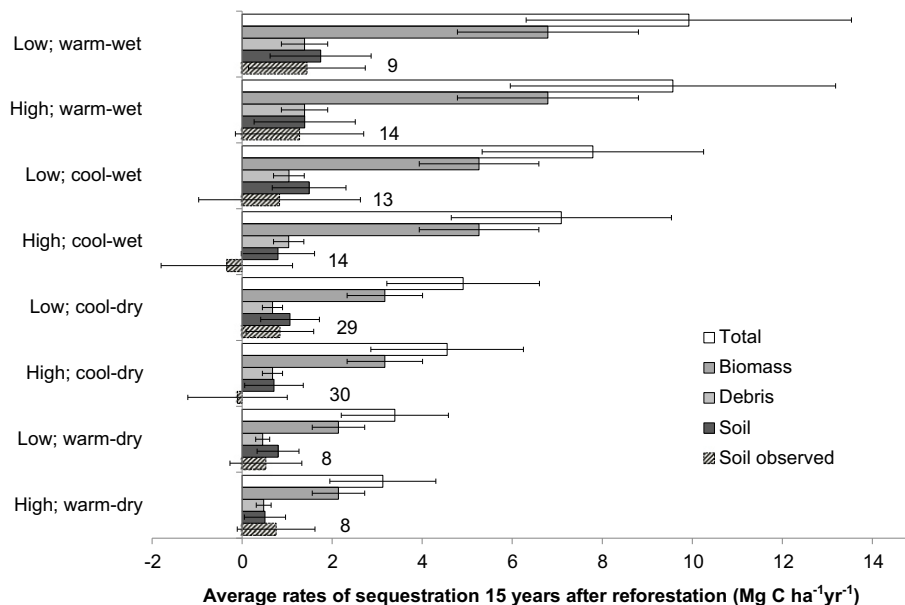


Fig. 7. Predicted rates of carbon accumulation in biomass, debris and soil in environmental plantings during the first 15 years following reforestation for contrasting categories of initial SOC (low or high, with low being $<45 \text{ Mg C ha}^{-1}$) by four categories of climate (warm-wet, cool-wet, cool-dry and warm-dry). For each category, means are presented for 13 differing types of temperate environmental plantings, each with differing rates of biomass accumulation based on planting width, tree density and proportion of eucalypts (Paul et al., 2015). Error bars represent the SD of prediction among these 13 planting types. Observed rates of SOC accumulation in each initial-SOC \times climate category are also presented for comparison (number of sites and SD bars indicated).

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