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Research article

Models of reforestation productivity and carbon sequestration for land use and climate change adaptation planning in South Australia

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ABSTRACT

Environmental management and regional land use planning has become more complex in recent years as growing world population, climate change, carbon markets and government policies for sustainability have emerged. Reforestation and agroforestry options for environmental benefits, carbon sequestration, economic development and biodiversity conservation are now important considerations of land use planners. New information has been collected and regionally-calibrated models have been developed to facilitate better regional land use planning decisions and counter the limitations of currently available models of reforestation productivity and carbon sequestration. Surveys of above-ground biomass of 264 reforestation sites (132 woodlots, 132 environmental plantings) within the agricultural regions of South Australia were conducted, and combined with spatial information on climate and soils, to develop new spatial and temporal models of plant density and above-ground biomass productivity from reforestation. The models can be used to estimate productivity and total carbon sequestration (i.e. above-ground + below-ground biomass) under a continuous range of planting designs (e.g. variable proportions of trees and shrubs or plant densities), timeframes and future climate scenarios. Representative spatial models (1 ha resolution) for 3 reforestation designs (i.e. woodlots, typical environmental planting, biodiverse environmental plantings) × 3 timeframes (i.e. 25, 45, 65 years) × 4 possible climates (i.e. no change, mild, moderate, severe warming and drying) were generated (i.e. 36 scenarios) for use within land use planning tools.

1. Introduction

In many regions of Australia and the world, the diversity of landscapes, climates, people and land uses creates a complex setting for governments, policy makers and planners to make well-informed decisions about managing regional natural resources for multi-purpose use, now and into the future (Bryan and Crossman, 2008; Wei et al., 2009; Parrot, 2011; Parrott and Meyer, 2012). To assist planning with this uncertainty, considerable efforts have been made to gather comprehensive regional natural resource information, develop analysis tools and provide assessment of land use planning options with a range of possible future scenarios and timeframes (Selman, 2006; Bryan et al., 2008; Polglase et al., 2008; Crossman and Bryan, 2009; Hobbs, 2009; Hobbs et al., 2010, 2013; Bryan et al., 2011; Polglase et al., 2013; Wise et al., 2014; Summers et al., 2015; Connor et al., 2015; Gao et al., 2016).

In southern Australia, future land use planning is aware that the majority of suitable land is privately owned, cleared of native vegetation and developed for agricultural production. Food and fibre industries (e.g. cereals, meat, wool, horticulture and forestry) dominate this production that supports the economic activity of local communities. Government policies support the existence of these industries and recognise the need to manage the soil and water resources on which these industries are based. In addition, policies and markets have evolved to support biodiversity conservation (e.g. native vegetation management), encourage carbon sequestration of atmospheric carbon dioxide through revegetation and adapt to expected changes in climates (Suppiah et al., 2006; IPCC, 2013, 2014). The opportunities and limitations that these emerging land uses present have been studied (Bartle et al., 2007; Polglase et al., 2008, 2013; Hobbs, 2009; Bryan et al., 2013, 2014; Paul et al., 2013a, 2015), with the conclusions always dependant

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on the reliability and generality of the input information. Consideration of current and future blends of traditional agricultural industries and new carbon or environmental plantings is dependent on credible comparisons between land use options. While the productivity and profitability of most traditional food and fibre industries is underpinned by sound science and economics, the quality of such information for reforestation productivity and carbon markets is limited (Bryan et al., 2011; Parrott and Meyer, 2012). Refining estimates of carbon sequestration by reforestation at regional and local scales is a high priority.

Reforestation or revegetation is a land use option sanctioned by the Australian government to sequester carbon dioxide from the atmosphere and to generate a carbon credit commodity that has an economic value within domestic carbon markets (i.e. Emissions Reduction Fund, Carbon Farming Initiative, Australian Government, 2011a,b, 2015; DOTE, 2015a). Carbon stored in reforestation is included in Australian National Greenhouse Accounts and reported under international obligations (DOTE, 2015a). Natural forest and reforested area extent are regularly assessed using satellite data. The carbon stocks from these spatial assessments are estimated with carbon models based on the Forest Productivity Index (FPI, Kesteven et al., 2004; DOTE, 2015b).

Several forest productivity models exist which are used to estimate biomass and carbon stocks from reforestation in Australia including FullCAM (Brack and Richards, 2002; Richards and Brack, 2004; Richards and Evans, 2004; Brack et al., 2006; Waterworth et al., 2007; Waterworth and Richards, 2008; DOTE, 2015b), 3-PG (Landsberg and Waring, 1997; Landsberg et al., 2003; Landsberg and Sands, 2011) and CABALA (Battaglia et al., 2004). They are mostly based on research results from commercial forestry species in higher rainfall zones of Australia. In recent years, these forestry models have been adapted to also represent environmental plantings and carbon accumulation in medium to lower rainfall regions. The resultant estimates have often underestimated biomass yields in reforestation (Montagu et al., 2003; Paul et al., 2008; Wood et al., 2008; Hobbs et al., 2010; Keith et al., 2010; Landsberg and Sands, 2011; Fensham et al., 2012; Paul et al., 2013b, 2015). Reliable calibration of these models for environmental plantings has been constrained by the lack of data collected outside of high-rainfall forestry species and regions. Some recent and significant improvements have been made in early growth calibrations for environmental planting models within FullCAM (Paul et al., 2013b, 2015).

Australia's main carbon accounting methodology for environmental plantings (i.e. Reforestation by Environmental or Mallee Plantings - FullCAM Method; Australian Government, 2014) is based on a point-based FullCAM model that uses spatial FPI data to estimate current and future reforestation productivity and carbon stocks with historic climatic conditions. The current version of FullCAM only provide broad classifications of planting designs (e.g. low, moderate, high plant stocking rates; Richards and Evans, 2004; DOTE, 2015b) which prevents these models from estimating within-class variations in productivity and carbon stock resulting from differences in plant density and competition effects. The magnitude of these variations is greatest for environmental plantings with low to moderate plant densities (Paul et al., 2013b, 2015). The accuracy of local applications of FullCAM for carbon accounting for reforestation projects is very limited due to the coarse scale of the underlying FPI data used in the model. The extrapolation of soil fertility modifiers developed for the FPI in high-rainfall conditions is likely to produce errors in lower-rainfall regions, where water is a more dominant growth factor (Kesteven et al., 2004; Landsberg and Sands, 2011). Process-based models (e.g. 3 PG, CABALA) have the potential to reliably estimate reforestation productivity and carbon stocks but insufficient data exists to provide reliable species (or mixed species) model calibrations or site parameterisations for models in many regions (Landsberg and Sands, 2011; Song et al., 2012).

In response to the limitations of current models and the sensitivity of carbon market analyses to variations in estimates of carbon sequestration from reforestation projects we developed locally-calibrated models of primary productivity and carbon sequestration from reforestation in the agricultural regions of South Australia. These models were intended to facilitate better regional land use planning by providing more reliable spatial and temporal estimates of primary productivity of reforestation options in the region, inform carbon markets of typical sequestration rates of these options, and anticipate the likely effects of climate change on future carbon stocks. Regional planners and natural resource managers can access this information through the South Australian Government's geographic information system and a land use planning tool (Landscape Futures Analysis Tool, Summers et al., 2015).

2. Methods

2.1. Study area

This study considers the 10.2 million hectares of agricultural land in South Australia. These lands are dominated by annual cereal cropping and livestock grazing productions systems with minor components of plantation forestry and high intensity agriculture (Fig. 1). The region experiences a Mediterranean climate with cool wet winters and warm dry summers. Mean annual rainfall in the study area currently ranges between 244 and 1056 mm year^{-1}, with mean annual potential evaporation between 1194 and 2489 mm year^{-1} and mean annual temperature between 12.4 and 18.6 °C. Most climate change forecasts suggest this region is likely to experience a decrease in rainfall, and increases in temperature and evaporation in the coming decades (Suppiah et al., 2006; IPCC, 2013).

2.2. Productivity of reforestation

Reforestation sites with reliably documented planting dates were surveyed to assess plant growth and carbon sequestration of Kyoto-compliant species (i.e. ≥2 m height at maturity) over a wide range of environmental conditions in the agricultural zone of South Australia (Fig. 1). These sites were chosen to represent two main planting designs: 1. woodlots (mainly monocultures); or 2. environmental plantings (mainly mixed species). Surveys focussed on block planting designs (i.e. >4 row plantations) but included some windbreak sites (i.e. ≤4 row plantations).

Sites were sub-sampled using 6 randomly located sections of continuous plants along rows (and avoiding ends of rows). Row sections typically comprised of 10 individuals in mixed species plantings and 6 individuals in monocultures. The larger number of observations in mixed species plantings was used to determine the proportion of biomass contribution by each species within the plantation. At each row section, individual species (≥2 m high) were recorded and plant measurements included height, crown width, life form (single-stemmed tree/multi-stemmed tree/shrub), distance to neighbouring plants, stem count and circumference at two lower section heights (basal and intermediate: 0.5 m and 1.3 m; for single-stemmed trees and multi-stemmed trees; and at 0.2 m and 0.8 m for shrubs). Exceptions to this protocol applied to an agroforestry field trial site (8 species blocks; average 249 individuals per block) and detailed surveys located at 3 sites where all individuals at each site were measured.

Distance to neighbouring plants (≥2 m high) for each individual

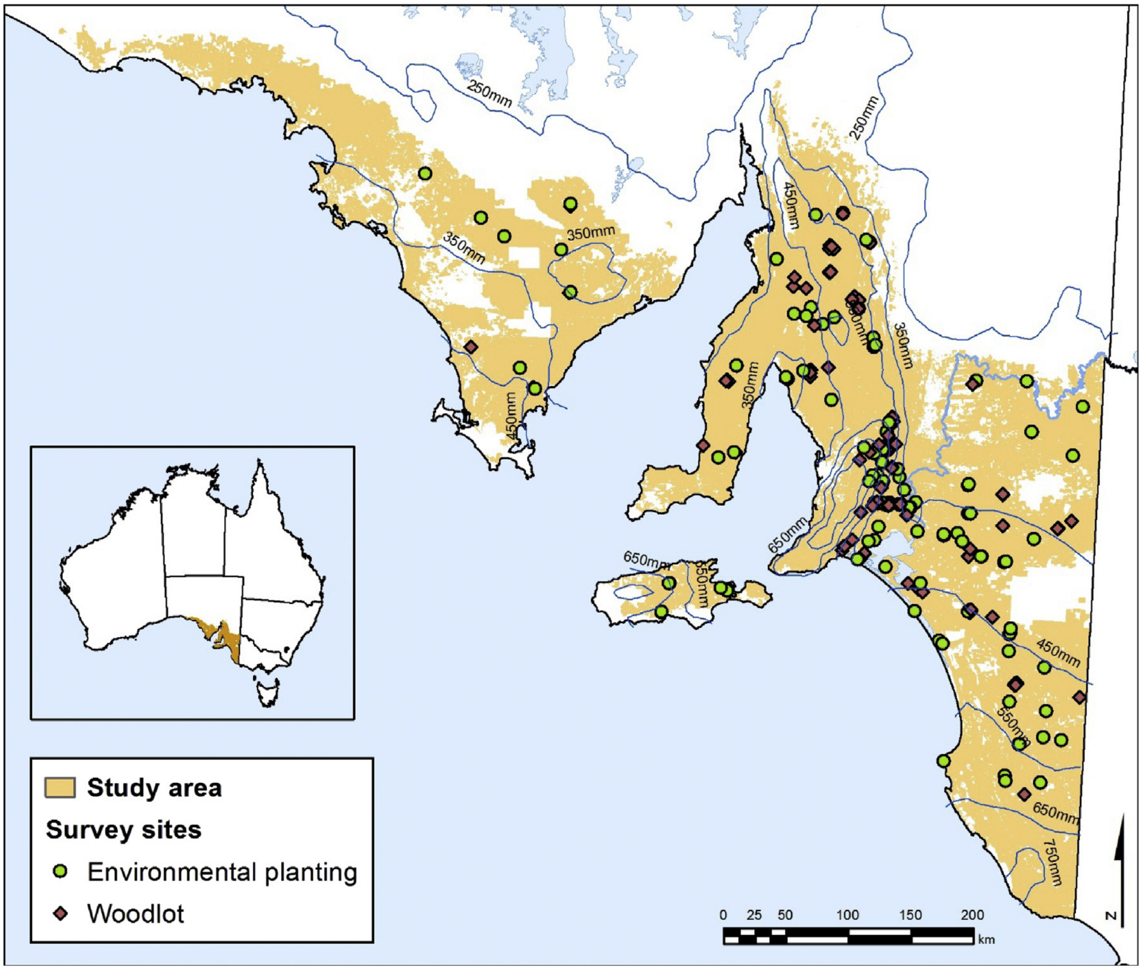

Fig. 1. Location of surveys of above-ground biomass at reforestation sites in South Australia. Shaded areas represent landscapes used for agricultural activities. Dark blue lines represent contours of mean annual rainfall (mm year^{-1}). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

permitted calculation of the area occupied for each plant. Where individuals were located on the edge of a vegetation stand the area occupied by each plant was consistently constrained to a nominal 5 m beyond the outermost plant. The plant density (PD; plants ha^{-1}) was determined from the number of individuals divided by the sum of areas occupied by individual plants. The proportion of trees versus shrubs (i.e. "Proportion Trees", Paul et al., 2013b, 2015) was also calculated for each survey site based on counts of individuals in each life form class.

Individual plant measurements were converted to a consistent set of biometrics to allow estimation of biomass and carbon content of individual plants. Basal (0.5 m height) and intermediate (1.3 m height) stem area (outer bark) at each measurement height was calculated using circumference measurements of each stem, and the sum of individual stem areas calculated for multi-stemmed species. The stem wood volume (outer bark) of each plant was calculated (SV, m^3 plant^{-1}) from stem height and stem area for each stem wood section (1. lower section - cylindrical volume; 2. mid-section - Smalian's frustum of a paraboloid volume, and 3. upper section - paraboloid volume).

The above-ground dry biomass of each measured individual (B_{ag}; kg plant^{-1}) was then estimated using a stemwood volume allometric model derived from direct measurements of biomass (Hobbs et al., 2013; $N = 535$; $R^2 = 0.95$; $P < 0.0001$; $AIC_c = 419.2$) as:

$$\log(B_{ag} + 1) = 0.9161 \times \log(SV + 1) + 0.5444 \quad (1)$$

where,

SV = Stemwood Volume (m^3 plant^{-1} × 1000).

The standing above-ground biomass per hectare was determined from the sum of estimated dry biomass of all individual trees and tall shrubs divided by the sum of physical space occupied by all individuals. The estimated total standing above-ground biomass (AGB; dry matter Mg ha^{-1}) at each site was then converted to an average annual accumulation rate (ΔAGB; dry matter Mg ha^{-1} year^{-1}) using the known age of each reforestation site.

2.3. Environmental data

Each survey site was accurately located using a Global Positioning System (GPS) to allow spatial data from other sources to be combined with survey data to evaluate the influence of environmental conditions on planting designs and sequestration rates. Spatial environmental data used in this study include:

National Carbon Accounting System.
(Australian Government, 250 m resolution).

- Mean annual Forest Productivity Index (FPI; Kesteven et al., 2004)

Climate data.
(ANUCLIM Version 6.1, Xu and Hutchinson, 2013; 100 m

resolution).

- Mean annual rainfall (1976–2005)
- Mean annual temperature (1976–2005)
- Mean annual pan evaporation (1976–2005)

Soil data.
(ACLEP ASRIS format, McKenzie et al., 2012; 300 m resolution, dominant soil, up to 5 soil profile layers).

- Soil depth (total and depth of each soil layer)
- Depth to impeding layer for the roots of perennial native vegetation
- Clay content
- Bulk density
- pH
- Volumetric water content
- Plant available water content for perennial native vegetation
- Saturated hydraulic conductivity
- Electrical conductivity
- Exchangeable bases
- Cation exchange capacity

2.4. Data analysis

Distributions of continuous variables were analysed to identify non-normal distributions in data, and where appropriate, natural logarithms (i.e. log[variable + 1]) were applied to reduce skew in distributions. Multiple-linear-regression modelling was used to determine whether age, planting designs (i.e. plant density or proportion of trees) and spatial environmental variables were statistically important in terms of their influence on above-ground biomass productivity rates. Preliminary analysis identified that rainfall, plant density, proportion trees, age and soil depth had the greatest influence on average productivity rates. We developed predictive models for both above-ground biomass productivity rates and plant density for different planting designs, site conditions and age. As soil data was missing from a small portion (<1%) of the study area it was necessary to develop models for “Climate Only” and “Climate plus Soils” situations.

A forward-stepwise model selection process, based on the Akaike Information Criteria (Venables and Ripley, 2002), was used to identify the best fit models for above-ground biomass productivity rates and plant density for “Climate plus Soils” and “Climate Only” models. Analyses included interactions between soil and climate variables, and reviews of model outputs for combinations of soil and climate parameters that generated unrealistic or extreme estimates of plant density and carbon sequestration rates within the study region.

2.5. Climate change scenarios

We used the four climate change scenarios specified in allied research (Bryan et al., 2011; Summers et al., 2015, Table 1). In addition to these rainfall and temperature variations, estimates of changes to potential evaporation rates for the four climate scenarios have been included, based on previous studies of the likely impact of climate change on crop productivity (Hayman et al., 2011) and water resources (Gibbs et al., 2011) in South Australia. Potential atmospheric carbon dioxide fertilisation effects were not considered.

2.6. Application of planting designs, spatial and temporal models

Our estimates of productivity, average plant density and carbon stocks were intended for use in a wide range of situations. For the purposes of exploring a variety of land use and climate change adaptation planning options in the study area the models were applied for a series of representative scenarios for different reforestation planting types, timeframes and potential climates.

Three planting types have been chosen to represent the continuum of reforestation options: 1. Woodlots (100% proportion of trees); 2. Tree-dominated environmental plantings (“typical”, 88% trees); and 3. Mixed-stratum environmental plantings (“biodiverse”, 50% trees). These designs are consistent with reforestation types used in the Australian Government’s national carbon accounting system for environmental plantings (FullCAM, DOTE, 2015b). As the productivity of reforestation sites changes over time and is affected by changes in rainfall, temperature and evaporation rates, the representative scenarios include different timeframes (i.e. 25 years, 45 years, 65 years) and 4 potential climate change options (i.e. baseline using historic data, and mild, moderate and severe warming and drying). The combination of planting types, timeframes and climates results in 36 scenarios (i.e. 3 × 3 × 4) to represent a wide range of situations or land use planning options.

Spatial environmental datasets were converted to a consistent gridded format (1 ha resolution) for the study area and models of plant density and productivity rates applied for each of the 36 scenarios. For the majority of the study area (>99%) the more reliable “Climate plus Soils” set of models were used to estimate typical plant densities for each scenario and the results then fed into productivity models. An identical process was used for the “Climate Only” set of models and the results used to fill in gaps in the “Climate plus Soils” gridded layers.

Above-ground biomass was calculated for each hectare (i.e. AGB_{site} = rate × time) and all scenarios. Below-ground (i.e. root) biomass (BGB_{site}) was estimated for each hectare from the average above-ground biomass of plants (i.e. AGB_{site} ÷ Plant density) using a generic allometric model developed from whole-plant destructive data in the study region (Hobbs et al., 2013; $N = 41$; $R^2 = 0.82$; $P < 0.0001$; $AIC_c = 41.6$):

$$\log\left(BGB_{plant} + 1\right) = 0.7426 \times \log\left(AGB_{plant} + 1\right) + 0.6073 \tag{2}$$

where,

AGB_{plant} = Above-ground biomass (kg plant^{-1})
BGB_{plant} = Below-ground biomass (kg plant^{-1})

Below-ground biomass of each hectare (BGB_{site}) was estimated from above-ground biomass (AGB_{site}) using the root to shoot ratio of average plants for each hectare (i.e. BGB_{plant}: AGB_{plant}).

To convert above-ground and below-ground dry biomass to tonnes of elemental carbon (C Mg ha^{-1}) a generic factor of 0.496 was applied (Stein and Tobiasen, 2007). Elemental carbon was converted to carbon dioxide equivalents (CO_2-e Mg ha^{-1}) using a factor of 3.67 (based on the atomic weights of C and O).

3. Results and discussion

3.1. Reforestation growth and plant density surveys

A total of 264 reforestation sites (132 woodlots, 132 environmental plantings) were surveyed (Fig. 1), including a total of 15,045 individual plants and 143 species. The average age of all sites was 22 years (range 3–131), with woodlots averaging 26 years (range 5–131) and environmental plantings averaging 17 years (range

Table 1
Climate change scenarios used to explore the influence of increases in temperature and potential evaporation, and decreases in annual rainfall, on carbon sequestration rates from reforestation.

Climate change scenario	Rate of change 1990 to 2070		
	Mean annual temperature	Mean annual potential evaporation	Mean annual rainfall
S0 Historic baseline	Historic	Historic	Historic
S1 Mild warming and drying	+1 °C	+3%	−5%
S2 Moderate warming and drying	+2 °C	+6%	−15%
S3 Severe warming and drying	+4 °C	+8%	−25%

Table 2
Improvements in estimating above-ground productivity rates from reforestation for Climate plus Soils and Climate Only models by the stepwise addition of significant variables.

Model of log(Above-ground productivity rate) Effect	R^2	AICc	P
Climate plus soils model (N = 264)			
Mean annual rainfall	0.317	497.6	<0.0001
+log(Hydraulic conductivity, surface layer)	0.412	460.0	<0.0001
+log(Plant density, all plants)	0.459	440.0	<0.0001
+Clay content, surface layer	0.513	414.4	<0.0001
+log(Plant density, shrubs)	0.563	388.2	<0.0001
+log(Age)	0.586	376.0	0.0001
+Mean annual rainfall × Soil depth for native vegetation	0.598	370.4	0.0061
Climate Only model (N = 264)			
Mean annual rainfall	0.317	497.6	<0.0001
+log(Plant density, all plants)	0.395	467.6	<0.0001
+log(Plant density, shrubs)	0.448	445.4	<0.0001
+log(Age)	0.475	434.2	0.0003

3–36). Block planting designs (i.e. >4 row plantations) dominated these surveys (229 sites) with fewer windbreak surveys (i.e. ≤4 row plantations; 35 sites). Average plant density of Kyoto-compliant species (i.e. ≥2 m tall at maturity) for all sites was 894 plants ha^{-1} with lower density in woodlots (i.e. 714; range 95–2205) in comparison to environmental plantings (i.e. 1074; range 159–8575). The proportion of trees was 89% for all reforestation types and 83% in mixed species environmental plantings. The average annual accumulation rate of above-ground biomass for all reforestation sites was 5.20 Mg ha^{-1} year^{-1} of dry matter (range 0.11–58.25) with higher average accumulation rates in woodlots (i.e. 6.25; range 0.11–58.25) in comparison to environmental plantings (i.e. 4.15; range 0.30–25.54).

3.2. Reforestation growth and plant density models

3.2.1. Above-ground biomass productivity rate

Mean annual rainfall was the dominant single environmental correlate of reforestation dry matter production in the study area and explaining 32% of the variation in productivity rates (Table 2). The planting design of reforestation sites (i.e. plant density and proportion of trees/shrubs) was also highly influential, explaining an additional 10% and 13% of the variation in growth, where higher planting densities and higher proportions of trees both increase average growth rates. Reforestation age accounts for an additional 2–3% of the variation in productivity and results in decreases in average rates for older-age sites. Other site factors that influence plant-soil-water balances and plant density (i.e. potential evaporation, soil texture, hydraulic conductivity, depth and water-holding capacity) also significantly contribute to estimates of productivity in reforestation (Table 2, Table 3).

The mean annual Forest Productivity Index (FPI$_{ave}$; Kesteven et al., 2004) was found to be poorly correlated to productivity in reforestation sites, explaining only 11% of the variation in growth and proving to be much less reliable than rainfall alone. Interrogation of a potential FPI$_{ave}$-based model revealed significant overestimates on clay-rich soils in low to medium rainfall regions (<800 mm year^{-1} mean annual rainfall). Due to these issues the FPI was deemed unreliable and not used further in this study.

The generalised linear modelling approach using stepwise additions of significant variables identified a combination of environmental and planting design factors correlated with above-ground biomass productivity rates from reforestation (Table 2). The Climate plus Soil model also identified a significant interaction between mean annual rainfall and depth of soil accessible to perennial native vegetation. The following equations show the model and parameter estimates:

Climate plus Soils

$$\begin{aligned}\log(\Delta AGB + 1) = {} & 0.003674 \times MAR + 0.4782 \times \log(KS_1 + 1) \\ & + 0.3092 \times \log(PD_{all} + 1) + 0.05543 \times CC_1 \\ & - 0.06986 \times \log(PD_s + 1) - 0.1959 \\ & \times \log(t + 1) + (0.0001750 \times MAR \times D_{nv}) \\ & - 4.422 \end{aligned} \tag{3}$$

Table 3
Improvements in estimating reforestation plant densities for Climate plus Soils and Climate Only models by the stepwise addition of significant variables.

Model of log(Plant density) Effect	R^2	AICc	P
Climate plus soils model (N = 264)			
log(Age)	0.116	579.4	<0.0001
+log(Mean annual potential evaporation)	0.167	565.7	0.0315
+Proportion of trees	0.202	556.6	0.0006
+Plant available water capacity, total	0.224	552.0	0.0038
+Mean annual rainfall	0.236	549.8	0.0409
Climate Only model (N = 264)			
log(Age)	0.116	579.4	<0.0001
+log(Mean annual potential evaporation)	0.167	565.7	0.0784
+Proportion of trees	0.202	556.6	0.0007
+Mean annual rainfall	0.209	556.3	0.1243

Climate Only

$$\log(\Delta AGB+1) = 0.003674\times MAR + 0.3092\times\log(PD_{all}+1) - 0.06986\times\log(PD_s+1) - 0.1959\times\log(t+1) - 1.403 \tag{4}$$

where,

ΔAGB = Mean above-ground biomass productivity rate (dry matter Mg ha^{-1} year^{-1})
CC_1 = Clay content of the soil surface, layer 1 (% by weight)
D_{nv} = Soil depth to impeding layer for the roots of perennial native vegetation (m)
KS_1 = Saturated hydraulic conductivity of the soil surface, layer 1 (mm hour^{-1})
MAR = Mean annual rainfall (mm year^{-1})
PD_{all} = Plant density, all plants (plants ha^{-1})
PD_s = Plant density, shrubs only, $\geq$2 m high at maturity (plants ha^{-1})
t = Age (years)

3.2.2. Plant density

Although this analysis has shown that total plant density at reforestation sites is influenced by age, climate and soils there were also strong influences of planting designs on plant density (Table 3). Human choices on species and structural composition (e.g. proportion of trees and shrubs planted) and initial plant establishment rates strongly influenced plant densities and site productivity. The models developed here provide users with estimates of typical plant densities based on user choices on planting designs and influenced by time, climate and soil factors. As productivity of reforestation sites is highly sensitive to plant density, the models presented here provide a function to estimate plant density at any time and for any planting design rather than be constrained to pre-set classifications of plant density and life form structure used in many models (e.g. FullCAM, DOTE, 2015b).

Models to estimate expected plant density have been developed for sites with and without soil data. Exploration of interactions between variables in the Climate plus Soils model identified that plant available water content of the soil was a significant site modifier. The following equations show the model and parameter estimates:

Climate plus Soils

$$\log(PD_{all}+1) = (-0.2983\times\log(t+1) - 1.3801\times\log(PE+1) - 0.6827\times PT + 0.0009736\times MAR + 17.70)\times(0.0003704\times W + 0.9346) \tag{5}$$

Climate Only

$$\log(PD_{all}+1) = -0.2983\times\log(t+1) - 1.3801\times\log(PE+1) - 0.6827\times PT + 0.0009736\times MAR + 17.70 \tag{6}$$

where,

MAR = Mean annual rainfall (mm year^{-1})
PD_{all} = Plant density, all plants (plants ha^{-1})
PE = Mean annual potential evaporation (mm year^{-1})
PT = Proportion of trees (count of trees/count of all plants $\geq$2 m high at maturity)
W = Plant available water capacity, total (mm)
t = Age (years)

3.3. Influence of future climate on productivity rates

Both productivity and plant density models were significantly influenced by climate variables (i.e. rainfall for both models and potential evaporation for the plant density model). Mean annual temperature and potential evaporation are correlated climatic variables, however, potential evaporation is a stronger predictor of reforestation biomass. As climate changes, the productivity and structural composition of reforestation will also change. While heightened levels of atmospheric carbon dioxide (CO_2) can increase plant growth responses, the benefit of this "fertilisation effect" may be constrained by the relatively poor nutrient status of Australian soils and limited water availability (Steffen and Canadell, 2005). As the CO_2 fertilisation effect on carbon sequestration rates in South Australian native plants and landscapes has not been studied, it is not possible to reliably include these effects within this study. The models detailed in the previous section can be used to estimate the dominant effects of a wide array of future climate scenarios and planting designs on the productivity of reforestation activities in the study area.

These models have been combined with representative climate change scenarios found in Table 1, and mean climate and soils statistics for cleared agricultural landscapes in the study area to generate a representative plot (Fig. 2) of anticipated above-ground carbon stocks for a typical tree-dominated environmental planting (88% trees) under 4 climate scenarios. The most severe scenario in this example, is likely to reduce above ground biomass by 35% (range 25–36% for different rainfall zones) over the next 65 years compared to a baseline scenario with no climate change. Longer-term influences (i.e. 65 years) on total carbon sequestration rates (i.e. above-ground + below-ground biomass) for all modelled climate change scenarios are illustrated in Fig. 3. This shows that even a mild change in climate will reduce carbon sequestration rates and stocks over time. More severe climate changes over 65 years will typically reduce carbon stocks of today's reforestation activities to 71% (range 67–73%) of carbon stocks that would have accumulated without climate change.

3.4. Application of planting designs, spatial and temporal models

Spatial estimates of carbon sequestration rates and plant density have been generated for 36 combinations of representative planting designs, timeframes and climate change scenarios in the study area (e.g. Fig. 4; see Appendix A). These maps and estimates allow regional managers and researchers to better anticipate the likely growth and structural dynamics of woodlots, typical environmental plantings and biodiverse reforestation options over the next 25, 45 and 65 years under 4 progressively hotter and drier climates. The underlying models are not constrained to these 36 possible combinations of conditions, but can be used to explore the influence of a vast array of possible planting designs, timeframes and environmental conditions on carbon sequestration rates and vegetation structure in South Australia. Summaries of spatial model outputs of carbon sequestration rates and plant density (first 25 years) for 3 planting types by rainfall zones within the study region are presented in Table 4, with additional information for all climate change and timeframe scenarios presented in Appendix A. Analysis of sequestration data from the static baseline climate scenario (i.e. S0, historic, no change) on agricultural lands revealed that changes in mean cumulative sequestration rates over time remained very consistent across planting types, resulting in an average 25, 45, 65 year sequestration ratio of 1: 0.795: 0.683.

Results of this study demonstrate that the spatial application of

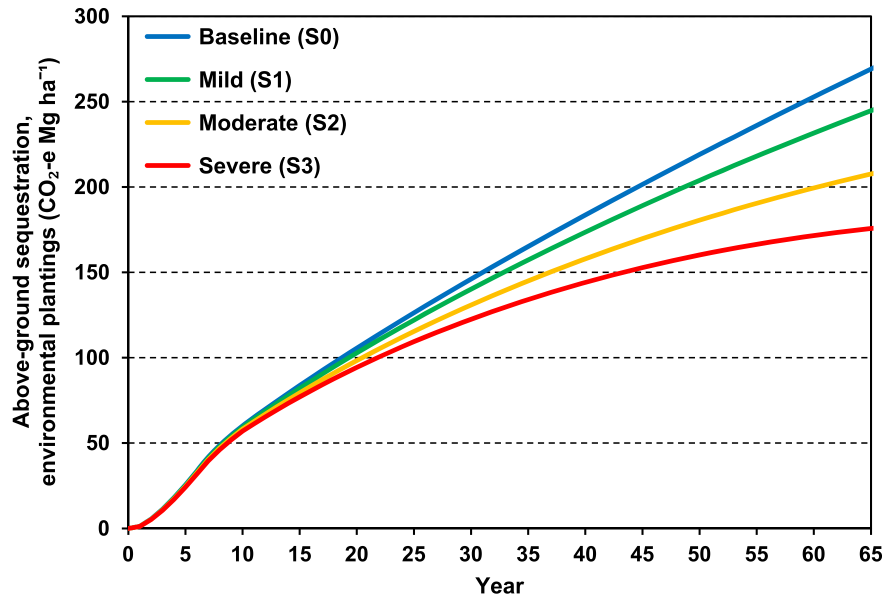

Fig. 2. Expected changes in average above-ground biomass carbon stocks held by typical tree-dominated environmental plantings (88% trees; S0 = 414 mm year^{-1} mean annual rainfall) under 4 potential climate change scenarios (S0-S3) in South Australia.

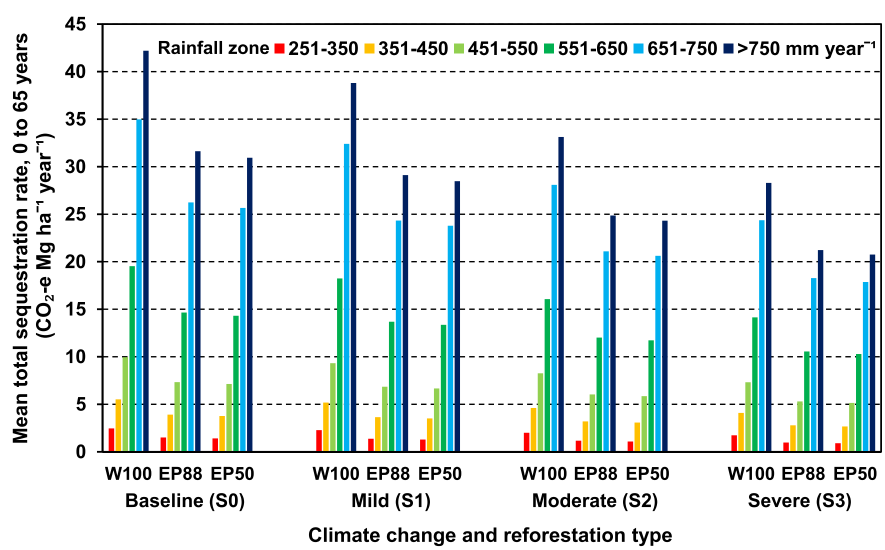

Fig. 3. Modelled changes in total carbon sequestration rates from different reforestation planting designs and rainfall zones, under 4 potential climate change scenarios (S0-S3), in cleared agricultural landscapes of South Australia. Planting designs include: W100 = Woodlots (100% trees); EP88 = Tree-dominated environmental plantings (88% trees); and EP50 = Mixed-stratum environmental plantings (50% trees).

the FPI model used for Australian National Greenhouse Accounts (DOTE, 2015a,b) produces unreliable results in low to medium rainfall regions (<800 mm mean annual rainfall) of southern Australia. The FPI model applies soil fertility factors quantified from predominantly higher rainfall (>800 mm mean annual rainfall) forestry observations (Kesteven et al., 2004) across all Australian landscapes. In the low to medium rainfall regions (<800 mm mean annual rainfall) water is the dominant growth-limiting factor (Paul et al., 2015) and hence FPI soil texture/fertility assumptions (i.e. clay soils are fertile and sandy soils are infertile) produce growth factors that are contradictive of soil water balances factors in drier landscapes (i.e. more rainfall infiltrates sandy soils and rainfall runoff is higher on clay soils).

Standard FullCAM point-based models for environmental reforestation (i.e. 'mixed species environmental plantings') prescribed in Australia's Emission Reduction Fund carbon trading scheme (Australian Government, 2011a,b; 2015) rely on spatial FPI models, fixed plant density classes (i.e. <500, 500–1500, >1500 plants ha^{-1}) and fixed tree proportion classes (i.e. <75%, ≥75%) to estimate carbon stocks from reforestation. Our study demonstrates that spatially unreliable growth factors and maximum biomass stock estimates from FPI model predictions, and insensitivity of FullCAM models to variations within plant density and vegetation structure classes, results in unreliable local-scale FPI/FullCAM estimates of carbon sequestration in the low to medium rainfall regions (<800 mm mean annual rainfall) of southern Australia. Current FPI/FullCAM models are unable to interrogate the likely influence of climate change on carbon sequestration in reforestation.

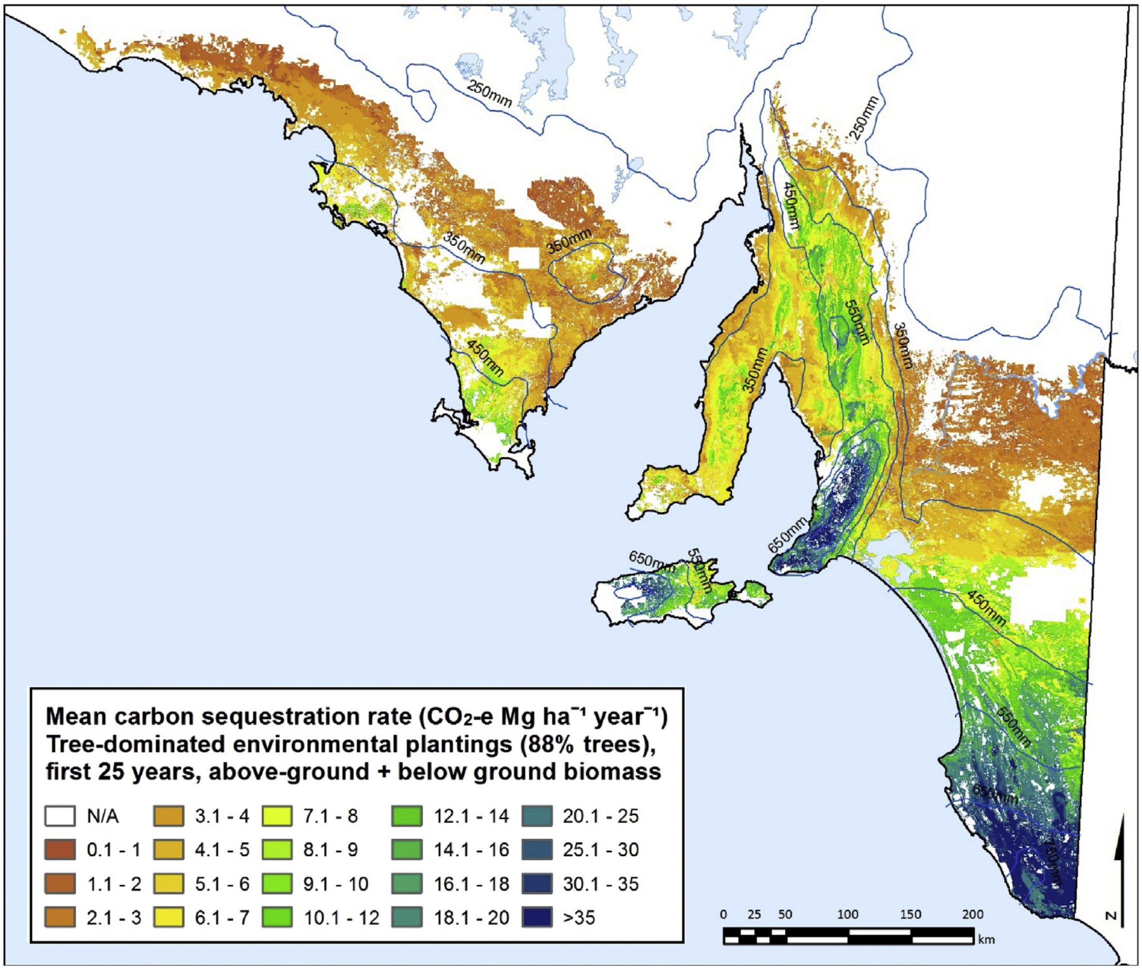

Fig. 4. Estimated average carbon sequestration rates (first 25 years) from a typical tree-dominated environmental planting (88% trees) in the agricultural regions of South Australia. Dark blue lines represent contours of mean annual rainfall (mm year^{-1}). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Summary of spatial model estimates of mean carbon sequestration rates (above-ground + below-ground biomass) and plant density by woodlots and environmental plantings, and rainfall zones, in the first 25 years of reforestation within cleared agricultural regions of South Australia under historic climate conditions.

Agricultural land and reforestation type	Rainfall zones, mean annual rainfall (mm year^{-1})					
	251–350	351–450	451–550	551–650	651–750	>750
Area (M ha)	3.684	3.181	1.797	0.753	0.505	0.236
Woodlots (100% trees)						
Mean sequestration rate (CO_2-e Mg ha^{-1} year^{-1})	4.37	8.68	14.95	28.44	50.09	60.10
Mean plant density (plants ha^{-1}), initial	667	818	1002	1220	1483	1590
Mean plant density (plants ha^{-1}), at 25 years	379	467	573	699	850	912
Tree-dominated env. plantings (88% trees)						
Mean sequestration rate (CO_2-e Mg ha^{-1} year^{-1})	2.94	6.28	11.05	21.21	37.24	44.59
Mean plant density (plants ha^{-1}), initial	724	888	1088	1323	1609	1725
Mean plant density (plants ha^{-1}), at 25 years	412	507	622	759	922	990
Mixed-stratum env. plantings (50% trees)						
Mean sequestration rate (CO_2-e Mg ha^{-1} year^{-1})	2.82	6.13	10.83	20.83	36.57	43.79
Mean plant density (plants ha^{-1}), initial	940	1152	1410	1714	2084	2233
Mean plant density (plants ha^{-1}), at 25 years	536	658	806	982	1195	1281

4. Conclusions

Reforestation for carbon sequestration and environmental management is encouraged by the Australian Government through the Emission Reduction Fund carbon trading scheme in lower rainfall regions (i.e. < 600 mm mean annual rainfall; Australian Government, 2011a,b; 2015). However, the lack of reliable information on carbon sequestration rates and their associated risks has constrained investments in reforestation. Our assessments of 264 new reforestation sites shows that carbon sequestration rates of woodlots and environmental plantings for this region are higher than previously estimated using process-based (e.g. 3 PG) or other empirical models (e.g. FPI/FullCAM). While this data have been used to recalibrate FullCAM's point-based models (Paul et al., 2013b, 2015) there are no reliable spatial applications of FullCAM models or ability for FullCAM to interrogate a wide variety of reforestation planting designs, climate change scenarios or environmental/commercial reforestation risks over time.

Our results shows that these government-prescribed FPI/FullCAM models, currently used for regional to national-scale carbon accounting (DOTE, 2015a,b), often produce unreliable estimates of carbon sequestration at the local scale. The use of inappropriate local-scale carbon accounting methods increase the risk of carbon traders exploiting FPI/FullCAM model errors for financial gain or well-meaning investors/farmers being underpaid for their sequestered carbon stocks. We have quantified and modelled the relationships between reforestation planting designs, climate, soils, plant density and carbon sequestration rates for use at the local-scale (i.e. 1 ha) to reduce errors in carbon estimates, evaluate risks over time, and facilitate better-informed investment and environmental management decisions using reforestation in agricultural landscapes. Our results clearly demonstrate that climate change can significantly reduce future carbon sequestration rates and stocks, with severe climate changes resulting in losses of around 29% over the next 65 years. Our spatially-explicit models of carbon sequestration rates and plant density for a variety of reforestation types, and their associated costs and benefits, can now be used in planning tools to compare the economics, viability and environmental outcomes of reforestation with existing agriculture or alternate land uses.

While these carbon sequestration and plant density models were developed for South Australian landscapes, they are likely to be applicable to similar environments and plant species across Australia or elsewhere. The soil and climate factors identified from our study can be recalibrated with new data from other parts of the world (especially in low to medium rainfall zones) without excessive investment in detailed data collection required by process-based models. The soil and climate properties identified by our models can also be used to inform the construction of new empirical or process-based productivity models in other parts of the world.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2016.06.049.

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