FOI 180513 – Explanatory Paper

Introduction

This package comprises an explanatory paper developed in response to your Freedom of Information request (Ref FOI 180513), along with more detailed supporting material referenced in the paper. The supporting material is publicly available except where noted.

The explanatory paper includes the elements (rationale; methods; causes; impacts; background) specified in the revised scope of your FOI request, which you agreed to by email on 15 June 2018. For this paper, the order of elements has been rearranged as follows to assist clarity:

- Section 1 outlines the methodology for deriving the time series in 'Data Table 2: Tracking Australia's emissions' in the June and September 2017 Quarterly Updates.

- Section 2 identifies the two changes made that drove the differences between the June and September 2017 Quarterly time series. These changes are: the use of more recent annual inventory data; and reporting the time series using the United Nations Framework Convention on Climate Change (UNFCCC) rather than the Kyoto Protocol inventory time series.

- Section 3 sets out the rationale for making the two changes that drove these differences. It explains that the changes were made to underpin confidence by ensuring that the Quarterly uses the latest accurate data, and to better inform stakeholders by ensuring the time series reporting classifications are consistent with Australia's projections and the approach Australia intends to adopt in reporting progress against the 2030 emissions target.

- Section 4 analyses the relative impacts of the two changes with a particular focus on their relative impacts on the apparent improvement in progress towards the 2030 target. It shows that:

  - the use of more recent (2016) national inventory estimates in the September 2017 Quarterly Update contributes most of the change in time series levels and all of the change in the trend over time;

  - the changes in level and trend mainly reflect improvements in the LULUCF sectoral estimation methodologies made for the 2016 National Inventory Report (NIR). These improvements, which are applied across the full time series, have a larger impact on more recent years than for earlier years including the 2005 base year.

  - the improvement from 9% to 12% progress toward the 2030 target is due to this uneven impact of the LULUCF inventory improvements over time, and would apply equally whether the Kyoto Protocol or UNFCCC framework had been used for reporting in the September2017 Quarterly.

- Section 5 provides Background on Australia's UNFCCC treaty commitments under the Cancun (2020) and Paris (2030) targets, and on quality assurance of the national greenhouse inventory estimates.

1 Methodology for deriving the time series in Data Table 2 of the Quarterly Updates.

The time series of annual net emissions estimates presented in the section entitled 'Data Table 2: Tracking Australia's emissions' of the June and September 2017 Quarterly Updates is based on the annual estimates reported in the most recent submission of Australia's National Inventory Report (NIR) to the United Nations Framework Convention on Climate Change (UNFCCC) that is available at the time the Quarterly Update is compiled.

As required by the UNFCCC, the NIR is submitted and published each year in the April/May timeframe and includes complete estimates, by financial year to June 30, for the period beginning in 1990 and ending two years prior to the year of submission – for example, the latest NIR was published in April 2018 and provides complete estimates up to and including the financial year ending 30 June 2016.

For time series years not yet covered by the NIR (e.g. 2016 and 2017 in the June 2017 Quarterly Update) the estimates are based on the NIR series augmented by more recent data where available. More information on the quarterly methodology is provided in Section 5.04 of the September 2017 Quarterly Update.

The UNFCCC requires that as a signatory to the Kyoto Protocol, Australia must report a time series of emissions under the standard UNFCCC classifications in accordance with the IPCC 2006 guidelines governing data collection, emissions estimation, QA/QC and reporting, and also under the related but separate Kyoto Protocol accounting classifications.

The two inventory time series differ only for the Land Use, Land Use Change and Forestry (LULUCF) sector and the data for the two time series is fully transparent, reconcilable and documented in the NIR. (See Section 3.2 of Australia's Third Biennial Report to the UNFCCC (Annex A to Australia's Seventh National Communication) for more information).

Prior to the Paris Agreement around a 2030 target, the reporting framework relevant to Australia's international commitments – Kyoto Protocol Second Commitment Period and Cancun 2020 target – was the Kyoto Protocol. As such, the time series in Data Table 2 has previously been reported using the Kyoto Protocol estimates.

It is important to recognise that it is the NIR estimates, based on the relevant inventory time series, which underpin Australia's performance in relation to its international emissions targets. (See Background for further information and references relating to QA/QC processes underpinning the NIR estimates).
The Quarterly Update, including Data Table 2, is simply a vehicle to assist stakeholders see how the nation is tracking towards these targets.

2 Nature/causes of differences between June and September 2017 Quarterly time series

The time series presented in the section entitled 'Data Table 2: Tracking Australia's emissions' in the September 2017 Quarterly differs from that presented in the same section of the June 2017 Quarterly for two reasons:

- First, more recent annual emissions estimates were available for the September 2017 Quarterly that were not yet available for inclusion in the June 2017 Quarterly.
  - Footnote 'a' to table 5 on p36 of the June 2017 Quarterly indicates that the Data Table 2 time series is based on the 2015 NIR (published in April 2017), while footnote 'a' to table 6 on p43 of the September 2017 Quarterly indicates that the time series for the September 2017 update is based on completed but unpublished estimates for the 2016 NIR (which was subsequently published in April 2018).
  - The emissions time series generally differ from one annual NIR submission to the next, potentially across the entire time series. These differences reflect:
    - ongoing improvements made to emissions estimation methodologies to comply with specific UNFCCC recommendations and more generally to ensure the estimates are updated to reflect the latest advances in data collection and emissions estimation methods[1]; and
    - the UNFCCC requirement that updates be estimated on a 'time series consistent' basis. This means that when methods or data are changed going forward, previous estimates also need to be revised (known as 'recalculation') to maintain consistency across the time series from 1990.

    Section 4.05 of the June 2017 Quarterly and section 5.05 of the September 2017 Quarterly, entitled 'Recalculations', provide more information and foreshadow forthcoming recalculations.
  - The 2016 NIR used in the September 2017 Quarterly reported significant improvements/updates made in emissions estimation methods for a number of sectors. These improvements are described in the 2016 NIR (e.g. Executive Summary Section ES.4 in Volume 1; and Section 10 in Volume 2).
    - Improvements made to estimates for the LULUCF sector were the main contributors to the reduction in the overall annual estimates. As section 4 of this paper indicates, this downward impact on net emissions was more pronounced in the later years of the time series.
  - As the analysis in section 4 of this paper shows, this cause explains most of the difference in annual emissions levels and virtually all of the change in trend across the time series reported for the June and September 2017 Quarterly Updates.
- Second, the time series of estimates for the September 2017 Quarterly is based on the standard UNFCCC accounting framework, while the time series for prior Quarterly Updates including June 2017 used the Kyoto Protocol accounting framework.
  - Changing the framework from the Kyoto Protocol framework to the standard UNFCCC framework produced a relatively small change in annual emissions levels and a negligible change in trend across the time series.

[1] The *2006 IPCC Guidelines for National Greenhouse Gas Inventories* sets out the methods and rules for National Inventory Reports to the UNFCCC. These provide specific guidance on revising and re-calculating previous emission estimates in IPCC 2006, Volume 1, Chapter 5.2.1 which states that it is good practice to change or refine methods when data has changed, or new methods become available. (IPCC 2006, Volume 1, Chapter 5.2.1, page 5.5)
For more information see **Attachment 2.A and Attachment 2.B**

- As explained in section 1 of this paper, the two frameworks differ only for the LULUCF sector. The difference primarily relates to the coverage of forest lands which is less comprehensive under the Kyoto framework, and to a lesser extent differences in the IPCC reporting rules, for example relating to international trade of harvested wood products and their eventual disposal in landfill.[2]

- The difference between classification frameworks result in lower net emissions (a larger net sink in more recent years) reported for the LULUCF sector under the UNFCCC time series in both the June and September 2017 quarters. However, the impact is much more evenly spread across the time series in absolute terms than the impact of updating the annual NIR estimates. (See section 4 of this paper for more details of the differences between the time series).

[2] See **Attachment 2.C**: Australia's Third Biennial Report to the UNFCCC (Annex A to Australia's Seventh National Communication on Climate Change), Chapter 4.2: Estimates of emission reductions and removals from LULUCF

3 Rationale for Changes between June and September 2017 Quarterly Updates

3.1 Rationale for using updated annual NIR estimates

- Section 5.05, p29 of the September 2017 Quarterly explains that periodic recalculations of the emission estimates are routinely undertaken to reflect the most accurate available data including the latest annual NIR.
  - As explained in section 2 of this paper, the updates to the NIR are subject to annual international expert review. To be consistent with international guidelines and underpin confidence in the integrity of the estimates, updates to estimation methodologies must be applied across the whole time series from 1990.
  - Not including the latest NIR-based estimates, which represent Australia's official estimates for international reporting, in the Quarterly Update time series would be misleading in terms of the state of play and progress towards meeting our international commitments.

3.2 Rationale for changing from the Kyoto Protocol to the UNFCCC reporting classifications

- The September 2017 Quarterly Update indicates (Section 5.05 on p28) that following the completion of the *2017 Review of Climate Change Policies* to ensure Government policies remain effective in achieving Australia's 2030 target and Paris Agreement commitments, the Quarterly Update has been refocussed to report emissions using classification systems consistent with that target.
  - Section 5.05 also indicates that the UNFCCC classification system provides for the inclusion of a broader and more comprehensive set of lands, and more readily permits the identification of emissions from land clearing events.
- Refocussing emissions reporting towards the UNFCCC classifications also brings the Quarterly Updates into line with Australia's Emissions Projections which now report out to 2030 using the UNFCCC classifications for consistency with Australia's intended accounting approach to the 2030 target (p34 of *Australia's Emissions Projections 2017*).
- As explained in section 1 of this paper, Australia's annual National Inventory Report to the UNFCCC includes inventory estimates prepared in accordance with our obligations under both the UNFCCC and the Kyoto Protocol.
  - The annual emissions time series for the June 2017 and prior Quarterly Updates were reported using the Kyoto Protocol classifications, which are used to report progress towards Australia's Cancun (2020)[3] and Kyoto Protocol Second Commitment Period targets.[4]
  - However, under the Paris Agreement, countries will no longer have Kyoto Protocol targets. In its intended nationally determined contribution, Australia has stated that it intends to account progress toward our Paris Agreement 2030 target using our UNFCCC inventory time series.[5]
  - Australia will continue to report both inventory time series in our annual NIR to the UNFCCC and to make this data available on the Department's Australian Greenhouse Emissions Information System (AGEIS) at http://ageis.climatechange.gov.au/.

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[3] See Section 4 of this paper, and **Attachment 3.2.A**: Australia's Third Biennial Report to the UNFCCC (Annex A to Australia's Seventh National Communication on Climate Change), Chapter 3.1 Details of Australia's 2020 Target

[4] See Section 4 of this paper, and **Attachment 3.2.B**: *Australia's Initial Report (Revised) (2016)* Report to facilitate the calculation of the Assigned Amount for the second commitment period of the Kyoto Protocol

[5] See Section 4 of this paper, and **Attachment 3.2.C**: Australia's Intended Nationally Determined Contribution to a new Climate Change Agreement | August 2015

4 Relative impacts of the changes made between the June and September 2017 Quarterly Updates to Data Table 2.

This section first quantifies the sectoral impacts of moving from Quarterly estimates based on the 2015 NIR to the 2016 NIR for both classification types. It then compares the impacts of the two component changes on levels and trends across the time series, focussing on the base year of 2005 for the Paris Agreement and the latest reported year from the Quarterly Updates (2017).

4.1 Impacts of improvements reported in the 2016 NIR on emissions estimates across the time series from 1990

As explained in section 2 of this paper, the 2016 NIR used in the September 2017 Quarterly reported significant improvements/updates made in emissions estimation methods for a number of sectors, of which the LULUCF sector was the main contributor. The LULUCF inventory improvements included:

- Broadening land coverage in response to international expert review team recommendations, to include ongoing net emissions (sequestration) from natural regrowth that occurred prior to 1990;[6] and

- Improvements in modelling and parameters for land subject to natural regrowth and commercial plantations, as part of ongoing implementation of CSIRO research.[7]

For more details see NIR 2016 Vol 2, Section 6.5.5

The tables below, derived from the 2015 and 2016 National Inventory Reports, quantify the effect of these improvements for both the Kyoto Protocol and UNFCCC inventory time series. These tables show the difference or the 'recalculation' between the estimates reported in the 2015 National Inventory Report and the revised estimates reported in the 2016 National Inventory Report.

Change in estimated emissions between NIR 2015 to NIR 2016

Kyoto Protocol time series: (Mt CO_2-e)	1990	2000	2003	2005	2007	2010	2011	2012	2013	2014	2015
LULUCF	-0.3	-3.1	7.1	3.4	4.7	-5.2	-10.8	-14.5	-11.6	-7.6	-11.8
All sectors (KP Classifications)	-0.1	-2.6	8.6	4.5	6.7	-3.2	-8.9	-12.1	-9.6	-6.0	-7.5

UNFCCC time series: (Mt CO_2-e)	1990	2000	2003	2005	2007	2010	2011	2012	2013	2014	2015
LULUCF	-2.8	-4.7	9.2	6.1	8.6	-2.1	-8.2	-12.8	-11.5	-7.4	-12.6
All sectors (UNFCCC Classifications)	-2.5	-4.3	10.6	7.3	10.6	-0.1	-6.3	-10.5	-9.5	-5.9	-8.4

- For both UNFCCC and Kyoto Protocol time series, the recalculation in the LULUCF sector is the largest in terms of overall emissions levels and trend across the time series.
  - The LULUCF recalculations are broadly similar in magnitude for both the UNFCCC and Kyoto Protocol inventory time series and closely similar in trend. The differences in magnitude between these two time series are due to the slightly smaller scope of emissions reported under the Kyoto Protocol.

[6] See ID# L.9 in **Attachment 4.1.A** the Annual Inventory Review Report for Australia's NIR 2014, submitted in 2016

[7] See **Attachment 4.1.B**: Roxburgh, S., Karunaratne, S., Paul, K., Lucas, R., Armston, J., Sun, S., 2017. *A revised above-ground maximum biomass layer for Australia's national carbon accounting system*. CSIRO; and
Attachment 4.1.C: Paul, K. and Roxburgh, S., 2017. *FullCAM: building capability via data-informed parameters*. CSIRO.

- As the LULUCF figures in the table above indicate, the impact of the improvements to the LULULCF estimates for the 2016 NIR was:
  - generally a net reduction in emissions (or increased net sink), except during the period 2003 to 2007 when emissions were revised upwards; and
  - larger in the more recent years (post 2010) than in earlier years.

4.2 Relative impacts of inventory improvements and change in reporting framework across the time series since 2005

The tables below show a comparison of estimates for both the UNFCCC and KP inventory time series based on the data available at the time of the June and September Quarterly updates

- To make direct comparison easier, we have compiled the additional UNFCCC and Kyoto Protocol time series information to show both time series in the tables below.
  - Quarterly estimates of UNFCCC inventory time series years to June 2016 and 2017 were not calculated at the time of the June 2017 Quarterly Update. In the June 2017 Quarterly table below, the UNFCCC time series for these years were derived based on the NIR 2015 data that was available at the time. This shows what these estimates *would have been* if the decision to change to UNFCCC time series reporting had been made in time for the June 2017 Quarterly Update.
  - Similarly, the KP inventory time series derived for the September 2017 Quarterly table below reflects the NIR 2016 data.

Table: Emissions data as available at the time of the June and September quarterlies: comparison of KP and UNFCCC inventory time series:

1. June 2017 quarterly	2005	Year to June 2017	Change 2005 to June 2017	
	Mt CO_2-e		Mt CO_2-e	%
A. KP time series	605.0	550.2	-54.8	-9%
B. UNFCCC time series (NIR 2015)	597.4	*544.7**	*-52.7**	*-9%**

* These estimates have not been published

2. Sept 2017 quarterly	2005	Year to September 2017	Change 2005 to September 2017	
	Mt CO_2-e		Mt CO_2-e	%
A. KP time series	609.5	*536.7*[+]	*-72.7*[+]	*-12%*[+]
B. UNFCCC time series (NIR 2015)	604.7	531.9	-72.8	-12%

[+] These estimates have not been published

- The percentage changes demonstrate that regardless of which inventory time series is used, the trend is the same. This shows that main reason for the difference in the emissions reduction since 2005 are the improvements in the 2016 NIR.

- In each of these tables, the UNFCCC time series estimates are slightly lower than the Kyoto Protocol inventory time series, however this difference has minimal impact on the trend.

5 Background

5.1 Accounting progress toward Australia's 2020 and 2030 targets

Australia's 2020 and 2030 emissions reductions targets are based on different inventory estimation frameworks, explained in NIR Vol 1 ES.2 (emphasis added):

> *[pg. xi] Under the UNFCCC Paris Agreement, the Australian Government committed to a quantified economy-wide nationally determined contribution (NDC) to reduce national emissions by between -26 and -28 per cent on 2005 levels by 2030. In its submission to the UNFCCC, the Australian Government indicated that it will report progress towards that commitment using* ***estimates of net emissions according to UNFCCC classifications****.*
>
> *…*
>
> *[pg. xii] Under the UNFCCC Cancun Agreement, the Australian Government committed to a quantified economy-wide emission reduction target (QEERT) of -5 per cent on 2000 levels by 2020. In its third Biennial Report, the Australian Government indicated that it will report progress towards that commitment using* ***estimates of net emissions according to KP classifications****.*

Australia's approach to its current 2020 target and emissions budget is detailed in Australia's NDC and Australia's Third Biennial Report to the UNFCCC (Attachment 3.1.B above).

5.2 Review and quality assurance of NIR estimates

The annual estimates of emissions in the National Inventory Report are robust, complete and have been subjected to rigorous quality-assurance processes during development:

- The data and methods for each sector are described in detail in the 2016 NIR, including quantification of revisions compared to the previous annual inventory report.
- Quality control and quality assurance of the national inventory estimates are described in the 2016 NIR. Additional measures include:
  - UNFCCC experts review our estimates each year;
  - The Department shares data with its counterparts in State & Territory agencies; and
- The ANAO recently undertook a performance audit of the national inventory over nine months (August 2016 to April 2017). Key findings included:
  - the Department has established appropriate processes to prepare, calculate and publish Australia's national inventory for the year 2014,
  - emissions estimates have been calculated using relevant contemporary data, and
  - appropriate quality assurance and control procedures are in place for inventory data processing, emissions calculations and reporting.

Attachments:

- **Attachment 2.A: *2006 IPCC Guidelines for National Greenhouse Gas Inventories* Volume 1, Chapter 5.2.1**
- **Attachment 2.B: UNFCCC Report of the Conference of the Parties on its nineteenth session, Warsaw 2013, Decision 24/CP.19 Annex I, Para 24**
- **Attachment 2.C: Australia's Third Biennial Report to the UNFCCC (Annex A to Australia's Seventh National Communication on Climate Change), Chapter 4.2: Estimates of emission reductions and removals from LULUCF**
- **Attachment 3.2.A: Australia's Third Biennial Report to the UNFCCC (Annex A to Australia's Seventh National Communication on Climate Change), Chapter 3.1 Details of Australia's 2020 Target.**
- **Attachment 3.2.B: *Australia's Initial Report (Revised) (2016)* Report to facilitate the calculation of the Assigned Amount for the second commitment period of the Kyoto Protocol**
- **Attachment 3.2.C: Australia's Intended Nationally Determined Contribution to a new Climate Change Agreement | August 2015**
- **Attachment 4.1.A: *Report on the individual review of the annual submission of Australia submitted in 2016. Note by the expert review team.* UNFCCC.**
- **Attachment 4.1.B: Roxburgh, S., Karunaratne, S., Paul, K., Lucas, R., Armston, J., Sun, S., 2017. *A revised above-ground maximum biomass layer for Australia's national carbon accounting system*. CSIRO.**
- **Attachment 4.1.C: Paul, K. and Roxburgh, S., 2017. *FullCAM: building capability via data-informed parameters*. CSIRO.**

5 TIME SERIES CONSISTENCY

5.1 INTRODUCTION

The time series is a central component of the greenhouse gas inventory because it provides information on historical emissions trends and tracks the effects of strategies to reduce emissions at the national level. As is the case with estimates for individual years, emission trends should be neither over nor underestimated as far as can be judged. All emissions estimates in a time series should be estimated consistently, which means that as far as possible, the time series should be calculated using the same method and data sources in all years. Using different methods and data in a time series could introduce bias because the estimated emission trend will reflect not only real changes in emissions or removals but also the pattern of methodological refinements.

This chapter describes *good practice* in ensuring time series consistency. Section 5.2 provides guidance on common situations in which time series consistency could be difficult to achieve: carrying out recalculations, on adding new categories, and on accounting for technological change. Section 5.3 describes techniques for combining or "splicing" different methods or data sets to compensate for incomplete or missing data. Additional guidance on reporting and documentation and QA/QC of time series consistency is given in Sections 5.4 and 5.5.

5.2 ENSURING A CONSISTENT TIME SERIES

5.2.1 Recalculations due to methodological changes and refinements

A methodological change in a category is a switch to a different tier from the one previously used. *Methodological changes* are often driven by the development of new and different data sets. An example of a methodological change is the new use of a higher tier method instead of a Tier 1 default method for an industrial category because a country has obtained site-specific emission measurement data that can be used directly or for development of national emission factors.

A *methodological refinement* occurs when an inventory compiler uses the same tier to estimate emissions but applies it using a different data source or a different level of aggregation. An example of a refinement would be if new data permit further disaggregation of a livestock enteric fermentation model, so that resulting animal categories are more homogenous or applies a more accurate emission factor. In this case, the estimate is still being developed using a Tier 2 method, but it is applied at a more detailed level of disaggregation. Another possibility is that data of a similar level of aggregation but higher quality data could be introduced, due to improved data collection methods.

Both methodological changes and refinements over time are an essential part of improving inventory quality. It is *good practice* to change or refine methods when:

- *Available data have changed*: The availability of data is a critical determinant of the appropriate method, and thus changes in available data may lead to changes or refinements in methods. As countries gain experience and devote additional resources to preparing greenhouse gas inventories, it is expected that data availability will improve.[1]
- *The previously used method is not consistent with the IPCC guidelines for that category*: Inventory compilers should review the guidance for each category in Volumes 2-5.
- *A category has become key*: A category might not be considered *key* in a previous inventory year, depending on the criteria used, but could become *key* in a future year. For example, many countries are only beginning to substitute HFCs and PFCs for ozone depleting substances being phased out under the Montreal Protocol. Although current emissions from this category are low, they could become *key* in the future based on trend or level. Countries anticipating significant growth in a category may want to consider this possibility before it becomes key.

[1] Sometimes collection of data may be reduced which can result in a less rigorous methodological outcome.

- *The previously used method is insufficient to reflect mitigation activities in a transparent manner*: As techniques and technologies for reducing emissions are introduced, inventory compilers should use methods that can account for the resulting change in emissions or removals in a transparent manner. Where the previously used methods are insufficiently transparent, it is *good practice* to change or refine them. See Section 5.2.3 for further guidance.
- *The capacity for inventory preparation has increased*: Over time, the human or financial capacity (or both) to prepare inventories may increase. If inventory compilers increase inventory capacity, it is *good practice* to change or refine methods so as to produce more accurate, complete and transparent estimates, particularly for *key categories*.
- *New inventory methods become available*: In the future, new inventory methods may be developed that take advantage of new technologies or improved scientific understanding. For example, remote-sensing technology improvements in emission monitoring technology may make it possible to monitor directly more types of emission sources.
- *Correction of errors*: It is possible that the implementation of the QA/QC procedures described in Chapter 6, Quality Assurance and Quality Control and Verification, will lead to the identification of errors or mistakes in the inventory. As noted in that chapter, it is *good practice* to correct errors in previously submitted estimates. In a strict sense, the correction of errors should not be considered a methodological change or refinement. This situation is noted here, however, because the general guidance on time series consistency should be taken into consideration when making necessary corrections.

BOX 5.1
RECALCULATION IN THE AGRICULTURE FORESTRY AND OTHER LAND USE (AFOLU) SECTOR

It is anticipated that the use of recalculation techniques in the AFOLU Sector will be particularly important. The development of inventory methods and interpolation/extrapolation tools (models) for this sector is ongoing and it is anticipated that changes to the methods of many countries will occur over time due to the complexity of the processes involved. In simple cases, sampling or experimentation may provide country-specific emission factors, which might require a time series recalculation. More complicated situations can also arise. For example:

- The instruments used to collect activity data may change through time, and it is impossible to go back in time to apply the new instrument. For example, land clearing events can be estimated by the use of satellite imagery, but the satellites available for this work change or degrade through time. In this case, the overlap method described in Section 5.3.3.1 is most applicable.
- Some data sources such as forest inventories required for AFOLU categories may not be available annually because of resource constraints. In this case, interpolation between years or extrapolation for years after the last year with measured data available may be most appropriate. Extrapolated data may be recalculated when final data become available (see Sections 5.3.3.3 and 5.3.3.4 on interpolation and extrapolation).
- Emissions and removals from AFOLU typically depend on past land use activity. Thus, data must cover a large historical period (20-100 years), and the quality of such data will often vary through time. Overlap, interpolation or extrapolation techniques may be necessary in these cases.
- The calculation of emission factors and other parameters in AFOLU may require a combination of sampling and modelling work. Time series consistency must apply to the modelling work as well. Models can be viewed as a way of transforming input data to produce output results. In most cases where changes are made to the data inputs or mathematical relationships in a model, the entire time series of estimates should be recalculated. In circumstances where this is not feasible due to available data, variations of the overlap method could be applied.

5.2.2 Adding new categories

The addition to the inventory of a new category or subcategory requires the calculation of an entire time series, and estimates should be included in the inventory from the year emissions or removals start to occur in the country. A country should make every effort to use the same method and data sets for each year. It may be

(e) Undertake specific functions relating to inventory planning, preparation and management.

Inventory planning

23. As part of its inventory planning, each Annex I Party should:

(a) Define and allocate specific responsibilities in the inventory development process, including those relating to choosing methods, data collection, particularly AD and EFs from statistical services and other entities, processing and archiving, and QA/QC. Such definition should specify the roles of, and the cooperation between, government agencies and other entities involved in the preparation of the inventory, as well as the institutional, legal and procedural arrangements made to prepare the inventory;

(b) Elaborate an inventory QA/QC plan as indicated in paragraph 19 above;

(c) Establish processes for the official consideration and approval of the inventory, including any recalculations, prior to its submission, and for responding to any issues raised in the inventory review process.

24. As part of its inventory planning, each Annex I Party should consider ways to improve the quality of AD, EFs, methods and other relevant technical elements of the inventory. Information obtained from the implementation of the QA/QC programme, the inventory review process and other verification activities should be considered in the development and/or revision of the QA/QC plan and the quality objectives.

Inventory preparation

25. As part of its inventory preparation, each Annex I Party should:

(a) Prepare estimates in accordance with the requirements defined in these reporting guidelines;

(b) Collect sufficient AD, process information and EFs as are necessary to support the methods selected for estimating anthropogenic GHG emissions by sources and removals by sinks;

(c) Make quantitative estimates of uncertainty for each category and for the inventory as a whole, as indicated in paragraph 15 above;

(d) Ensure that any recalculations are prepared in accordance with paragraphs 16–18 above;

(e) Compile the NIR and the CRF tables in accordance with these reporting guidelines;

(f) Implement general inventory QC procedures in accordance with its QA/QC plan, following the 2006 IPCC Guidelines.

26. As part of its inventory preparation, each Annex I Party should:

(a) Apply category-specific QC procedures for key categories and for those individual categories in which significant methodological and/or data revisions have occurred, in accordance with the 2006 IPCC Guidelines;

(b) Provide for a basic review of the inventory by personnel that have not been involved in the inventory development process, preferably an independent third party, before the submission of the inventory, in accordance with the planned QA procedures referred to in paragraph 19 above;

Table 4.1: Net emissions associated with Australia's QEERT

KP Classification sector and subsector	Emissions (Mt CO_2-e)								
	2000	2013	2014	2015	2016	2017	2018	2019	2020
1. *Energy*	364.0	414.3	408.6	419.6	431.7	432.8	430.9	431.4	432.9
2. *Industrial Processes and Product Use*	26.8	32.5	32.4	32.3	33.1	34.1	34.1	34.2	34.3
3. *Agriculture*	78.6	72.7	72.8	70.0	68.7	71.5	71.6	73.2	74.8
4. *LULUCF activities*	69.6	-1.9	4.9	4.6	-2.4	6.3	4.4	4.7	2.6
5. *Waste*	15.4	11.8	12.0	11.4	11.6	10.7	10.0	9.7	9.5
Total net emissions (including *LULUCF*)	554.4	529.5	530.7	537.9	542.8	555.5	550.9	553.2	554.1
Cumulative total	-	529.5	1060.2	1598.0	2140.8	2696.3	3247.2	3800.4	4354.5

The estimates in Table 4.1, as per the latest National Inventory Report 2017 (NIR 2017) and Australia's emissions projections 2017 (Kyoto Protocol classifications), include emissions and removals from energy, industrial processes and product use, agriculture and waste sectors and the following *KP-LULUCF subclassifications: deforestation, afforestation, reforestation, forest management, cropland management, grazing land management* and *revegetation*.

Australia's policies and measures that have contributed to the reductions of greenhouse gases in these sectors are described in this section and in CTF Table 3.

4.2 ESTIMATES OF EMISSION REDUCTIONS AND REMOVALS FROM *LULUCF*

Australia has used the KP classification system for reporting estimates from the *LULUCF* sector, as discussed in section 3.2. For all *LULUCF* classifications, emission estimates in the reporting period are compared with estimates in the base-year, which is 2000. In summary, the net emissions from the *LULUCF* sector were 4.6 Mt CO_2-e in 2015, which were 65.0 Mt CO_2-e less than net emissions in 2000. Information on the contribution of the *LULUCF* sector to Australia's progress towards its QEERT is provided in CTF Tables 4, 4(a)I and 4(b).

4.2.1 Coverage

Australia reported net emissions from *deforestation, afforestation/reforestation, forest management, cropland management, grazing land management and revegetation*. The concordance between the two classification systems is set out in Table 4.2.

Table 4.2: Reconciliation table between UNFCCC and KP classifications

UNFCCC	Kyoto Protocol
Forest land	-
Forest land – multiple use forests	Forest Management
Forest land – pre-1990 plantations	Forest Management
Forest land – private native forests	Monitored for Forest Management activity
Forest land – conservation reserves	Monitored for Forest Management activity
Forest land – other native forest	Monitored for Forest Management activity

UNFCCC	Kyoto Protocol
Land converted to forest	-
New plantations since 1990	Afforestation / Reforestation
Native regeneration since 1990 – direct human induced	Afforestation / Reforestation
Cropland	-
Croplands – permanent	Cropland management
Forest converted to crops	Deforestation
Grassland converted to crops	Cropland management
Grassland	-
Grasslands – permanent	Grazing land management
Forest converted to grass since 1990 – direct human induced	Deforestation
Forest converted to grass – pre-1990 conversion – direct human induced	Grazing land management
Crop converted to grass	Grazing land management
Settlements	Revegetation
Wetlands	Revegetation

4.2.1.1 Deforestation

The net emissions from *Deforestation* were 31.1 Mt CO_2-e in 2015, which was 37.6 Mt CO_2-e less than in 2000. The classification definitions and the methodologies used to derive the estimates are described in the latest NIR 2017 Volume 3.

4.2.1.2 Afforestation / Reforestation

The net emissions from the *Afforestation / Reforestation* classification were -12.6 Mt CO_2-e in 2015, which was 5.5 Mt CO_2-e less than in 2000. The classification definitions and the methodologies used to derive the estimates are described in the NIR 2017 Volume 3.

4.2.1.3 Forest Management

The net emissions from *Forest Management* classification were -18.4 Mt CO_2-e in 2015, which was 10.9 Mt CO_2-e less than in 2000. For *Forest Management*, reference level accounting, as is applicable under the KP, has not been applied. Instead, *Forest Management* is treated the same way as is any other sector.

Harvested wood products are estimated using the IPCC production approach.

Natural disturbance (fire, cyclones) impacts are not excluded from the accounting but are subject to a national methodology approach that takes into account the IPCC method for treatment of natural disturbances as explained in the latest NIR 2017 Volume 3.

Natural disturbance impacts are "beyond control" and "not materially influenced" by Australia, as they occur in spite of significant and costly efforts to manage disturbance. Australia engages in on-going efforts to prevent, manage and control natural disturbances to the extent practicable (and as reported in the latest NIR 2017).

Australia's national forest carbon monitoring system is used to estimate the emissions and is also used to identify any subsequent removals from the lands affected by natural disturbances, as well as to monitor lands affected by natural disturbances for salvage logging or subsequent land-use change in order to account for any associated emissions.

Australia does not apply a cap in accounting for Forest Management.

4.2.1.4 Cropland Management

The net emissions from Cropland Management classification were -4.2 Mt CO_2-e in 2015, which was 5.2 Mt CO_2-e less than in 2000. The classification definitions and the methodologies used to derive the estimates are described in the NIR 2017 Volume 3.

4.2.1.5 Grazing land Management

The net emissions from Grazing land Management were 8.7 Mt CO_2-e for 2015, which was 5.5 Mt CO_2-e less than in 2000. The classification definitions and the methodologies used to derive the estimates are described in the NIR 2017 Volume 3.

4.2.1.6 Revegetation

The net emissions from Revegetation were -0.11 Mt CO_2-e for 2015, which was 0.29 Mt CO_2-e less than in 2000. The classification definitions and the methodologies used to derive the estimates are described in the NIR 2017 Volume 3.

4.2.1.7 Other

Australia does not include estimates of emissions from drainage and re-wetting of organic soils.

3. QUANTIFIED ECONOMY-WIDE EMISSION REDUCTION TARGET

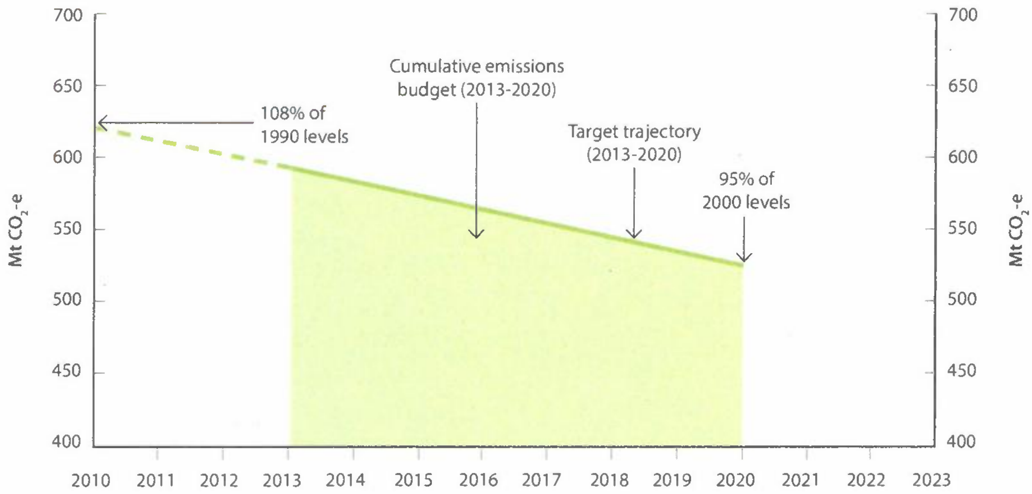
The Australian Government is committed to an unconditional Quantified Economy-wide Emission Reduction Target (QEERT) of five per cent on 2000 levels by 2020 (see CTF Table 2(a)). Australia's target represents a substantial reduction from business-as-usual emissions on a range of indicators. Australia is tracking progress in this report against its unconditional QEERT under the Convention. In tracking progress against the unconditional QEERT, Australia applies Kyoto Protocol (KP) classifications for the land use, land use change and forestry (LULUCF) sector, as described below and in Chapter 5 of the Seventh National Communication.

3.1 DETAILS OF AUSTRALIA'S 2020 TARGET

Australia's unconditional QEERT is a decrease of five per cent on 2000 levels by 2020 (see CTF Table 2(a)). Australia assesses its progress towards the QEERT using an emissions budget approach for the period 2013 to 2020. As shown in Figure 1, the emissions budget is calculated using a trajectory from Australia's first commitment period target (CP1) under the KP to the 2020 target. A linear decrease is taken, from 2010 to 2020, beginning from the KP CP1 target level which was 108 per cent of 1990 levels and finishing at five per cent below 2000 levels in 2020. The area under the trajectory for the period 2013-2020 is the emissions budget.

The current estimate of the emissions budget for 2013 to 2020 is 4,500Mt of CO2-e. This value is subject to change based on recalculations to Australia's national greenhouse gas inventory.

Figure 3.1: Australia's QEERT



Source: Department of the Environment and Energy 2017

Australia's QEERT is based on its Kyoto Protocol inventory, submitted as supplementary information in its annual national inventory report (Chapters ES.2.2 and 11)[3]. The QEERT includes emissions and removals from the energy, industrial processes and product use, agriculture and waste sectors and the following KP *LULUCF* sub-classifications: deforestation, afforestation, reforestation, forest management, cropland management, grazing land management and revegetation. The target includes all greenhouse gas emissions (GHG)s included in the UNFCCC Annex I inventory reporting guidelines, namely CO_2, CH_4, N_2O, HFCs, PFCs, SF_6 and NF_3. The global warming potentials (GWPs) used are from the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report prescribed in decision 24/CP.19 (see CTF Table 2(b)). Carbon dioxide equivalents (CO_2-e) of these gases are calculated using the GWP for a 100-year time horizon (see CTF Table 2(c)). Australia's target represents net emissions.

3. Australia's 2017 National Inventory Report Submission is available on the UNFCCC website: https://unfccc.int/process/transparency-and-reporting/reporting-and-review-under-the-convention/greenhouse-gas-inventories-annex-i-parties/submissions/national-inventory-submissions-2017.

Australian Government
Department of the Environment and Energy

Australia's Initial Report (revised)

Australia's Report to Facilitate the Calculation of the Assigned Amount pursuant to Article 3, paragraphs 7bis, 8 and 8bis, of the Kyoto Protocol for the second commitment period of the Kyoto Protocol

October 2016

1. Introduction

This Report is a submission of the Australian Government to the secretariat of the United Nations Framework Convention on Climate Change (UNFCCC) to facilitate the calculation of the assigned amount pursuant to Article 3, paragraphs 7bis, 8 and 8bis for the second commitment period (CP2) of the Kyoto Protocol (KP). It constitutes a resubmission of the Report submitted by the Australian Government in May 2016. The Report is submitted in accordance with decisions 2/CMP.11, 3/CMP.11 and 1/CMP.8 that provides, pending the entry into force of the KP Doha Amendment that establishes the CP2, KP Parties will continue to implement KP commitments and other responsibilities in a manner consistent with their national legislation and domestic processes. In December 2015, at the 11th session of the Conference of the Parties serving as the meeting of the Parties to the KP, the Australian Government announced it will ratify the Doha Amendment.

The accompanying *National Inventory Report 2014 (revised)* provides a full time series of greenhouse gas emission and removal estimates for Australia for the period 1990 – 2014. This inventory has been used to estimate Australia's assigned amount and base year emissions.

2. Requirements of the report to facilitate the calculation of the assigned amount for the CP2

According to decision 2/CMP.8, as revised by paragraph 4 of annex I to decision 3/CMP.11, if a Party had a target under the first commitment period of the KP, the report to facilitate the calculation of the assigned amount for the CP2 shall contain the following information:

- Complete inventories of anthropogenic emissions by sources and removals by sinks of greenhouse gases not controlled by the Montreal Protocol, recalculated in accordance with decision 4/CMP.7 for all years from 1990, to the most recent year available. If the report is submitted at the same time as the submission of the Party's annual greenhouse gas inventory, only one inventory submission should be provided and both reports should be submitted in conjunction;
- Identification of the selected base year for nitrogen trifluoride;
- The agreement under Article 4, where the Party has reached such an agreement to fulfill its commitments under Article 3 jointly with other Parties;
- Calculation of the assigned amount pursuant to Article 3, paragraphs 7bis, 8 and 8bis, on the basis of its inventory of anthropogenic emissions by sources and removals by sinks of greenhouse gases not controlled by the Montreal Protocol;
- Calculation of the difference between the assigned amount for the second commitment period and average emissions for the first three years of the preceding commitment period multiplied by eight, pursuant to Article 3, paragraph 7 ter, and in accordance with paragraphs 8 ter and 8 quater of annex I to decision 3/CMP.11;
- Calculation of the commitment period reserve in accordance with decision 11/CMP.1 or any subsequent revision thereof related to the calculation of the commitment period reserve;
- Selected values for tree crown cover, land area and tree height for use in accounting for activities under Article 3, paragraphs 3 and 4 of the KP shall be the same as for the first commitment period;

- Identification of the election of activities under Article 3, paragraph 4, of the KP for inclusion in accounting for the CP2, in addition to those activities under Article 3, paragraph 4, of the KP that were elected in the first commitment period, together with information on how the national system will identify land areas associated with all additional elected activities and how land that was accounted for under activities under Article 3, paragraphs 3 and 4, of the KP in the first commitment period continues to be accounted for in subsequent commitment periods, in accordance with decisions 16/CMP.1 and 2/CMP.7;
- Identification of whether, for each activity under Article 3, paragraphs 3 and 4, accounting will occur annually or for the entire commitment period;
- The forest management reference level as inscribed in the appendix to the annex to decision 2/CMP.7, any technical corrections as contained in the inventory report for the first year of CP2 and references to those sections in the Report where such information is reported consistent with the requirements of decision 2/CMP.7, annex, paragraph 14;
- Information on how emissions from harvested wood products originating from forests prior to the start of the CP2 have been calculated in the reference level in accordance with decision 2/CMP.7, annex, paragraph 16;
- An indication of whether there is an intention to apply the provisions to exclude emissions from natural disturbances for the accounting for *afforestation* and *reforestation* under Article 3, paragraph 3, of the KP and/or *forest management* under Article 3, paragraph 4, of the KP during the CP2, including:
  - Country-specific information on the background level of emissions associated with annual natural disturbances that have been included in its forest management reference level;
  - Information on how the background level(s) for *afforestation* and *reforestation* under Article 3, paragraph 3, of the KP and/or *forest management* under Article 3, paragraph 4, of the KP have been estimated, and information on how it avoids the expectation of net credits or net debits during the commitment period, including information on how a margin is established, if a margin is needed.

In accordance with the annex to decision 2/CMP.8, this Report does not contain a description of the national system or the national registry as Australia had a quantified emission limitation and reduction target in the first commitment period of the KP.

a. Complete inventories of anthropogenic emissions by sources and removals by sinks of greenhouse gases not controlled by the Montreal Protocol, for all years from 1990

Australia's most recently completed inventory – the *National Inventory Report 2014 (revised)* – the associated Common Reporting Format tables and this Report have been submitted to the UNFCCC Secretariat.

The submitted documents provide detailed information and a full time series of greenhouse gas emission and removal estimates for Australia for the period 1990–2014 based on UNFCCC classifications. These emission estimates have been used to estimate Australia's assigned amount and base year emissions. Table 1 provides summary data on Australia's greenhouse gas emissions from 1990-2014.

Table 1: Australia's Greenhouse Gas Emissions 1990-2014

Year	CO_2-e emissions excluding land use, land use change and forestry (kt CO_2-e)	Total CO_2-e emissions including land use, land use change and forestry (kt CO_2-e)
1990	418,623.050	547,595.933
1991	418,674.057	520,343.398
1992	423,080.108	487,533.502
1993	423,764.933	483,414.840
1994	424,092.959	501,298.210
1995	433,478.651	480,420.851
1996	439,803.962	497,973.061
1997	451,721.718	519,170.071
1998	466,382.112	516,979.322
1999	472,245.991	531,512.304
2000	483,445.827	549,951.534
2001	491,441.696	544,755.196
2002	494,740.101	568,094.323
2003	495,154.086	551,693.070
2004	511,710.242	566,259.382
2005	518,850.759	595,231.996
2006	522,517.192	612,144.345
2007	529,842.870	583,887.827
2008	533,693.508	584,795.083
2009	537,889.893	586,327.181
2010	533,917.436	555,692.078
2011	534,089.799	541,159.033
2012	537,377.571	540,425.605
2013	526,882.667	529,947.644
2014	522,397.091	523,879.774

Source: Australian Greenhouse Emissions Information System (AGEIS), http://ageis.climatechange.gov.au/

b. Base year for nitrogen trifluoride

Australia has decided to use 1990 as the base year for nitrogen trifluoride, which is consistent with the base year for all gases included in the *National Inventory Report 2014 (revised)*.

c. Agreement under Article 4 of the Kyoto Protocol

Australia will not be a participant in any Article 4 agreements.

d. Calculation of Australia's Assigned Amount

Based on the data contained in the *National Inventory Report 2014 (revised)* and Common Reporting Format tables, Australia's assigned amount for the CP2 of the KP is 4,511,619,826 t CO_2-e. Details of this calculation are provided in Table 2.

Table 2: Determination of Australia's Assigned Amount

Sector	t CO_2-e
Energy	292,802,453
Industrial Processes and Product Use	26,108,523
Agriculture	80,060,540
Waste	19,651,533
Land use change[1]	148,163,361
Total base year emissions estimate	**566,786,410**
99.5% of base year estimate[2]	563,952,478
Australia's Assigned Amount (8 times 99.5% of base year estimates)	**4,511,619,826**

[1] In accordance with Article 3.7bis, and consistent with the calculation of the base for CP1, as *land use change and forestry* (all emissions by sources and removals by sinks under category 4 of the *Revised Guidelines for the preparation of national communication by Parties included in Annex I to the Convention, Part 1: UNFCCC reporting guidelines on annual greenhouse gas inventories*) constituted a net source for Australia in 1990 (128,972,883 kt CO_2-e), the emissions from land use change in 1990 are included in the emissions estimate for the base year for the purposes of calculating Australia's CP2 assigned amount. *Land use change* is defined to include net emissions from *Forest Conversion to Cropland, Grassland, Wetlands, Settlements* and *Other lands*, and exclude net emissions from nitrogen leaching, nitrogen run-off, and net emissions from fire from these lands.

[2] Annex B to the Kyoto Protocol lists Australia's quantified emission limitation or reduction commitment as 99.5 per cent of the base year over 2013-2020.

e. Application of Article 3.7 ter

Article 3.7 ter requires the calculation of a threshold beyond which a cancellation of CP2 assigned amount units (AAUs) is undertaken equal to any positive difference between a Party's CP2 assigned amount and eight times its average annual emissions for 2008, 2009 and 2010.

Decision 2/CMP.11 also requires that Parties clarify in their Report whether they have used, in the calculation of the average annual emissions for the first three years of the preceding commitment period: (a) the gases and sources listed in Annex A to the Kyoto Protocol; or (b) the same greenhouse gases, sectors and source categories as those used to calculate the assigned amount for CP2.

As determined from Table 2, Australia's CP2 assigned amount is estimated from net emissions from *land-use change*, *energy*, *industrial processes and product use*, *agriculture,* and *waste* in the 1990 emissions base year.

The same approach is used to calculate average annual emissions for 2008 – 2010. As indicated in Table 3, the estimate of Australia's CP2 assigned amount is below the calculated threshold for AAU cancellation derived from the estimate of Australia's average annual emissions for 2008 to 2010. Therefore, cancellation of AAUs is not required in accordance with Article 3.7 ter.

Table 3: Determination of Australia's Assigned Amount

Calculation of the Threshold for AAU cancellation	t CO_2-e
Emissions[a] – 2008	595,037,994
Emissions[a] – 2009	600,179,201
Emissions[a] – 2010	585,641,316
Average emissions 2008–2010	593,619,504
Threshold for AAU cancellation: average emissions 2008 to 2010 times eight	4,748,956,028
Comparison of Total Assigned Amount with threshold for AAU cancellation	
Total Assigned Amount[b]	4,511,619,826
Threshold for AAU cancellation	4,748,956,028
Total Assigned Amount minus threshold for AAU cancellation	**-237,336,202**
AAUs to be cancelled	**0**

a Calculated as emissions from *energy*, *industrial processes and product use*, *agriculture*, *land use change*, and *waste* consistent with the greenhouse gases, sectors and source categories used to calculate the assigned amount for CP2.
b As per the calculation in Table 2.

f. Calculation of the commitment period reserve

The commitment period reserve should not drop below 90 per cent of the Party's assigned amount or 100 per cent of eight times its most recently reviewed inventory, whichever is lowest.

As indicated in Table 4, the commitment period reserve for CP2 is calculated to be 4,060,457,843 t CO_2-e, calculated as 90 per cent of the estimated CP2 assigned amount.

Table 4: Calculation of the commitment period reserve

Item	t CO_2-e
Eight times the most recently reviewed inventory[a] including Land Use Change (8 times 559,104,914)	4,472,839,310
90% of the Assigned Amount (0.9 times 4,511,619,826)	4,060,457,843
Commitment period reserve	4,060,457,843

a Australia interprets "the most recently reviewed inventory" to be the same greenhouse gases, sectors and source categories as those used to calculate the assigned amount for CP2, namely the sources listed in Annex A to the KP and Land Use Change. The estimate relates to inventory year 2014 and is based on data contained in the *National Inventory Report 2014 and Revised Kyoto Protocol National Inventory Report 2013* and common reporting format tables that are submitted in conjunction with this report.

g. Identification of selected values for tree crown cover, land area and tree height for use in accounting for activities under Article 3, paragraphs 3 and 4

Selected values for tree crown cover, land area and tree height for use in accounting for activities under Article 3, paragraphs 3 and 4 of the KP are the same as for the first commitment period. Australia's first commitment period definition is defined in *The Australian Government's Initial Report Under the Kyoto Protocol (2008)*[1].

1 http://unfccc.int/national_reports/initial_reports_under_the_kyoto_protocol/first_commitment_period_2008-2012/items/3765.php

h. Election of activities under Article 3.4 for accounting in the period 2013–2020

Australia accounted for the mandatory Article 3.3 activities *deforestation* and *afforestation/reforestation* in the first commitment period of the KP.

In the CP2, Australia will continue to account for *deforestation* and *afforestation/reforestation* as well as the Article 3.4 activity, *forest management*, which is mandatory for CP2. In addition, Australia elects to account for the following voluntary activities under Article 3 paragraph 4:

- *Cropland management*;
- *Grazing land management*; and
- *Revegetation*.

Chapters 6 and 11 of the *National Inventory Report 2014 (revised)* describe how Australia's national system will identify land areas associated with all Article 3.3 and Article 3.4 activities and how land accounted for under Article 3.3 activities in the first commitment period continue to be accounted in the CP2.

i. Accounting for Article 3.3 and Article 3.4 activities

Australia will account for all Article 3.3 activities annually in the CP2, in a continuation of the approach selected for the first commitment period.

Australia will account for *forest management* and elected Article 3.4 activities for the entire commitment period at the end of the CP2.

Table 5: Accounting mode elected by Australia for Article 3.3 and Article 3.4 activities

Article	Activity	Accounting mode
Article 3.3	*Deforestation*	Annual
Article 3.3	*Afforestation/reforestation*	Annual
Article 3.4	*Forest Management*	Entire commitment period
Article 3.4	*Cropland Management*	Entire commitment period
Article 3.4	*Grazing land Management*	Entire commitment period
Article 3.4	*Revegetation*	Entire commitment period

j. Australia's forest management reference level and technical corrections

The forest management reference level inscribed in the appendix to the annex to decision 2/CMP.7 was 4.7 Mt CO_2-e per year for Australia.

There have been a number of methodological refinements since this reference level was submitted, which include changes to address subsequently agreed rules for implementing the natural disturbance provision and calculating emissions from harvested wood products (decisions 2/CMP.7, 2/CMP.8 and *2013 Revised Supplementary Methods and Good Practice Guidance Arising from the Kyoto Protocol* (IPCC 2014)) as well as refinements to other methodological elements used in the estimation of forest management emissions (IPCC 2014). As a result, a technical correction of -4.785 Mt CO_2-e has been applied to Australia's forest management reference level. Australia's adjusted forest management reference level for the CP2 is -0.085 Mt CO_2-e per year.

Table 6: Forest Management Reference Level

Item	Technical Correction (Mt CO_2-e/year)	Forest Management Reference Level (Mt CO_2-e/year)
Forest management reference level inscribed in the appendix to the annex to decision 2/CMP.7	–	4.700
National Inventory Report 2014 – second year of CP2	-4.785	-0.085

The technical correction and methodological refinements are described in detail in section 11.6.5 of the *National Inventory Report 2014 (revised).*

Forest Management Cap

For CP2, additions to the assigned amount of a Party resulting from forest management shall, in accordance with paragraph 13 of the annex to decision 2/CMP.7, not exceed 3.5 per cent of the national total emissions excluding LULUCF in the base year times eight. The forest management cap is calculated in Table 7.

Table 7: Calculation of the forest management cap

Item	Kt CO_2-e
1990 emissions, excluding LULUCF	418,623.050
3.5 per cent of 1990 emissions, excluding LULUCF	14,651.807
Forest management cap: 3.5 per cent of 1990 emissions, excluding LULUCF, times eight	117,214.454

k. The treatment of harvested wood products originating from forests prior to the start of the CP2

Australia's forest management reference level includes emissions from harvested wood products produced since 1940. Refer to sections 11.6.4, 11.10 and 4.6 of the *National Inventory Report 2014 (revised)* for information on the treatment of harvested wood products in Australia's forest management reference level as well as the models and methodologies used to estimate carbon stock changes from harvested wood products.

I. Natural disturbances

Australia intends to apply the provision to exclude emissions from natural disturbances to accounting for *forest management* during the CP2. Australia does not intend to apply this provision to emissions from *afforestation/reforestation*.

As described in section 11.6.3 of the *National Inventory Report 2014 (revised)*, Australia has calculated a background level and margin of wildfire natural disturbance emissions for forest management lands using the IPCC default method (see IPCC 2014, page 2.48-2.50). The background level and margin are presented in Table 8.

Table 8: Components of Australia's background level and margin for wildfire natural disturbances

Components	
Calibration period	2000-2012
Method used	IPCC default
Background level	3.90 Mt CO_2-e
Margin	5.92 Mt CO_2-e
Background level plus margin	9.81 Mt CO_2-e
Number of excluded years	Three
Excluded years	2003, 2007, 2010

Australia intends to apply a background level of zero for all other natural disturbances, including for drought, storm damage, tropical cyclones and pests and pathogens. In this case, there is no expectation of net credits or debits being generated by these natural disturbances.

Section 11.6.3 of the *National Inventory Report 2014 (revised)* provides a detailed explanation of the methodology used to calculate the background level and margin of wildfire natural disturbance emissions for forest management lands and how the methodology avoids the expectation of net credits or debits.

3. References

Department of Climate Change, 2008, *The Australian Government's Initial Report Under the Kyoto Protocol*, Department of Climate Change, Canberra.
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http://www.ipcc-nggip.iges.or.jp/public/kpsg/index.html

environment.gov.au

AUSTRALIA

Australia's Intended Nationally Determined Contribution to a new Climate Change Agreement | August 2015

I. Australia's commitment

Australia wants the United Nations climate change conference in Paris to deliver a strong and effective new global climate change agreement, applicable to all UNFCCC Parties.

Australia has a strong record of meeting our commitments, and we are on track to meet our 2020 target. Our direct action policy, including the Emissions Reduction Fund, is supporting businesses and the community to reduce emissions, while improving productivity and sustaining economic growth.

Australia will continue to play our part in an effective global response to climate change. Under a Paris Agreement applicable to all, Australia will implement an **economy-wide target to reduce greenhouse gas emissions by 26 to 28 per cent below 2005 levels by 2030.** The details of Australia's contribution are set out in the attachment to aid transparency, clarity and understanding.

Australia's target is unconditional based on assumptions set out in the attachment. We will implement the 28 per cent target should circumstances allow, taking into account opportunities to reduce emissions and factors such as the costs of technology. Australia reserves the right to adjust our target and its parameters before it is finalised under a new global agreement should the rules and other underpinning arrangements of the agreement differ in a way that materially impacts the definition of our target.

II. A fair and ambitious contribution to deliver the Convention's objective

Australia's intended nationally determined contribution is an ambitious, fair and responsible contribution to global efforts toward meeting the objective of the UNFCCC with the goal of limiting global average temperature rise to below two degrees Celsius.

The target is a significant progression beyond Australia's 2020 commitment to cut emissions by five per cent below 2000 levels (equivalent to 13 per cent below 2005 levels). The target approximately doubles Australia's rate of emissions reductions, and significantly reduces emissions per capita and per unit of GDP, when compared to the 2020 target. Across a range of metrics, Australia's target is comparable to the targets of other advanced economies. Against 2005 levels, Australia's target represents projected cuts of 50 to 52 per cent in emissions per capita by 2030 and 64 to 65 per cent per unit of GDP by 2030.

The target represents serious and ambitious effort for Australia. This effort takes account of Australia's unique national circumstances, including a growing population and economy, role as a leading global resources provider, our current energy infrastructure, and higher than average abatement costs. The target places Australia on a stable pathway towards longer term emissions reductions in the context of future global action and technological innovation.

III. Planning processes towards achieving Australia's target

Australia's Emissions Reduction Fund supports Australian businesses to reduce emissions while improving productivity. The first auction under the Fund was held in April 2015, and successfully purchased over 47 million tonnes of abatement at an average price of AU$13.95. The Government is finalising a safeguard mechanism to ensure emissions reductions purchased under the Fund are not offset by significant rises in emissions elsewhere in the economy. Australia has additional policy measures in place to promote the deployment of renewable energy and improve energy efficiency. Under Australia's Renewable Energy Target scheme, over 23 per cent of Australia's electricity will come from renewable sources by 2020.

The Australian Government is working to build climate resilience and support adaptation to climate change. Australia will develop a National Climate Resilience and Adaptation Strategy during 2015.

The Australian Government is commencing the development of a range of policies that will reduce emissions into the post-2020 period, including a National Energy Productivity Plan with a National Energy Productivity Target of a 40 per cent improvement between 2015 and 2030, the investigation of opportunities to improve the efficiency of light and heavy vehicles, and the enhanced management of synthetic greenhouse gas emissions under ozone protection laws and the Montreal Protocol.

Building from these measures, the Australian Government will in 2017-2018 undertake consultation to determine further post-2020 domestic emissions reduction policies. The Government will ensure that policies used in the post-2020 period are efficient and complementary with one another, and are appropriately calibrated towards achieving Australia's 2030 target. As a part of this process, the Government will consider a potential long term emissions reduction goal for Australia, beyond 2030, taking into account international trends and technology developments.

Attachment: Australia's intended nationally determined contribution

Target: 26 to 28 per cent below 2005 levels by 2030

Reference point	
Base year	2005
Time frames	
Period covered	2021 – 2030
Scope and Coverage	
Target type	Absolute economy-wide emissions reduction by 2030, to be developed into an emissions budget covering the period 2021-2030
Gases covered	Carbon dioxide (CO_2); Methane (CH_4); Nitrous oxide (N_2O); Hydrofluorocarbons (HFCs); Perfluorocarbons (PFCs); Sulphur hexafluoride (SF_6); Nitrogen trifluoride (NF_3)
Sectors covered	Energy; Industrial processes and product use; Agriculture; Land-use, land-use change and forestry; Waste
% of base year emissions covered	100 per cent of greenhouse gas emissions and removals in Australia's national greenhouse gas inventory
Assumptions and methodological approaches for emissions estimates and accounting	
Metrics	Australia intends to apply 100 year Global Warming Potentials (GWPs) as contained in inventory reporting guidelines, currently IPCC Fourth Assessment Report 100 year GWPs, or as otherwise agreed.
Emissions estimation methodology	Australia intends to apply the IPCC 2006 Guidelines and IPCC 2013 Revised Supplementary Methods, or as otherwise agreed.
Accounting approach	Australia intends to account based on UNFCCC inventory reporting categories using a net-net approach. Australia will apply IPCC guidance for treatment of natural disturbance and variation. Australia's INDC assumes that accounting provisions under the Paris agreement will: - Preserve the integrity of the agreement by ensuring claimed emissions reductions are genuine and are not double counted; and - Recognise emissions reductions from all sectors.
Australia reserves the right to adjust our target and its parameters before it is finalised under a new global agreement should the rules and other underpinning arrangements of the agreement differ in a way that materially impacts the definition of our target.	

ID#	*Issue and/or problem classification[a, b]*	*Recommendation made in previous review report*	*ERT assessment and rationale*
L.5	4.A.1 Forest land remaining forest land (L.9, 2015) (57, 2014) Transparency	Include in the NIR additional information regarding the mapping of plantations established/recorded from 1940 to 1989, and the associated estimates	Resolved. In table 6.19 of the NIR (volume 2), Australia reported the areas of land converted to plantation from 1940 to 1989. Australia has also included a broad description of the methods employed, including the use of the national plantation inventory
L.6	4.A.1 Forest land remaining forest land – CO_2 (L.27, 2015) Accuracy	Implement the suggested improvements in accuracy, regarding the assumption for the time period for subsequent regrowth after a fire event	Resolved. Following the recommendation of the previous ERT, the five-year linear recovery of biomass after wildfires (two years following prescribed fires) used in previous submissions has been modified to use Olson curves calibrated to empirical data for each state and territory and for each fire type (NIR, volume 2, page 49)
L.7	4.A.2 Land converted to forest land – CO_2, CH_4 and N_2O (L.28, 2015) Consistency	Implement the planned improvement to allocate the AD and emissions/removals from forest conversion events that occurred before 1990 and that are followed by natural regeneration in a consistent manner and in accordance with the 2006 IPCC Guidelines	Not resolved. In the NIR (volume 3, page 194), the Party stated that improvement of the allocation of lands in these complex circumstances is included in the inventory improvement plan
L.8	4.A.2 Land converted to forest land – CO_2, CH_4 and N_2O (L.28, 2015) Consistency	In the specific case of subsequent land-use changes within a period shorter than 50 years, base the rule for the allocation of AD and estimates in each reporting year on the end-use category of the land in that year	Not resolved. In the NIR (volume 3, page 194), the Party stated that improvement of the allocation of lands in these complex circumstances is included in the inventory improvement plan
L.9	4.A.2 Land converted to forest land – CO_2, CH_4 and N_2O (L.29, 2015) Completeness	Report emissions/removals occurring throughout the reporting period owing to natural forest regeneration before 1990	Not resolved. According to the NIR (volume 2, section 6.5.5), Australia is planning to continue refinements to the FullCAM modelling parameters for forest/plantation growth and regeneration (including for the pre-1990 period), informed by empirical

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A revised above-ground maximum biomass layer for Australia's national carbon accounting system

Prepared for the Department of the Environment

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Important disclaimer

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Summary

The carbon accounting model FullCAM is applied in Australia's National Greenhous Gas Inventory to provide estimates of carbon stock changes and emissions in response to deforestation and afforestation or reforestation. FullCAM-predicted above-ground woody biomass is heavily influenced by the parameter *M*, which defines the maximum upper limit to biomass accumulation for any location within the Australian continent. Here we update the *M* spatial input layer using the Random Forest ensemble machine learning algorithm, through combining an extensive database of 5,739 site-based records of above-ground biomass from minimally disturbed vegetation with a variety of environmental predictor covariates. A Monte-Carlo approach was used, allowing estimates of uncertainty to be calculated. Overall, the new biomass predictions for woodlands, with 20-50% canopy cover, were on average 49.5±1.3 (s.d.) t DM ha^{-1}, and very similar to existing model predictions of 48.5 t DM ha^{-1}. This validates the original FullCAM model calibrations, which had a particular focus on accounting for greenhouse gas emissions in Australian woodlands. In contrast, the prediction of biomass of forests with a canopy cover >50% increased significantly, from 172.1 t DM ha^{-1}, to 234.4±5.1 t DM ha^{-1}. The change in forest biomass was most pronounced at sub-continental scales, with the largest increases in the states of Tasmania (166 to 351±22 t DM ha^{-1}), Victoria (201 to 333±14 t DM ha^{-1}), New South Wales (210 to 287±9 t DM ha^{-1}) and Western Australia (103 to 264±14 s.d. t DM ha^{-1}). Testing of model predictions against independent data from the savanna woodlands of northern Australia, and from the high biomass *Eucalyptus regnans* forests of Victoria, provided confidence in the predictions across a wide range of forest types and standing biomass. When applied to the Australian National Inventory land clearing accounts there was an overall increase of 6% in continental emissions over the period 1970-2016. Greater changes were seen at sub-continental scales calculated within 6° x 4° analysis tiles, with differences in emissions varying from -21% to +35%. Further testing of the impacts of embedding the revised *M* layer within the FullCAM modelling framework is required for other land management activities covered by the national inventory, such as reforestation; and at more local scales for sequestration projects that utilise FullCAM for determining abatement credits.

1 Introduction

FullCAM (Full Carbon Accounting Model) is a freely available software system for tracking greenhouse gas emissions and changes in carbon stocks associated with land use and management in Australian agricultural and forest systems (Richards 2001; Richards and Brack, 2004; Richards and Evans 2004; Brack et al. 2006; Waterworth et al. 2007). It is applied at the national scale for land sector greenhouse gas emissions accounting (Australian Government 2018), and at the local scale for monitoring and reporting carbon sequestration projects, such as revegetation and the management of regrowth (Paul et al. 2015a,b).

FullCAM predicts the accumulation of above-ground biomass (AGB) in woody vegetation using a hybrid of empirical and process-based modelling via the implementation of the Tree Yield Formula (TYF; Waterworth et al. 2007). The process-based modelling component utilises the forest growth model 3-PG (Landsberg and Waring, 1997) to derive a dimensionless index (the Forest Productivity Index, or FPI) that summarises potential site productivity for any given location based on NDVI, soil fertility, vapour pressure deficit, soil water content, and temperature (Kesteven and Landsburg 2004). The empirical component is a statistical relationship between field-based observations of AGB (from minimally disturbed stands) and the FPI (Richards and Brack 2004; Figure 1). This relationship is used to calculate the parameter *M* (the predicted maximum AGB for a given FPI), and is given by

$$M = \left(6.011 \times \sqrt{FPI} - 5.291\right)^2. \qquad \text{Equation 1}$$

Parameter *M* is constant for any location in Australia, and is embedded within the FullCAM database as a spatial input layer with a resolution of 0.0025 degrees (or approximately 250 m). Computationally, *M* exerts a strong influence on forest growth, affecting the rate of AGB accumulation, as well as defining the upper maximum biomass limit. *M* is also an important ecosystem property, with links to environmental productivity as well as a being a key indicator of ecosystem structure.

Over recent years evidence has accumulated that predictions of *M* for some vegetation types were biased, particularly for higher-biomass temperate forests, with lower *M* than observations would suggest (Montagu et al. 2003; Waterworth et al. 2007; Wood et al.

2008; Lowson 2008; Keith et al. 2010; Roxburgh et al. 2010; Fensham et al. 2012; Preece et al. 2012). The presence of such bias may be due to the initial focus during FullCAM development on estimating carbon emissions and sequestration within Australia's woodland ecosystems, due to their ongoing active management. The forest types represented in the original field-based biomass estimates used in the relationship to predict *M* (Equation 1) had a strong representation of woodlands, but with <10% of observations from higher-biomass (> 250 t DM ha^{-1}) temperate forests.

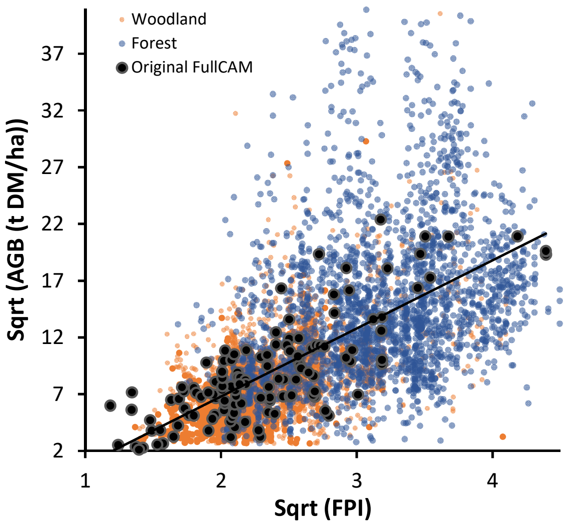


Figure 1. Relationship between observed field data and FPI, where the black circles are the original FullCAM-*M* relationship (Richards and Brack 2004), and the coloured circles are the 5739 new observations from the National Biomass Library, classified based on the broad vegetation classes of forests (>50% canopy cover), and woodlands (<50% canopy cover, respectively).

Since the development of FullCAM there has been a large increase in the availability of forest biomass data from across Australia, including from relatively undisturbed high biomass temperate forests. It was therefore timely to explore how these new data can be used to improve the estimation of *M*. The aim of this study was therefore to use these new datasets to update FullCAM's *M* layer, and thus improve the accuracy of predictions of woody biomass growth for Australian woodlands and forests, and hence, Australia's National Greenhouse Gas Inventory.

2 Methods

Whilst it is possible to create *de novo* a new replacement biomass layer, by e.g. updating the existing FPI vs observed biomass relationship on which the existing estimates of *M* are based (Figure 1), the approach adopted here was to update rather than replace the current *M* layer. This was to maintain continuity and consistency with the existing FullCAM modelling environment, and to allow new data to be applied only to regions with adequate data representation.

The detailed analysis steps are shown in Figure 2, but can be summarised as follows:

1. Identify site biomass records that fulfil the criteria of being minimally disturbed, consistent with the definition of maximum biomass, *M*.
2. For each record *i*, calculate the ratio λ_i

   $$\lambda_i = \frac{M_i}{O_i}, \qquad \text{Equation 2}$$

   where M_i is the current prediction of maximum biomass (Equation 1), and O_i is the field observation.

3. Use the Random forest machine learning algorithm (Brieman 2001) to statistically model and predict λ across the continent, using a range of climatic and edaphic variables.
4. Update the existing *M* layer to *M'* by multiplying by the model-predicted λ

   $$M' = \lambda M \qquad \text{Equation 3}$$

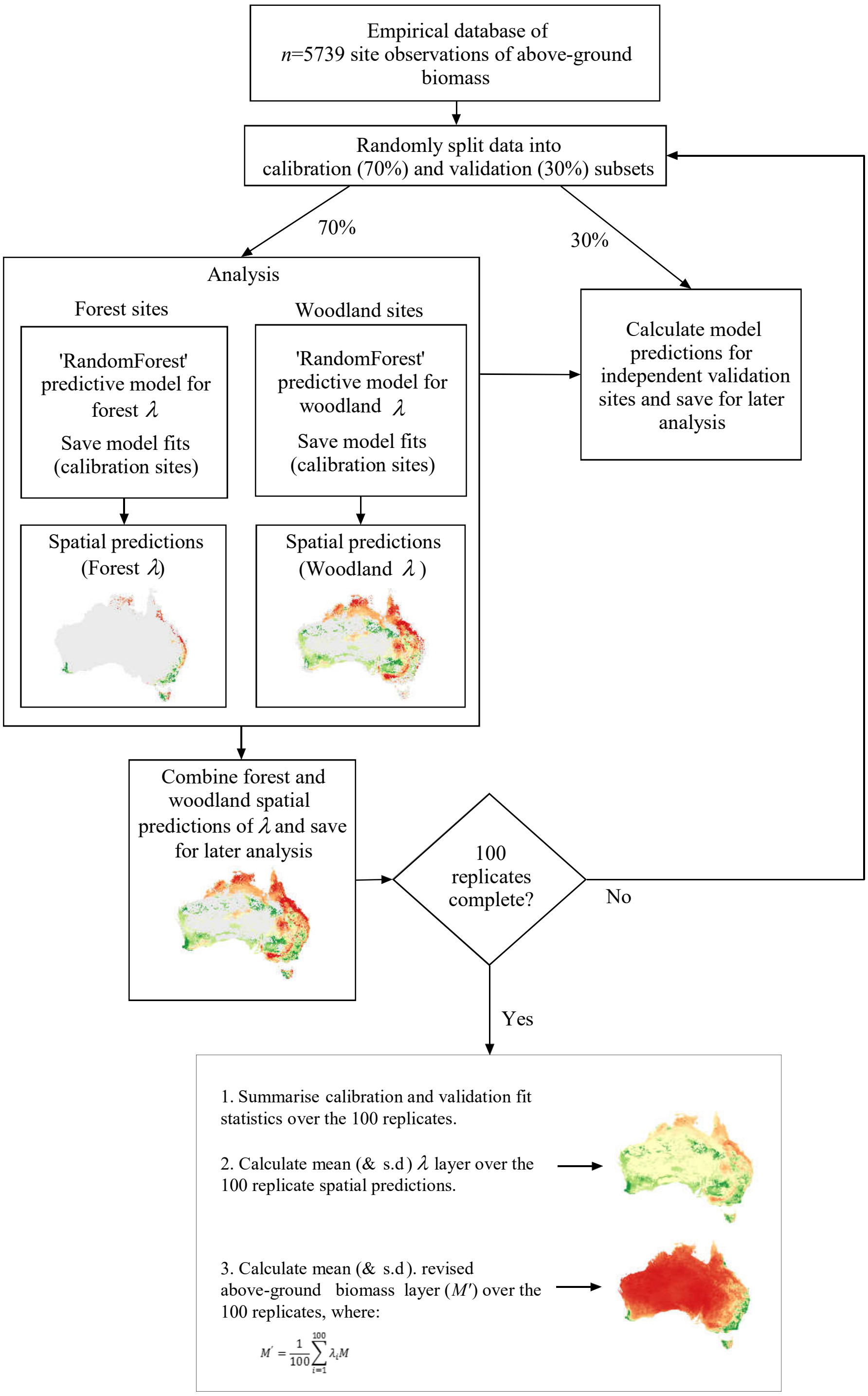


Figure 2. Summary flowchart of analysis steps.

2.1 Database preparation

The primary source of AGB observation data was the TERN/Auscover National Biomass Library (NBL), available at http://www.auscover.org.au/purl/biomass-plot-library. This library is a collation of stem inventory and biomass estimates compiled from federal, state and local government departments, universities, private companies and other agencies. The biomass library contains (as of December 2017) 14,453 sites, 887,639 individual tree diameter measurements (> 5cm), and 1,467 species.

For inclusion in the analysis, the AGB estimates were required to represent predominantly mature and undisturbed vegetation (i.e. vegetation that has been minimally impacted by anthropogenic disturbances, and has not had a recent natural disturbance such as a wildfire or cyclone). Because not all sites within the NBL were located in vegetation that could be considered 'mature', it was first necessary to filter the database and exclude those observations that were most likely collected from disturbed vegetation. This was achieved by collating ancillary spatial datasets at both a national and state level that identified areas within which forests were most likely to be undisturbed (such as conservation lands), and also to identify areas where disturbance was more likely, for example areas subject to multiple use, including timber harvesting (Roxburgh et al. 2016). Information was also gathered from the custodians of the NBL data where this indicated a measurement was located in disturbed or undisturbed (often referred to as remnant) vegetation. Records were also excluded if the observations were non-representative of the broader landscape, such as a number of Tasmanian records that specifically targeted forested areas with higher than average biomass (labelled 'LIMA' and 'LIMI' in the database; D. Mannes pers. comm.). A total of 5,739 site records remained following this filtering (Figure 3; Table 1). To provide an additional check of the temporal continuity of forest cover, spatial forest cover mapping (>20% cover) based on 25 Landsat images extending back to the 1970's were used to confirm woody vegetation cover over the period, thus indicating the absence of major disturbance (Australian Government 2018). Forest cover was defined as the mode within a 3 ×3 pixel window (approximately 75 m × 75 m) centred on the observation.

Preliminary analyses suggested improved empirical model performance could be obtained by stratifying the data and running separate statistical models based on two broad vegetation types corresponding to 'Forests' (with canopy cover > 50%) and 'Woodlands' (with canopy covers between 20–50%). The classification of sites within the database was based on forest and woodland cover as defined by the Australian National Forest Inventory (ABARES 2014)

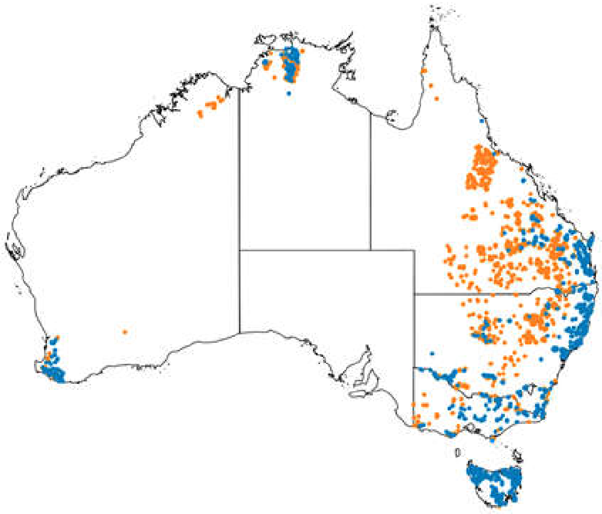


Figure 3. Spatial distribution of the 5739 observational data points of remnant/minimally disturbed woody vegetation selected for analysis. Forest sites (blue) and woodland sites (orange).

Table 1. Number of observations for each state and vegetation class.

	Forest	Woodland	Total
NSW	661	791	1452
NT	193	427	770
QLD	604	2073	2262
TAS	920	66	986
VIC	101	55	156
WA	64	48	112
SA	0	1	1
Total	2543	3195	5739

2.2 Vegetation classification for model prediction

Because *M* represents biomass at forest maturity, the spatial interpolation of the statistical models should represent the potential vegetation that an area could support, not the current vegetation distribution which reflects past land management, such as clearing of woody vegetation. The spatial interpolation was therefore based on the NVIS v4.2 1750 Major Vegetation Subgroups (MVS) classification (NVIS 2016), which maps the extent of Australia's major vegetation types prior to extensive land clearing, at a 100 m resolution.

The NVIS subgroup for each of the 5,739 records was extracted, and any subgroup that was represented by 50 observations or more was included within the extent of the revised mapping calculation. The Forest and Woodland predictive models were applied on a subgroup-by-subgroup basis according to Table 2. In addition to the above criteria, data limitations restricted the extents of MVS classes 20, 27 and 45 (Table 2) to eastern Australia only (i.e. east of 132° longitude); and a small number of 'Forest' areas that fell outside the

600 mm annual rainfall isocline were reclassified as ‘Woodland’, recognising that arid ‘forests’ are closer to woodlands in terms of biomass and structure. Finally, a 3×3 majority smoothing filter was applied to the classification to remove isolated grid cells and gaps. The final extent (Figure 4) defines the areas within which the existing *M* estimates were updated (‘Included forests’, and ‘Included woodland’), and the areas with insufficient data and thus where the current *M* estimates were retained (‘Excluded/non-woody’).

Table 2. Primary classification of NVIS Major Vegetation System (MVS) vegetation classes into Forests (F) and Woodlands (W). Additional modifications to the primary classification are described in the text.

MVS Code	Forest Class	MVS Name
1	F	Cool temperate rainforest
2	F	Tropical or sub-tropical rainforest
3	F	Eucalyptus (+/- tall) open forest with a dense broad-leaved and/or tree-fern understorey (wet sclerophyll)
4	F	Eucalyptus open forests with a shrubby understorey
5	F	Eucalyptus open forests with a grassy understorey
6	F	Warm Temperate Rainforest
54	F	Eucalyptus tall open forest with a fine-leaved shrubby understorey
60	F	Eucalyptus tall open forests and open forests with ferns, herbs, sedges, rushes or wet tussock grasses
62	F	Dry rainforest or vine thickets
7	W	Tropical Eucalyptus forests and woodlands with a tall annual tussock grass understorey
8	W	Eucalyptus woodlands with a shrubby understorey
9	W	Eucalyptus woodlands with a tussock grass understorey
10	W	Eucalyptus woodlands with a hummock grass understorey
12	W	Callitris forests and woodlands
13	W	Brigalow (*Acacia harpophylla*) forests and woodlands
14	W	Other Acacia forests and woodlands
18	W	Eucalyptus low open woodlands with hummock grass
20	W	Mulga (*Acacia aneura*) woodlands and shrublands +/- tussock grass +/- forbs
27	W	Mallee with hummock grass
45	W	Mulga (*Acacia aneura*) open woodlands and sparse shrublands +/- tussock grass
47	W	Eucalyptus open woodlands with shrubby understorey
48	W	Eucalyptus open woodlands with a grassy understorey

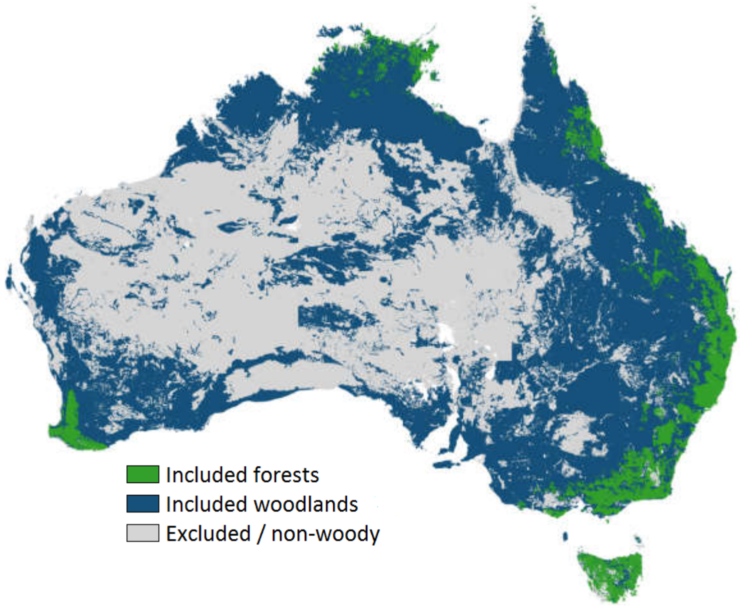


Figure 4. Vegetation classification used to spatially map the separate Forest and Woodland predictive models for calculating the revised maximum biomass layer *M'*.

2.3 Ensemble machine learning regression modelling with Random Forest

The aim of the analysis was to use modern machine learning regression methods to predict, for each of the 5739 data points, the difference (or 'residual') between the current FullCAM estimates of *M*, and the NBL biomass estimates, defined as the ratio λ (Equation 2). Predictions of λ were then interpolated spatially and used to update *M* to *M'* (Equation 3)

The highly variable nature of the biomass data precluded the use of traditional statistical techniques, such as multiple regression, due to serious violation of the assumptions of normality and variance homogeneity. To overcome this, the Random Forest machine learning algorithm was used as the basis for prediction (Brieman 2001). This method is based on random re-sampling of the data followed by the fitting of binary 'decision trees' that seek to minimise the error between observations and predictions. There were 23 predictor variables in the analysis (Table 3), comprising continental maps of soil carbon content (Viscarra Rossel et al. 2014), elevation (Jarvis et al. 2008), and 21 WorldClim v1.4 climate factors (Hijmans et al. 2005) obtained from the freely available WorldClim database (http://www.worldclim.org). Continuous maps of predictor variables were required to allow spatial interpolation of the resulting models. Latitude and longitude were also initially included as predictor variables to account for unexplained spatial variability, however they were excluded from the final analysis as they tended to lead to overfitting and the introduction of spatial artefacts. Model results were spatially interpolated using the 23 predictor variables at a resolution of 0.01 degrees, or approximately 1km. For reporting of spatial results, all layers were first transformed into Lamberts equal area projection prior to calculation.

Table 3. Independent variables used to predict λ .

Variable	Description
Alt	Altitude (m a.s.l) (ref)
SOC	Soil organic carbon (t ha^{-1}) (ref)
t_{max}	Mean monthly maximum temperature
t_{min}	Mean monthly minimum temperature
Bio_1	Annual Mean Temperature
Bio_2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
Bio_3	Isothermality (BIO2/BIO7) (* 100)
Bio_4	Temperature Seasonality (standard deviation *100)
Bio_5	Max Temperature of Warmest Month
Bio_6	Min Temperature of Coldest Month
Bio_7	Temperature Annual Range (BIO5-BIO6)
Bio_8	Mean Temperature of Wettest Quarter
Bio_9	Mean Temperature of Driest Quarter
Bio_{10}	Mean Temperature of Warmest Quarter
Bio_{11}	Mean Temperature of Coldest Quarter
Bio_{12}	Annual Precipitation
Bio_{13}	Precipitation of Wettest Month
Bio_{14}	Precipitation of Driest Month
Bio_{15}	Precipitation Seasonality (Coefficient of Variation)
Bio_{16}	Precipitation of Wettest Quarter
Bio_{17}	Precipitation of Driest Quarter
Bio_{18}	Precipitation of Warmest Quarter
Bio_{19}	Precipitation of Coldest Quarter

Model fitting was based on 1,000 Random Forest regression decision trees, with model predictions calculated as the median prediction over all 1,000 trees (Meinshausen 2006). As described in Sections 2.2., initial exploration of the data indicated better model performance could be obtained by stratifying the data and running separate Random Forest models for the Woodland and Forest vegetation types.

A Monte-Carlo approach was used to assess the prediction error of the model fits, with the data randomly split into a 70% subset for model fitting, and a 30% subset that was excluded and retained for independent validation (Figure 1). One-hundred such data splits were made, with separate 'Forest' and 'Woodland' Random Forest models fitted to each of the 100 iterations, allowing the mean and standard deviation of results across the 100 replicates to be calculated. The data was randomly split by Constrained Latin Hypercube (Minasny and McBratney 2006), to ensure representativeness across the predictor variable distributions between the calibration and the validation subsets.

For both the calibration and validation datasets four fit statistics were calculated, each summarising different aspects of the model performance. The first two summarise the main aspects of model accuracy; bias (quantified as Mean Absolute Error (ME)), and precision/accuracy (quantified as the Root Mean Squared Error (RMSE)). In addition, model efficiency (EF, Nash and Sutcliffe 1970) and Lin's concordance correlation coefficient (LCC, Lin 2000) were calculated to provide overall assessments of model performance. EF is given by

$$EF = 1 - \frac{\sum_{i=1}^{n}(O_i - E_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad \text{Equation 4}$$

where O_i is the observed value of record *i*, E_i is the predicted value for record *i*, and $\bar{O}$ is the mean of the observations. A model efficiency of 1.0 indicates perfect prediction, and a value of 0.0 indicates the predictions are no better than the global mean of the observations. LCC is given by:

$$LCC = \frac{2S_{OE}^2}{S_O^2 + S_E^2 + (\bar{O} - \bar{E})^2} \qquad \text{Equation 5}$$

Where S_O^2 and S_E^2 are the variance of the observations and predictions respectively, S_{OE}^2 is the covariance, and $\bar{O}$ and $\bar{E}$ are the mean of the observations and predictions respectively. LCC is an index that measures the agreement between predictions and the 1:1 line, and is scaled between -1.0 and 1.0, with 1.0 indicating complete concordance.

Spatial autocorrelation

Because the NBL comprises a heterogeneous mixture of data collected at a range of spatial scales, a concern for the analysis was the clustering of sample points within close proximity to one-another. Such clustering has the potential to invalidate the assumption of independence amongst observations, leading to bias in the predictor models. To address this the spatial correlation across sites was quantified, with the results suggesting minimal correlations (< 0.2) at distances between sites greater than approximately 10km (Figure 5).

To reduce the effects of spatial non-independence the data were therefore first balanced prior to analysis through the method of bootstrap up-sampling (Kuhn et al. 2018), thus ensuring equality in the number of observations at the scale of 10km x 10km. Results from analyses conducted both with and without spatial up-sampling showed similar overall predictive performance, although with less bias when the data were first spatially balanced.

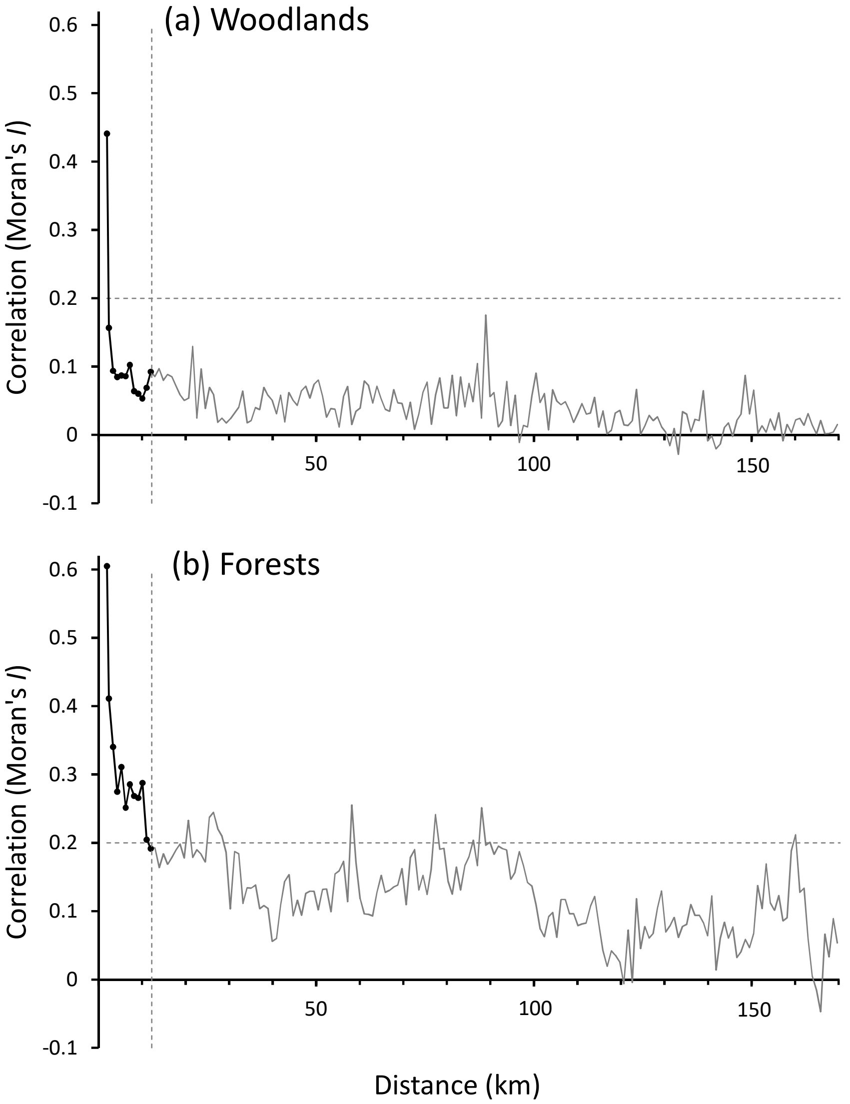


Figure 5. Spatial correlograms of observed above-ground biomass for (a) Woodlands and (b) Forests. Dashed horizontal lines indicate a spatial correlation of 0.2. Dashed vertical lines indicate a lag distance of 10km.

All analyses were performed within the R statistical modelling environment (R Core Team 2016). Random Forest model fitting was performed using the R library 'quantregForest' (Meinshausen 2016); conditional latin hypercube sampling was performed using the 'cLHS' library (Roudier 2011), and the 'caret' library function 'upSample' was used to spatially balance the data (Kuhn et al. 2018). All spatial mapping analyses were performed using the libraries 'raster' (Hijmans 2016) and 'rgdal' (Bivand et al. 2016).

2.4 Model testing

In addition to the analysis of the hold-out validation records, that provide an internal estimate of the prediction error of the models when applied to new observations, the model predictions were also compared against two datasets that were not included in the analysis. In the first, predictions of *M'* were compared with the analysis of Cook et al. (2015), who estimated woody AGB for 23 biogeographic regions across northern Australia. This provided the opportunity to compare estimates of *M* and *M'* against an extensive set of biomass estimates for arid and savanna ecosystems. The second dataset comprised 78 observations of biomass in old-growth (<250 year old) *Eucalyptus regnans* forests, collected from the central highlands of Victoria (Volkova et al. 2018). These forests are among the most biomass dense globally (Keith et al. 2009), and provide an opportunity to compare model predictions with independent observations collected within a forest type known to be under-predicted by the current estimates of *M*.

The Random Forest model predictions were also compared against other published modelled estimates of biomass for the Australian continent. Although this is a weaker test than comparing model predictions against empirical data, such cross-model comparisons are a useful tool for benchmarking, and for assessing overall congruence amongst approaches. Four models were compared; the BiosEquil model of Raupach et al. (2001), the VAST 2.0 model of Barrett (2002), the TMSC model of Berry & Roderick (2006), and the BIOS2 model of Haverd et al. (2013). For these model comparisons, where necessary total living biomass was converted to AGB assuming a root:shoot ratio of 0.25, and biomass carbon was transformed to dry mass by multiplying by 2.0.

3 Results

3.1 Empirical Database

Identifying biomass records that reflect potential maximum biomass, or biomass that has been minimally disturbed, is problematic given much of Australia is subject to regular disturbance such as fire, cyclones (in the far north), and with extensive anthropogenic modification such as clearing, grazing, timber harvesting and prescribed burning (Raison et al. 2003). The approach adopted here was to combine multiple lines of evidence to exclude sites most likely affected by prior disturbance, which included querying the source metadata and confirming with data custodians the status of particular records; the use of spatial data quantifying known disturbances such as harvesting; the use of tenure maps to identify areas least likely to be subject to anthropogenic disturbance; and use of the historical satellite record to confirm continuity of vegetation cover over time. We note that none of these methods are perfect, and that the theoretical ideal of vegetation at maximum biomass is likely very rarely, if ever, met in reality. The result of the above filtering was a reduction of the initial records by approximately 60%, from 14,453 to 5739.

For the development of the existing *M* layer, Richards and Brack (2004) determined forest stand age from disturbances detected from 12 Landsat remotely sensed coverages collected between 1972 and 2002. A similar analysis conducted here, based on 25 coverages spanning the period 1972 to 2016, showed over 90% of records were classified as forest cover for more than 20/25 of the annual coverages, with over 75% showing continuous forest cover (Figure 6). Given the majority (>70%) of records that showed intermittent forest cover were located in woodlands rather than forests, changes in cover classification are likely due to temporal variability in woodland tree canopy cover. Uncertainty in the geo-locations of the records and/or variability in satellite image quality may also contribute to this variability, although the forest cover detection based on a 3 x 3 window around the target locations was designed to minimise such errors.

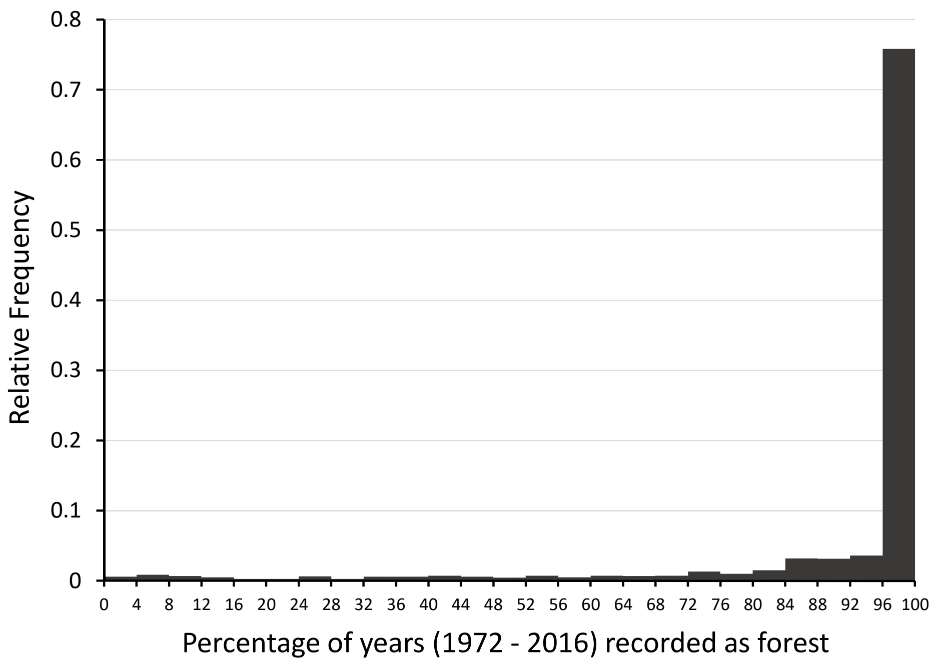


Figure 6. Relative frequency distribution of the percentage of years over the period 1972-2016 in which 5044 sites with canopy cover >20% were recorded as having forest cover, as determined by analysis of 25 Landsat satellite epochs.

3.2 Model fit statistics

The Random Forest model fit statistics, for both calibration (when the records were used as part of model fitting) and validation (when records were withheld from model fitting) were based on comparisons between observed biomass, and model predictions for each record. For calibration, estimates for each record were based on the average over the approximately 70/100 replicates where each site was used for fitting; and for validation the average of the approximately 30/100 replicates where each site was withheld from fitting. An alternative analyses where a single Random Forest run utilising all 5,739 records and using the internally calculated out-of-bag (OOB) estimates for validation yielded almost identical results; however the Monte-Carlo approach adopted here additionally allows uncertainty estimates for the predicted *M'* layer to be readily calculated.

The overall predictions of λ when records were used for model calibration were unbiased (ME = 0.0), with a RMSE of 0.4 and high values of EF (0.93) and LCC (0.96) (Table 4), thus indicating strong overall agreement between observations and predictions (Figure 7a). When records were used for validation there was evidence for some bias (ME = 0.1) with lower precision, and correspondingly lower values for EF and LCC (Table 4; Figure 7b). Note for purposes of display the figure axes are logarithmically transformed, but all model fitting and the calculation of the fit statistics was based on untransformed data.

The fit statistics were also calculated for the final predicted maximum biomass estimate, *M'* (Equation 3). This has the additional advantage of allowing equivalent statistics to be calculated for the current *M* layer.

Comparison of the current *M* estimates with the observations shows an overall bias (under-prediction) of -35.3 t DM ha^{-1}, with a RMSE of 239.1 t DM ha^{-1}, and with low indices for the statistics quantifying overall fit (EF = 0.14; LCC = 0.25) (Table 4). This is reflected in the scatter of observed vs predicted biomass (Figure 8a), where the bias is particularly apparent for high biomass observations, with observations greater than 500 t DM ha^{-1} all predicted to be lower than 500 DM ha^{-1} (Figure 8a). In contrast, the revised *M'* modelled estimates for the calibration analysis are effectively unbiased (ME = -0.2 t DM ha^{-1}), and the RMSE has approximately quartered, from -239 t DM ha^{-1} down to 62 t DM ha^{-1}, with correspondingly high values for EF (0.94) and LCC (0.97) (Table 4). When applied to the validation data, there was evidence for a bias of -8 t DM ha^{-1}, and a corresponding reduction in precision, with a RMSE of 200 t DM ha^{-1}. At the continental scale, this bias equates to an error of approximately 5% under-prediction.

Table 4. Fit statistics between observations (*n*=5739) and model predictions for λ, and for the existing (*M*) and revised (*M'*) estimates for maximum above-ground biomass.

Scope	ME	RMSE	EF	LCC
λ - Calibration	0.0	0.4	0.93	0.96
λ - Validation	-0.1	1.3	0.26	0.52
Original M	-35.3	239.1	0.14	0.25
M' - Calibration	-0.2	62.0	0.94	0.97
M' - Validation	-8.0	200.7	0.40	0.62

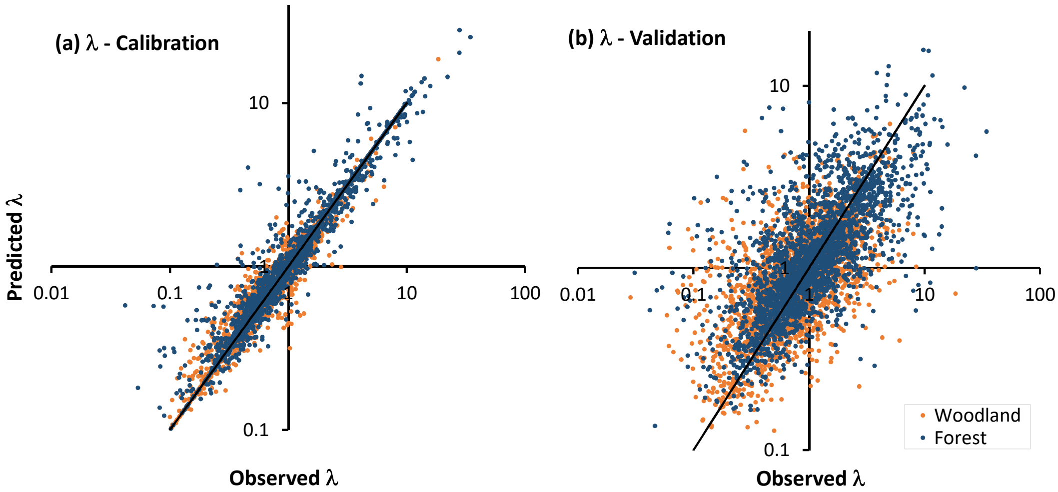


Figure 7. Observed vs. Random Forest model-predicted λ for (a) the 5739 data points when utilised for model calibration; and (b) the 5739 data points when withheld for independent validation. Fit statistics are given in Table 4.

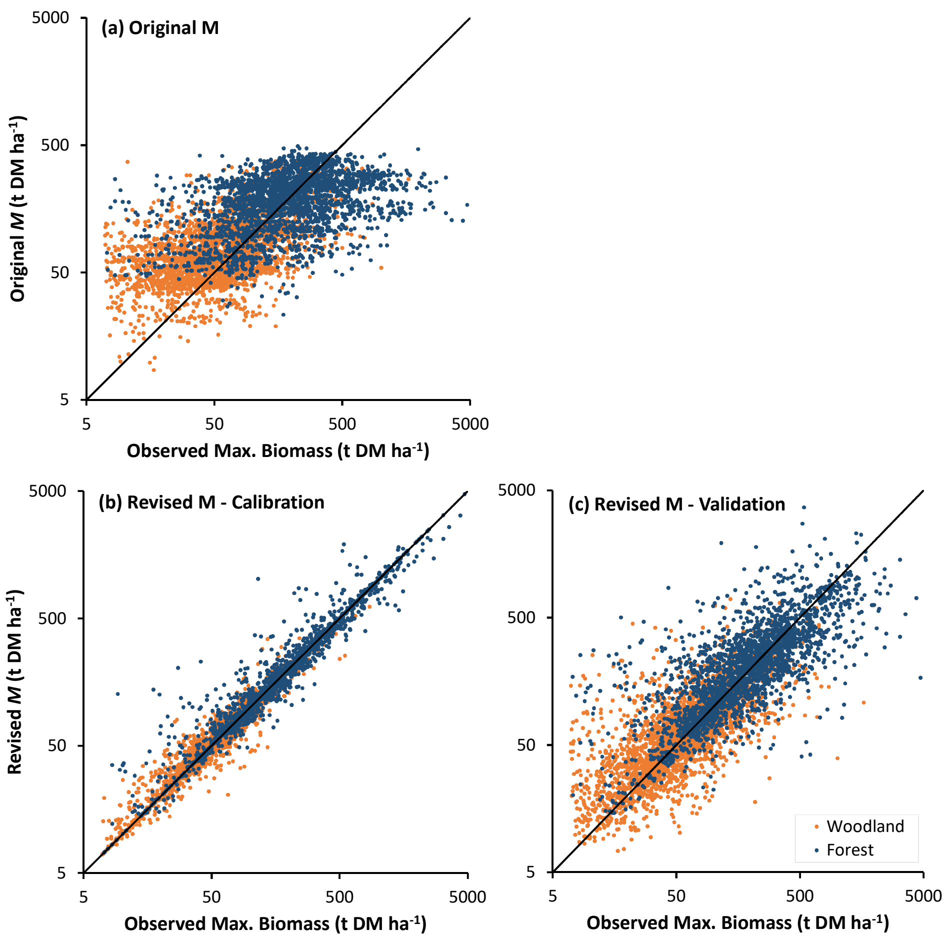


Figure 8. Observed vs. Predicted above-ground biomass for each of the 5739 data points, for (a) the original FullCAM *M* estimates; and (b) and (c) the revised estimates *M'* for the calibration and validation results through application of the modifier λ. Fit statistics are given in Table 4.

Of the 23 predictor variables, soil organic carbon was the most important explanatory variable for the Woodlands model, and precipitation of the driest month for the forest model (Figure 9). Variable importance was quantified as the percent increase in the model fit error following the removal of the target variable.

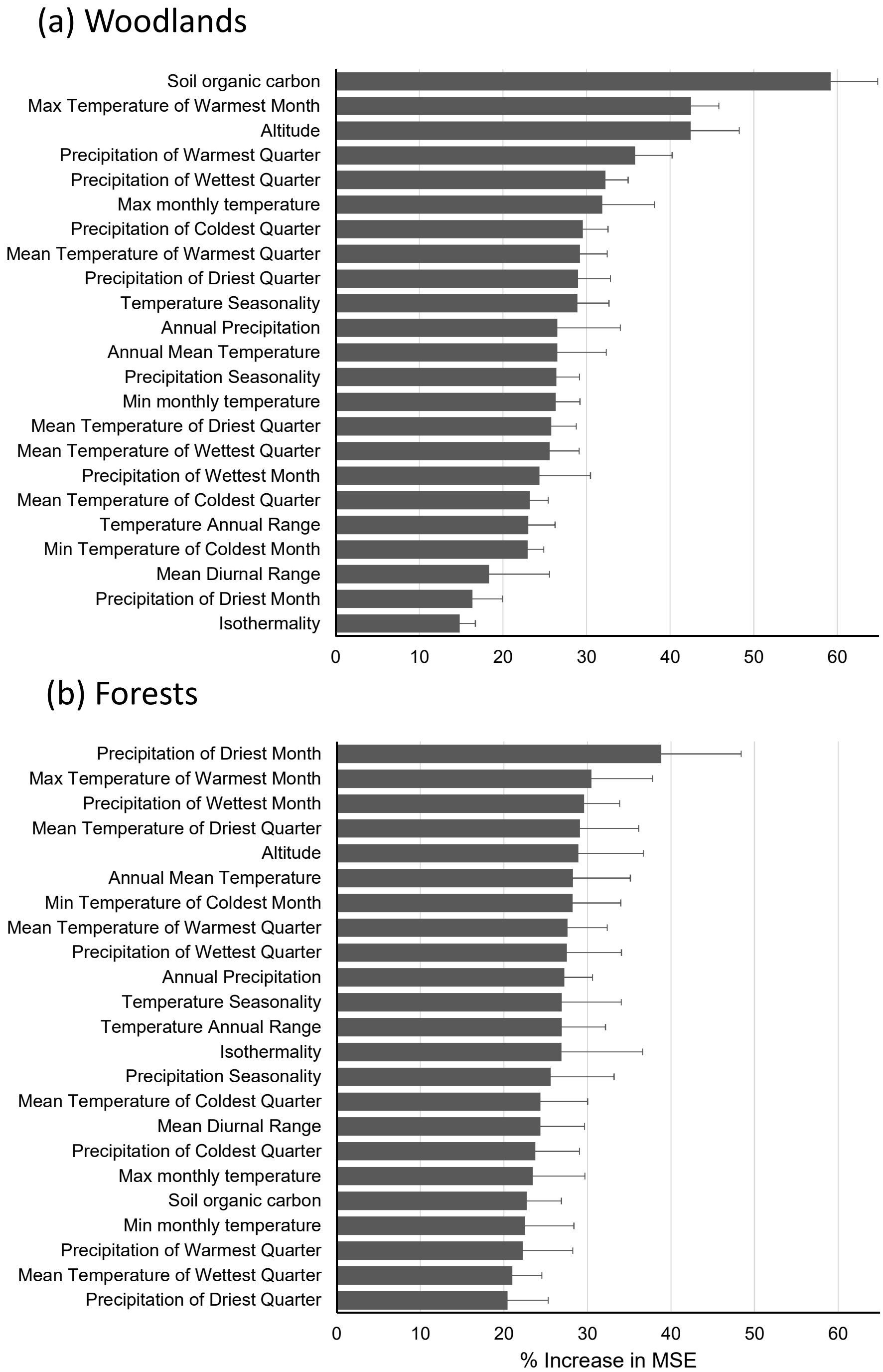
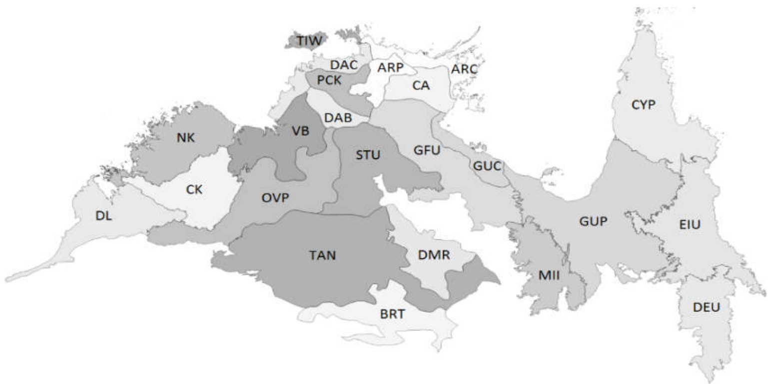


Figure 9. Random Forest variable importance plots for (a) Woodlands, and (b) Forests. Error bars are the standard deviations over the 100 replicate runs.

3.3 Model testing

For much of northern Australia the revised estimates of maximum biomass (*M'*) were lower than predicted by the current *M* (Figure 10). This reduction is consistent with the data of Cook et al. (2015), that also showed generally lower biomass compared with existing *M*. Overall, the estimates of revised *M'* are now closer to the values reported by Cook et al. (2015), with the overall average of the revised estimate (31±1 t DM ha^{-1}) falling between the estimates based on the two calculation methods of Cook et al. (2015) (25 – 33 t DM ha^{-1}). This contrasts with the current *M* estimate of 37 t DM ha^{-1}. At the scale of individual analysis regions there were some discrepancies, with *M'* predictions ranging from -57% to 43% of observations, depending on the region (Figure 10b).

(a)



(b)

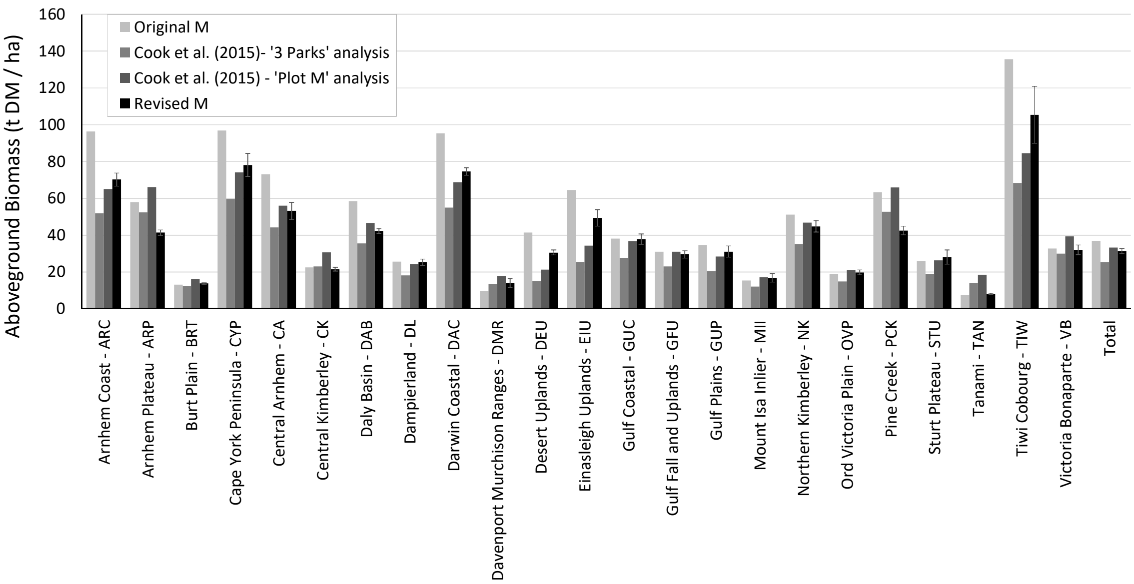


Figure 10. Comparison of the original and revised maximum above-ground biomass with the independent analysis of Cook et al. (2015). (a) the IBRA regions of Northern Australia (b). Aboveground biomass estimates for each IBRA region.

For the high biomass *Eucalyptus regnans* forests of Victoria the current mean biomass predicted by *M* is 266 t DM ha^{-1} (and never predicted to exceed 500 t DM ha^{-1}), with a relatively narrow range of values and a large peak in the frequency distribution in the 250 – 350 t DM ha^{-1} class (Figure 11b). This is well below the observed biomass, with a mean of 886 t DM ha^{-1}, with some observations exceeding 1500 t DM ha^{-1}. The revised estimates *M'* show a frequency distribution that has shifted to overlap with those of the observations, with the mean biomass increasing from 266 t DM ha^{-1} to 656 t DM ha^{-1}, and with predictions up to 1500 t DM ha^{-1} (Figure 11).

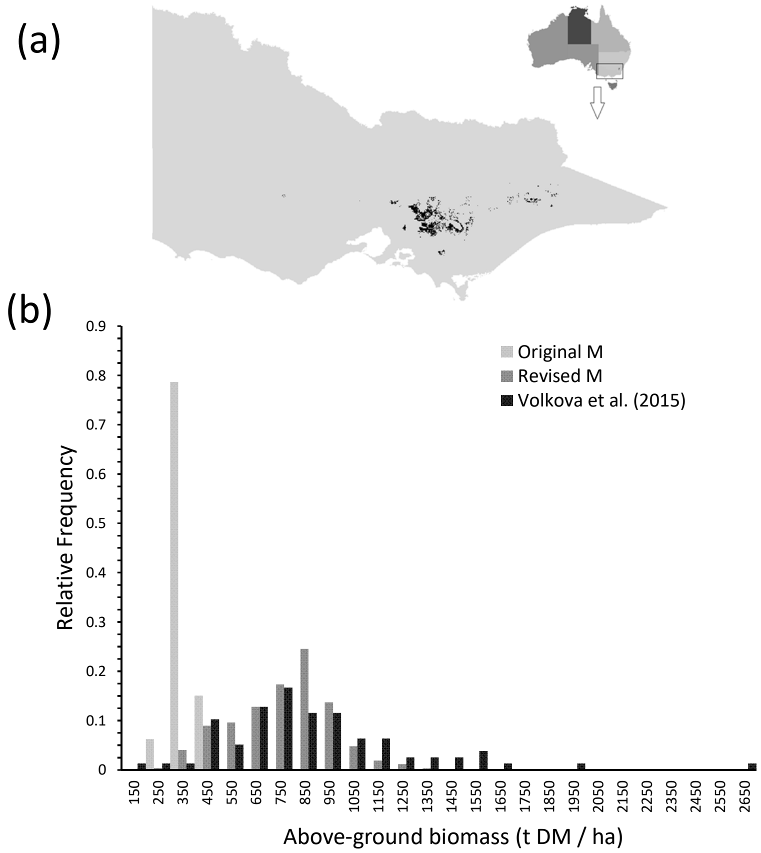


Figure 11. Comparison of the original and revised maximum above-ground biomass with the independent observational database of Volkova et al. (2018), of *n*=78 old-growth (>= 250 year old) *Eucalyptus regnans* forest biomass sites in the Central Highlands area of Victoria. (a) Location map showing the distribution of *Eucalyptus regnans* in the central highlands region of Victoria. (b) Relative frequency distribution of biomass for the 78 old-growth observations, and for the original and revised model predictions of *M*.

When compared against the four continental-scaled modelled estimates of biomass, *M'* was within the reported range for the broad vegetation classes depicted in Figure 4 (Table 5). The mean *M'* continental Forest biomass of 234 t DM ha^{-1} compares with 210-278 t DM ha^{-1} across the four models, and the mean woodland estimate of 50 t DM ha^{-1} compares with 49-54 t DM ha^{-1}.

Table 5. Predicted above-ground biomass (t DM ha^{-1}) for four continental-scale modelled estimates of biomass, and the estimates for *M* and *M'*. Values in parentheses for *M'* are the standard deviations over 100 replicate analyses. No 'Excluded / non-woody' value is given for *M'*, as the current *M* values are assumed for those areas. [1]Haverd et al. (2013); [2]Berry & Roderick (2006); [3]Barrett (2002); [4]Raupach et al. (2001).

	M	*M'*	BIOS2[1]	TMS[2]	VAST 2.0[3]	BiosEquil[4]
Forest	172.1	234.4 (5.1)	209.7	217.5	221.3	278.2
Woodland	48.5	49.5 (1.3)	52.1	53.9	49.3	50.2
Excluded / non-woody	16.1	-	17.0	11.2	13.8	14.5

3.4 Spatial predictions

A comparison of the original (*M*, Figure 12a) with the revised (*M'*, Figure 12c) maximum biomass layer shows the major differences to be in the temperate forest ecosystems, particularly in Western Australia, Eastern Tasmania, Victoria and New South Wales where there have been significant increases in predicted AGB. Areas where *M'* has declined relative to *M* include much of northern Australia and far north Queensland (Figure 12b; see also Figure 10).

These trends are more apparent when summarised on a state-by-state basis, either through comparison of the mean biomass across the 5739 records used in the analysis, which simultaneously shows *M*, *M'*, as well as the field observations (Figure 13), or through comparison when averaged spatially (Figure 14).

At the continental scale there was a slight bias in the predictions of the independent validation subset of the data, in the order of 5% under-prediction, driven by the higher-biomass 'forests' (Figure 13a). Overall, there was a significant improvement in the agreement between the model predictions and the observations compared to the current *M* estimates.

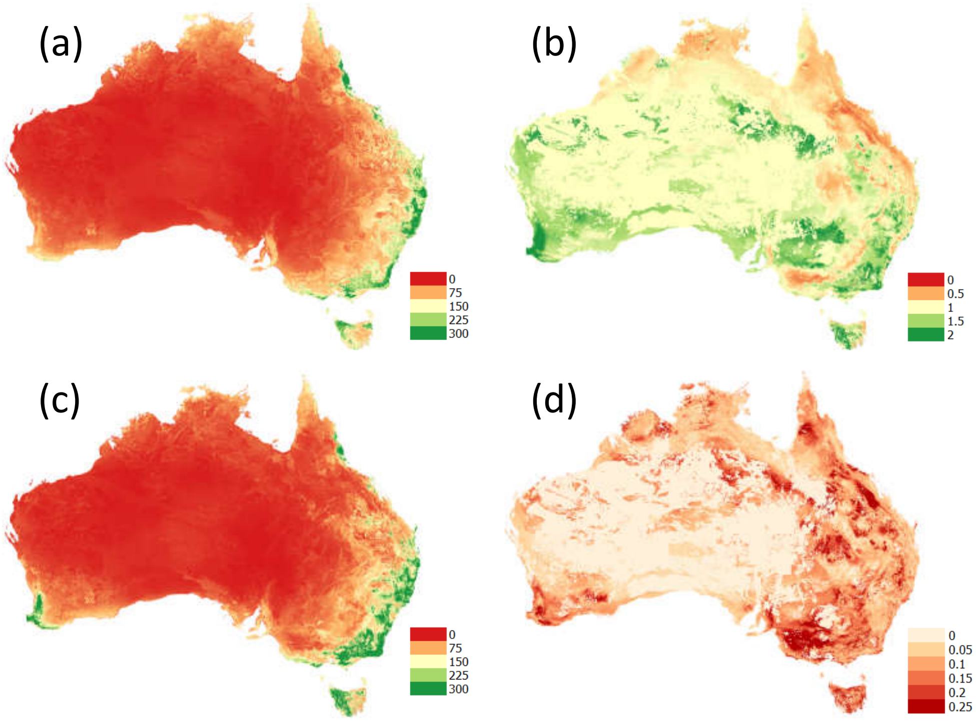


Figure 12. (a) Original FullCAM maximum biomass layer (M, t DM ha^{-1}). (b) Maximum biomass modifier layer (λ) predicted from the Random Forest model (dimensionless multiplier). (c) Revised maximum biomass layer, calculated from a x b (M', t DM ha^{-1}). (d) Coefficient of variation (standard deviation / mean) of M', calculated over 100 Random Forest model fits.

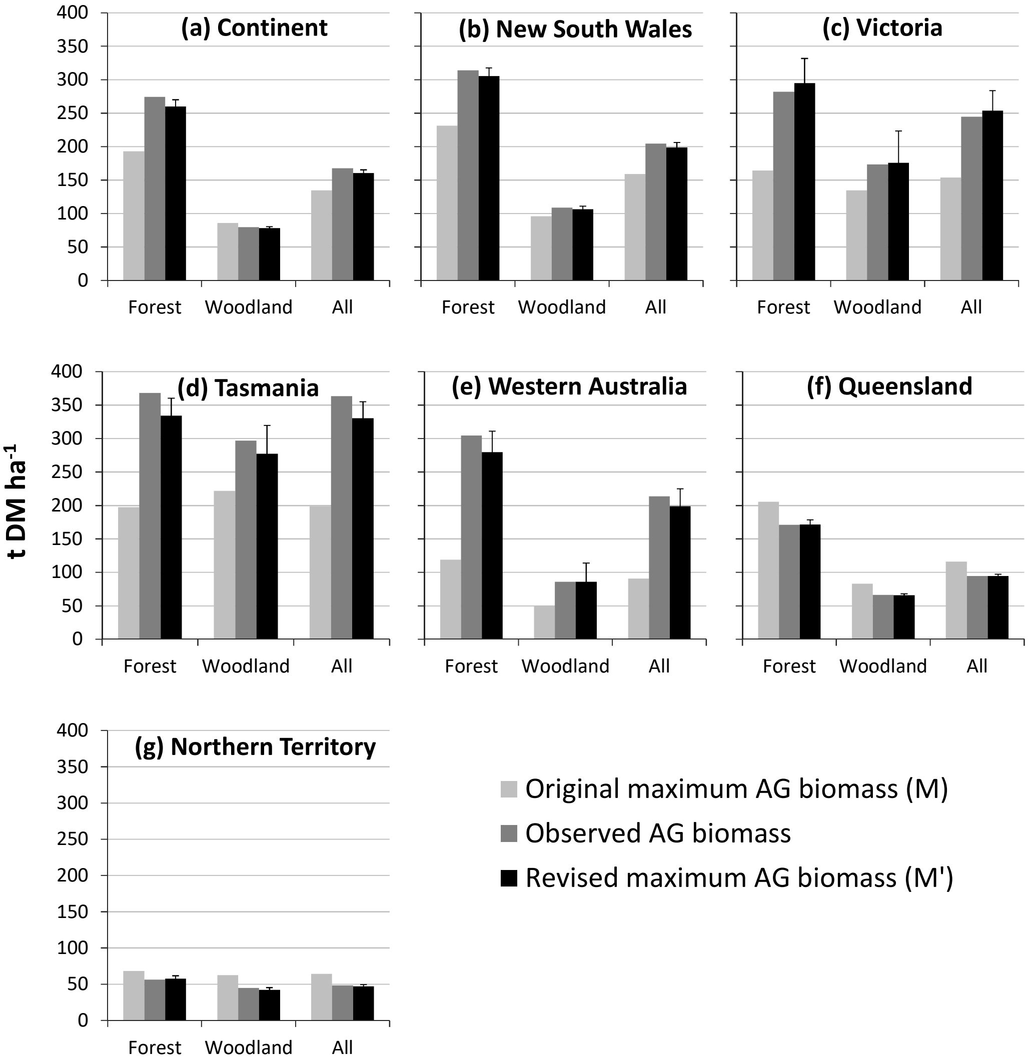


Figure 13. Comparison of the mean above-ground biomass across the 5739 observed data points with the mean biomass from the original (*M*) and revised (*M′*) predictions of above-ground biomass. South Australia is excluded due to lack of data. The number of observations for each state x vegetation type combination are given in Table 1.

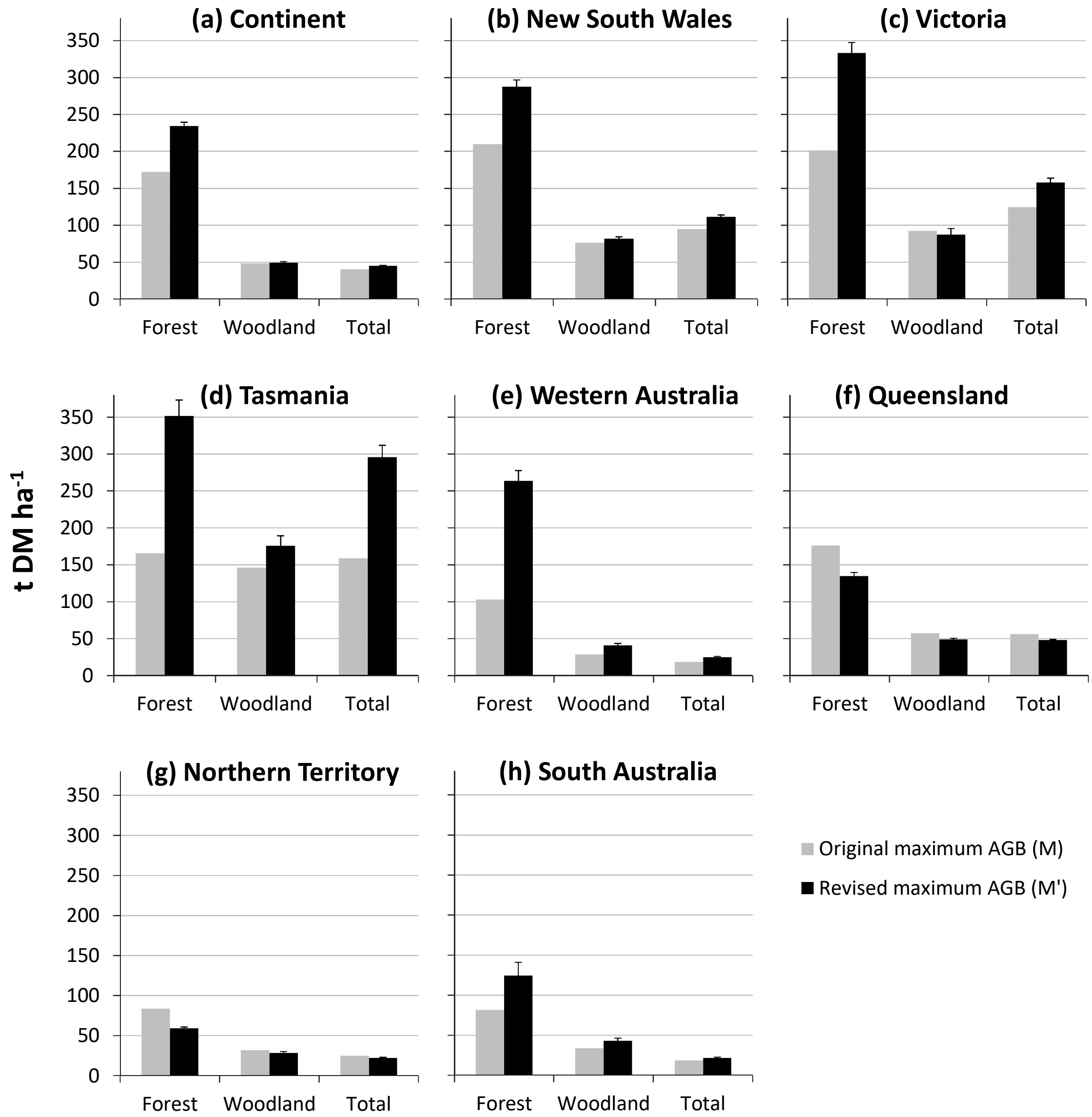


Figure 14. Comparison of the spatially-averaged above-ground biomass for the original predictions (*M*) and the revised predictions (*M′*).

4 Discussion

Woody biomass growth within FullCAM is strongly influenced by the parameter *M*, which defines the maximum upper limit to biomass accumulation at a given location. As noted in the introduction several analyses have suggested *M* currently under-predicts biomass in some forest types, particularly temperate forests. For example, Waterworth et al. (2007) had to apply growth modifiers to increase the biomass predictions of FullCAM for plantation forests. Similarly, for mallee and environmental plantings Paul et al. (2015a, b) addressed

FullCAM's biomass under-prediction through modifying FullCAM parameters other than *M* directly. Here we provide a more general solution by developing an updated biomass layer, *M*', that can be applied to any location within Australia.

Overall, the Random Forest statistical modelling and the resulting updated biomass layer *M'* improved the current maximum biomass predictions, with bias at the continental scale reducing from -35 t DM ha^{-1} down to negligible levels for the fitted model, and down to -8.0 t DM ha^{-1} (or approximately 5% error on average) when the model is applied operationally to new data (Table 4; Figure 8). The source of this remaining bias is uncertain, but is possibly due to over-fitting of the Random Forest algorithm to the calibration data. Precision in the biomass predictions improved from 239 t DM ha^{-1} down to 62 t DM ha^{-1} for the calibration data, and down to 201 t DM ha^{-1} when applied to new data (Table 4; Figure 8). The improvements in model prediction were particularly marked for forests with above-ground biomass > 500 t DM ha^{-1}.

At the continental scale, and for the lower-biomass woodland vegetation with a canopy cover 20–50%, there were minimal differences in predicted biomass between the new *M'* (49.5±1.3 t DM ha^{-1}, mean and s.d.) and the existing *M* (48.5 t DM ha^{-1}) (Figure 14a, Figure 15a). This provides strong support for the original FullCAM calibrations, where the focus was primarily on woodland ecosystems due to their active management, and thus importance for national greenhouse gas accounting. In contrast, predictions of forest biomass (with canopy cover >50%) greatly increased between *M* and *M'*, from a continental average of 172 t DM ha^{-1} to 234±5.1 t DM ha^{-1} (Figure 14a). For individual states, increases in predicted maximum forest biomass were typically much greater; the original *M* for Western Australia was 103 t DM ha^{-1}, compared with 264±14 t DM ha^{-1} under the revised analysis. Similar increases were found for Tasmania (166 to 351±22 t DM ha^{-1}), Victoria (201 to 333±14 t DM ha^{-1}) and New South Wales (210 to 287±9 t DM ha^{-1}).

When compared against AGB predictions from four independent continental-scale models, the *M'* estimates for all vegetation classes (forest, woodland and excluded/non-woody) fell within the range of the published models (Table 5), noting that forests with a canopy cover >50% were initially outside of the range prior to updating (172.1 t DM ha^{-1}, compared to model predictions of 210 - 278 t DM ha^{-1}).

The new *M′* biomass predictions compared favourably when tested against independent data not included in the modelling procedure. For Northern Australia the decline in predicted biomass from the current *M* estimates (37 t DM ha^{-1}) to *M′* (31±1 t DM ha^{-1}) is consistent with the analysis of Cook et al. (2015), who gave an overall estimate of 25 - 33 t DM ha^{-1}. The upper estimate of Cook et al. (2015) is based on an assumed stem diameter distribution that is representative of a more mature forest structure (their 'Plot M' analysis), and is thus likely to be closer to the assumed minimal disturbance assumption of the *M* parameter.

For the old-growth high biomass *Eucalyptus regnans* forests of Victoria the average AGB across the field observations was 886 t DM ha^{-1}, which is similar to the heartwood-decay adjusted estimate of Sillett et al. (2015) of 935 t DM ha^{-1} and the catchment-scale mean of 1002 t DM ha^{-1} of Keith et al. (2009), and is within the range reported by Dean et al. (2004) for the same forest type (840 – 1305 t DM ha^{-1}, varying by site index). The revised *M′* estimate increased the mean predicted biomass of the *E. regnans* from 266 to 656±31 t DM ha^{-1}, with a spatial distribution of values that shifted to be broadly consistent with the observations, though with a tendency to under-predict the highest biomass locations in the landscape (Figure 11b). This under-estimation likely results from the constraints imposed by simultaneously optimising all possible forest types within Australia. Higher accuracy at the local scale could be achieved by further sub-dividing the forest and woodland classes, though data limitations for many vegetation types would be a barrier to the general application of such an approach.

In a study concentrating solely on the forests south-east Australia, Keith et al. (2010) predicted a mean maximum AGB of approximately 434 t DM ha^{-1}, which is 28% higher than the 313 t DM ha^{-1} predicted by *M′* for the combined forests of Tasmania, Victoria and New South Wales. Keith et al. (2010) discuss a number of sources of uncertainty that could contribute to such a discrepancy, such as differences in the allometric models applied to estimate field biomass, the extent to which field data are representative of the diversity across the landscape, and the methods used to spatially extrapolate the data. An additional contributing factor could be differences in the spatial extents of the two studies. Given the broad scope of the NBL and the wide range of contributing data sources, it is also likely that residual impacts of historical anthropogenic disturbance are present in some of the records, which would tend to make our estimates conservative.

FullCAM is primarily used for calculating greenhouse gas emissions from the land sector as part of national greenhouse gas reporting requirements (Australian Government 2018). Within this context, a thorough investigation of the impacts of updating the maximum biomass layer can only be made by embedding *M′* within the FullCAM modelling environment, and running simulations that include not only the growth of AGB, but also the flow-on effects to the allocation of this new growth to stems, branches, bark, leaves and roots, and ultimately to the influence of clearing, harvesting or fire events on carbon pool dynamics, and the production and decay of debris and soil organic carbon. An initial investigation of the potential implications for changes in net ecosystem emissions between *M* and *M′* resulting from deforestation and subsequent regrowth over the period 1970-2016 showed an increase in emissions, at the continental scale, of 6%. However, at a regional level, with emissions reported within 6° x 4° analysis tiles, the differences ranged from a 35% increase in emissions (south-west Western Australia) to a 21% decrease (central-east Queensland). The overall low impact of the updated *M′* at the continental scale is because most of the land clearing in Australia since 1970 has occurred in woodland ecosystems, and these systems showed little overall change between *M* and *M′*. Much larger differences would be expected in areas of reforestation of higher-biomass forests, or when accounts are calculated in the higher biomass forests of Australia.

Caveats and future work

Applying the concept of maximum potential biomass is problematic for many Australian ecosystems due to the ubiquitous occurrence of fire and other disturbances that can lead to mortality and the reduction of living biomass (Raison et al. 2003). This makes it difficult to identify and validate site-based data that has been minimally disturbed; and when undisturbed areas are identified there may be questions over how well they represent the broader landscape, particularly when they occur as remnant patches. Here we used a combination of different lines of evidence to filter the available database to exclude sites that were likely to have been recently disturbed. Ideally, sites would be individually investigated in detail to confirm their status, such as done by Raison et al. (2003) for the initial FullCAM calibrations. However, with over 14,000 site estimates currently available such detailed site-by-site investigations are impractical. There is thus a trade-off between including a small number of sites where the site history has been researched in detail, with the associated risk that they may be non-representative at the continental scale, and the inclusion of a broader sample such as adopted here, with the risk that some sites included for analysis may have been subject to historical disturbance, either natural or anthropogenic. The general agreement between the independent data of Cook et al. (2015) and Volkova et al. (2018) and *M′* give us confidence that gross errors of classification have been avoided, but an extra layer of detailed checking, for example on a random subset of the 14,000 available records, would provide additional confidence in the results.

Whilst the revised *M′* was applicable to the approximately 54% of the continent that is covered by woodlands and forests (Figure 4), there was insufficient data to adequately assess the current performance of *M* for the most arid regions, which includes large areas of the Australian rangelands, such as the hummock grasslands, and the mulga woodlands in the western half of the continent. The collation and assimilation of rangelands data, similar to the development of the National Biomass Library for woodlands and forests, would allow the TYF to be extended into these lower-biomass systems. Such an activity would provide additional support and confidence for the development of methods for managing rangelands for improved greenhouse gas outcomes.

Further assessment of the implications of *M′* when embedded within the FullCAM software environment are required. Although application to the deforestation account within the national greenhouse gas accounting system showed minimal impacts at the continental scale, this was due to minimal changes between *M* and *M′* for the woodland systems within which most clearing and regrowth activity has taken place. The next steps for testing include similar analyses for other areas of the national accounts, such as reforestation and the sequestration/emissions associated with environmental plantings, and perform model re-calibration as necessary. We further note that operationalising *M*′ within the current FullCAM system has implications for vegetation that has already undergone separate calibration, such as mallee and environmental plantings. For such cases additional modifications to the FullCAM system will be required to avoid issues of ‘double calibration’. Further work is also required to investigate the potential impacts of updating *M* on those project activities under the Australian government's Emissions Reduction Fund (ERF, Australian Government 2014) that use FullCAM for calculating sequestration credits. This will particularly involve activities associated with avoided deforestation, and the management of regrowth.

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Appendix A – Spatial masking of *M'* for implementation in FullCAM

Currently, the *M* values used in FullCAM are drawn from the tiles located in O:\InventoryData\NewSpatial\Forest\MaxTreeBiomass_11_09. For inclusion in the analyses described above the tiles were merged into a single continental layer. The coastal extent of the current *M* layer have been spatially extended a few kilometres, and the inland waterways spatially interpolated, to prevent errors when Data Builder locations are selected close to the boundaries of these waterways.

The analysis presented in this paper generates 100 replicate continental maps of the multiplier λ, at a resolution of 0.01 degrees. To obtain the final revised biomass layer *M'* that has the same spatial coordinates, extent and masking as *M* the following steps were followed:

1. Calculate the mean λ layer over the 100 replicates

2. Re-sample the 1km mean λ layer to 250m, ensuring the spatial extents of *M'* are the same as *M*.

3. Spatially extend the coastline such that the land mask of *M'* is the same as *M*. This was achieved in R using the 'raster' library, through repeatedly applying a random re-sampling function (based on a 5x5 window) to extend the coastline one grid cell at a time, followed by masking to the extent of *M*.

4. Multiply the result from 3 by the original *M* map, to give the final result.

5. Finally, steps 1-4 were repeated to give the standard deviation layer of *M'*.

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FullCAM: building capability via data-informed parameters

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Contents

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1 Background

The objective of this study was to draw on recent research and new datasets to update some of the key parameters used in FullCAM for simulation of carbon (C) fluxes within forest systems. This work complements changes made to maximum aboveground biomass calibrations (*M*, Roxburgh *et al*. 2017); a key parameter used in FullCAMs Tree Yield Formula, TYF.

1.1 Allocation of biomass

How FullCAM simulates allocation of biomass

With the exception of some algorithms used in the predicting accumulation of aboveground biomass via site-productivity modifiers of the Tree Yield Formula (TYF), FullCAM is an empirical model. It does *not* predict the balance between partitioning of photsynthate and turnover of tissues that result in allocation of biomass to components (Thornley 1972; Thornley & Johnson 1990; Bijlsma & Lambers 2000; Yang and Midmore 2005; Barnes *et al*. 2007). For example, in process-based models, foliage and fine roots have a high partitioning of photsynthate, but a relative low allocation of biomass because of high turnover rates of these tissues (e.g. Wardlow 1990; Mooney 1991; Poorter *et al*. 2011). Instead, FullCAM's allocation input table is utilised to apply simple empirically predicted allometric scaling (Cheng & Niklas 2007; Yang & Luo 2011; Niklas & Enquist 2001). This time-series input table specifies biomass allocation for each year of growth, thereby enabling the prediction of how growth is attributed to the six components of biomass over time: stem, branches, bark, foliage, coarse roots and fine roots. There are alternative units of data input available. Generally, the units used in the allocation input table are growth increments of branches, bark, foliage, coarse roots and fine roots components relative to that of the stem, with the input for stem thereby being 1.00 at each time step.

Why accurate simulation of allocation of biomass is important

There are three main reasons why accuracy of the allocation input tables in FullCAM is important, and therefore why it was important to refine these parameters based on a recently expanded datasets of biomass partitioning. Allocation of biomass:

1. Governs the prediction of belowground biomass (BGB). For aboveground biomass (AGB), allocation input tables only adjust the relative allocation to wood, branches, bark and foliage, with the total AGB being set by FullCAM's TYF. In contrast, predicted BGB is determined by allocation to coarse and fine roots as defined in the allocation input table.
2. Determines the management- or disturbance-induced impacts on C stocks. Accurate biomass allocation predictions are important when predicting changes in on-site C stocks following events such as fire, pruning, thinning or harvesting. This is because these events affect the different pools of biomass in different ways.
3. Determine allocation to the fast-turnover pools of foliage and fine roots. For forests with high initial rates of growth (e.g. dense belt plantings), allocation to the high turnover foliage and fine roots components in the first 2-3 years of growth coincided periods of with peak growth rates. Previously under such scenarios, an unrealistically large transfer to C into the debris pool was simulated, thereby highlighting issues with the original defaults for allocation of biomass in some forest systems.

Approach required to revise allocation of biomass parameters

As outlined by DoEE (2016, Section 6.4.2.1 & 6.5.1.1), the original defaults used in the allocation input tables of FullCAM were based on expansion factors reported in Snowdon *et al*. (2000) and Mokany *et al*.

(2006). Each of the 51 different forest types simulated in FullCAM had an input table for allocation of biomass. In addition, the 16 tree species comprising the various hardwood plantations, and the seven tree species comprising the various softwood plantations, had low, medium and high productivity classes in which a multiplier for the allocation of biomass to stem wood was set to 0.95, 1.00 and 1.05, respectively (DoEE 2016). Hence, for plantations, allocation of biomass varied not only with species, but also with productivity.

Expansion factors reviewed by Snowdon *et al*. (2000) and Mokany *et al*. (2006) were useful to provide guidance on broad estimates of total AGB relative to stem wood, or of the ratio of BGB_C:AGB. Since then, new datasets from Australian forests have become available to inform comprehensive empirical models of allocation of biomass. The approach used in this study was to analyses these new collated datasets on allocation of AGB and BGB components of trees and shrubs. In this analysis, three main considerations were required:

1. *Influence of forest type*. To account for differences in allocation between forest types, three separate datasets on AGB and BGB sampling were collated:
   I. Mixed-species environmental plantings (which contain many species of both trees and shrubs), and plantations of mallee eucalypt trees. A large database of biomass sampling and analysis for these systems was already conducted by Paul & Waterworth (2015), and so was briefly outlined here.
   II. Native forests or woodland systems, grouped into those from low rainfall regions (mean annual rainfall, MAR<500 mm yr^{-1}) or high rainfall regions (MAR≥500 mm yr^{-1}). These datasets were collated by Paul *et al*. (2016).
   III. Other monoculture tree plantations, grouped into hardwoods (e.g. *Eucalyptus globulus*, *E. grandis, E. pilularis* etc.) or softwoods (e.g. *Pinus radiata*, *P. pinaster* etc.). These datasets were also collated by Paul *et al*. (2016).
2. *Influence of climate and management factors*. While allometric equations using the diameter of the stem to predict *total* AGB or BGB are generic in that they are relatively insensitive to regional variations in climate and stand management (Paul *et al*. 2016), this is not the case when such allometric equations are developed to predict *components* of biomass; they are less generalizable (e.g. Forrester *et al.* 2017). For example, biomass partitioning has been shown to vary with stand age, height, soil moisture and fertility, and climate factors (e.g. Hui *et al*. 2014). This suggests that for FullCAM to accurately predict biomass of components across different forest types, the allocation input tables used in FullCAM need to be informed by empirical allometrics models that account for such impacting factors.
3. *Scaling-up to the individual- to stand-scale*. As FullCAM models the stand as a whole, the allocation input tables are required to be at the stand-scale. However, measurements of biomass components are made at the scale of the individual tree or shrub. Factors influencing allocation at the stand-scale (e.g. stand density, mix of species) may differ to those influencing allocation at the individual-scale (e.g. size). For mixed-species plantings such as environmental plantings, or for native systems, a two-step process to estimation of stand-scale allocation of biomass is therefore required; (i) analysis at the individual-scale, and; (ii) applying these to the stand-scale based on the species mix and their densities/size.

1.2 Litter fall

How FullCAM simulates litter fall

In FullCAM turnover parameters (% DM yr^{-1}) are used to simulate turnover of branches, bark and foliage, and slough of coarse and fine roots. There is much more data available on litter fall than the more resource-intensive process to measure of root slough. Hence, the approach used to revise root turnover rates is outlined separately (see Section 1.4), with the focus here being on dataset collation from litter trap studies that monitored turnover of branches, bark and foliage.

There are two other processes of note in FullCAM with regard to turnover:

1. Turnover of stem wood is modelled separately via FullCAM's tree mortality parameters. These mortality parameters are generally rarely utilised, e.g. DoEE (2016). This is because FullCAM's TYF already inherently encompasses natural cycles of mortality-regeneration given these yields are calibrated to observations of AGB in remnant native forests or woodlands, with such stands having been naturally impacted by disturbances such as fire and prolonged droughts (Roxburgh *et al.* 2017). In addition, simulated events of fire or thinning enable the explicit simulation of stem mortality, thereby providing a more realistic 'disturbance-event-based' simulation of mortality of stems.
2. FullCAM had functionality for the user to input a maximum (or cap) on the AGB, such that when the model predicts AGB accumulation values that are in excess of this maximum value, each pool of biomass are assumed to 'drop' the excess C into turnover. This was assumed to occur for all pools of biomass: stem wood; branches; bark; foliage, and; coarse and fine roots. However, given recent work to significantly improve the confidence in FullCAM-predicted maximum AGB (Roxburgh *et al*. 2017), and given that this process of simulation of turnover to facilitate the a user-imposed 'cap' of AGB is unrealistic, this functionality was recently removed in FullCAM.

Why accurate simulation of litter fall is important

In FullCAM, the TYF models empirically observed *yields* of accumulation of biomass (Roxburgh *et al.* 2017). Hence, as outlined above (Section 1.1), in contrast to process-based models (e.g. 3PG) that explicitly simulate net primary production, in FullCAM, live pools of AGB and BGB are simulated independently of turnover, with additional C effectively being 'created' via assumptions made regarding turnover rates. Hence, in FullCAM, turnover inputs are very important given they contribute to the assumptions about net primary production, or the net 'capture' of C from plants on-site.

Having accurate simulation of rates of litter fall is therefore important in FullCAM as they affect the predicted input of C into debris: a significant C stock under forests. Furthermore, litter fall rates not only influence the amount of C entering the debris, but also the composition of the debris pool with regard to the relative contribution of decomposable debris (e.g. foliage litter) and more resistant debris (e.g. deadwood). Depending on its size and composition, the debris pool can make a significant contribution to net emissions following harvesting or fire events. The size and composition of the debris pool in turn also affects the input of C into soil: another significant C stock under forests.

Approach required to revise litter fall parameters

The original values applied to turnover rates of each plant component are shown in Table 6.14 of DoEE (2016). It was therefore timely to revise these input parameters given a recent review of litter trap field studies (Paul *et al*. 2017b; England *et al*. 2017) greatly expanded a previous Australian database of turnover rates under forests (Paul *et al*. 2004; Paul and Polgase 2004a).

1.3 Decomposition of litter

How FullCAM simulates decomposition of litter

Although modelling the inputs of C to the debris is relatively straightforward (simple turnover rates), modelling the outputs of C is relatively complicated. There are three separate processes, and corresponding sets of FullCAM parameters, that drive rates of decomposition of debris:

1. Substrate quality, i.e. the potential split of debris into decomposable (fast decomposing) and resistant (slow decomposing) pools;
2. Breakdown rates (% DM yr^{-1}) of the various pools of debris, both above the ground in the litter, and below the ground as dead roots, and;
3. Climate impacts, i.e. the influence of temperate and rainfall on these rates of decomposition.

There is much more data available on decomposition of litter (which tends to occur largely on the soil surface) than that available on root decomposition (which occurs within the soil, and probably varying greatly with soil depth). Measurement of root decomposition is much more resource-intensive than measurement of litter decomposition. Hence, the approach used to revise root decomposition rates was outlined separately (see Section 1.4), with the focus here being on dataset collated from litter bag studies that monitored decomposition of deadwood, bark litter and foliage litter.

Why accurate simulation of decomposition of litter is important

As per litter fall (Section 1.2), having accurate simulation of rates of litter decomposition is important in FullCAM as it affect both the size and composition of the debris pool: a significant C stock under forests, and one influencing emissions following harvesting or fire events. Additionally, decomposition of debris is particularly important as it affects the emissions of CO_2-C on decomposition, and thereby the C remaining on-site post decomposition that is assumed to become the soil C input. Indeed, the impact of the C inputs to the soil via changes in debris and its decomposition, and how this is influenced by land use or management, will have a significant impact on net sequestration of C in soil (e.g. Paul and Polglase 2004b).

Approach required to revise litter decomposition parameters

As outlined by DoEE (2016, e.g. Table 6.15), the original decomposition rates for the different pools of debris were drawn from the best available information, including Mackensen *et al.* (2003), Mackensen and Bauhaus (1999), O'Connell (1997) and Paul and Polglase (2004a). But recent work on reviewing field studies with litter bags (England *et al*. 2017) has greatly expanded the database of forest litter decomposition rates based on that previously available. Given this, it was timely to revise these input parameters.

1.4 Parameters influencing soil C

How FullCAM simulates soil C under forests

In FullCAM, predicted stocks of soil C are the result of the balance between predicted inputs of C to the soil from decomposition of debris, and the predicted output of C due to turnover of soil pools. The latter process of soil C turnover (i.e. and therefore loss of CO_2-C from the soil C pools) is simulated in FullCAM using the RothC sub-model. RothC simulates pools of differing rates of decomposition. The inert soil C pool (IOM) changes relatively little, but can be determined via measurement (Baldock *et al.* 2013a,b). The two largest pools (RPM and HUM) have the slowest rates of decomposition, and are the most important to parameterise, with this being facilitated via their measurement (Baldock *et al.* 2013a,b). The two smallest pools (BIO and DPM) have high rates of turnover, and are relatively unimportant to parameterise. Like decomposition of debris, turnover of pools of soil C are influenced by climate in accordance with RothC algorithms. However, in the RothC sub-model, turnover rates of pools of soil C are also influenced by the clay content of the soil.

Why accurate simulation of soil C is important

Soil is the largest stock of C in many forests, and many pools of soil C significantly change in response to land use change, or changes in management. However, the modelling of stocks of soil C is complicated given: (i) stocks are the balance of C inputs from debris decomposition, and outputs from turnover of soil pools, and; (ii) many of the important processes influencing soil C are difficult to measure. Indeed, there is a paucity of data for inputs such as root turnover and decomposition, the fraction of C lost as CO_2 on decomposition. Having measurements of the various pools of soil C simulated by FullCAM (e.g. the RothC sub-model's IOM, RPM and HUM pools, Baldock *et al*. 2013a,b) has been essential to facilitate constraining the calibration of some of these 'difficult-to-measure' parameters (e.g. Paul and Polglase 2004b; Paul *et al*. 2017b).

Approach required to revise litter parameters influencing soil C

A recent national study of soil C changes following reforestation with environmental plantings (Paul *et al*. 2017b) greatly expanded the datasets available from long-term irrigation and fertiliser trials in temperate plantations (Paul *et al*. 2004; Paul and Polgase 2004a). In these studies, measurements of pools of soil C (i.e. IOM, RPM and HUM) were made. These datasets on pools of soil C, together with measurements of biomass, litter fall and litter mass, were utilised to constrain calibration of root turnover and decomposition, and CO_2-C loss on decomposition. In other words, the approach used was to effectively 'tune' rates of root turnover and decomposition, and the fraction of CO_2-C loss on decomposition, to ensure that predicted pools of soil C match that observed, while at the same time constraining predictions of biomass, litter fall and litter mass to that observed. The general approach used was to:

1. Provide justification for parameters of root turnover and decomposition, and CO_2-C loss on decomposition, with constant values being applied across forest types unless there was evidence otherwise.
2. Maintain the RothC parameters constant across the various forest calibration sites, while at the same time also making these parameters consistent with those recently derived for a wide range of Australian agricultural soils (Chappel and Baldock 2013; DoEE 2016, Table 6.B.5).

1.5 Initialising pools of biomass and debris

How FullCAM initialises simulations

When simulating a planting or regeneration event, estimates of the initial pools of biomass are assumed to be relatively small, and vary with stocking (DoEE 2016). However, when simulating an existing mature forests, initial biomass estimates are large, and are populated for each location in Australia based on the empirical calibrations of *M* in the TYF (Roxburgh *et al*. 2017). Here we focus on the initial composition of the pools of biomass in response to revisions made to partitioning assumptions (Section 1.1), not the *total* AGB per se. For the composition of initial forest biomass, there are alternative options available for the units in which these initial values are entered. As a default, the units required are the percentages of maximum tree biomass that is allocated to stem, branches, bark, foliage and coarse and fine roots. These values correspond to the nominated age of the stand at the start of simulation.

In terms of initial pools of debris pools, values required in FullCAM were the actual C masses of the decomposable and resistant pools of deadwood, bark litter, leaf litter, coarse dead roots and fine dead roots. If turnover and decomposition parameters are revised (Sections 1.2 and 1.3), these initial pools of debris will also require updating.

In FullCAM, inputs are required for the initial C stocks in each pool of biomass, debris and soil. As described by DoEE (2016), the initial pools of soil C are currently estimated using a national soil carbon map (Viscarra-Rossel *et al.* 2006; Hicks *et al*. 2015). Further work is required to revise these initial pools of soil C in accordance with the assumed historic land use and management regimes associated with each location. Such further improvements are currently under consideration.

Why accurate initialisation is important

Clearly, the size of the initial stocks of C are important when simulating changes in these stocks due to a change in land use or management. However, the composition of these stocks is also very important. For example, when simulating the biomass residues following a post-clearing fire, a relatively high proportion of the deadwood and dead root are assumed to remain in the debris pool when compared to other component of biomass. Similarly, a relatively high proportion foliage and bark litter is assumed to be incorporated into the inert pool of soil when compared to other components of the debris pool. Therefore, we would expect that net emissions resulting from post-clearing fires is highly sensitive to not only the total size, but also the initial composition of the biomass and debris pools.

For debris pools, it is also of paramount importance that the composition of these pools is also reflective of the state of equilibrium for the given site quality and climate. Otherwise, the predicted changes in C stocks of debris and soil may be attributable to the fact that the pool composition is changing simply due to its equilibrating to the site quality and climate, with little of this change being attributable to the actual change in land use or management *per se*.

Approach required to update initialisation

In FullCAMs database, there are 51 different forest types, each having a nominated stand age if assumed to be present at the start of a simulation. The original model parameters for the composition of biomass pools were based on the original allocation parameters. As outlined by DoEE (2016, Table 6.41), the original initial amount of forest debris for each forest type was based upon model simulations run to equilibrium. These estimates were cross-checked with published estimates of debris in Australian forests (Hingston *et al*. 1981; Mackensen and Bauhus 1999; Murphy *et al*. 2002; Griffin *et al.* 2002; Harms and Dalal 2003; Harms *et al*. 2005; Woldendorp and Keenan 2005). Here, a similar approach was used to initialise biomass and debris pools following the revision to the parameters governing the prediction of biomass (Section 1.1) or debris (Sections 1.2-1.3).

2 Methods

2.1 Allocation of biomass

2.1.1 Above-ground biomass components

Datasets on AGB biomass were collated from across numerous different studies; some of which had coarse AGB partitioned into only bole and crown components, while others had detailed AGB partitioning which included stem wood, bark, branches and foliage. Here, the bole is defined as stem wood together with the larger >20-50 mm diameter branches that could easily be separated from the crown by technicians using loppers. As shown in Fig. 1, the bole is comprised of bark and bough (= branches of various size classes greater than 20 mm diameter). The crown is made up of 'twigs' (<20 mm diameter branches) and foliage.

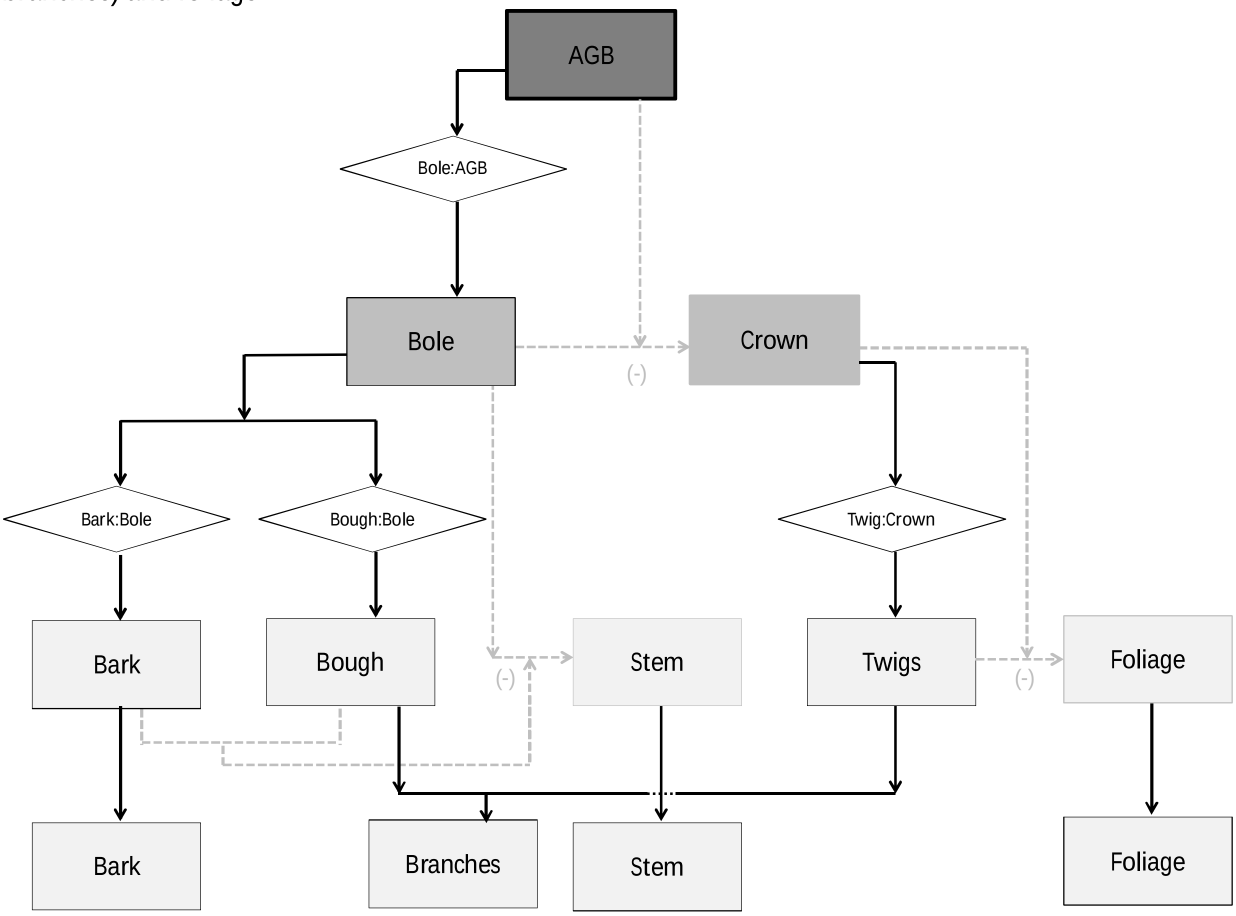

Figure 1: Procedure used to partition AGB into components of bark, branches, stem and foliage. Diamond shapes represent the four different models derived to allocate AGB into these components.

Given the differences in the types of data available for different forest types, these datasets were analyses separately as described below.

Environmental and mallee plantings

There has already been significant investment in the analysis of AGB allocation of these types of plantings (Paul & Waterworth 2015). In this relatively detailed study, there were two distinct steps undertaken to improve FullCAM-predictions of stand-scale allocation of biomass of mixed-species environmental plantings and mallee eucalypt plantings:

1. Collating datasets of components of biomass from individual trees or shrubs that had been destructively sampled. This dataset, together with including auxiliary data (e.g. stand age, stand density, climatic conditions etc.) were used to develop empirical models for biomass partitioning at the scale of the individual tree or shrub;
2. Application of these individual-scale empirical models to datasets of plot- and site-based inventories of stem diameters obtained from a diversity of forest types. Statistical analysis were then used to develop empirical models for allocation at the stand-scale.

There were 1,401 measurements of one or more components of AGB of an individual tree or shrub (Table 1). A majority of these data (68%) included information on the split between canopy and bole, with the remainder of the datasets having more detailed partitioning data.

These datasets were compiled in terms of Bole:AGB (N=1,334), Bough:Bole (N=73), Bark:Bole (N=183), and Twigs:Crown (N=498), with these partitioning terms being used to provide estimates of all four components of the AGB (Fig. 1).

In addition to biomass of components, auxiliary information were collated on key aspects of the stand from which the individual was harvested. These included:

1. Growth habit, defined as either a mallee, other tree or shrub;
2. Stand age;
3. Mean annual rainfall (MAR, mm yr^{-1}) that occurred over the years during which the stand was growing;
4. Stand density (individuals ha^{-1});
5. Planting configuration (i.e. belt or bock planting as defined by Paul *et al.* 2014ab), and;
6. Proportion of eucalypts (or dominant trees) in the stand from which the individual was harvested (PropEuc), and/or the species planted if the forest was a monoculture planting.

Stepwise Generalised Linear Modelling (GLM) using least squares means was used to assess which factors had a statistically significant impact on Bole:AGB, Bough:Bole, Bark:Bole, and Twigs:Crown, with the denominator of these fractions being used as the primary explanatory variable, but with the above six auxiliary variables being utilised to explore whether they improved the efficiency of prediction. Natural log transformations were used for AGB and stand age explanatory variables. Second order interactions were considered. Non-significant terms were systematically removed from the model fit starting with the higher-order interactions until a final parsimonious model was produced. Residuals from the model were inspected for a normal and heterogeneous distribution without influential outliers.

Once the individual-level analysis was completed to determine factors influencing allocation, stand-based estimates of AGB components could be generated. This was done using 1,127 stand-level inventories of stem diameters (and associated predictions of AGB, Paul *et al.* 2013a,b; Table 2). For each of these stands, the individual-scale models predicting AGB allocation were applied to predict stand-scale estimates of Bole:AGB, Bough:Bole, Bark:Bole, and Twigs:Crown. Given allocation is most variable within younger stands, the focus of this database was younger stands; typically <15 years. The stand-scale auxiliary data available included those listed above.

As at the individual-scale, there are factors likely to influence AGB allocation at the stand-scale. Hence, as described for the individual-scale, at the stand-scale, GLM was utilised to derive the allocation ratio models based on total AGB and the stand-scale auxiliary data (auxiliary variables 1-5 listed above).

Table 1. For environmental or mallee plantings, the number of individual trees and shrubs included in the dataset that represented different species and/or growth-habits. HR ad LR indicates individuals were sampled from stands from regions of high and low rainfall (MAR>500 or <500 mm yr^{-1}), respectively. The subscript 'Trees' and 'Mix' indicate that individuals were sampled from stands were PropEuc>0.75 and PropEuc<0.75, respectively. Data were collected from 15 different sources as described in detail by Paul & Waterworth (2015).

	Mallee		Other tree		Shrubs	
Type	**N**	**Sites**	**N**	**Sites**	**N**	**Sites**
HR_{Tree}	24	5	352	25	33	10
HR_{Mix}	NA	NA	92	14	53	10
LR_{Tree}	494	40	83	9	10	3
LR_{Mix}	NA	NA	166	12	94	16
Total	*518*	*45*	*693*	*60*	*190*	*39*

Table 2. Number of mallee and environmental planting stands included in the stand-based analysis of AGB allocation, where HR and LR indicate stands from regions of high and low rainfall (MAR>500 or <500 mm yr^{-1}), respectively. The subscript 'Trees' and 'Mix' indicate stands where PropEuc>0.75 and PropEuc<0.75, respectively. Data were collected from numerous different sources as described in detail by and Paul & Waterworth (2015).

	Mallee plantings	Environmental plantings
Type	**N**	**N**
HR_{Tree}	76	90
HR_{Mix}	NA	159
LR_{Tree}	315	273
LR_{Mix}	NA	214
Total	*391*	*736*

Native forests, woodlands and shrublands

Despite the vast diversity of native systems across high and low rainfall regions of Australia, biomass datasets were only available for 2,408 individuals sampled from a few hundred sites (Paul *et al.* 2016; Paul *et al.* 2017a). These individuals were categorised into four different plant functional types:

1. Typically single- stemmed hardwood trees from the genus *Eucalyptus* and closely related genera of *Corymbia* and *Angophora* (F_{Euc});
2. Multi-stemmed hardwood (angiosperm) trees, including mallees from the genus Eucalyptus, and trees from the genus *Acacia* (F_{Multi});
3. Other tree species that typically have single stems and relatively high wood density (mean 0.67 g cm^{-3}) ($F_{Other\text{-}H}$), and;
4. Shrubs or small trees characterized by being relatively short (generally <2 m height) and typically multi-stemmed or highly branched, with a relatively small (<7 cm) stem diameter (F_{Shrub}).

Just under half (46%) of the individual-scale datasets were partitioned for AGB in such a way that the biomass of Bole and Crown components could be estimated, with the remainder being partitioned into one or more other components of AGB; namely stem wood, bark, branches or foliage (Fig. 1).

Allometry of biomass of individuals from native forests or woodlands was found to be consistent with those from younger stands of environmental plantings (Paul *et al.* 2016). Furthermore, unlike for environmental plantings (Paul & Waterworth 2015), comprehensive data collation and subsequent analysis of biomass allocation has yet to be undertaken to inform accurate estimates of allocation of biomass for the large diversity of native ecosystems across Australia (i.e. varying greatly in their composition of plant functional types, stand densities and site qualities). Until such comprehensive datasets are available to inform the impacts of these factors on biomass, empirical models predicting AGB allocation were not developed as per environmental plantings, and only broad assumptions regarding biomass allocation in native systems could be made.

Hence, the approach used was to use collated datasets from various individual trees or shrubs sampled from native systems (Table 3) to provide estimates of typical biomass partitioning in these systems. These estimates were used to verify whether the stand-scale models derived for environmental plantings were adaptable for application to predict AGB allocation in native systems. For both high and low rainfall regions, the average (and standard deviation, SD) ratios observed for Wood:AGB, Bark:AGB, Branch:AGB, Foliage:AGB and Bole:AGB (Table 3) were compared to that predicted using typical simulations of mature (100 year old) stands. Assumptions made in this approach were that:

1. Native forests from regions of relatively high rainfall (>500 mm yr^{-1}) will have different allocation of biomass to native woodland/shrubland systems from regions of relatively low rainfall (<500 mm yr^{-1}). Therefore, the analysis here considered these two broad classes of native ecosystems; high rainfall forests (N=1,478) and low rainfall woodland/shrublands (N=930) (Table 3).
2. Data available from these sampled individuals (Table 3) were representative (in size and mix of plant functional types) of what would be observed in mature stands from these respective regions. This assumption was necessary given the paucity of data informing the variability between different stands in terms of their mix of plant functional types.
3. When adapting and validating stand-based empirical models based on environmental plantings to predict AGB allocation of mature native systems, three key assumptions were made:
    a. *Generic rates of growth*. Rates of biomass accumulation were based on current FullCAM defaults. Hence, regardless of the type of native forests, woodland or shrubland, the *G* and *y* parameters in the TYF were consistently 10 years and 1.00, respectively.
    b. *Ratio of trees to shrubs within the stand*. Growth rates in the empirical AGB allocation models were also influenced by the assumed PropEuc>0.75 within the stand. Native forests (where MAR≥500 mm yr^{-1}) were represented by environmental plantings with PropEuc>0.75, while woodlands or shrublands (where MAR<500 mm yr^{-1}) were represented by environmental plantings with PropEuc<0.75. This was because data from Table 3 suggests that in regions of high rainfall, the F_{Euc} plant functional type is highly dominant, averaging 91% of the individuals sampled. In contrast, in regions of low rainfall, F_{Euc} was less dominant, averaging only 32% of the individuals sampled.
    c. *Stand density inputs*. Growth rates in the empirical AGB allocation models were also influenced by the assumed stocking rates within the stand. Stand density was taken to be the lowest available stand density category; <500 individuals ha^{-1}. This was because when compared to high stand density plantations managed for biomass or wood products, native ecosystems tend to have moderate-low stand densities, particularly in mature self-thinned ecosystems.

Table 3. Number of datasets collated (N) on individual tree or shrub biomass derived from biomass sampling under a range of locations (Sites) within native forests or woodlands in regions of Australia. Datasets were collected from 46 and 7 different sources for regions of high (>500 mm yr^{-1}) and low (<500 mm yr^{-1}) rainfall, respectively. Further details about these sources and the datasets are provided by Paul *et al*. (2016). See text above for the definition of the various Plant Functional Types.

Plant Functional Type	High rainfall		Low rainfall	
	N	Sites	N	Sites
	Wood:AGB			
F_{Euc}	930	39	84	24
F_{Multi}	43	6	73	18
$F_{Other-H}$	34	5	115	20
F_{Shrub}	NA	NA	107	26
Total	*1,007*	*50*	*379*	*88*
	Bark:AGB			
F_{Euc}	856	34	28	4
F_{Multi}	39	4	27	9
$F_{Other-H}$	NA	NA	6	2
F_{Shrub}	NA	NA	NA	NA
Total	*895*	*38*	*64*	*15*
	Branch:AGB			
F_{Euc}	404	35	69	23
F_{Multi}	18	3	52	15
$F_{Other-H}$	25	2	42	17
F_{Shrub}	NA	NA	99	26
Total	*447*	*40*	262	81
	Foliage:AGB			
F_{Euc}	600	44	28	4
F_{Multi}	18	3	46	10
$F_{Other-H}$	47	4	6	2
F_{Shrub}	9	1	3	1
Total	*674*	*52*	83	4
	Bole:AGB			
F_{Euc}	684	50	228	14
F_{Multi}	11	5	218	40
$F_{Other-H}$	70	8	128	23
F_{Shrub}	NA	NA	126	27
Total	*765*	*63*	*700*	*127*

Hardwood and Softwood plantations

Hardwood and softwood plantations are generally stands of a single species, and of a single age. Allocation of AGB at the individual-level was thereby assumed to be applicable to the stand-level. So AGB allocation data collated at the individual-level was directly used to develop empirical models applied at the stand-level.

Over 1,084 and 520 measurements of one or more components of AGB of an individual tree were collated from a hardwood and softwood plantations, respectively (Table 4). Most (70%) of these individuals sampled from hardwood plantations were either *Eucalyptus globulus* or *E. grandis,* but other species were also represented (e.g. *E. pilularis*, *C. maculata*, and some species of *Acacia*). Similarly, most (98%) of the individuals sampled from softwood plantations were *Pinus radiata*, but other species were also represented (e.g. *P. elliottii*). For these plantations, individuals sampled were generally separated into stem wood, bark, branch and foliage (Fig. 1).

Auxiliary data on stand age, MAR, stand density and planting configuration were often unavailable from the studies from which the datasets were collated. Hence, using the individual tree datasets collated, empirical models of ratios of Wood:AGB, Bark:AGB, Branch:AGB and Foliage:AGB were developed using only AGB as the explanatory variable. Where AGB-based empirical models were not significant, the average (and SD) of the ratio was calculated.

Table 4. Number of datasets collated (N) on biomass derived from different numbers of trees sampled from hardwood and softwood plantations across Australia. Datasets were collected from 25 and 22 different sources for the hardwood and softwood plantation datasets, respectively. Further details about these sources and the datasets are provided by Paul *et al*. (2016).

	Hardwood		Softwood	
Ratio	**N**	**Sites**	**N**	**Sites**
Wood:AGB	1,008	37	421	60
Bark:AGB	1,012	48	320	55
Branch:AGB	981	37	520	61
Foliage:AGB	1,084	56	520	61

2.1.2 Below-ground biomass components

Here, data collated was predominately of coarse root biomass BGB_C; the roots of ≥ 2 mm diameter which comprise a majority of the BGB. Data on fine root biomass (BGB_F) was not collated given their negligible contribution to biomass C and the inconsistency in methodologies applied across various studies to obtain estimates of BGB_F. For all forest types, BGB_F was added to predict total BGB_T (=BGB_C+ BGB_F) mass for each stand studied. This was done using the relationship derived by Mokany & Raison (2004) following a global review of root biomass datasets: BGB_F: BGB_T = – 0.049.Ln(AGB) + 0.388, where the AGB is that of the stand (Mg ha^{-1}) (R^2=0.4, N=31).

Environmental and mallee plantings

Measurements of BGB_C were available from 770 individuals sampled from environmental and mallee plantings (Table 5). These datasets were used to develop allometic equations of BGB_C based on plant functional type as reported by Paul *et al*. (2013a,b, 2014a); namely mallee tree, other trees and shrubs. For all trees and shrubs at each stand listed in Table 2, data on plant stem diameter measured at 10 cm height were collated (D10). For individuals where diameter was measured at 130 cm height, conversion to an equivalent D10 estimates were derived (Paul *et al*. 2014a). When the D10-based allometric models were applied to predict both AGB (Paul *et al*. 2013a,b) and BGB (of Paul *et al*. 2014a) at each site, estimates of stand-level BGB_C:AGB were calculated. Then as descried above for testing empirical stand-level AGB allocation models, GLM was applied to explore whether AGB, or any auxiliary factors, influenced stand-scale BGB_C:AGB. This analysis was done separately for environmental and mallee plantings.

Table 5. Number of datasets collated (N) on BGB_C:AGB derived from different numbers of planting sites (Sites) of varying ages. Data were collected from 14 different sources as described in detail by Paul *et al.* (2014a).

Type of individual sampled					
Mallee tree		**Other tree**		**Shrub**	
N	**Sites**	**N**	**Sites**	**N**	**Sites**
306	44	368	47	96	21

Given D10-based allometric models were applied to obtain estimates of stand-level BGB_C:AGB, some statistical analysis was also undertaken to explore factors influencing stand-level D10, and thereby partly explaining the variations in BGB_C:AGB between contrasting stands. Linear regression and ANOVA analysis were also used to assess which stand-level auxiliary factors significantly influenced the plant average D10 within the stands. This analysis was done separately for environmental and mallee plantings. Measurements of stand density were natural log-transformed. Datasets from stands with sph>5,000 in environmental plantings were excluded from the analysis. This was because a descriptive statistical analysis of sph data from these plantings showed this dataset not to be normally distributed, with a long tail of distribution of larger sph values.

Native forests, woodlands and shrublands

A total of only 346 different individuals of various plant functional types from various types of native ecosystems were sampled for BGB_C (Table 6); about half from regions of high rainfall (N=168), and about half from regions of low rainfall (N=178). Consistent with the AGB datasets from native systems, the paucity of auxiliary information on growth rates, stocking densities and species-mix in various types of native systems led to the approach of utilising the collated datasets to verify the adaption of stand-level empirical models developed for environmental plantings, with the same assumptions used as specified above (Section 2.1.1). As found for the collated datasets of AGB allocation ratios (Table 3), the datasets BGB_C:AGB ratio datasets (Table 6) also supported that assumption that PropEuc>0.75 was appropriate for native forests (i.e. 65% of the individuals sampled were of the F_{Euc} plant functional type), whereas PropEuc<0.75 was appropriate for a woodlands/shrublands (i.e. only 26% of the individuals sampled were of the F_{Euc} plant functional type).

Table 6. Number of datasets collated (N) on individual tree or shrub BGB_C:AGB derived from different locations (Sites) from native forests and woodlands across Australia. Datasets were collected from 46 and 7 different sources for high (>500 mm yr^{-1}) and low (<500 mm yr^{-1}) rainfall regions, respectively. Further details about these sources and the datasets are provided by Paul *et al*. (2016). See text in previous Section for the definition of the various Plant Functional Types.

Plant Functional Type	High rainfall native forests		Low rainfall woodlands & shrublands	
	N	Sites	N	Sites
F_{Euc}	102	17	46	5
F_{Multi}	1	1	22	3
$F_{Other-H}$	32	9	4	1
F_{Shrub}	33	3	106	2
Total	*168*	*30*	*178*	*11*

For both high and low rainfall regions, we compared the average (± SD) of all observed BGB_C:AGB ratios (Table 6) with that predicted under scenarios of a wide range of representative mature (100 year old) stands. Only such broad average comparisons could be made given there was insufficient data from the various plant functional types to quantifying the impact of these on BGB_C:AGB. There was also insufficient data from young individuals to have any confidence in quantifying the impact of age on BGB_C:AGB, with <5% of the dataset being from stands with a stand age of <20 years (data not shown). This paucity of datasets from younger native systems requires addressing given that when compared to allocation of components of AGB, the BGB_C:AGB ratio is anticipated to be relatively sensitive to stand age (Mokany *et al.* 2006).

Hardwood and softwood plantations

Given hardwood and softwood plantations are stands of a single species of a given age, as when exploring the AGB allocation, the simplifying assumption was made that BGB_C:AGB at the individual-level were also applicable to the stand-level. Therefore for plantation systems, the approach used was to use collated BGB_C:AGB estimates at the individual-level to develop empirical models of allocation that could be directly applied at the stand-level.

A total of 97 and 248 different individuals of from hardwood and softwood plantations were sampled for both AGB and BGB_C, respectively, thereby providing estimates of BGB_C:AGB (Table 7). In these datasets, hardwood plantations were predominantly (40%) *E. globulus* or (18%) *E. nitens*, but data were also collated from plantations of five other species (*E. citriodora*, *E. cladocalyx*, *C. maculata*, *E. microcorys*, and *E. saligna*). For softwood plantations, the dataset was divided into only two key species; *P. radiata* from regions of relatively high rainfall, and *P. pinaster* from regions of moderate-low rainfall (<620 mm yr^{-1}).

Table 7. Number of datasets collated (N) on BGB_C:AGB derived from different numbers of planting sites (Sites) of hardwood and softwood plantations. Hardwood plantations were predominantly (40%) *E. globulus* or (18%) *E. nitens*. Softwood plantations could be grouped according to the species planted. Data were collected from 5 different sources as described in detail by Paul *et al*. (2016).

Type of plantation	Species	N	Sites
Hardwood		97	15
Softwood	*P. radiata*	134	4
	P. pinaster	114	15

Because most (86-95%) were from stands of relatively young age (<20 years), it was not feasible to develop models of BGB_C:AGB using stand age as an explanatory variable. Hence, for each dataset shown in Table 7, empirical models of BGB_C:AGB were developed, using AGB as the single explanatory variable given there was a paucity of auxiliary data other stand factors (e.g. age, MAR, stand density and planting configuration). Where not significant, the average (± SD) of all observed BGB_C:AGB were calculated.

2.1.3 Biomass Allocation Calculator & Scenario Analysis

Biomass Allocation Calculator

The stand-scale empirical models developed were used to construct a Biomass Allocation Calculator in MS Excel (Fig. 2). The purpose of this Calculator was to utilise these data-informed models to derive recommended defaults for use in FullCAM's stand-age based allocation tables when simulating different types of forests. The key input required in the Calculator was the yield curve for the stands AGB. This was derived from TYF, and hence, required the TYF parameters (*M*, *G*, *y* and *r*). Other inputs to the Calculator included any of the statistically significant explanatory variables, which varied for the five different empirical models incorporated within this Calculator:

1. Environmental and mallee plantings, where in addition to the TYF parameters, other inputs required included:
    a. Type of planting, including whether the planting has PropEuc>0.75 or PropEuc<0.75 if an environmental planting, and the species planted if a mallee eucalypt;
    b. Planting established in temperate or tropical regions, and if temperate, whether the MAR>500 mm yr^{-1} or MAR<500 mm^{-1};
    c. Category of stand density (sparse, standard or dense), and;
    d. Category of planting configuration (block, wide belt or narrow belt.
2. Native forests, where MAR was assumed to be >500 mm yr^{-1}, PropEuc>0.75, <500 stems ha^{-1} and a block planting configuration. Only inputs required were the TYF parameters.

3. Woodlands/shrublands, where MAR was assumed to be <500 mm yr^{-1}, PropEuc<0.75, <500 stems ha^{-1} and a block planting configuration. Only inputs required were the TYF parameters.
4. Hardwood plantations, where the only inputs required were the TYF parameters.
5. Softwood plantations, where the only inputs required were the TYF parameters.

The output of this Calculator is a table of relative allocation to braches, bark, foliage, coarse roots and fine roots, each expressed relative to the allocation of the stem at each year of growth. As such, these outputs may be copied and pasted into the allocation input tables within FullCAM when configured to simulate the same TYF.

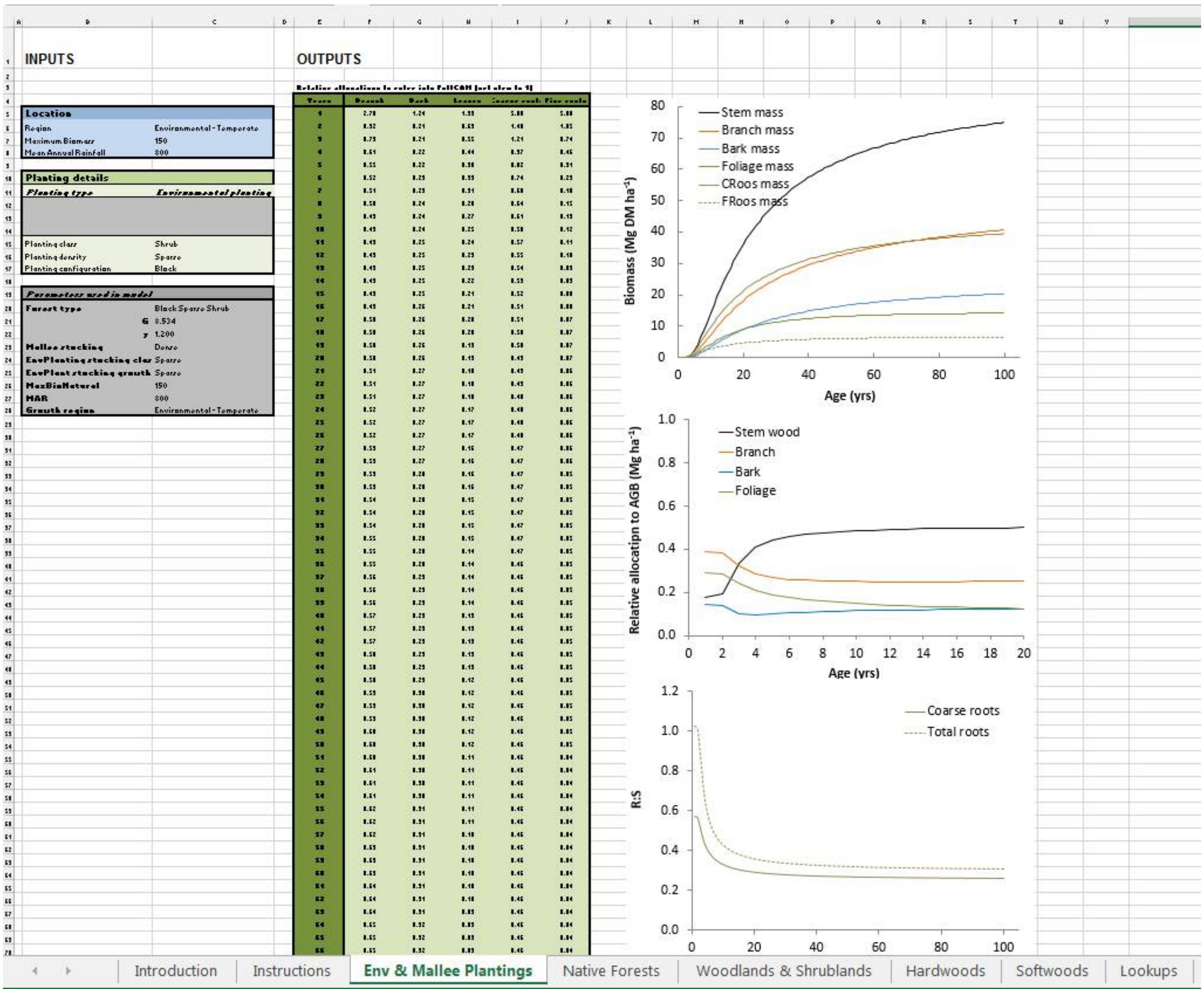

Figure 2: Example of a scenario of one type of environmental planting being simulated within the 'Allocation Calculator'. Outputs of this Calculator are estimates annual allocation of branches, bark, foliage, coarse and fine root components when expressed relative to that of the stem. These outputs can be used as inputs in the FullCAM allocation tables for this given forest type scenario, and hence, rates of accumulation of AGB.

Scenario Analysis

The Calculator was applied to generate 41 scenarios (Table 8) for exploring differences in predicted AGB and BGB allocation between contrasting forests types at stand age of 5, 10, 50 and 100 years. The TYF parameters of *G, y*, *r* applied were the default values for these types of plantings currently simulated in FullCAM v 4.1.6.19417 (2016). Although it is acknowledged that each of these forests types may grow across a wide range of climates, the simulations were run at hypothetical locations that had a site productivity (and typical climate) based on the average *M* observed across the represented domain of each forest type.

Table 8. Scenarios used to compare the revised Calculator-predicted biomass allocation with the original FullCAM-predicted biomass allocation. The different types of forest simulated are indicated: MR-LR and MP-HR, mallee plantings in low and high rainfall, respectively; EP-LR, EP-HR, EP-Trop, environmental planting in low rainfall, high rainfall and tropical regions, respectively; NF-HR, native forests in high rainfall regions; WS-LR, woodlands/shrublands in low rainfall regions; HW, hardwood plantations, and; SW, softwood plantations. Low and high rainfall are defined as <500 mm yr^{-1} and ≥500 mm yr^{-1}, respectively. For MP plantings, the stand density category is also provided as either sparse (<2300 sph) or dense (≥2300 sph). Similarly for EP plantings, the stand density category is also provided as either sparse (<500 sph), standard (<1500 sph) or dense (>1500 sph). For both MP and EP, the planting configuration category is provided as either narrow belt, wide belt or block. For NF and WS, the type of planting is based on the standard regimes used for the given National Plantation Inventory region.

Scenario	Species	Type	*M* (t DM ha^{-1})
Mallee planting	*E. loxophleba*	MP-LR; >2300; Narrow	47.6^{++}
	E. loxophleba	MP-LR; <2300; Wide	38.4^{++}
	E. loxophleba	MP-LR; <2300; Block	51.2^{++}
	E. polybractea	MP-HR; <2300; Block	73.4^{++}
Env. plantings	PropEuc < 0.75	EP-LR; PropEuc<0.75; >1500; Narrow	74.9^{+}
		EP-LR; PropEuc<0.75; <1500; Wide	78.8^{+}
		EP-LR; PropEuc<0.75; >1500; Block	66.3^{+}
		EP-LR; PropEuc<0.75; <500; Block	67.3^{+}
		EP-HR; PropEuc<0.75; >1500; Narrow	105.9^{+}
		EP-HR; PropEuc<0.75; <1500; Wide	106.3^{+}
		EP-HR; PropEuc<0.75; >1500; Block	117.8^{+}
		EP-HR; PropEuc<0.75; <500; Block	127.5^{+}
	PropEuc ≥ 0.75	EP-LR; PropEuc≥0.75; >1500; Narrow	67.0^{+}
		EP-LR; PropEuc≥0.75; <1500; Wide	67.8^{+}
		EP-LR; PropEuc≥0.75; >1500; Block	67.3^{+}
		EP-LR; PropEuc≥0.75; <500; Block	53.7^{+}
		EP-HR; PropEuc≥0.75; >1500; Narrow	114.7^{+}
		EP-HR; PropEuc≥0.75; <1500; Wide	98.7^{+}
		EP-HR; PropEuc≥0.75; >1500; Block	117.8^{+}
		EP-HR; PropEuc≥0.75; <500; Block	135.2^{+}
	PropEuc ≥ 0.75	EP-Trop; PropEuc≥0.75; <500; Block	366.1^{+}
Native Forest	PropEuc ≥ 0.75	NF-HR; Rainforest and vine thickets	319.3*
		NF-HR; Eucalypt open forest	206.1*
		NF-HR; Eucalyptus tall open forest	326.8*
		NF-HR; Tropical euc. woodlands/grassland	39.4*
Woodland Shrublands	PropEuc < 0.75	WS-LR; Eucalypt open woodlands	19.8*
		WS-LR; Acacia open woodlands	13.3*
		WS-LR; Acacia forest and woodlands	16.2*
		WS-LR; Eucalypt woodland	48.1*
		WS-LR; Acacia Shrublands	14.7*
Hardwood	*Eucalypts globulus SR*	HW; Western Australia	105.4^
	Eucalypts globulus SR	HW; Green Triangle	129.7^
	Acacia	HW; Northern Territory	147.1^
	Eucalypts globulus LR	HW; Bombala- East Gippsland	175.2^
	North Coast eucalypts	HW; North Coast	209.2^
	Eucalypts nitens LR	HW; Central Gippsland	268.4

Softwood	*Pinus pinaster*	SW; Western Australia	77.5^
	Pinus radiata	SW; Green Triangle	122.3^
	Pinus radiata	SW; Central Gippsland	162.4^
	Pinus radiata	SW; Tasmania	188.2^
	Hoop pine	SW; Northern Queensland	235.9^

*Source: S. Karunaratne, pers com. (2017) ;++Source; Paul *et al*. (2014c); +Source; Paul *et al*. (2014b); ^Source; Waterworth *et al*. (2007).

2.2 Litter fall

Data on litter fall were collated from 156 estimates of annual litter fall obtained from litter trap studies reviewed by Paul and Polglase (2004a), and updated by England *et al*. (2017) and Paul *et al.* (2017b). These comprise a range of forest types (Table 9), including: environmental plantings (N=4); hardwood plantations (N=15); softwood plantations (N=29); native forests (N=83), and; woodlands (N=24). All of these datasets were sources from Australian studies. The only exception was for 10 datasets from the softwood plantations (South Africa, Versfield, 1981; New Zealand, Baker *et al*. 1986, and; Greece, Kavvadiaas *et al*. 2001).

Where required, average %Foliage, %Twig and %Bark observed in litter fall for the different forest types was used to 'fill-gaps' for studies where the total litter fall was not partitioned into these components. Similarly, where the stand-based mass of foliage, twigs and bark were not measured, these were predicted using FullCAM and the revised biomass allocation input tables (Section 2.1). Average 'observed' rates of turnover were thereby calculated for each forest type.

Table 9. Datasets collated from field studies with litter fall traps monitored under environmental planitngs, native forests, woodlands, hardwood plantations and softwood plantations. All forest types had observations of total litter fall mass (N varying from 4 to 83, depending on the forest type), with a percentage of these further sub-sampled to attained observations of the relative contribution of foliage, twig and bark components to this total litter fall.

Forest type	Total N	Foliage % of N	Twig % of N	Bark % of N	Source
Env. plantings	4	100	0	0	Paul *et al*. (2017b)
Native forests	83	70	52	36	England *et al*. (2017)
Woodland	24	33	25	21	England *et al*. (2017)
Hardwood	16	50	44	44	England *et al*. (2017)
Softwood	29*	100	0	0	Paul & Polglase (2004a)
Total	156	69	36	27	Paul & Polglase (2004a)

*Source: Total litter fall was attributed to pine needles.

Using all datasets, three ANOVA analyses were applied to determine whether forest type had a significant influence on litter fall of foliage, litter fall of twigs, or litter fall of bark. These results were then used to inform average rates of litter fall that were appropriate for each forest type, or groups of forests types.

2.3 Decomposition of litter

As outlined in Table 10, a total of 123 litter bags studies of decomposition were reviewed from a range of forest types, inluding: deadwood, bark litter and foliage litter from under eucalypt-dominant stands (N=23, 13 and 59, respectively), and; pine needle litter under softwood plantations (N=28). Data were only used from studies where the litter in the bags was collected from litter fall (i.e. data from collection of green leaves etc. were excluded).

Table 10. Datasets collated from field studies with litter bag monitored under eucalypt-dominant stands, or under softwood plantations.

Forest type	Litter type	N	Source
Eucalypt-dominant	Deadwood	23	England *et al*. (2017)
	Bark litter	13	
	Foliage litter	59	
Softwood	Pine needle litter	28	Paul & Polglase (2004a)
Total		123	

Although some workers have also calcualted long-term rates of decomposition from the ratio of litter fall to the mass of litter, such estimates are only reliable when both of these processes are accurately measured, and are in a steady-state equilibrium (Olson, 1963). Hence, when compared to litter bag studies, estimates of decomposition derived using this approach were inferior, and so such estimates were not used here to inform rates of decomposition.

In litterbag studies, mass loss is described by exponential decay functions. Although the single exponential decay model is the most widely used, the double exponential decay model often provides a better description of decomposition of leaf and some bark material (e.g. O'Connell 1988). The single exponential decay model (e.g. Olson, 1963) assumes that substrate is of constant quality and that a constant fraction is lost at each time step:

$$W_t = W_0 e^{-kt} \quad \text{(Equation 1)}$$

where W_0 is the initial litter dry weight, W_t is the dry weight at time t, and k the instantaneous decay constant. By comparison, the double exponential decay model assumes that there is an early rapid loss of labile compounds (e.g. soluble matter and non-lignified organic carbon), and that resistant compounds are slowly decomposed later in the decomposition process (e.g. Minderman, 1968):

$$W_t = W_l e^{-k't} + (W_0 - W_l)\, e^{-kt} \quad \text{(Equation 2)}$$

where W_l is the amount of labile component present in a litter fraction, ($W_0 - W_l$) represents the resistant component, and k' and k are the decay constants of the labile and resistant components, respectively.

As found previously by Paul and Polglase (2004a), in general, double exponential decay models best described the leaf decomposition, while single exponential decay models were adequate to describe decomposition of bark and wood. Hence for all forest types, FullCAM inputs for the fraction of debris that was resistant were set to 100% for deadwood and bark, while for foliage it was set to the average values observed from the fitting of the double-pool decay function to litterbag studies of foliage litter.

Rates of decomposition in FullCAM are influenced by temperature and rainfall either using the 'Mulch-style' or 'Soil-style' sensitivity. Decomposition was particularly sensivite to climate when applying the 'Soil-style' approach. Given the lack of data on how climate impacts rates of decomposition, the more conservative approach of using 'Mulch-style' sensitivity was applied; with sensitivitie values of 1 being used as per DoEE (2016). Using the scenarios listed in Table 8, it was tested whether the predictions of decomposition using this 'Mulch-style' sensitivity of decomposition to climate were within the bounds of that expected; namely the 20th and 80th percale values of the empirical decay models fitted to observations attained from litterbag studies.

FullCAM predicts C stocks of debris pools, and yet measurements are often made of the dry matter within two separate components of debris; (i) litter, and; (ii) coarse woody debris (CWD, deadwood with diameters generally >1.0-2.5 cm). To be able to reconcile FullCAM predictions against measurements, assumptions made were that debris was 45% carbon (DoEE 2016), and that 70% of deadwood debris is CWD, with only 30% of deadwood debris being dead twigs as part of the litter component. It was assumed that all of foliage and bark debris are measured within the litter component.

As indicated in Table 11, data on mass of litter and CWD under Australian forests were previously collated. These datasets were used to calculate estimates of the average (and standard deviation) of observed litter and CWD under the various forest types. These estimates provided verification of the revised parameters for litter fall and litter decomposition as testing using the 41 scenarios given in Table 8. The upper bounds of litter and CWD expected were simulated post harvesting events. Hence, for the mature woodlands and native forest scenarios, two simulations were run; the first being under uncleared mature vegetation, and second being a year after clearing a mature stand. Similarly, for plantation scenarios two estimates were made over a 100 year simulation that included multiple rotations; first being under the mature stand of the final rotation within this period, and the second being after harvesting in the final harvest cycle within this 100 year period.

Table 11. Datasets collated from field studies with litter bag monitored under eucalypt-dominant stands, or under softwood plantations. Studies in eucalypt-dominant stands included assessments of decomposition of deadwood, bark litter and foliage litter. But under softwood plantations, only pine needle litter was assessed.

Forest type	Litter (Mg DM ha^{-1})	CWD (Mg DM ha^{-1})	Source
Environmental plantings	115	NA	Paul *et al*. (2017b)
Hardwood plantations	24	14	Woldendorp and Keenan (2005)
	12	NA	England *et al*. (2017)
	7	NA	Snowdon *et al*. (2005)
Softwood plantations	17	11	Woldendorp and Keenan (2005)
	10	NA	Snowdon *et al*. (2005)
	1	NA	Bubb *et al*. (1998)
Native forests	71	60	Woldendorp and Keenan (2005)
	51	NA	England *et al*. (2017)
	46	NA	Snowdon *et al*. (2005)
	2	NA	O'Connell (1997)
	1	1	Hingston *et al.* (1981)
Woodlands	27	NA	Harms *et al*. 2005
	13	5	Woldendorp and Keenan (2005)
	10	NA	Murphy *et al*. (2002)
	5	NA	England *et al*. (2017)
	NA	19	Prior *et al*. (2016)
Total	*412*	*110*	

2.4 Parameters influencing soil C

Previous work by Chappell and Baldock (2013) provided recommendations and justification for soil C turnover parameters applied in the RothC sub-model. This included an RPM pool turnover rate of 0.17 % yr^{-1}, and a HUM pool turnover rate of 0.02 % yr^{-1}. All other RothC parameters were as per the original model calibration (e.g. Jenkinson *et al.* 1991).

A recent national study of soil C changes following reforestation with environmental plantings (Paul *et al.* 2017b) greatly expanded the datasets available from long-term irrigation and fertiliser trials in temperate plantations (Paul *et al.* 2004; Paul and Polgase 2004a). In all of these studies, measurements of pools of soil C (i.e. IOM, RPM and HUM) were made together with measurements of stand biomass, litter fall and litter mass. In each of these field studies, measurement were also made for assessment of biomass, litter fall and litter mass. The collation of datasets from across these studies provided 158 sites (and/or treatment plots) where predictions of pools of soil C could be 'tuned' to that observed (Table 12).

Due to being relatively resource-intensive to measure, there is a paucity of data for FullCAM input parameters for root turnover and decomposition, and the fraction of C lost as CO_2 on decomposition of debris. The approach used here was to calibrate rates of root turnover and decomposition, and the fraction of CO_2-C loss on decomposition, to ensure that predicted pools of soil C match that observed, while at the same time: (i) constraining predictions of biomass to that observed at these sites (Paul and Polglase 2004b; Paul *et al.* 2017b), and; (ii) applying the revised parameters for allocation of biomass, litter fall and decomposition of litter. This was done using the RothC parameters as per Chappell and Baldock (2013). In the absence of any justification to assume otherwise, parameters for root turnover and decomposition, and the fraction of CO_2-C loss on decomposition of resistant and decomposable debris pools, were each assumed to be constant across the different forest types.

Given these assumptions, and uncertainties in measurements of pools of soil C and biomass, and given the application of generic rates of allocation of biomass, litter fall and decomposition of litter, prediction of soil C pools is unlikely to be highly accurate at the site-level. The aim was to achieve the best overall model fit for parameters influencing soil C for which there is a paucity of information. To provide an assessment of the success of this model fit, efficiencies of model prediction across the 158 sites listed in Table 12 were calculated for total soil C, as well as the two large pools of soil C measured; RPM and HUM.

Table 12. Details of the soil C study sites (or treatments within a site) under environmental plantings (Env. plantings), hardwood plantations (*E. grandis*) and softwood plantations (*P. radiata*). Included here is the region of Australia from which sites were located (SE= south east; S= central south; NE= north-east, and; SW= south-west of Australia), number of sites (N), stand age, and previous land use (PLU: G = grazing; C = cropping or rotational cropping/grazing; P = *Pinus radiata* plantation).

Forest type	Region	N	Age (yrs)	PLU	MAR (mm yr^{-1})	Source
Env. plantings	SE	36	5-46	G	448-794	Cunningham *et al.* (2015)
Env. plantings	SE	20	1-19	G	550-884	Read (2016)
Env. plantings	SE	7	8-16	G, C	352-1112	Baker, T., unpublished data
Env. plantings	SE, Intensive	3	5	G	427-965	Paul *et al.* (2017b)
Env. plantings	SE, Repeat#	21	5-20	G, C	509-696	Paul *et al.* (2017b)
Env. plantings	SE, Riparian	10	9-23	G, C	407-774	Paul *et al.* (2017b)
Env. plantings	SE	19	9-20	G, C	365-1423	Paul *et al.* (2017b)
Env. plantings	S	4	6-29	C	372-652	Paul *et al.* (2017b)
Env. plantings	NE	3	5-19	G	852-1474	Paul *et al.* (2017b)
Env. plantings	SW	2	15-16	C	370-422	Paul *et al.* (2017b)
Softwood	SE^	18	10-20	P	791	Paul & Polglase (2004b)
Hardwood	SE+	8	1-10	G	570	Paul & Polglase (2004b)
Softwood	SE+	8	1-10	G	570	Paul & Polglase (2004b)
Total		158				

#Sites were measured two or three times.
^The BFG experiment, including treatment plots of: (i) control; (ii) once-only solid fertiliser applied; (iii) irrigation only; (iv) irrigation and once-only solid fertiliser applied; (v) irrigation and liquid fertiliser applied weekly; (vi) once-only solid fertiliser applied, but left unthinned.
+The WEPP experiment, including treatment plots of: (i) irrigation at low rates, and; (ii) irrigation at medium-high rates.

2.5 Initialising pools of biomass and debris

Each of the 51 different forest types in FullCAMs database has a default initial age at the start of simulation; Environmental and mallee plantings with various regimes, 0 years; Hardwood plantations, between 10 and 35 years, depending on the species, and; Softwood plantations, 35 years, and; Native systems, 50 years.

For each of the 51 forest types, the Allocation Calculator was applied to generate outputs of the percentage contribution of each biomass pool to total biomass at the nominated initial stand age. It was again ensured that the simulations were undertaken for a region (and hence climatic conditions and growth rates) typical of that forest type.

Using the revised parameters outlined in Sections 2.1-2.4, a plot file was generated for each of the 51 different forest types, again ensuring that the simulation was for a typical region. The predicted decomposable and resistant pools of deadwood, bark litter, foliage litter, and dead coarse and fine roots were then recorded at the nominated stand ages at initialisation. These debris pools where then used as the revised initial pools of debris for each of these 51 forest types. Note for plantations, the debris pool at the nominated stand age was taken from the last rotation simulated with a 100 year period, and thus, included the legacy impacts of harvesting residues from previous rotations.

3 Results and Discussion

3.1 Allocation of biomass

3.1.1 Empirical models of allocation of AGB

Environmental and mallee plantings

Allocation models for environmental and mallee plantings were obtained for prediction of Bole:AGB, Bough:Bole, Bark:Bole and Twigs:Canopy at both the individual- and stand-scale (Table 13). These models demonstrated that allocation of biomass was influenced by not just biomass and stand age, but also by rainfall, stand density, and PropEuc.

Table 13. Models derived for prediction of Bole:AGB, Bough:Bole, Bark:Bole and, Twig:Crown at the individual- and stand-scale for environmental plantings (EP) and mallee plantings (MP). Statistically significant variables, and whether they have a positive or negative influence on the ratio, are listed. The model's statistical significance (P-value), R^2 and sample number (N) are also provided. Resulting models are provided in detail by Paul & Waterworth (2015).

Model	Type	Significant variables	P	R^2	N
		Individual-scale			
Bole:AGB	Tree	+Ln(AGB); +MAR; +PropEuc	<0.01	0.36	693
	Shrub	+Ln(AGB)	<0.01	0.05	123
	Mallee	+Ln(AGB)	<0.01	0.26	518
Bough:Bole		+Ln(Bole)	<0.01	0.13	73
Bark:Bole		None, constant of 0.17	NA	NA	183
Twig:Crown		Growth habit; +Mallee tree, and +Shrub	<0.01	0.07	498
		Stand-scale			
Bole:AGB	EP	+ Ln(AGB)[1]; +Ln(Age)[2]; – $\text{Dense}_{[1,0]}$[3]; – $\text{PropEuc<0.75}_{[1,0]}$[4]; +$\text{MAR>500}_{[1,0]}$[5]	<0.01	0.91	736
	MP	+Ln(AGB)[6]; +Ln(Age)[7]; – $\text{Dense}_{[1,0]}$	<0.01	0.94	391
Bough:Bole	EP	+Ln(Bole); +Ln(Age)[8]; $\text{PropEuc>0.75}_{[1,0]}$	<0.01	0.54	736
	MP	+Ln(Bole); +Ln(Age)	<0.01	0.88	391
Bark:Bole		None, constant of 0.170	NA	NA	1,127
Twig:Crown	EP	– $\text{PropEuc>0.75}_{[1,0]}$; – Ln(Crown)[9]	<0.01	0.22	736
	MP	None, constant of 0.554	NA	NA	391

[1] Particularly with increased Age, and/or particularly Tropical forests, and/or less so when Sparse
[2] Less so for tropical forests.
[3] Particularly for tropical forests.
[4] Particularly when sparse or very sparse, and/or $\text{MAR<500}_{[1,0]}$.
[5] Particularly when tropical forest, and/or PropT>0.75.
[6] Less so when Sparse.
[7] Particularly when Sparse.
[8] Particlarly when high Bole and/or $\text{PropT>0.75}_{[1,0]}$
[9] Particlarly when $\text{PropT<0.75}_{[1,0]}$.

As indicated by results shown in Fig. 3, all individual-scale models obtained were highly significant (P<0.01) and un-biased, and when applied explained some (>47%) of the variation in component biomass. At the stand-scale, 'observed' biomass of components were actually calculated values based on the application of the individual-scale models. Therefore as expected, stand-scale model performance was very high (EF>0.97), and the residuals were relatively low (<12 % variation in AGB) (data not shown).

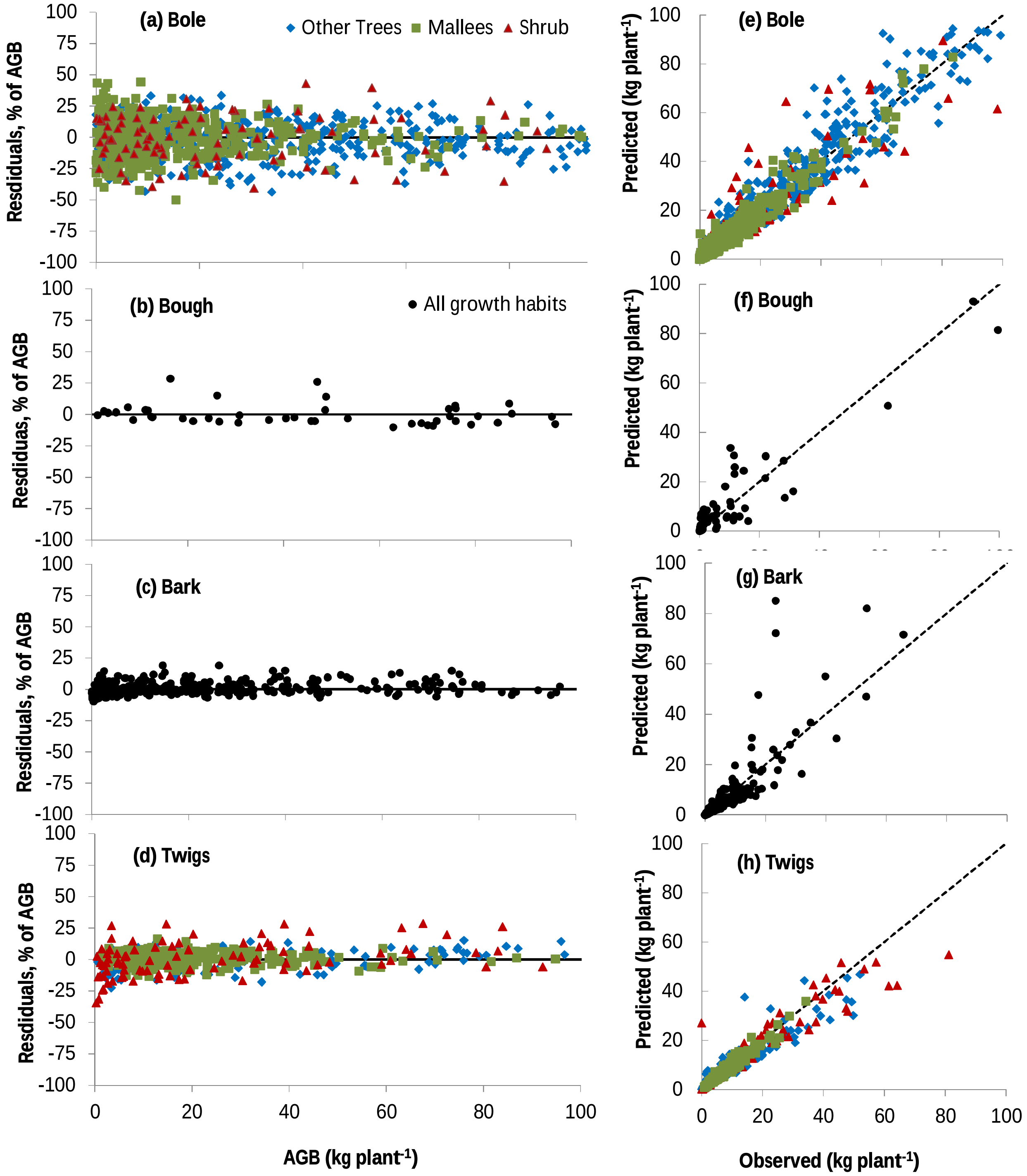

Figure 3: Plots of residuals in predicted biomass, expressed as a percentage of AGB, for predictions of the components of; (a) Bole, (b) Bough, (c) Bark, and (d) Twig, and the corresponding relationships between observed and predicted biomass of these components of; (e) Bole (Overall EF=0.99, N=1401; Tree EF=0.99, N=693; Shrub EF=0.77, N=190; Mallee EF=0.95, N=518), (f) Bough (Overall EF=0.74, N=145), (g) Bark (Overall EF=0.47, N=434, or for trees <100 kg, EF=0.98, N=383), and (h) Twig (Overall EF=0.97, N=498; Tree EF=0.98, N=142; Shrub EF=0.77, N=190; Mallee EF=0.90, N=94).

Native forests, woodlands and shrublands

Results in Table 14 show comparison between the average (±SD) observed Wood:AGB, Bark:AGB, Branch:AGB, Foliage:AGB and Bole:AGB for native forests (or woodlands/ shrublands) and that predicted from a range of relevant scenarios when applying the stand-level allocation models derived for low density environmental plantings with PropEuc>0.75 (or PropEuc<0.75). Predictions were generally within ± 1SD of the average observed. The only exception was the over-prediction of Branch:AGB in high rainfall regions. Conversely, there was a slight under-prediction of Branch:AGB in low rainfall regions.

These results indicate that although there is an increased bole mass in areas of relatively high rainfall, in native systems, this increase is mainly attributable to an increase in stem wood, and not attributable to an increase in the biomass of branches. If verified, the empirical model for Bough:Bole calibrated to environmental plantings may require refinement for native ecosystems to reflect this. But otherwise, current results suggest that stand-level allocation models derived for low density environmental plantings with PropEuc>0.75 (or PropEuc<0.75) were largely appropriate for the application to native forests (or woodlands/ shrublands).

Table 14. Average (±SD) observed and predicted range of biomass allocation ratios. Datasets were collected from 46 and 7 different sources for high (≥500 mm yr^{-1}, native forests) and low (<500 mm yr^{-1}, woodlands and shrubland)rainfall regions, respectively. Further details about these sources and the datasets are provided by Paul *et al*. (2016) and Paul *et al.* (2017a).

	High rainfall native forests		Low rainfall woodlands & shurblands	
Ratio	**Observed**	**Predicted**	**Observed**	**Predicted**
Wood:AGB	0.65 ± 0.12	0.52-0.54	0.41 ± 0.21	0.43-0.46
Bark:AGB	0.12 ± 0.06	0.14-0.15	0.12 ± 0.04	0.11-0.12
Branch:AGB	0.14 ± 0.09	0.25-0.26	0.32 ± 0.18	0.28-0.29
Foliage:AGB	0.05 ± 0.06	0.06-0.09	0.11 ± 0.07	0.13-0.17
Bole:AGB	0.84 ± 0.10	0.82-0.88	0.61 ± 0.18	0.62-0.71

Hardwood and softwood plantations

For both hardwood and softwood plantations, allocation of AGB to stem wood increased with AGB. This came at the expense of allocation of AGB to foliage, which declined with increased AGB (Table 15). The other AGB components of branches and bark were relatively constant over a range of tree sizes. As outlined below (Section 3.1.2), the increased proportion of stem wood with increased AGB is well documented for commercial forests (Schroeder *et al*., 1997; Snowdon *et al*., 2000; Kantola & Mäkelä, 2006), as is the finding that this increased stem wood production comes at the expense of foliage production (Dewar & McMurtrie, 1996; Albaugh *et al.*, 1998; Lehtonen, 2005).

Table 15. Models derived for prediction of Wood:AGB, Branch:Bole, Bark:Bole and, Foliage:AGB at the individual-scale for hardwood and softwood plantations. These models were also assumed to apply at the stand-scale given these plantings have a single species of a specific stand age and hence, specific size range. Statistically significant variables, and whether they have a positive or negative influence on the ratio, are listed. The model's statistical significance (P-value), R^2 and sample number (N) are also provided.

Model	Type	Significant variables	P	R^2	N
Wood:AGB	Hardwood	+Ln(AGB)	<0.01	0.53	1,008
	Softwood	+Ln(AGB)	<0.01	0.31	421
Branch:AGB	Hardwood	None, constant of 0.25±0.09	NA	NA	981
	Softwood	None, constant of 0.19±0.09	NA	NA	520
Bark:AGB	Hardwood	None, constant of 0.09±0.04	NA	NA	1,012
	Softwood	None, constant of 0.09±0.03	NA	NA	320
Foliage:AGB	Hardwood	– AGB	<0.01	0.72	1,084
	Softwood	– AGB	<0.01	0.29	520

3.1.2 Key factors influencing allocation of AGB

For each forest type, variations in partitioning of AGB biomass were originally predicted based only on stand age. In contrast, when the new empirical models predicting partitioning of AGB biomass are applied via generating revised allocation inputs tables using the Allocation Calculator, numerous factors are also accounted for. These are outlined below.

Forest type

As expected, empirical modelling indicated that allocation of AGB to stem is relatively high (and allocation to branches relatively low) in hardwood and softwood plantations given these are managed for wood production (Fig. 4c,d). In contrast, allocation of AGB to stem was relatively low (and allocation to branches relatively high) in low rainfall systems such as many woodland systems (Fig. 4f). The increased allocation to structural components as the stands mature was offset by a decreased allocation to foliage, such that in mature stands, foliage biomass was predicted to be relatively small.

The observed differences in allocation of AGB between forest types is consistent with the understanding that biomass partitioning is partly genetically controlled (e.g. Cannell *et al*. 1983; Berninger & Nikinmass 1997), with differences in partitioning partly explained by photosynthetic efficiency related to plant architecture (e.g. Gower *et al*. 1994). A specific example of this was found in the differences between the portion of the canopy that was twigs between mallee eucalypts and other trees (Table 13). At the individual-scale, mean twig proportion to the total crown ratio (Twig:Crown values) of 0.62 was observed for mallee eucalypts, whereas Twigs:Crown was only 0.52 for other trees. For a given canopy size, mallees (which generally grow in hash low rainfall environments) tend to have a relatively high proportion of twigs in order to support their relatively larger umbrella-like leaf canopy (ANBG 2004), and have relatively high ratio of photosynthesic mass to body mass as a consequence of thicker leaves and relatively smaller body size (e.g. Xu *et al*. 2014).

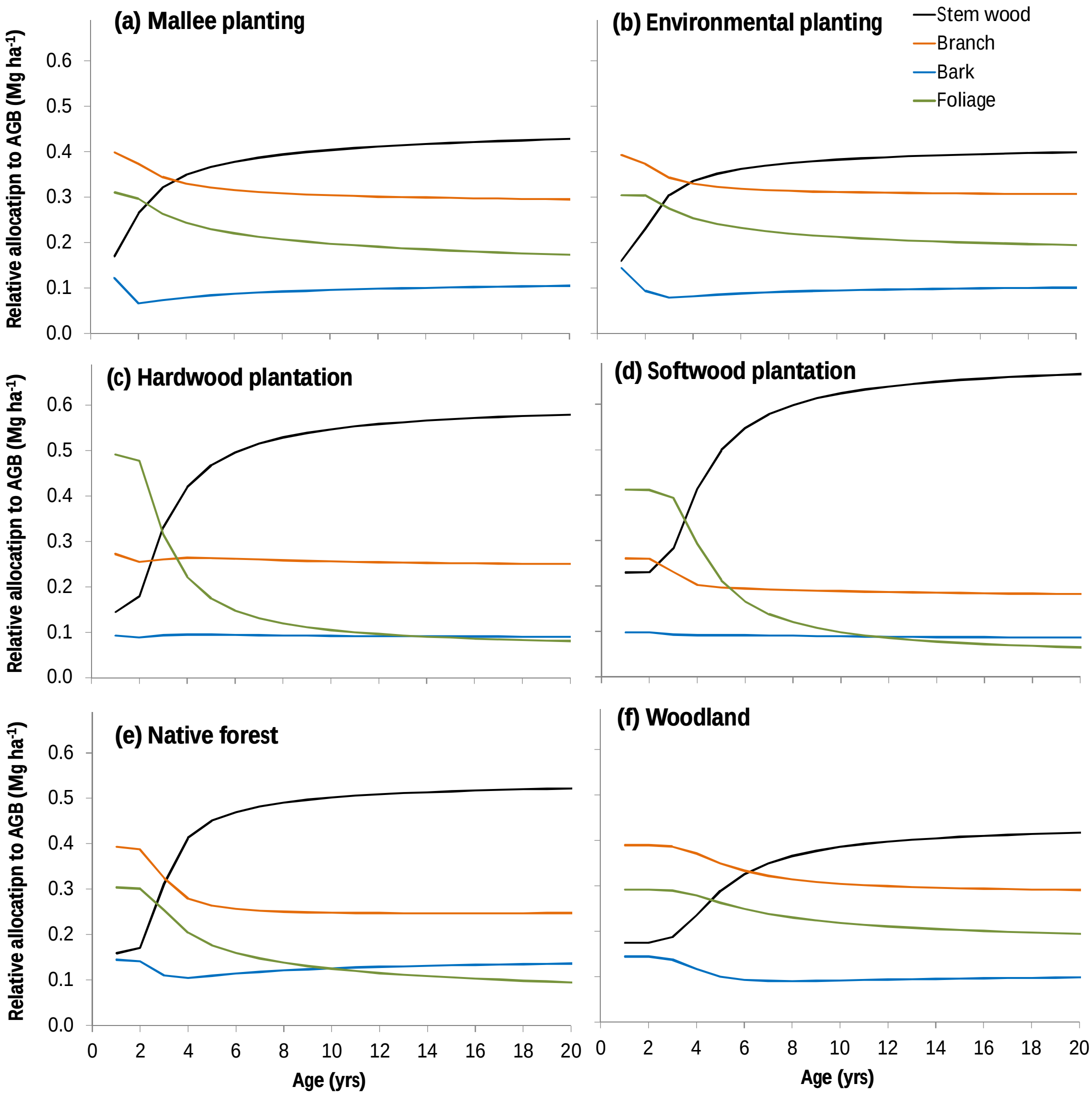

Figure 4: Examples of differences in allocation of AGB between the key categories of forest types. In (a), the mallee plantings were *E. loxophleba lissophloia* established as wide belts in a low rainfall region. In (b), the environmental planting was established in a region of low rainfall in a block configuration with a tree-dominant species mix using standard densities. In (c), the hardwood plantation was *E. globulus* established in the south-west of Western Australia. In (d), the softwood plantation was *P. radiata* established in the East Gippsland region of Victoria. In (e) and (f) the native systems were Eucalyptus Tall Open Forest in regions of high rainfall, and Eucalyptus Open Woodland in regions of low rainfall, respectively.

Growth habits of mixed-species plantings, forests, woodlands or shrublands

Although there are broad differences in allocation of AGB between key forest types, within stands of mixed-species, some additional variability in the allocation of AGB can be attributable to the relative mix of trees to shrubs. Results given in Table 13 and Fig. 5a show that when compared to stands that had a good mix of trees and shrubs (PropEuc<0.75), Bole:AGB was higher in mixed-species stands that were predominately trees (PropEuc≥0.75).

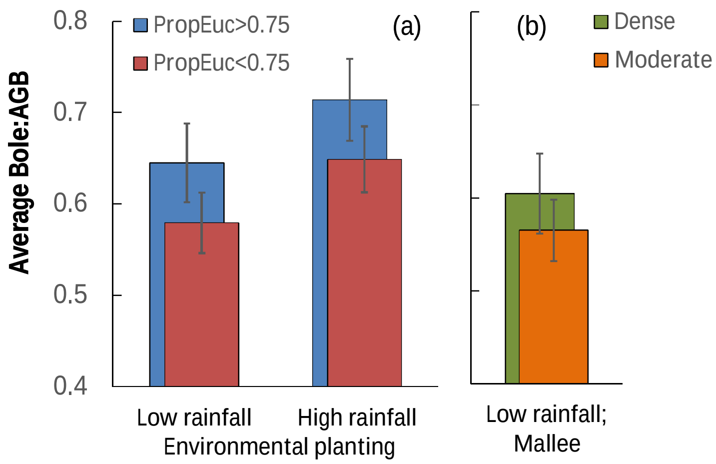

Figure 5: Average Bole:AGB in: (a) low and high rainfall environmental plantings that were either tree dominant (PropEuc≥0.75), or had a good mix of trees and shrubs (PropEuc<0.75), and; (b) low rainfall mallee plantings established in wide belts of either high density (≥2,300 sph) or moderate-low density (<2,300 sph). In (a), averages were obtained from across plantings of various configurations and stand densities. In (b), averages were obtained from across plantings of various species.

There was also evidence that when compared to low rainfall woodland/shrublands, the average Bole:AGB was observed higher in higher rainfall native forests (Table 14). These results were consistent with the review of Poorter *et al*. (2011). They showed that temperate forests had a higher stem mass fraction and lower leaf mass fraction than those of woodlands and shrublands. They also showed vegetation type accounted for 66% of the variation across observations of stem mass fraction. Stands dominated by trees have a relatively high allocation to stems (and thus bole) given trees have more bole than shrubs (e.g. Stewart *et al*. 1979; Birk *et al*. 1995), and because in woody species, allometric constraints cause plants to increasingly invest in stems when size increase, and trees are larger than shrubs (e.g. Poorter *et al*. 2011).

Biomass and age

Statistical analysis of the large environmental and mallee plantings dataset demonstrated that AGB or age were not able to explain variations in allocation to non-structural components of twigs, and particularly bark (Table 13). Hence, allocation of AGB to branches (which comprise twigs as well as some larger branches) and bark were less responsive to changes in stand age than stem wood and foliage (Fig. 4).

The constant Bark:Bole of 0.17 was just as efficient at predicting bark biomass as more complicated models. Confidence in the use of a constant ratio between bark and bole (dominated by stem) is provided by previous findings that bark varies proportionally to stem wood, particularly in stands >3 years (Madgwick *et al.*, 1977; Paul & Polglase *et al.*, 2004b).

In contrast, given structural components such as the bole and bough grow cumulatively with AGB, the AGB was a key determinant of allocation to these components (Table 13). Most of the accumulation of AGB as stands mature may be attributable to an increase in stem biomass and, with the exception of some plantation species, a corresponding increase in branch biomass (Fig. 4). As discussed above, allometric constraints cause woody plants to increasingly invest in stems when size increases (Schroeder *et al.*, 1997; Snowdon *et al.*, 2000; Kantola & Mäkelä, 2006; Poorter *et al.* 2011).

Another interesting observation in the analysis of the large environmental and mallee plantings datasets was that the importance of stand age on allocation of was only important only at the stand-scale, not the individual-scale (Table 13). Individuals sampled for biomass were selected from a range of stands; a small tree for example could have been harvested from a young stand, or alternatively, from an older stand of with relatively poor growth rates. This made AGB of individual trees and shrubs, and hence allocation of biomass, poorly correlated with age. In contrast, at the stand-scale the total sum biomass of all plants within the stand were more likely to be related to age. However, stand age is often difficult to accurately ascertain in many forests types, particularly those of individuals of mixed-age. Hence, the revised empirical models that take into account AGB as well as estimate of stand age are preferable over the original input tables that are based on age alone.

Climate

Environmental plantings and native systems are distributed across a wide range of climates. Hence, for these systems, there was a significant positive impact of MAR on Bole:AGB (Tables 13 and 14, Fig. 5a). These findings may be explained by increased MAR, and hence productivity, resulting in an increased allocation to stem wood (e.g. Campoe *et al*. 2012), as demonstrated when productivity was influenced by water manipulation (Giardina *et al*. 2003; Stape *et al*. 2008; Ryan *et al*. 2010). Consequently, Bole:AGB was higher in tropical than temperate regions (Table 13), consistent with the findings of others (e.g. Poorter *et al*. 2011).

For both environmental plantings and native systems, allocation of AGB to foliage was found to increase with decreased MAR, and this was at the expense of a decreased allocation of AGB to stem wood. For example, results from native systems across Australia showed that in regions of relatively low MAR, there was a relatively small Bole:AGB (and Wood:AGB), while Foliage:AGB was relatively high, when compared to that observed in regions of relatively high MAR (Table 14). This may be because trees in hash environments have relatively high ratio of photosynthesic mass to body mass as a consequence of thicker leaves and relatively smaller body size (e.g. Xu *et al*. 2014). Indeed Bole:AGB was particularly low in mallee plantings given these tree species are well adapted to drought conditions (ANBG 2004), and so tend to be established in regions of relatively low MAR. However, given the branch pool in FullCAM includes the twig component of the crown, the relatively low Bole:AGB of mallee plantings is not obvious from Fig. 4-5. Further work is required to refine FullCAM biomass allocation inputs to separate twigs from the branch pool, particularly given these will have differing rates of turnover.

Stand density

The statistical analysis of the large environmental and mallee planting dataset suggested that an increase in stand density was associated with an increase in allocation to the stem at the expense of allocation to foliage and twigs (Table 13). This is demonstrated in Fig. 5b, where Bole:AGB, which is dominated by the stem, is relatively high in stands of relatively high density. This observation was consistent with the fact that many of the highest density stands in the database were from narrow belt plantings where edge trees seeking additional light resources branch-out into the area between belts. This would explain why these results were inconsistent with those obtained from competition studies. Such previous studies indicated that as competition between trees increases, allocation to the stem increases at the expense of foliage. This was thought to be as a result of these species responding to closed canopies by positioning foliage at the top of the canopy via increasing their length per unit stem mass (e.g. Schmitt *et al*. 1999; Poorter *et al*. 2011). Further work is required to ascertain the impact of stand density of allocation of AGB for other combinations of plantations species and planting configurations.

3.1.3 Empirical models of BGB_C:AGB

The changes in allocation of AGB discussed above do not affect the total biomass C per se (as AGB is determined by the TYF), and therefore only influence the C budget in terms of input of C into the debris pools via turnover or disturbance events. In contrast, the allocation to BGB_C:AGB directly affects total biomass C. Changes in BGB_C:AGB ratios are therefore of particular interest, and hence, discussed separately here.

As discussed previously, BGB_F are typically the smaller pool of BGB_T (e.g. Keyes & Grier 1981; Snowdon *et al*. 2000; Mokany *et al*. 2006) and is therefore of less concern for biomass carbon accounting. This was confirmed by our results; BGB_T being only marginally greater than BGB_C. Fine roots are nonetheless one of the most dynamic pools of biomass (Vogt *et al*. 1996), and thereby a major driver of soil nutrient and carbon dynamics following reforestation. Here we have related BGB_F to AGB, although there is some evidence suggesting that BGB_F reaches a max at canopy closure, after which it stabilises or slowly decreases (Jackson *et al*. 1996; Snowdon *et al*. 2000). Further work is required to explore whether BGB_F predictions may be improved by BGB_F to foliage rather than the total AGB (Shackleton *et al*. 1988; Litton *et al*. 2003).

Environmental and mallee plantings

In environmental and mallee plantings, BGB_C:AGB of individual trees or shrubs tended to be much higher than the typically-applied default of 0.25 (Mokany & Raison 2004), but varied greatly depending on the size of the individual and its life-form (Fig. 6). On average, mallee eucalypts trees had exceptionally high BGB_C:AGB (Fig. 6b). There were also differences between life-forms in the sensitivity of BGB_C:AGB to plant size. Trees, particularly mallee eucalypt trees, had a relatively high sensitivity of BGB_C:AGB to plant size (Fig. 6). In contrast, shrub life-forms had BGB_C:AGB that varied very little with plant size.

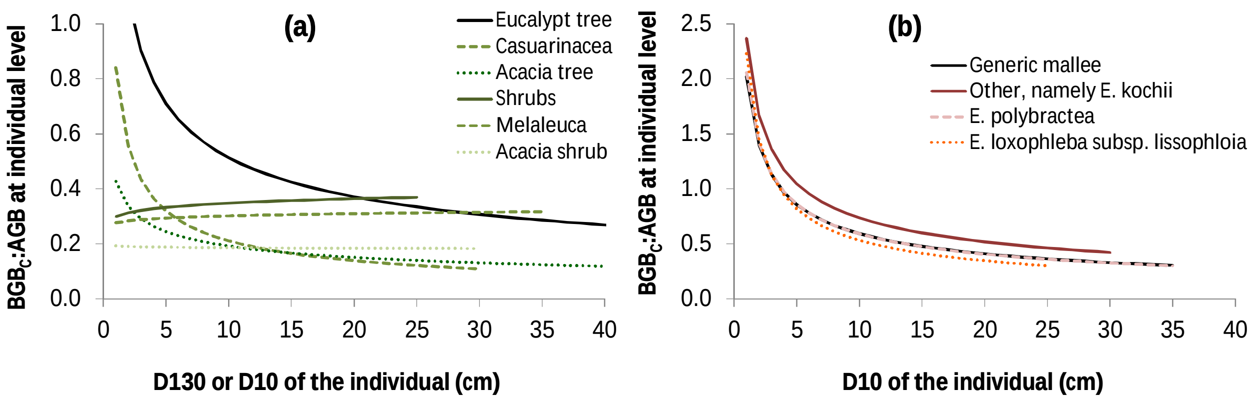

Figure 6: Relationship between BGB_C:AGB and stem diameter for different groups of species or life-forms in; (a) environmental plantings, and (b) mallee plantings. These relationships were derived from the application of allometric equations as described by Paul *et al.* 2014a,b,c.

When the individual-scale BGB_C:AGB estimates were applied to the stand-scale, it was found that the efficiency of prediction of stand-level BGB_C:AGB was only 43% across the wide diversity of environmental plantings, but was much higher (73%) for the more uniform mallee plantings (Table 16, Fig. 7). This empirical modelling of BGB_C:AGB at the stand-scale demonstrated that an increase in stand density resulted in a decrease in BGB_C:AGB for both environmental and mallee plantings (Table 16). This may be at least partly explained by the observation that across the stands of environmental and mallee plantings studied, average D10 of live plants within the stands decreased with increased density of the stand, or plants per hectare (Fig. 8).

Table 16. Models derived for prediction of BGB_C:AGB at the stand-scale. Statistically significant variables, and whether they have a positive or negative influence, are listed. Statistical significance (P-value), R^2 and sample number (N) are provided. Resulting models are provided in detail by Paul & Waterworth (2015).

Type	Significant variables	P	R^2	N
Mixed	– Ln(AGB)[1]; + PropEuc>0.75$_{[0,1]}$[2]; – Sparse or very sparse$_{[0,1]}$[3]	<0.01	0.43	736
Mono	– Ln(AGB)[4]; – Ln(Age)[7]; – Sparse$_{[0,1]}$; + Dense$_{[0,1]}$	<0.01	0.73	369

[1] When PropEuc<0.75.
[2] Less so when relatively high Ln(AGB).
[3] Particularly with relatively high Ln(AGB), and/or when PropEuc<0.75.
[4] Less so when relatively high Age.

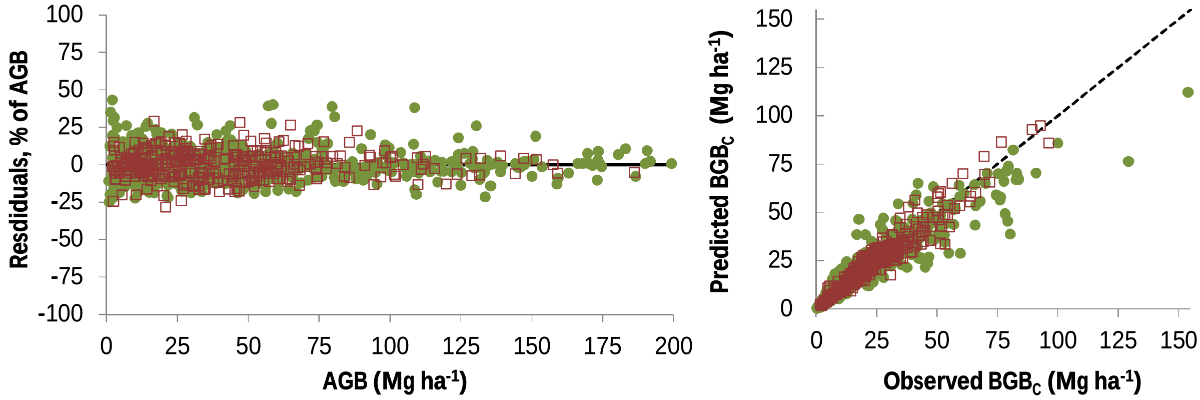

Figure 7: Plots of residuals in predicted stand-level BGB_C, expressed as a percentage of stand-level AGB, and the corresponding relationships between observed and predicted BGB_C for: environmental plantings (green circles), EF=0.43, N=736; mallee plantations (red squares) EF=0.73, N=369.

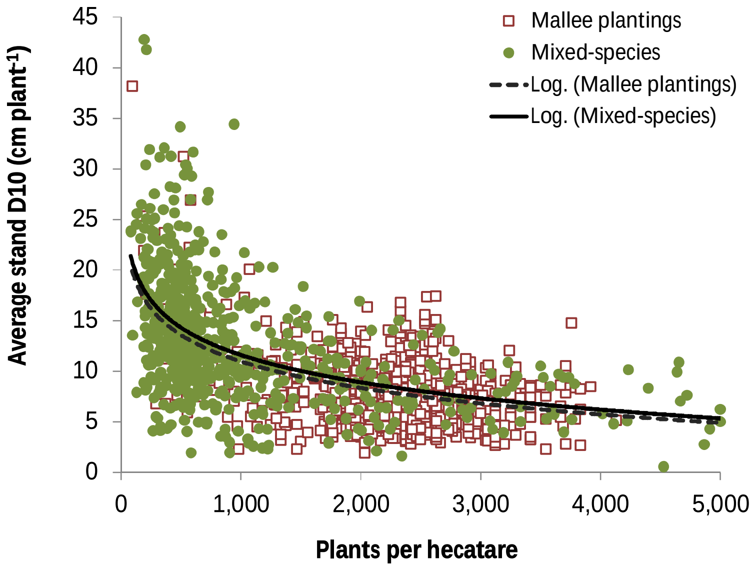

Figure 8: Relationship between average diameter of stems (at 10 cm height above the ground; D10 cm) of live plants within a stand, and the density of that stand (number of live plants per hectare measured).

In addition to stand density, AGB was also a key factor determining BGB_C:AGB, with this ratio declining in stands of both environmental and mallee plantings as AGB increases (Table 16). For environmental plantings, the PropEuc was also a statistically significant explanatory variable (BGB_C:AGB being higher in stands with PropEuc≤0.75 when compared to those with PropEuc>0.75), while for mallee plantations, stand age was important (BGB_C:AGB being relatively high in young stands).

Other explanatory variables considered (planting configuration, MAR during the years of growth, FPI and the AGB-growth category of planting) were either statistically insignificant, or increased the amount of explained variation in BGB_C:AGB by <2%. Although there was some evidence that different species of mallee eucalypts had differing BGB_C:AGB, the impact was weak, with species only explaining 12% of the variation in BGB_C:AGB for mallees (data not shown). Moreover, the explanatory variable of species of mallee eucalypt lost its statistical significant once other factors were also considered, thereby suggesting that any impact of species on BGB_C:AGB may have only been an artefact of other confounding factors.

Native forests, woodlands and shrublands

As expected, the BGB_C:AGB observed in native systems was found to be higher woodlands and shrublands in regions of relatively low rainfall, and which were found to have more observations of F_{Mulit} and F_{Shrubs} than found in stands of native forests from regions of relatively high rainfall (Table 17). The empirical modelling of BGB_C:AGB discussed above suggests that this was probably attributable to the combination of both the lower MAR, and the increased proportion of plant functional types known to have relatively high BGB_C:AGB ratios, e.g. shrubs and multi-stemmed trees such as mallee eucalypts. Indeed results obtained indicated that the application of the stand-level model for low (< 500 sph) density environmental plantings with PropEuc>0.75 (or PropEuc<0.75) was appropriate for a wide range of native forests (or woodlands/ shrublands) from high (or low) rainfall regions. The predicted BGB_C:AGB ratios for a wide range of scenario of stands (Table 8) of between 20 and 100 years of age were within ±1 SD of that averaged observed (Table 17).

Table 17. Mean (± SD) observed BGB_C:AGB at the individual-scale for various species of within high rainfall native forests and low rainfall woodlands/shrublands, and the comparison of these observations to that predicted in relevant 20-100 year old stands.

Native ecosystem	Observed	Predicted
Native forests	0.33 ± 0.14 (N=168)	0.19-0.39
Woodlands/shrublands	0.41 ± 0.19 (N=178)	0.29-0.40

Although previous work (Westman & Rogers 1977; Ash & Helman 1990; Gonzalez *et al*. 2013) and results from the environmental planting datasets showed that allocation to BGB in shrubs is relatively small when compared to trees, results obtained here confirm that this does not necessarily imply that shrublands have relatively low BGB_C:AGB. The finding that BGB_C:AGB was higher in the relatively F_{Shrub}-dominant woodland/shrublands than in the F_{Euc}-dominant native forests (Table 17) was consistent with the findings from the global review of Mokany *et al*. (2006). They showed shrublands had much higher BGB_C:AGB than temperate eucalypt forests/plantations (i.e. BGB_C:AGB average of 1.84 compared to 0.20-0.44). Caution is therefore needed when considering BGB_C:AGB of shrubs; these ratios may depend on whether the shrubs are integrated with trees in mixed-species plantings, or whether they are shrublands that may be comprised of a quite different cohort of species of shrubs, and which tends to be in regions of relatively low MAR.

Hardwood and softwood plantations

The average BGB_C:AGB observed was moderate (0.24 ± 0.13) for hardwood plantations, relatively low for plantations of *Pinus radiata* (0.20 ± 0.06), and relatively high for plantations of *P. pinaster* (Table 18). These results were consistent with the global review of Mokany and Raison (2004, Fig. 20). They showed that the mean BGB_C:AGB of temperate conifer plantations were generally less than that of temperate eucalypt plantations, but that these differences were less pronounced for conifer plantations that had relatively low biomass (<50 Mg ha^{-1}, e.g. many stands of *P. pinaster*).

Table 18. Mean (± SD) observed BGB_C:AGB at the individual-scale for various species of Australian hardwood and softwood plantations.

Type of plantation	Species	Observed
Hardwood		0.24 ± 0.13 (N=97)
Softwood	*P. radiata*	0.20 ± 0.06 (N=134)
	P. pinaster	0.54 ± 0.23 (N=114)

3.1.4 Key factors influencing BGB_C:AGB

For each planting type, variations in BGB_C:AGB predicted by FullCAM were originally based on stand age only. When the new empirical models predicting BGB_C:AGB are applied via the Allocation Calculator, numerous factors are also accounted for. These are outlined below.

Forest type

The highest BGB_C:AGB was predicted to be in the stands growing in relatively harsh low rainfall environments; mallee planting and *Pinus pinaster* softwood plantations (Fig. 9a, and insert in Fig. 9d). The BGB_C:AGB was also predicted to be relatively high for low rainfall environmental plantings and woodlands/shrublands (Fig. 9b, f). In contrast, BGB_C:AGB tended to be relatively low for high rainfall environmental plantings and native forests (Fig. 9e). The lowest BGB_C:AGB predicted were those from hardwood plantings (average 0.30 at age 10 years), and particularly softwood plantations grown in regions of relatively high rainfall (average 0.25 at age 10 years) (Fig. 9c,d).

These wide range in BGB_C:AGB between different forests types is expected based on previous findings. For example, many workers (e.g. Cuevas *et al.* 1991; Vogt *et al*. 1996; Mokany *et al*. 2006) have found that forest plantations have lower BGB_C:AGB than natural forests. Furthermore, Paul *et al*. (2014a) found differences in allometry for BGB_C between different groupings of genera. They reported that for a given stem diameter, BGB_C of an individual was highest for mallee trees and lowest for shrubs. This finding was consistent with other reports (Jonson & Freudenberger 2011). Such differences in allometry between growth habits explained why BGB_C:AGB was highest in stands of mallee eucalypt, and lowest in mixed-species forests that had PropEuc<0.75, e.g. woodlands/shrublands.

Differences in BGB_C:AGB between forest types of differing tree species, and PropEuc, may be attributable to three evolutionary-based factors. Firstly, shrubs have shallower rooting systems than trees as they tend to be smaller, and thereby did not have the same evolutionary pressure as trees to develop the large structural roots that contain large quantities of biomass (e.g. Ludwig 1977; Wilson 1993; Mokany *et al*. 2006). Secondly, BGB_C:AGB tend to be larger in species that re-sprout from root stock following disturbance compared to those that regenerate by seed (Higgins *et al*. 1987; Low & Lamont 1990). Most eucalypt trees, and particularly mallee eucalypts, are prolific re-sprouting species whereas most of the shrubs in environmental plantings regenerate from seed (e.g. ANBG 2004). Third, BGB_C:AGB may be particularly high for mallee eucalypts as these species have evolved to survive hash environments and prolonged drought by storing water in larger structural storage organs in their rooting systems (lignotubers) (ANBG 2004; Hilbert & Canadell 1995). These lignotubers would be anticipated to add additional biomass to the rooting systems above that required for structural purposes.

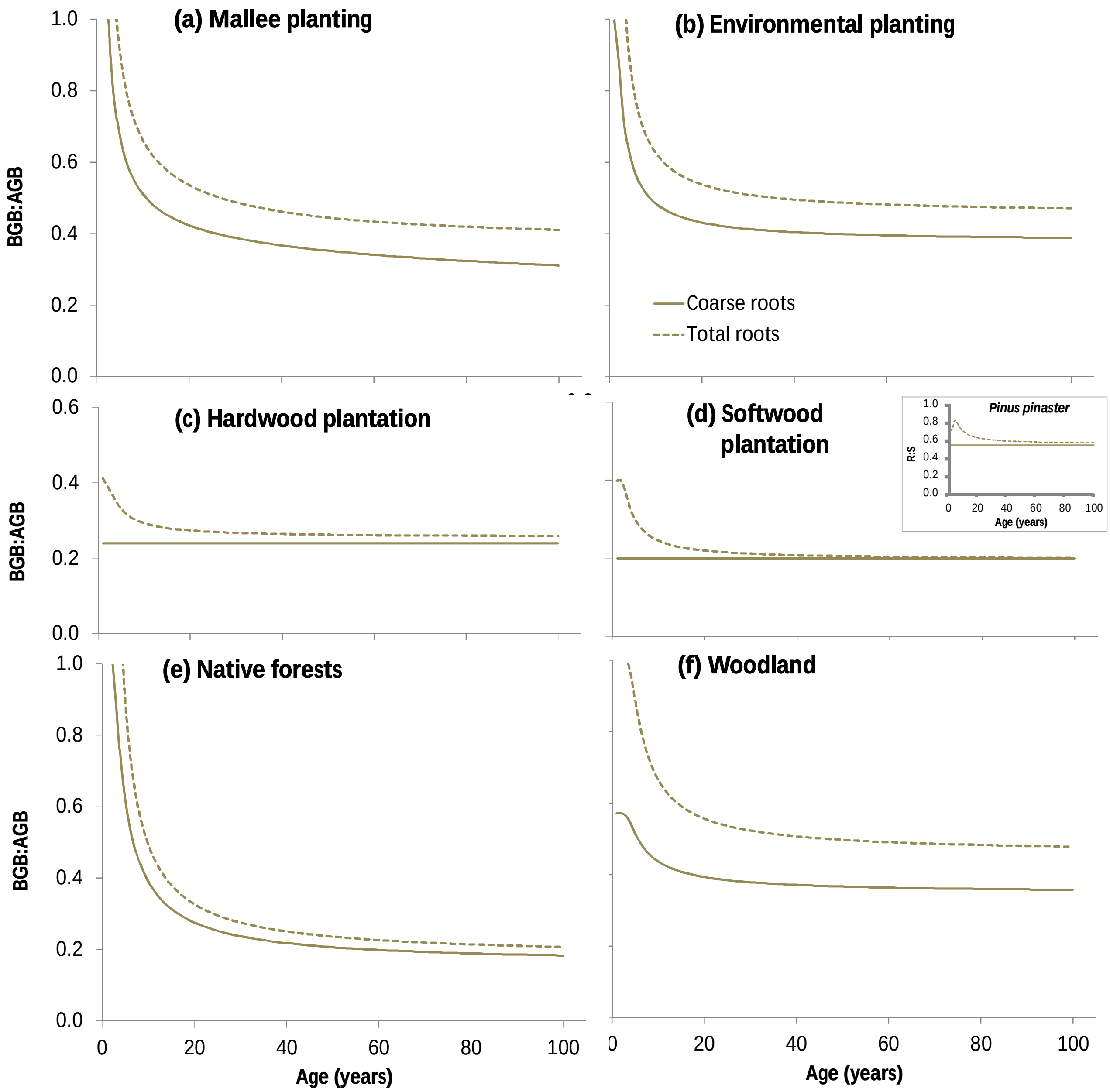

Figure 9: Examples of differences in BGB$_C$:AGB between the key categories of forest types. In (a), the mallee plantings were *E. loxophleba lissophloia* established as wide belts in a low rainfall region. In (b), the environmental planting was established in a region of low rainfall in a block configuration with a tree-dominant species mix using standard densities. In (c), the hardwood plantation was *E. globulus* established in the south-west of Western Australia. In (d), the softwood plantation was *P. radiata* established in the East Gippsland region of Victoria, with output in the box showing the *P. pinaster* established in south-west of Western Australia. In (e) and (f) the native systems were Eucalyptus Tall Open Forest in regions of high rainfall, and Eucalyptus Open Woodland in regions of low rainfall, respectively.

Growth habits of mixed-species plantings, forests, woodlands or shrublands

Although there are broad differences in BGB$_C$:AGB between key forest types, within stands of mixed-species, some additional variability in BGB$_C$:AGB can be attributable to the relative mix of trees to shrubs. Results indicate that for environmental plantings, BGB$_C$:AGB was higher in stands dominated by trees (PropEuc≥0.75) relative to that found in stands with a good mix of trees and shrubs (PropEuc<0.75), especially in regions of low rainfall (Table 16; Fig. 10a).

These results were consistent with previous work showing that at the stand-scale, allocation to BGB in shrubs or under-story species is relatively small compared to over-story species (Westman & Rogers 1977; Ash & Helman 1990; Gonzalez *et al*. 2013). As discussed above, shrubs have shallower rooting systems than trees as they tend to be smaller, thereby they do not have the same evolutionary pressure as trees to develop the large structural roots that contain large quantities of biomass (e.g. Ludwig 1977; Wilson 1993b; Keith *et al*. 2000).

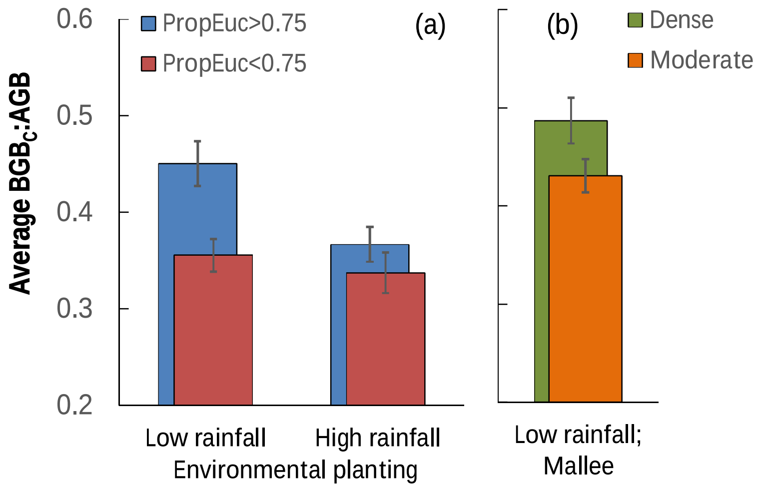

Figure 10: Average BGB_C:AGB in: (a) low and high rainfall environmental plantings that were either tree dominant (PropEuc≥0.75), or had a good mix of trees and shrubs (PropEuc<0.75), and; (b) low rainfall mallee plantings established in wide belts of either high density (≥2,300 sph) or moderate-low density (<2,300 sph). In (a), averages were obtained from across plantings of various configurations and stand densities. In (b), averages were obtained from across plantings of various species.

In some cases, there may however be a confounding influence of MAR on BGB_C:AGB in stands with relatively high proportions of shrubs. For example, woodland/shrublands appeared to have relatively high proportions of shrubs than native forests (Tables 3 & 6). Despite this, woodland/shrublands had significantly higher BGB_C:AGB than native forests (Table 17). As discussed below, this was presumably due to the fact that woodland/shrublands are generally from regions of relatively low rainfall when compared to native forests.

Stand biomass and age

The relatively large BGB_C:AGB dataset for environmental and mallee plantings enables the assessment of the impacts of stand biomass and age on partitioning to BGB. The observed influence of AGB on BGB_C:AGB was consistent with previous reviews of collated datasets for forests and woodlands showing that BGB_C:AGB decreases significantly as the AGB increases (e.g. Ovington 1957; Applegate 1982; Negi & Sharm 1985; Ruark & Bockeim 1987; Gerhardt and Fredriksson 1995). For example, Mokany *et al*. (2006) found temperate eucalypt forests/plantations of AGB <50, 50-150 or >150 Mg ha^{-1} had BGB_C:AGB of 0.44, 0.28 and 0.20, respectively (N=10, 11 and 6).

The influence of AGB on BGB_C:AGB has been attributable to the ‘functional equilibrium’ theory; BGB_C:AGB will be determined by the equilibrium between AGB and BGB to ensure that the assimilation of C by the AGB is kept in balance with the uptake of water and nutrients by the BGB (e.g. Brouwer 1963). This theory may explain why factors resulting in an increase AGB will have a negative influence on BGB_C:AGB (e.g. Nihlgård & Lindgren 1977; Keyes & Grier 1981; Brown & Lugo 1982; Nadelhoffer *et al.* 1985; Murphy & Lugo 1986; Roa-Fuentes *et al*. 2012; Gower *et al*. 1992; Brand 1999; Cairn *et al*. 1997).

Accumulation of AGB can be related to stand age for monoculture plantings established within a constrained range of climates. This may explain why for mallee eucalypt plantings, stand age was also a significant factor explaining variations in BGB_C:AGB. In contrast, for mixed-species forests established across a much greater diversity of climates and mix of species, stand age had little impact on BGB_C:AGB.

Hence, the observed decline in BGB_C:AGB with increased stand age in Fig. 9 is largely attributable to the fact that AGB is increasing with stand age, and is perhaps often not directly related to stand age per se.

A caveat on the results obtained was that the most of the environmental and mallee plantings studied (Table 5) were relatively young, with the 95th percentile of stand age in study sites being only 24 and 14 years for the mixed-species forests and mallee eucalypt plantations, respectively (Paul *et al*. 2013a,b; 2014a). This fact may partly contribute to the relatively high BGB_C:AGB observed. To improve our understanding of the impacts of stand age and AGB on BGB_C:AGB, further work is required to expand the BGB_C:AGB datasets for more mature stands of a wider range of forest types.

Climate

Results obtained suggest that the only impact of MAR on BGB_C:AGB of stands studied here was an indirect via AGB. Our results indicated that BGB_C:AGB was not statistically influenced by MAR per se. This was consistent with the fact that BGB_C allometry was not significantly influenced by MAR (Paul *et al*. 2014a). This may be partly explained by the fact that most (87%) of the datasets collated were from MARs of only 250-850 mm yr^{-1}, with relatively few (<10%) from regions where MAR>1,500 mm yr^{-1}. Differences in the range of MARs considered may explain why some workers have found MAR influences BGB_C:AGB (e.g. Nihlgård & Lindgren 1977; Keyes & Grier 1981; Brown & Lugo 1982; Nadelhoffer *et al*. 1985; Murphy & Lugo 1986; Roa-Fuentes *et al*. 2012; Gower *et al*. 1992; Brand 1999; Comeau & Kimmins 1989), while others have found the opposite (Cairns *et al*. 1997; Compton *et al*. 1999; Joslin *et al*. 2000). For example, Mokany *et al*. (2006) found a trend of decreased BGB_C:AGB with increased MAR, but that this trend was only apparent when including BGB_C:AGB datasets from sites with MARs>1000 mm yr^{-1}. There was no effect in lower MAR regions. Further work is required to verify these findings for Australian forest types.

Stand density

Evidence was obtained from this study that the BGB_C:AGB of individual trees (but not shrubs) increases inversely with stand-average stem diameter (Fig. 6b), which in turn increases inversely with stand density (Fig. 8). Therefore, consistent with the findings of others others (Pearson *et al*. 1984; Litton *et al*. 2003; Luo *et al*. 2014), stands with higher density had higher BGB_C:AGB (e.g. Fig. 10b). Indeed in a global review, Mokany *et al*. (2006) reported that BGB_C:AGB of forests and woodlands tended to increase with stand density.

In contrast, other studies have found smaller BGB_C:AGB with increased stand density (Puri *et al*. 1994; Ritson & Sochacki 2003), presumably because these trees were competing for light. The 'functional equilibrium' theory might be used to infer either an increase or decrease in BGB_C:AGB with stand density, depending on whether trees were predominately competing for water (which results in a relative increased BGB allocation) or light (which results in a relative increased AGB allocation) (van Wijk *et al*. 2003; Comeau & Kimmins 1989; Wilson 1993; Litton *et al*. 2003). As most of the stands of environmental and mallee plantings studied were in regions of low-moderate average MAR (87% of the dataset from regions with MAR of only 250-850 mm yr^{-1}), it is anticipated that they were predominately competing for water, particularly for older stands in block planting configurations.

Given these conflicting results, it is recommended that additional datasets be collated in order to ascertain the impact of stand density on BGB_C:AGB for different forest types, climatic conditions and planting configurations.

3.2 Litter fall

The sample numbers (N) were relatively high for measurement of foliage litter fall, but relatively low for the twig and bark litter fall (Table 19). As a result, there was evidence to justify differing rates of foliage litter fall for the five different forest types (Table 20). Results suggested that average rates of foliage litter fall tended to increase with decreasing aridity of climates in which the forest generally grows; woodlands

< environmental and mallee plantings < native forests < softwood plantations < hardwood plantations. In contrast, given the lack of statistical differences between forest types, an overall average rates of litter fall were applied across all forests for twigs (8.5 % yr^{-1}) and bark (4.8% yr^{-1}) (Table 20).

Table 19. Mean (as well as standard deviation, SD; and range, Min and Max) observed rates of litter fall under five contrasting forest types, and the mean (as well as standard deviation, SD; and range, Min and Max) observed percentage contribution of this litter fall from foliage, twigs and bark litter. The sample numbers (N) were relatively high for measurement of total litter fall and foliage litter fall, but relatively low for the twig and bark litter fall.

Forest type	Annual litter fall (Mg DM ha^{-1} yr^{-1})	Mean	SD	Min	Max	N
Env. plantings	Total	3.26	0.47	2.49	3.65	4
	%Foliage	40	14	17	55	4
	%Twig	NA	NA	NA	NA	NA
	%Bark	NA	NA	NA	NA	NA
Native forests	Total	5.11	2.06	1.13	10.4	83
	%Foliage	58	12	28	89	58
	%Twig	19	7	1	32	43
	%Bark	16	10	2	46	30
Woodland	Total	1.92	0.97	0.72	5.14	24
	%Foliage	49	16	22	73	8
	%Twig	28	8	20	39	6
	%Bark	6	3	20	10	5
Hardwood plantation	Total	5.58	2.54	1.72	9.60	16
	%Foliage	78	20	51	98	3
	%Twig	5	4	0	9	2
	%Bark	4	2	1	6	2
Softwood plantation	Total*	2.83	1.05	1.30	6.00	29
	%Foliage	68	15	51	98	8
	%Twig	14	7	0	21	7
	%Bark	8	4	1	13	7

*Total litter fall was attributable to pine needles.

Table 20. Calculated average rates of litter fall for the foliage, twigs and bark under contrasting forest types. Within each column, estimates with differing letters represent significant (P<0.05) differences were found between forest types.

Forest type	Foliage (% yr^{-1})	Twigs (% yr^{-1})	Bark (% yr^{-1})
Env. plantings	15.7 ^{b,c}	NA	NA
Native forests	30.3 ^{b}	9.6 ^{a}	5.6 ^{a}
Woodland	14.3 ^{c}	7.2 ^{a,b}	4.3 ^{a,b}
Hardwood	40.4 ^{a}	4.7 ^{b}	2.5 ^{b}
Softwood	31.2 ^{a,b}	NA	NA
Total	28.7	8.5	4.8

3.3 Decomposition of litter

Table 21 provides the parameters for the emprical exponential decay models (Section 2.3) that were calibrated to the datasets collated from litter bag studies. For deadwood and bark, there was clear evidence that a sinlge exponential decay model is suffice (Eq. 1, Section 2.3), while for foliage litter, a double exponential decay model is required (Eq. 2, Section 2.3). Therefore, deadwood and bark litter were both be assumed to be 100% resistant, and thereby the W_l parameter was not required (Table 21). The collated datasets for eucalypt-dominant stands indicated that typical resistant fractions for foliage litter was 77%, with the remaining 23% therefore being decomposable (Table 21). Pine needs were more recalcitrant, with the collated datasets for softwood plantations indicating that typical resistant fractions are 85%, with the remaining 15% therefore being decomposable. Based on these findings, revised FullCAM parameter for resistant fraction of foliage debris was set to 85% for softwood plantaitons, and 77% for all other forest types.

Decomposition rates for deadwood and bark indicated that on average, 14% of deadwood would be lost after 1 year, while 16% of bark litter would be lost after 1 year (Table 21). In the absence of data to justify otherwise, it was assumed that all forest types had the same decomposition rates for deadwood and bark litter. Rates of deadwood decomposition decline exponentially as the diameter of the wood increases (Mackensen and Bauhus 1999).

The decomposition rates of 14% yr^{-1} for deadwood (*k* of 0.14) was consistent with twigs and small branches (<10 cm diameter). Much slower rates of decomposition (i.e. *k* of 0.07 to 0.01 as diameter decreases from 10 cm to 100 cm diameter) are anticipated for larger branches and logs in coarse woody debris (CWD, Mackensen and Bauhus 1999). Further work may therefore be required to further refine rates of decomposition under FullCAM scenarios where significant amounts of CWD remains on-site as 'slash' post disturbance events such as fire or thinning/clearing. One options currently being explore is to effectively slow the decomposition of slash via the simulation of a 'standing dead' pool of debris, with C from this pool only slowly becoming available for decomposition.

For foliage litter, rates of decomposition for decomposable components exceeded the allowable maximum in FullCAM of 100% yr^{-1}; avering 1,316% yr^{-1} under eucalypt-dominant stands, and 327% yr^{-1} under softwood plantations (Table 21). Therefore, for all forest types, the revised parameter for decomposable pools of foliage litter was set to the maximum rate of decomposition; 100% yr^{-1}. The more reclcitrant resistant pool of folliage litter decomposed an an average rate of 32% yr^{-1} under eucalypt-dominant stands, and 22% yr^{-1} under softwood plantations. However as indicated in Table 21 through the 20th and 80th percentiles observed, there was much variation in these estimates between studies. Indeed this variation was between 18-27% yr^{-1} under eucalypt-dominant stands, and between 15-27% yr^{-1} under softwood plantations. Given the larger variation in observed rates of decomposition of foliage litter, and because it is anticipated that decomposition in litter bags may be faster than undisturbed foliage litter, the conservative approach of using a slightly lower rate than the average observed was applied. Hence, revised parameter values in FullCAM for decomposition of resistant pools of foliage litter were assumed to be about 10% less than the average observed; or 28% yr^{-1} under eucalypt-dominant stands, and 20% yr^{-1} under softwood plantations.

Table 21. Average (and range, based on the 20th and 80th percentiles) labile component present in a litter fraction (W_l, or the fraction of debris that is decomposable, with the rest being resistant), instantaneous decay constant of resistant debris (*k*, or % debris lost after 1 year), and the instantaneous decay constant for the decomposable debris (*k'*, or % debris lost after 1 year).

Forest type	Litter type	N	W_l	*k*	*k'*
Eucalypt-dominant	Deadwood	23	NA	14 (9-21)	NA
Eucalypt-dominant	Bark litter	13	NA	16 (13-22)	NA
Eucalypt-dominant	Foliage litter	59	23 (18-27)	32 (14-47)	1316 (234-1570)
Softwood	Pine needle litter	28	15 (8-19)	22 (15-27)	327 (20-500)

When applying these revised parameter values for decomposition, the predicted rates of loss of pools of deadwood, bark litter and foliage litter were reflective of that expected based on the observed typical decay functions for these pools (Fig. 11). The slight variation between FullCAM-predicted rates of decomposition of a given component of debris (e.g. for deadwood, as shown in box inserted in Fig. 11a) was attributable to the differing temperature and rainfall among the various locations simulated, with these affecting decomposition rates in accordance with the 'Mulch-style' sensitivity (Section 2.3).

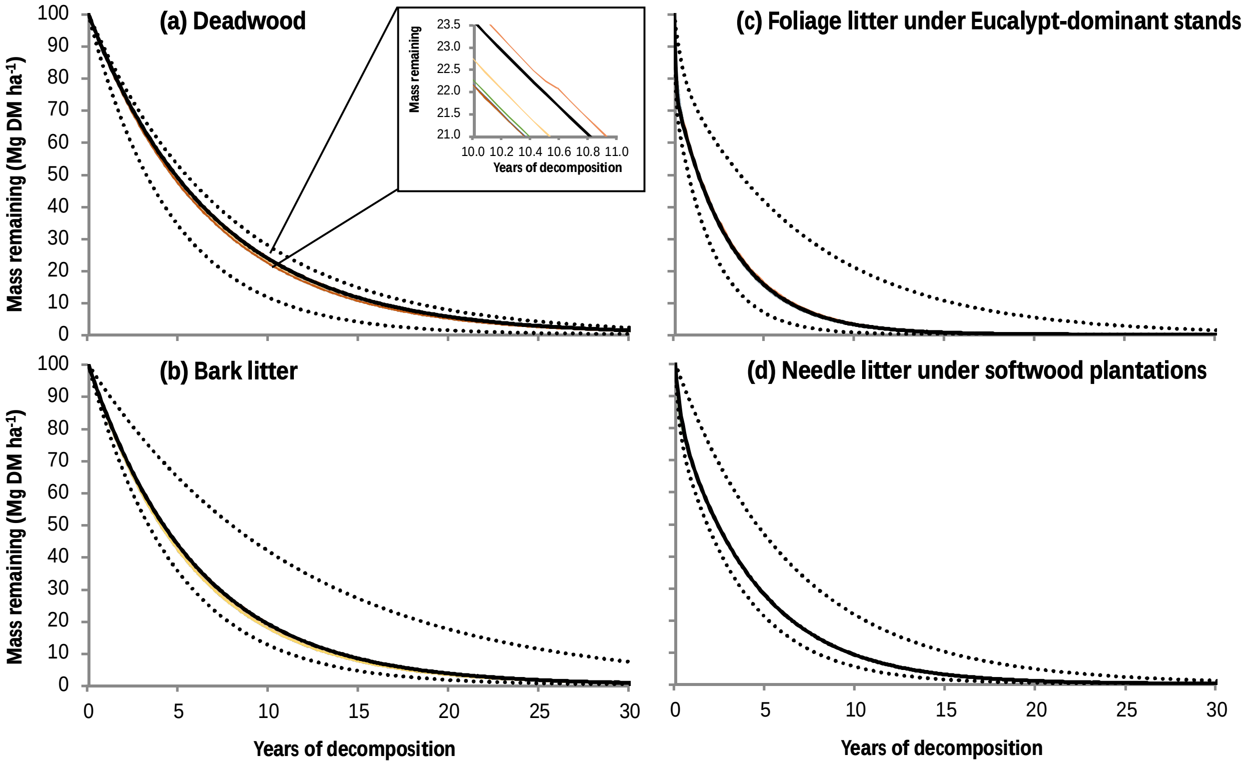

Figure 11. Simulated decomposition of 100 Mg DM ha^{-1} of deadwood and various types of litter when applying the revised litter decomposition parameters together with the 'Mulch style' sensitivity to temperature and rainfall. Simulations were for the 41 example plot files outlined in Table 8, but which were configured such that there was no forest growth, and the initial pools of debris were 100 Mg DM ha^{-1}. Although outputs from all 41 plot files are included, as indicated in the box in (a), these are difficult to distinguish given there was little variation in outputs between plots; especially those from similar climates. Solid black line represent the average observed decay functions as outlined by parameters provided in Table 21. Dashed black lines represent the observed decay functions when the 20th and 80th values were applied for the decay functions parameter (Table 21).

Figure 12 summarises predicted litter and CWD in the 41 representative plots files (Table 8), and that observed across different Australian forest types (Table 11). The average predicted litter and CWD across multiple rotations of the hardwood and softwood plantations were in general agreement with the averages observed, particualrly given the relatively large SD in the average observed, and the fact that observations of litter and CWD were made under stands of varying ages and management regimes. Similalry, for relatively young (20 year old) environmental and mallee plantings, and for mature (100 year old) native systems, predictions of litter and CWD were in broad agreement with the averages observed. The upper bounds of litter and CWD expected were represented by that predicted to be on-site as residue or slash following a harvesting event (stripped bars, Fig. 12). As expected, observed averages of litter and CWD were well below this predicted 'upper limit'. The only exception was for under softwood plantations where CWD in harvest residues appears to be under-predicted on average. However, in these stands the variation in observed CWD was relatively high, as indicated by the relative high SDs for softwood plantations (Fig. 12b).

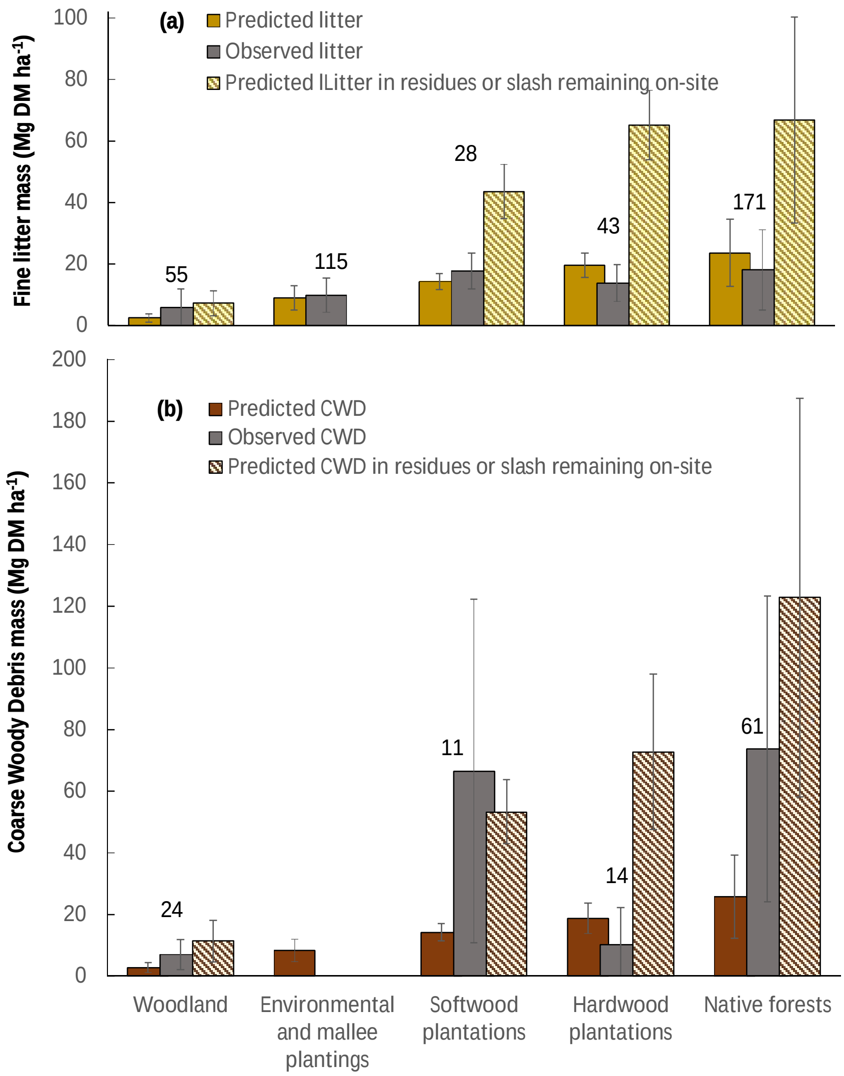

Figure 12. Predicted and observed (a) litter mass, and (b) coarse woody debris (CWD) under various forest types, including: mature (100 year) woodlands; relatively young (20 year) environmental and mallee plantings; softwood plantations of multiple rotations; hardwood plantations of multiple rotations, and; mature (100 year) native forests. For woodlands and native forests, predictions are at 100 years when left uncleared, and when assumed to be cleared the year 99 of simulation. For plantations, predictions the average observed across multiple rotations simulated over a 100 year period, or that predicted in the year post the final clearing event. Number labels represent the number of observations that were used to calculated the average observed litter or CWD. Error bars represent the standard deviations of the means. Predicted means were based on the simulation of 5 woodlands, 21 environmental or mallee plantings, 5 softwood plantations, 6 hardwood plantations, and 4 native forests (Table 8).

3.4 Parameters influencing soil C

Figure 13 shows the efficiency of prediction of pools of soil C across the 158 forest sites where pools of soil C were measured (Table 12), and where parameters calibrated to achieve these efficiencies included root turnover and decomposition, and CO_2-C loss on decomposition of debris. Overall, the efficiency of prediction of total soil C was 46%. For the two largest pools of this soil C, the efficiencies of prediction were 36% for RPM, and 73% for HUM. These efficiencies of prediction of pools of soil C were relatively high given: (i) the RothC parameters recommended by Chappell and Baldock (2013) for agricultural soils was assumed to apply here for forest soils, (ii) large uncertainties in measurement of pools of soil C, mainly due to sampling errors (Cunningham *et al.* 2017); (iii) large uncertainties in the measured biomass that were used to constrain the predictions (Paul and Polglase 2004b; Paul *et al.* 2017b), and; (iv) the application of the revised generic default parameters for allocation of biomass, litter fall and decomposition of litter across all 158 calibration sites, despite observations of these pools and fluxes at these sites suggested significant site-to-site variability.

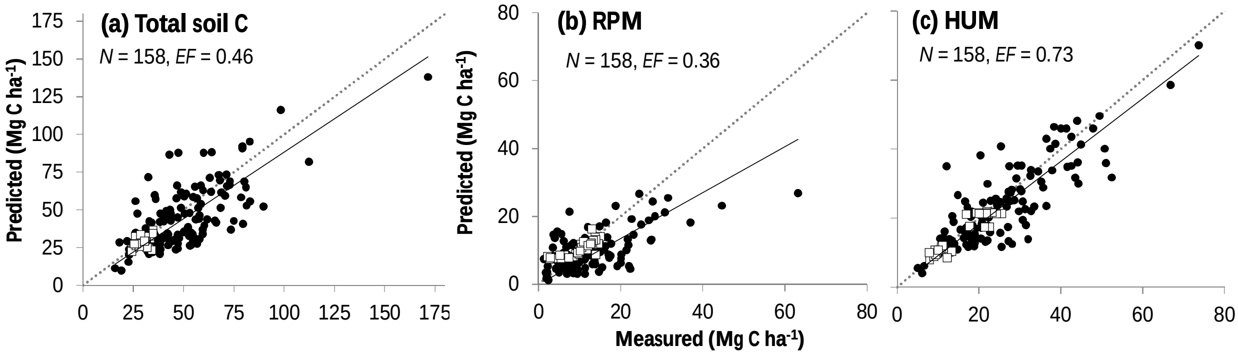

Figure 13. Relationship between observed and predicted carbon stocks (Mg C ha^{-1}) in surface soil (0-30 cm) for: (a) total soil organic carbon; (b) RPM pool of soil C; and (c) HUM pool of soil C. Datasets used are listed in Table 12. Black circles represent the paired-site environmental plantings (Paul *et al.* 2017b). White squares represent the hardwood and softwood repeated-measured forestry trials (Paul and Polglase 2014b).

The calibrated rates of root turnover were 10% yr^{-1} for coarse roots and 80% yr^{-1} for fine roots. Decomposition rates were calibrated to be 30% yr^{-1} for coarse roots and 100% yr^{-1} for fine roots. These values were applied across all forest types.

In contrast, when calibrating the parameters for CO_2-C loss on decomposition of debris across the 158 sites, it was found that as stands matured and a litter layer developed, inputs of C into the soil from debris decomposition needed to be decreased. In the absence of any clear justification for a relationship between CO_2-C loss and the development of a litter layer, it was simply assumed here than stands <10 years old had higher rates of C entering the soil (i.e. lower CO_2-C loss) from debris decomposition than did older stands. Highest model efficiencies were attained when CO_2-C loss on decomposition of decomposable and resistant pools of debris were 77^{-1} and 40 % yr^{-1} for stands <10 years old. For stands older than this, CO_2-C loss on decomposition of decomposable and resistant pools of debris were set to 90^{-1} and 80 % yr^{-1}.

Given the evidence of a decrease in the rates of C input into the soil (as currently simulated by increased CO_2-C loss on decomposition of debris) as stands mature, further research is required to verify this, and ascertain the cause of this decline. Currently in FullCAM, the parameters for CO_2-C loss on decomposition of debris are not able to be varied with stand age; they are set constant for the entire simulation period. Hence, until research has been completed to inform any re-coding of FullCAM, it is recommended that simulations of afforestation of young stands use CO_2-C loss on decomposition of decomposable and resistant pools of debris were 77^{-1} and 40 % yr^{-1}, respectively. But when simulating older stands, such as in deforestation events, the CO_2-C loss on decomposition of decomposable and resistant pools of debris should be set to 90^{-1} and 80 % yr^{-1}, respectively.

3.5 Initialising pools of biomass and debris

At the nominated initial stand age, the revised initial relative allocation of total biomass to the various pools (stem, branches, bark, foliage and coarse and fine roots), were based on the changes to biomass allocation described in Section 3.1 (data not shown). They therefore differed for each of the 51 forest types given their different initial age and/or climatic conditions and growth rates typical of that forest type. The initial debris pool also greatly varied between the 51 forest types, depending on the different initial age and/or climatic conditions and typical growth rates (data not shown).

4 Impacts of the revised parameters

4.1 Approach used

Plot file simulations were used to assess the impact of the revised parameters (Section 3) on C stocks (Section 4.2), and the NIR (Section 4.3). For each parameter revised, @Risk was applied to assess the sensitivities of the change on total on-site C stocks. This was done by applying a uniform probability distribution to each parameter that was revised; with the minimum and maximum range determined by the original and new parameter values. A Monte Carlo analysis was then run (over 10,000 iterations) to observe the impact of this variation in parameter value on the on-site C stocks at a given time step. Due to interactions being important, all parameters were assess during the same Monte Carlo simulation. The only exception were the allocation of biomass input tables. The impact of these parameters had to be analysed separately. This was done by using 40 demonstrative plot files, representing key forests types and their typical management regimes, to indicate the extent of impact on predicted pools of biomass because of the changes to the allocation input tables.

4.2 Impact of changes in parameters on stocks of C

4.2.1 Allocation of biomass

Using collated biomass datasets, the time-series inputs of allocation of biomass to tree components were changed (Section 3.1). The most significant change was a general decrease in allocation to stem wood (Fig. 14), and a general increase in allocation to branch wood (Fig. 15). There was also an increase to foliage allocation for woodlands and shrublands (Fig. 17).

The changes in allocation of AGB discussed above do not affect the total biomass C per se (as AGB is determined by the TYF), and therefore only influence the C budget when there are disturbance or management events, or in terms of input of C into the debris pools via turnover. In contrast, the allocation to BGB_C directly affects total biomass C. Changes in BGB_C:AGB ratios are therefore of particular interest. For planted systems, the BGB_C:AGB increased, with this being particularly pronounced for mallee plantings, environmental plantings, and *Pinus pinaster* plantations (Fig. 20). In contrast, for native systems the allocation to roots was previously set relatively high, particularly for many woodlands and shrublands where there was generally a decrease in the BGB_C:AGB.

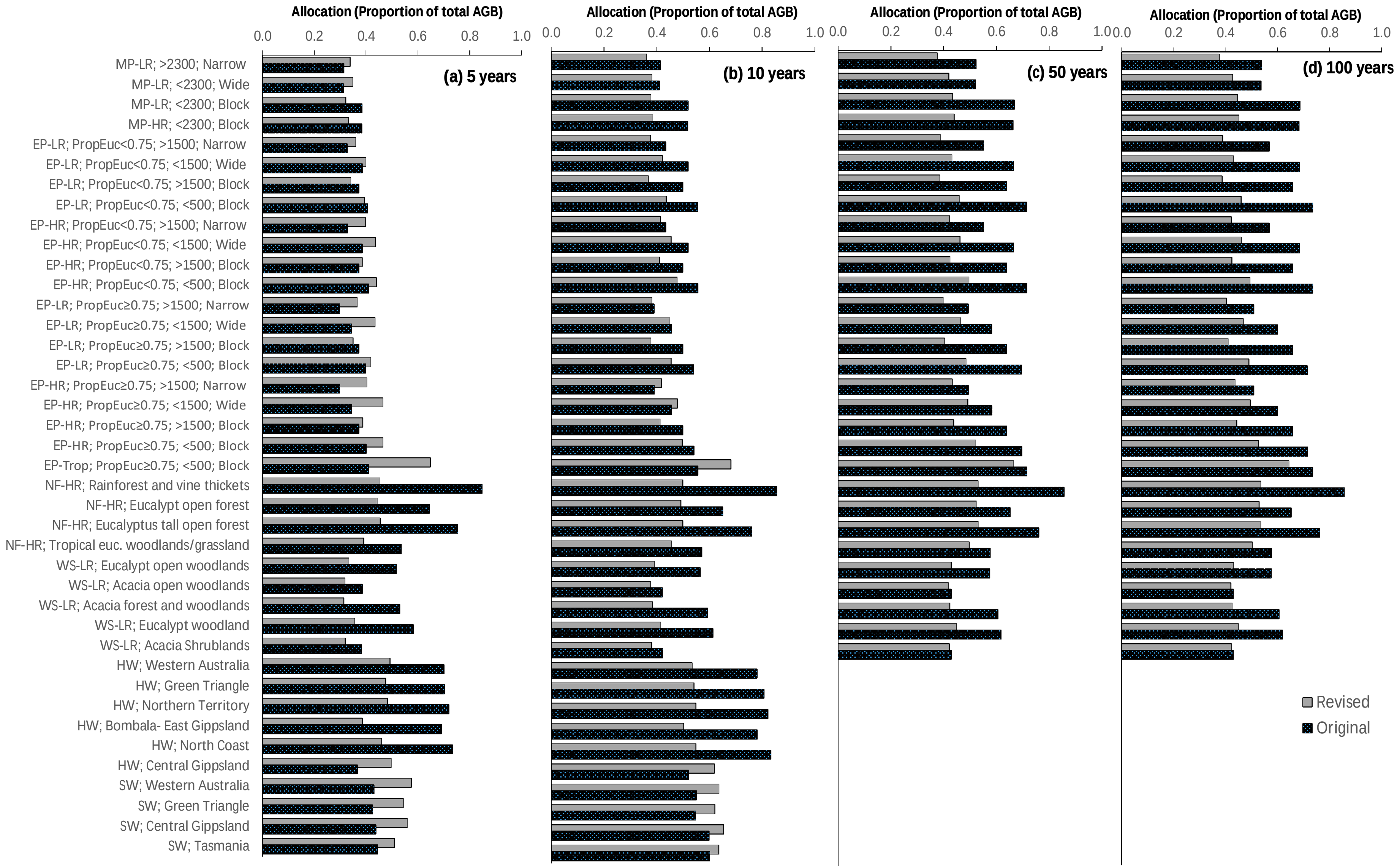

Figure 14: Comparison of revised Calculator-predicted proportion of AGB that is **stem wood** biomass and that predicted using the original FullCAM defaults at stand age of: (a) 5 years; (b) 10 years; (c) 50 years, and; (d) 100 years. Abbreviations of the different scenarios of forest types are provided in Table 8, with each being simulated under average values of *M* for the specific domain of that forest type.

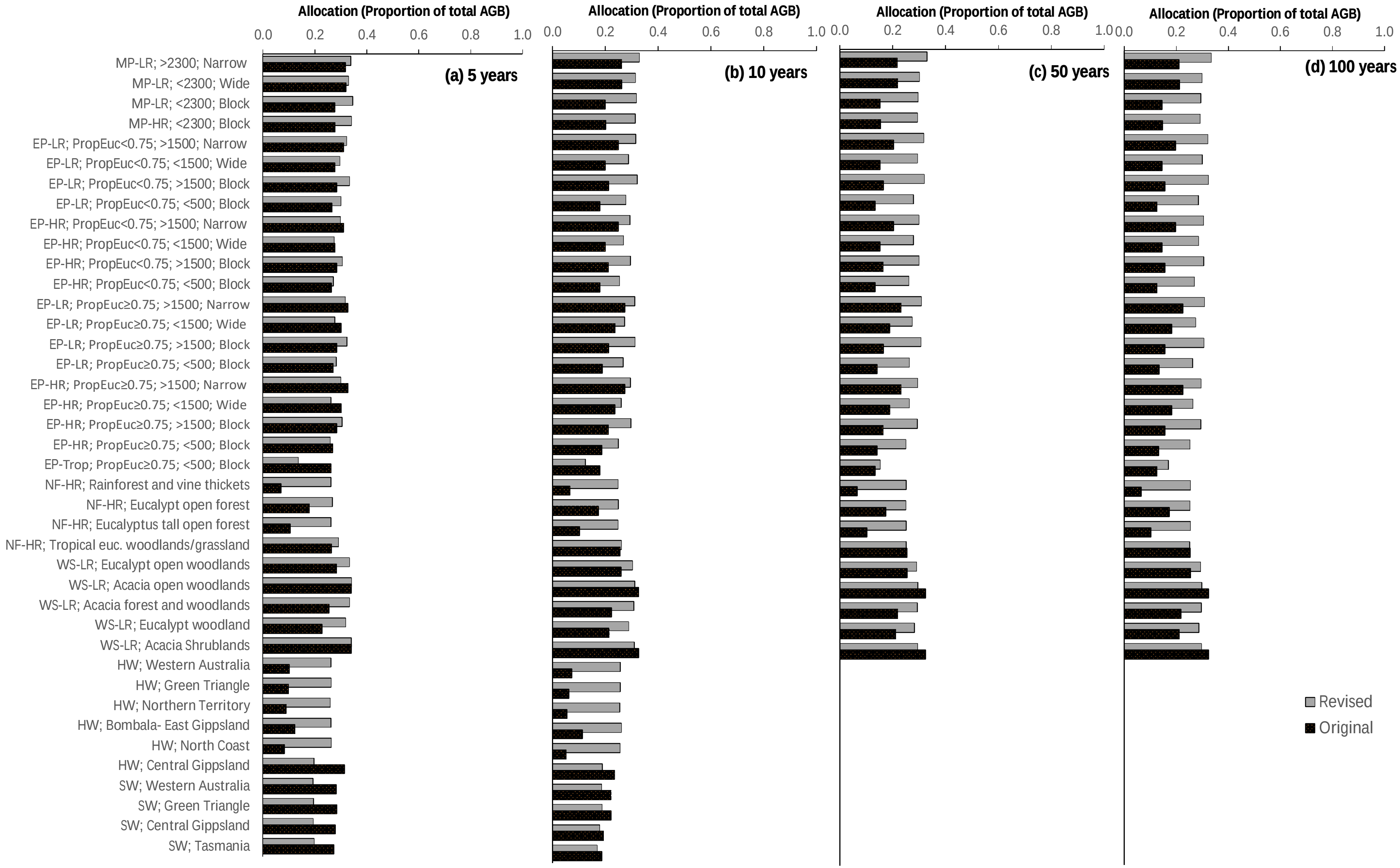

Figure 15: Comparison of revised Calculator-predicted proportion of AGB that is **branch** biomass and that predicted using the original FullCAM defaults at stand age of: (a) 5 years; (b) 10 years; (c) 50 years, and; (d) 100 years. Abbreviations of the different scenarios of forest types are provided in Table 8, with each being simulated under average values of *M* for the specific domain of that forest type.

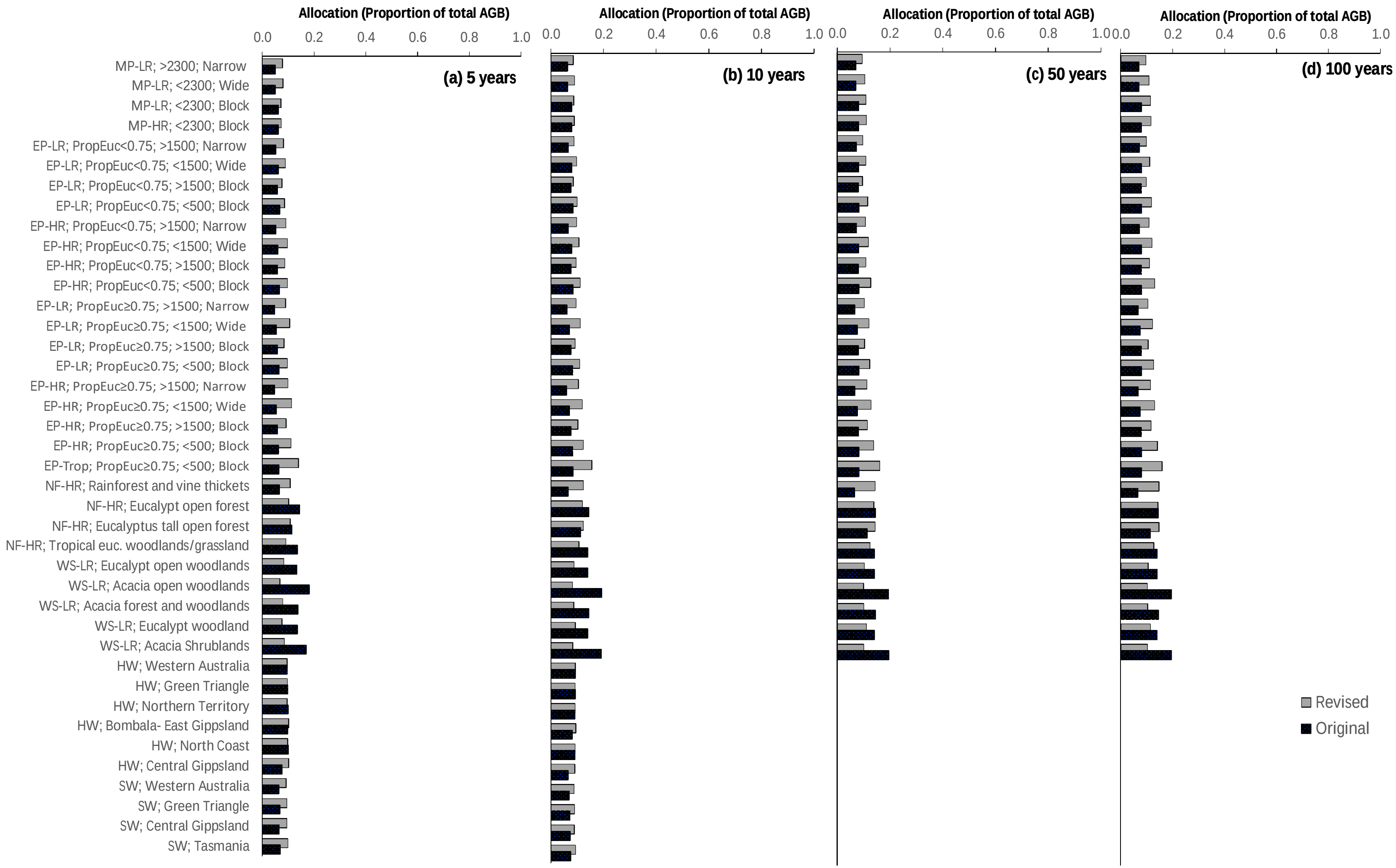

Figure 16: Comparison of revised Calculator-predicted proportion of AGB that is **bark** biomass and that predicted using the original FullCAM defaults at stand age of: (a) 5 years; (b) 10 years; (c) 50 years, and; (d) 100 years. Abbreviations of the different scenarios of forest types are provided in Table 8, with each being simulated under average values of *M* for the specific domain of that forest type.

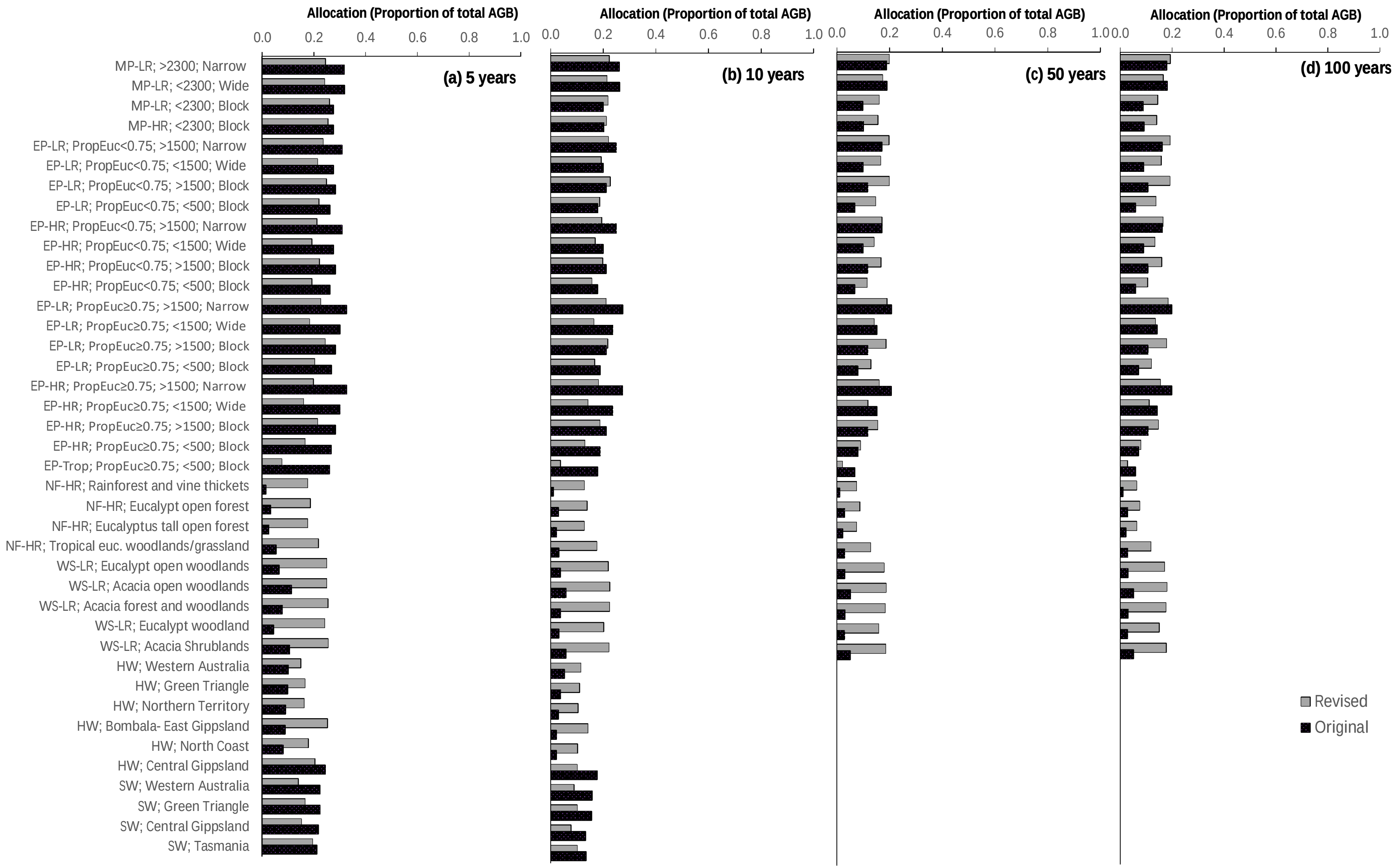

Figure 17: Comparison of revised Calculator-predicted proportion of AGB that is **foliage** biomass and that predicted using the original FullCAM defaults at stand age of: (a) 5 years; (b) 10 years; (c) 50 years, and; (d) 100 years. Abbreviations of the different scenarios of forest types are provided in Table 8, with each being simulated under average values of *M* for the specific domain of that forest type.

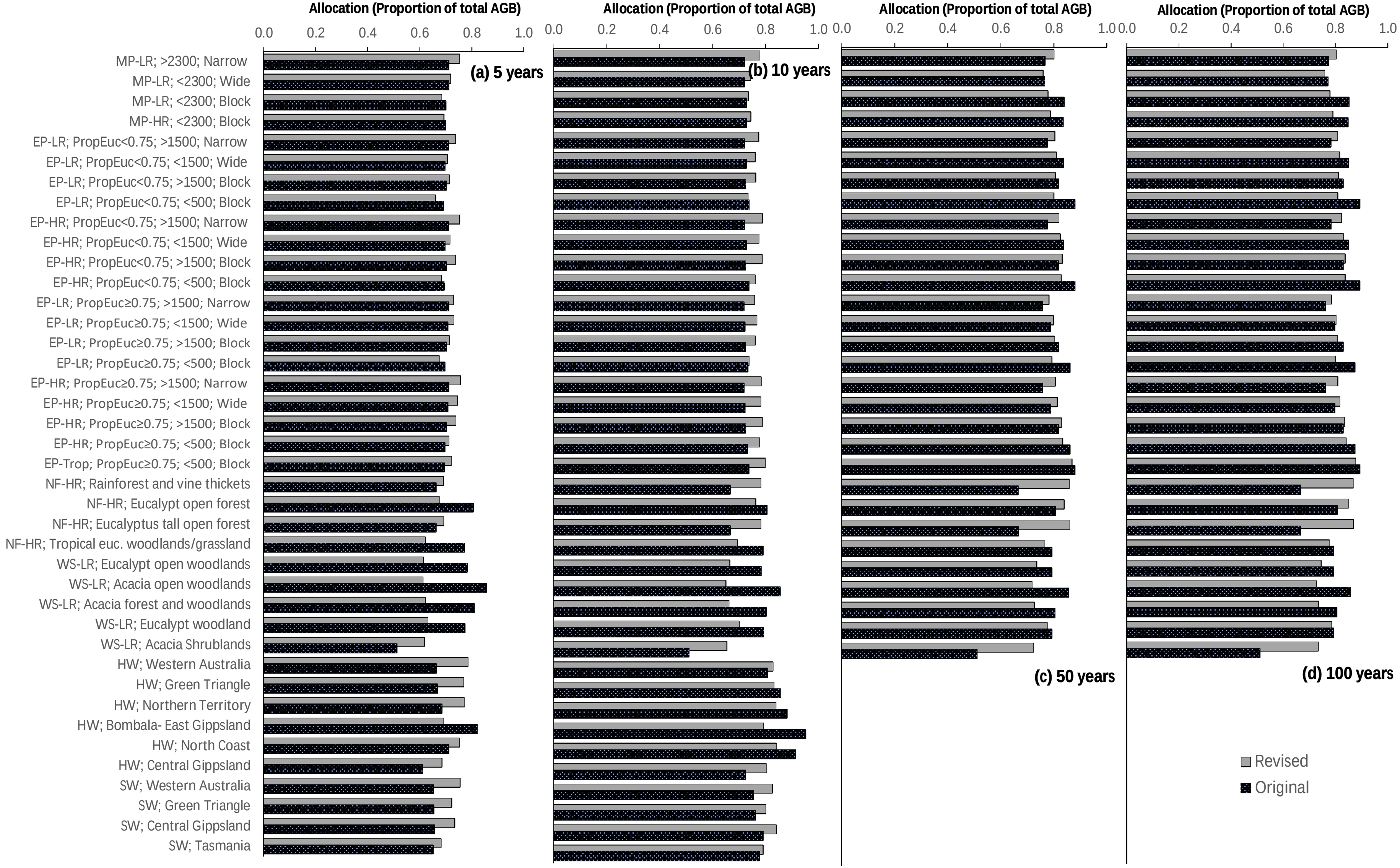

Figure 18: Comparison of revised Calculator-predicted proportion of BGB that is **coarse root** biomass and that predicted using the original FullCAM defaults at stand age of: (a) 5 years; (b) 10 years; (c) 50 years, and; (d) 100 years. Abbreviations of the different scenarios of forest types are provided in Table 8, with each being simulated under average values of *M* for the specific domain of that forest type.

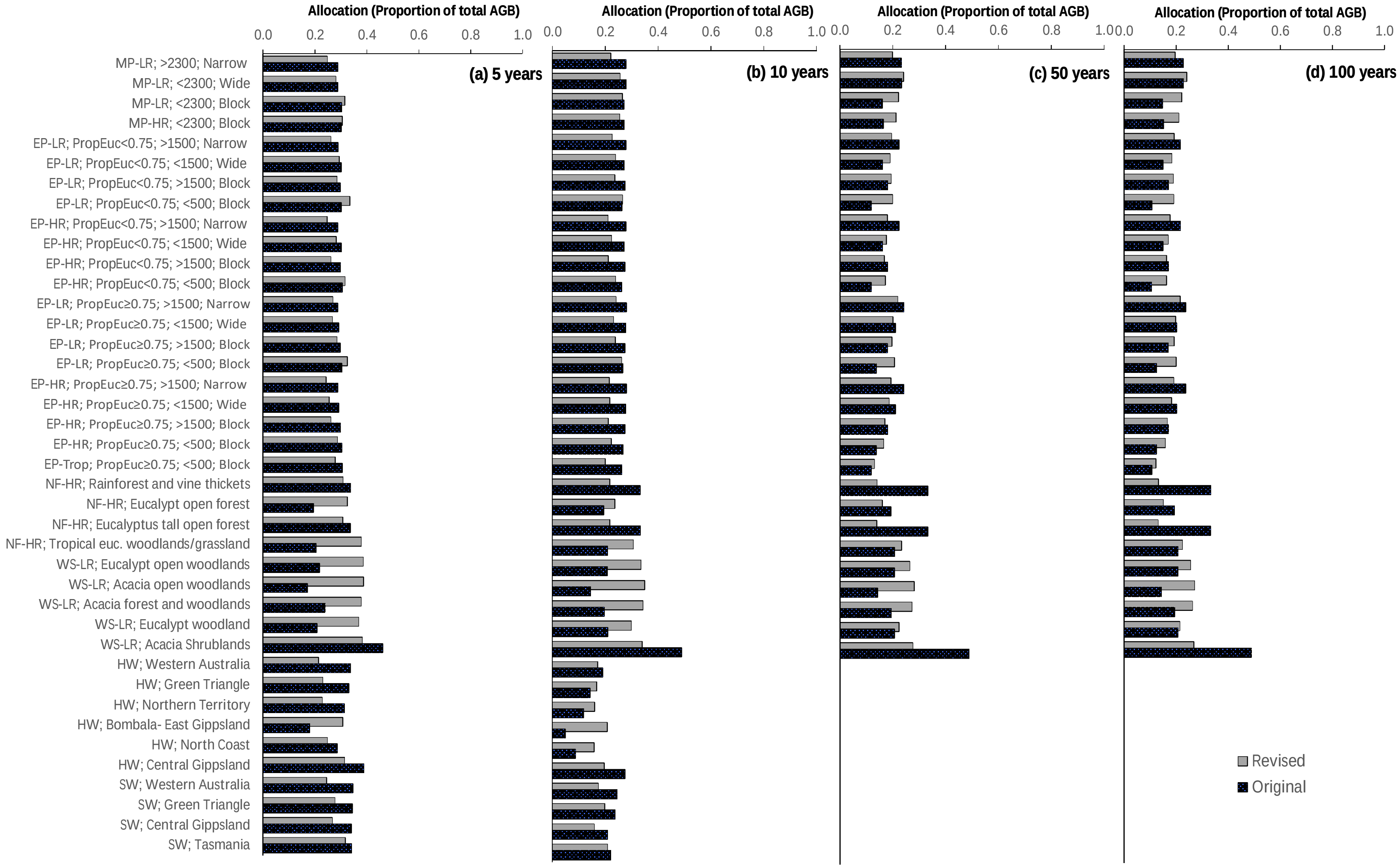

Figure 19: Comparison of revised Calculator-predicted proportion of BGB that is **fine root** biomass and that predicted using the original FullCAM defaults at stand age of: (a) 5 years; (b) 10 years; (c) 50 years, and; (d) 100 years. Abbreviations of the different scenarios of forest types are provided in Table 8, with each being simulated under average values of *M* for the specific domain of that forest type.

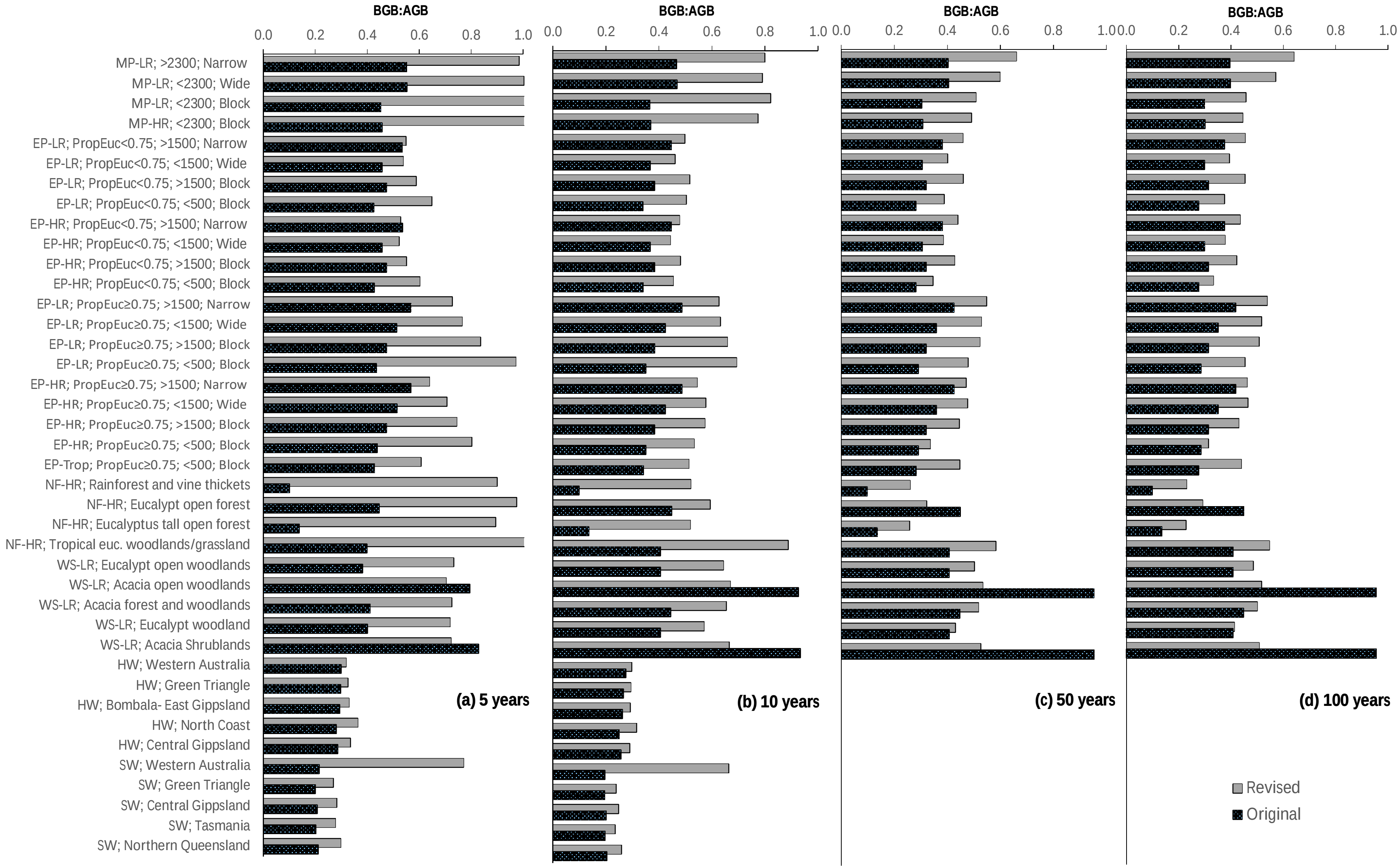

Figure 20: Comparison of revised Calculator-predicted proportion of BGB$_C$:AGB and that predicted using the original FullCAM defaults at stand age of: (a) 5 years; (b) 10 years; (c) 50 years, and; (d) 100 years. Abbreviations of the different scenarios of forest types are provided in Table 8, with each being simulated under average values of *M* for the specific domain of that forest type.

4.2.2 Turnover (litter fall)

Using collated datasets from litter trap studies, the inputs of turnover of tree components were changed (Fig. 21). Due to the error in data entry of turnover inputs for native systems, turnover of all pools significantly increased with the revised inputs. For the planted forests, in general, branch turnover increased (with the exception of environmental and mallee plantings), and bark turnover decreased (with the exception of softwood plantations). When compared to the original defaults, turnover rates of foliage changed little for softwoods, but decreased slightly for other planting types, especially environmental and mallee plantings, and for hardwood plantations.

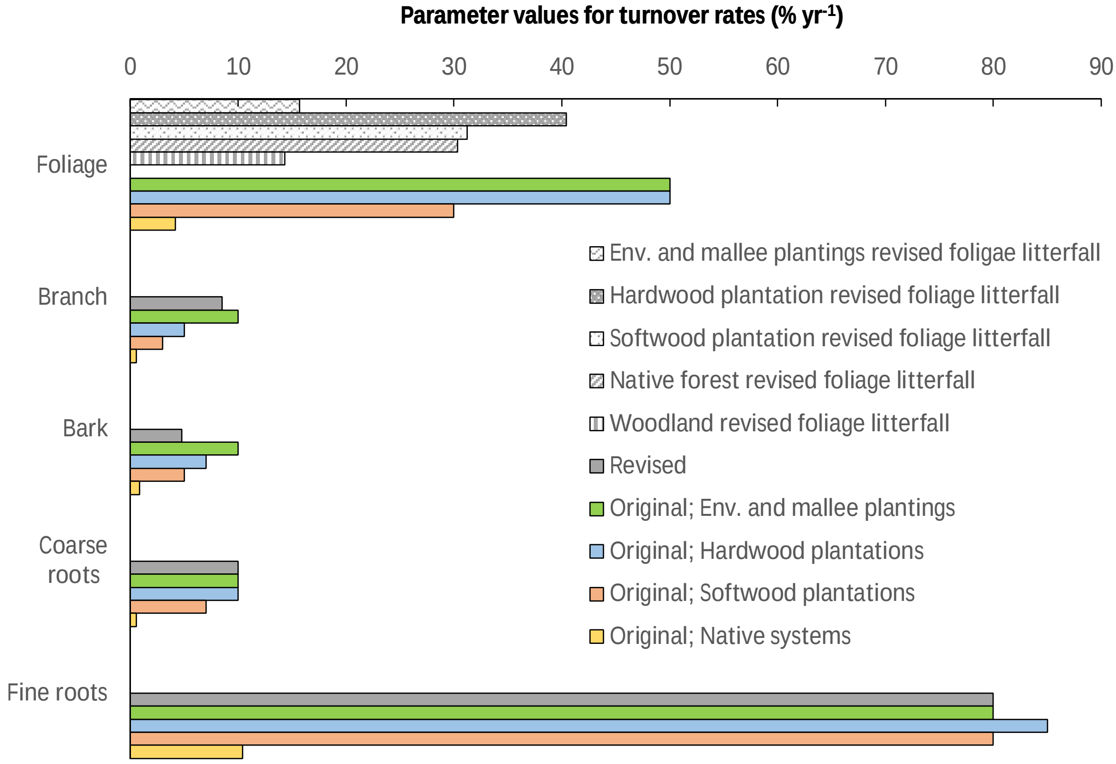

Figure 21: Revised and original parameter values for turnover of the various pools of biomass simulated by FullCAM.

4.2.3 Decomposition of debris

Using collated datasets from litter bag studies, changes were made to the inputs of resistant fractions of debris, breakdown rates and the influence of climate on these rates. It was assumed that all forest types have the same parameters for decomposition until there was evidence to prove otherwise (Fig. 22). As a result, decomposition of pools of debris under native systems were generally slower (particularly for foliage litter, Fig. 23), the only exception being for deadwood and dead fine roots. In contrast, in planted systems, the changes generally resulted in faster rates of decomposition, with the exception of bark litter and dead coarse roots under environmental and mallee plantings.

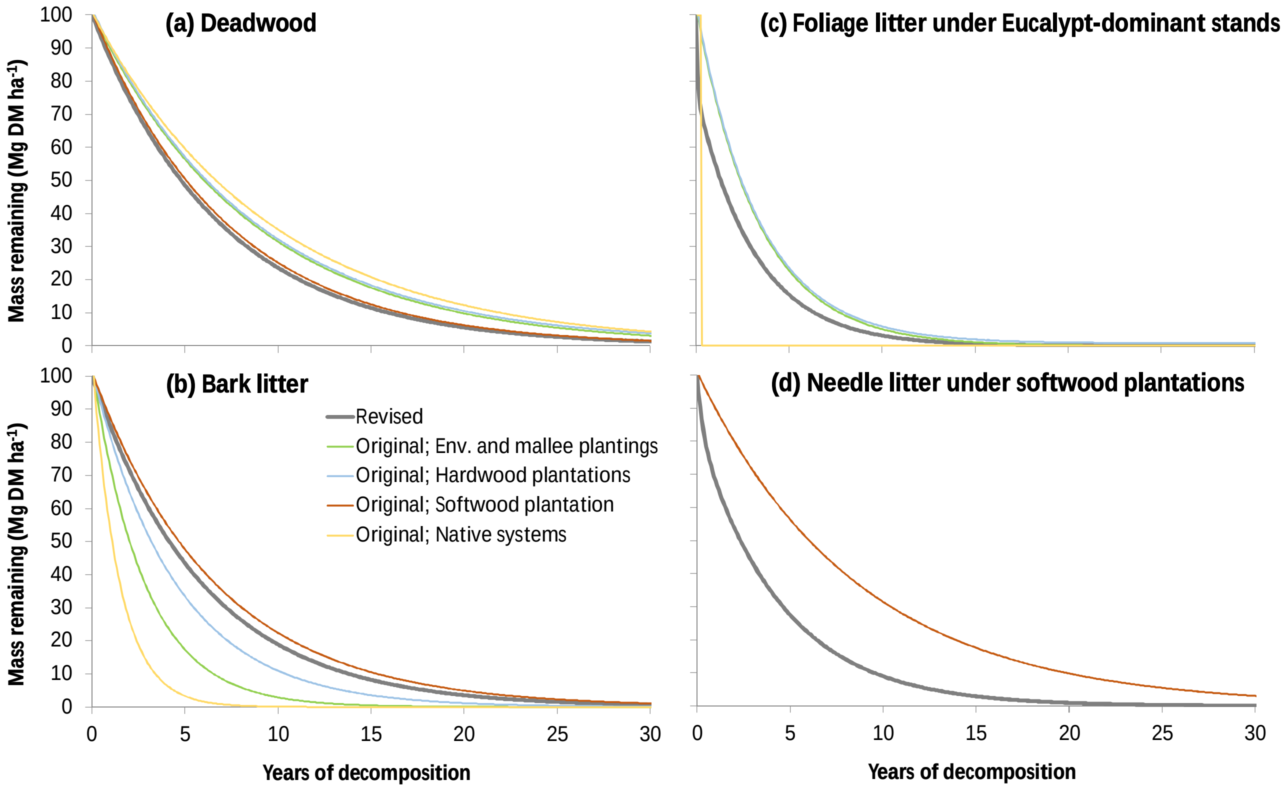

Figure 22: Demonstration of predicted rates of breakdown in of various litter pools of litter when using the revised and original parameters for decomposition.

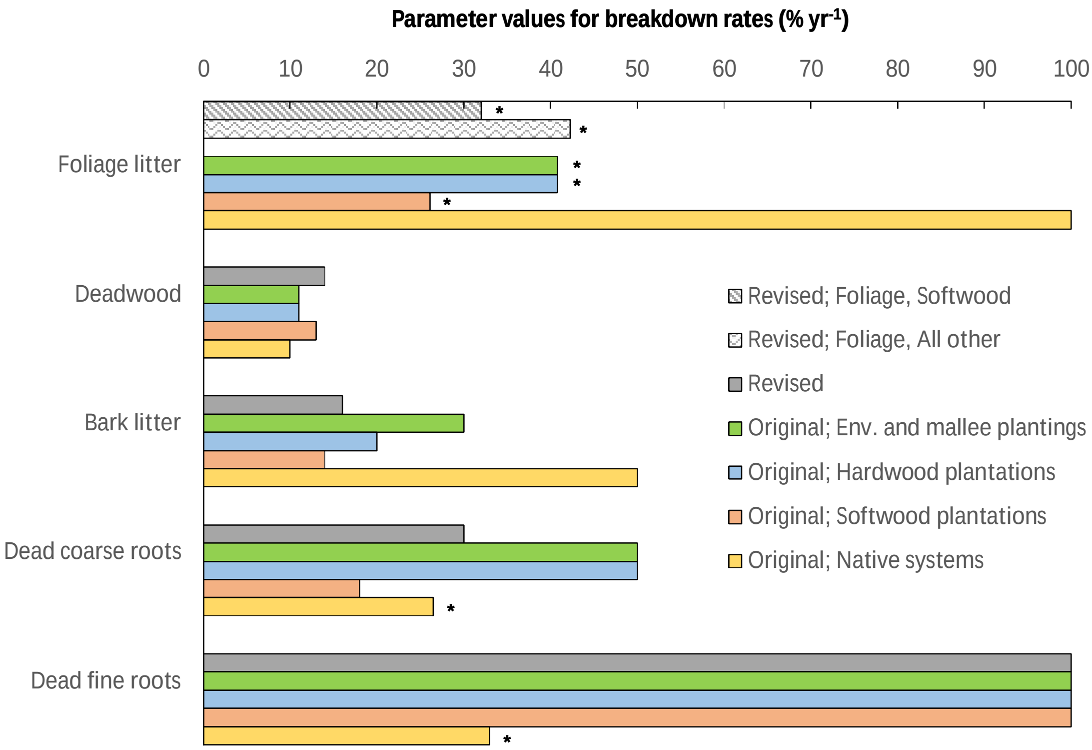

Figure 23: Revised and original parameter values for breakdown rates of the various pools of debris simulated by FullCAM. Some pools of debris were assumed to have decomposable and resistant components. * indicates breakdown rates shown were the weighted average of the decomposable and resistant components of the given pool of debris.

4.2.4 Parameters influencing soil C

It was assumed that all forest types have the same parameters for root turnover until there was evidence to prove otherwise. This generally resulted in a significant increase in total root turnover (Fig. 21). The only exception was for environmental and mallee plantings, where root turnover parameters were maintained.

Again, it was also assumed that all forest types have the same parameters for decomposition of dead roots until there was evidence to prove otherwise. This generally resulted in an increased decomposition of dead roots in native systems and softwood plantings, but a decrease in decomposition rates of dead roots (namely dead coarse roots) under all other forest types (Fig. 22).

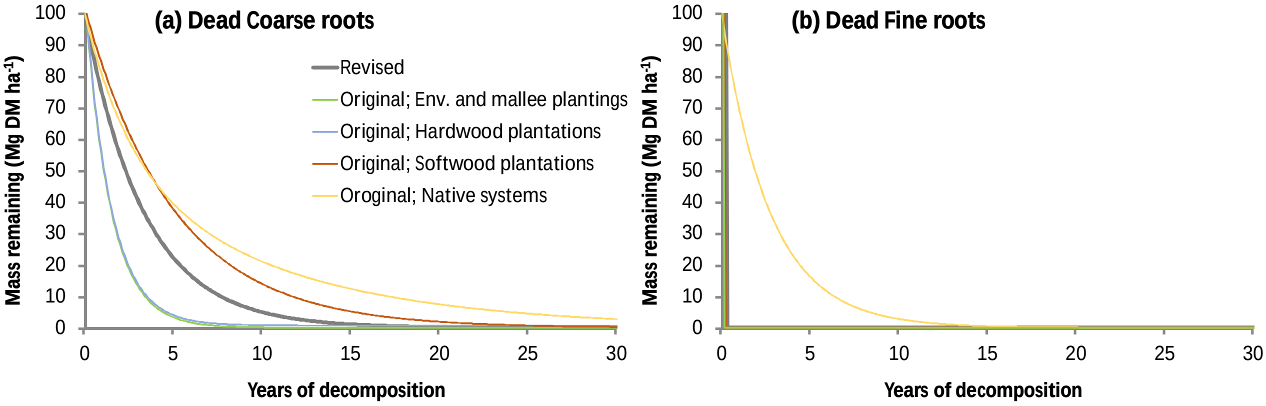

Figure 24: Demonstration of predicted rates of breakdown in of pools of dead roots when using the revised and original parameters for decomposition.

The original parameters for CO_2-C loss on decomposition were 87.5% for native systems, and 77% for all other forest types. The parameters defining the CO_2-C loss on decomposition were changed in three ways:

1. Vary there parameters between the resistant and decomposable pools given there was some evidence to suggest that more of the C lost on decomposition of debris reaches the soil on decomposition of resistant pools when compared to decomposable pools (Paul and Polglase 2004b).
2. Make these parameters for native systems consistent with those from planted systems.
3. Vary these parameters based on stand age. Until research has been completed to inform any re-coding of FullCAM, it is recommended that simulations of afforestation of young stands use CO_2-C loss on decomposition of decomposable and resistant pools of debris were 77^{-1} and 40% yr^{-1}, respectively. But when simulating older stands, such as in deforestation events, the CO_2-C loss on decomposition of decomposable and resistant pools of debris should be set to 90^{-1} and 80% yr^{-1}, respectively.

These changes resulted in significant decreases in rates of C entering the soil pools in planted systems, and a slight increase for native systems.

4.2.5 Initial pools of biomass and debris

The revised initial pools of biomass are based on the changes to allocation of biomass. Given the default initial age for environmental and mallee plantings was taken as zero, the initial pools of biomass were also assumed to be zero in both the original and revised settings. For all other forest types (with the exception of woodlands), there was a decline in the proportion of total biomass that was assumed to be stem wood, and an increase in the proportion of total biomass that was in other AGB components and in the BGB (Fig. 25). For woodlands, the allocation to stem wood and BGB was originally relatively low and high, respectively. Therefore, for these forest types, the there was only a slight decrease in allocation to stem wood and BGB, and a resulting increase in allocation to non-stem components of the AGB.

Figure 25: Revised and original parameter values for initial allocation of biomass to stem wood, other pools of AGB (or bark, branches and foliage), or to the BGB (coarse and fine roots).

For hardwood and softwood plantations, there was generally an increase in the initial debris pool, particularly for deadwood, but also for litter under hardwood plantations (Fig. 26). For native systems, there was substantial decline in initial deadwood and dead roots for native forests, but for woodlands, there was only a slight decline in all initial pools of debris. Given the default initial age for environmental and mallee plantings was taken as zero, the initial pools of debris were also assumed to be zero in both the original and revised settings.

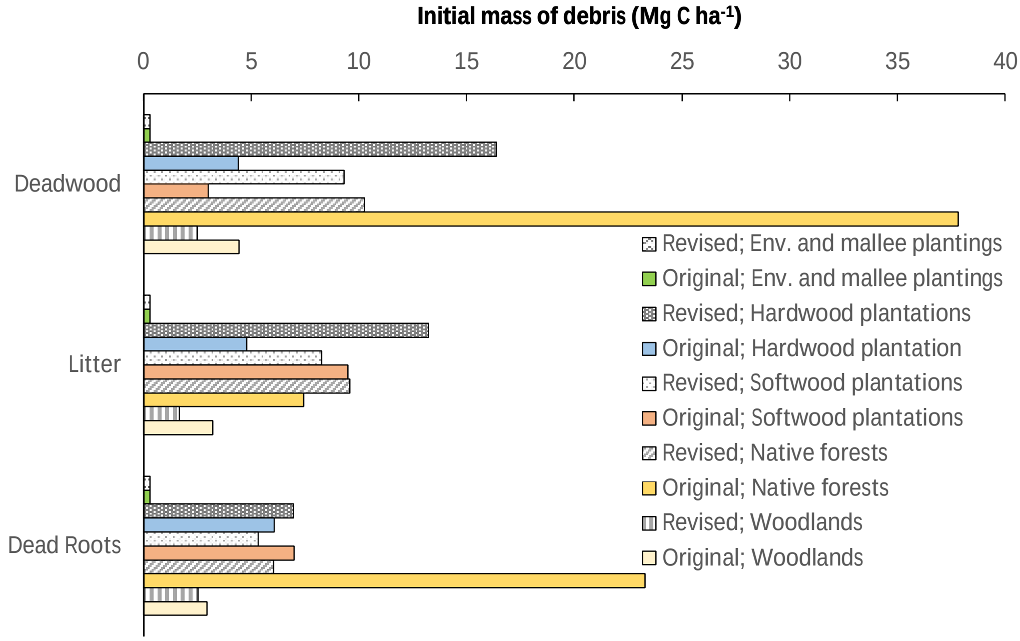

Figure 26: Revised and original parameter values for initial mass of debris. Values of litter are the sum of the decomposable and resistant pools of bark litter and foliage litter, while the dead roots are the sum of the decomposable and resistant pools of dead coarse roots and dead fine roots.

5 Conclusions

5.1 Overall impacts on predictions of C sequestration by forests

In preparation for the update of DoEE (2016), various FullCAM simulations were generated to determine the impact of the revised parameters on predicted sequestration of C following land use change. These revealed that the overall impact of these changes was an increase in C sequestration following afforestation and reforestation. The largest increases were found in natural regeneration, e.g. of woodlands post clearing events. This was mainly attributable to increased rates of turnover assumed in native systems. Indeed, in all forest types, the greatest increases in sequestration of C was simulation in debris and soil pools. There was generally little change in sequestration of C in biomass. The only exception was an increase in biomass C sequestration for systems where BGB_C:AGB increased (Fig. 20).

5.2 Recommendations for further work

5.2.1 Allocation of biomass

This study utilised available data and information on allocation of AGB, and BGB_C:AGB, to develop and verify empirical models predicting allocation of biomass under a range of different forest types. There were a number of important caveats to this work which are summarised below, and which provide the recommendations for further work:

1. The environmental and mallee plantings datasets had age-limitations, being mostly derived from relatively young stands. Confidence in predictions of biomass allocation in older stands (greater than 24 and 14 years for the mixed-species forests and mallee eucalypt plantations, respectively) is therefore relatively uncertain. As these stands mature, monitoring of AGB and its components is required to verify, and perhaps refine, these models. This is particularly important for BGB_C:AGB given: (i) the young nature of the stands assessed may have partly contribute to the relatively high BGB_C:AGB observed, and (ii) although AGB is determine in FullCAM via the TYF, accurate inputs of assumed allocation of biomass to coarse roots will be important in ensuring accurate FullCAM-predictions of BGB, and hence, total biomass.
2. There was a paucity of biomass allocation data at the stand-scale for native forests, woodlands and shrublands. This necessitated an approach of using the individual-scale data available to verify predictions resulting from the adaption of empirical models developed for environmental plantings. Additional datasets of biomass allocation are required from these systems in order to provide specific empirical models.
3. There was some evidence that for plantations, different species have differing allocation of AGB, e.g. *Pinus pinaster cf*. other softwood species. Further work is required to verify predictions of allocation for hardwood and softwood plantations across a wider ranges of species from a diversity of locations. Further work is also required to explore allocation of biomass in plantations systems given thinning events may influence the relationships between allocation of biomass and the stand age and total biomass.
4. There was some evidence that the split of AGB into crown and bole differed between stands in high and low rainfall regions, e.g. Bole:AGB ratio being low for mallee plantations relative to plantings established in regions of higher rainfall. This is difficult to simulate in FullCAM given the branch pool contains the twig components of the crown. It is therefore recommended that further work be undertaken to refine FullCAM biomass allocation inputs to separate twigs from the branch pool, particularly given these will have differing rates of turnover.

5. Results obtains from this study conflict with those observed by other with respect to the impact of stand density on allocation of biomass, namely the BGB_C:AGB. Additional datasets are required to be collated in order to ascertain the impact of stand density of allocation of AGB for different forest types, climatic conditions and planting configurations.
6. There was some evidence that climate (MAR) had a direct impact on allocation of AGB in some forests types, but that the impact of climate on BGB_C:AGB was via an indirect influence on AGB per se. Further work is required to improved confidence of the direct and indirect influences of climate of allocation of biomass for different Australian forest types.
7. We made the naïve assumption that BGB_F may be predicted from stand AGB based on a generic global relationship. Although this may be suffice for quantification of biomass C given the negligible size of BGB_F, given their relatively high rate of turnover, allocation to BGB_F will be important in accurate prediction of C entering the debris, and hence soil, pools.

5.2.2 Litter fall and decomposition of litter

The main limitation to both parameters of litter fall and rates of decomposition of litter are that they are not comprehensive enough (i.e. insufficient sample sizes, N) to ascertain whether there are statistical differences between the different forest types. To provide justification for having differing parameters for litter fall and litter decomposition across contrasting forest types or locations, further litter trap and litter bag studies are required in strategically placed forests and climates.

5.2.3 Parameters influencing soil C

The calibration of root turnover and decomposition, and the CO_2-C loss on decomposition were based on only two long term repeat-measured planation field trials (of differing treatments of fertiliser and irrigation) located in temperate regions, and one national project on paired-site environmental plantings. So these parameter values are probably most relevant to planted systems. Further field work is required across contrasting native systems to provide verification that these calibrations are indeed widely applicable.

The prediction of soil C accumulation under forests is highly sensitive to parameters of CO_2-C loss on decomposition (Paul *et al.* 2003). Given the evidence of a decrease in the rates of C input into the soil (as currently simulated by increased CO_2-C loss on decomposition of debris) as stands mature, further research is required to verify this, and ascertain the processes involved so that these may be more accurately inherently modelled. This might entail undertaking laboratory studies designed to specifically monitor $^{14}CO_2$-C loss from incubated ^{14}C labelled forest litter.

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