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# A novel integrated assessment framework to inform Australia's net zero transition

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## Abstract

Australia has set an ambitious goal of achieving net-zero greenhouse gas emissions by 2050. Attaining this target will require important transformations across multiple sectors of the economy. Integrated assessment models can provide valuable insights into the interactions across sectors of the economy, including land, agriculture and energy, to guide these complex transformations. However, many existing global integrated assessment models either do not include Australia as a distinct region or lack alignment with national statistics, particularly with regards to agriculture and land use change. To address these limitations, we develop an updated version of the Global Biosphere Management model (GLOBIOM), specifically validated for Australia. The model is then integrated with the Global Trade and Environment Model (GTEM), a computable general equilibrium model, enabling the projection of emissions across all economic sectors, while also providing detailed assessment of implications for the agriculture and land use sectors. The resulting emissions pathway indicates that net zero emissions would be achieved by 2040 for Australia's agriculture and land-use change sectors, and by 2050 for the whole economy with net emissions from agriculture and land use sectors of

-178 Mt $CO_2$eq per year. This would be realised through 1.5 million hectares of additional reforested area through environmental plantings and 23.7 million hectares of regenerated native vegetation. Future improvements in the framework are expected to include the simulation of bioenergy demand and supply, and the uptake of agricultural technologies to mitigate emissions to provide comprehensive climate and agricultural policy recommendations for Australia.

# 1. Introduction

Australia is one of over 100 countries that has pledged to achieve net-zero emissions (NZE) by 2050 (United Nations Environment Programme, 2024). This decarbonisation will require key sectors of the economy, including energy, transport, industry, agriculture and land use, to adapt or fundamentally transform their production and consumption patterns over the coming decades.

This transformation is particularly significant for Australia, a major global exporter of agricultural commodities such as wheat, barley, canola, cotton, beef, and sheep meat. Australian agricultural production is valued at approximately A$100 billion annually and employs approximately 240,000 people, mostly in regional areas (ABARES, 2025, 2023). At the same time, decarbonisation of the economy is expected to be achieved through substantial land-based carbon removals to offset residual emissions, mainly from agriculture, transport and industry sectors (DAFF, 2025). This could lead to strong competition for productive land between carbon sequestration and agricultural production. It is therefore critical to explore emissions pathways that will enable the attainment of NZE while mitigating such trade-offs and reducing costs on society.

Existing analytical tools applied to project emission pathways in Australia often focus on a single (or a subset of) sector(s) at a time, which may underrepresent some sectors critical for decarbonisation. This limitation constrains the ability of existing approaches to assess the combined contribution of all sectors to the national emissions reduction potential. For example, computable general equilibrium (CGE) models provide comprehensive assessments of economy-wide impacts of climate policies (Nong et al., 2025) but lack endogenous representation of land-use change and resulting emissions. This omission is significant given that a large share of negative emissions required to offset residual emissions to achieve net zero, including those from the agricultural sector, are largely expected to come from the land use, land-use change, and forestry (LULUCF) sector (DAFF, 2025; Verikios et al., 2025).

In contrast, land-use and agricultural dynamics are evaluated in detail by partial equilibrium (PE) and spatial models of agriculture and land-use change that have been specifically developed to assess environmental impacts and drivers of change, particularly land-based climate change mitigation potentials (Bryan et al., 2016; Frank et al., 2021; Humpenöder et al., 2014; Morris et al., 2025). However, these sector-specific models inherently lack representation of other economic sectors and therefore cannot comprehensively simulate climate policies and the decarbonisation of the whole economy endogenously.

Integrating multisectoral and sector-specific models reduces the limitations of each modelling approach, and underpins several integrated assessment models (IAMs) that enable insights into economic and emission pathways given their inclusion of interactions and feedback between climate, land use, energy, and economic systems (Riahi et al., 2017; van Beek et al., 2020).

However, given important differences between the structure of multisectoral and detailed sectoral models, model coupling is generally undertaken using one-way links, where the outputs of one model are used once as input in the second model (Cantele et al., 2021; Schreiber et al., 2025). While useful to exchange information between models, this type of linkage does not allow feedback or guarantee consistency between the two types of model (OECD, 2024).

Although some IAMs have been tailored to better represent specific countries (Tong et al., 2020), most models are developed and applied at the global scale with highly aggregated world regions, providing limited insights to inform policies in specific countries, such as Australia. For instance, most IAMs represent Australia as part of a composite Oceania region that also includes New Zealand and, in some cases, Pacific Island countries.

Moreover, none of the most prominent IAMs are calibrated to reflect Australia's distinct land and agricultural systems, an essential step to ensure reliability of projections. Improving country-level representation within global models enables national modellers to engage with widely used, peer-reviewed global frameworks and to better align national findings with the global literature. At the same time, it allows global modellers to more accurately represent a major food and fibre exporter such as Australia.

While equilibrium-based models and IAMs are intended as exploratory tools to provide insights into future trajectories rather than predicting accurate outcomes in the near term, it is critical to assess their empirical validity to build trust around model results. This reliability check is particularly important as they are increasingly used for policy analysis, for instance, to inform low-emission transitions (Valenzuela et al., 2007; Wigley et al., 2021).

To overcome these limitations, we develop a new integrated modelling framework that couples the CGE model Global Trade and Environment Model (GTEM) (Nong et al., 2025) and the PE model of agriculture and land use Global Biosphere Management Model Australia (GLOBIOM-Australia). The two models were specifically calibrated for Australia, while also covering other regions of the world. We then use GTEM–GLOBIOM-Australia to project emissions in all sectors of the economy endogenously within one framework under a NZE scenario and examine the impacts of such transition on land-use change. This novel analytical tool enables the evaluation of economy-wide decarbonisation strategies that explicitly account for interactions between land use, agriculture and other sectors. The insights generated by this modelling framework can inform the design of cost-effective climate policies that account for Australia's distinct land and agricultural context, supporting the net zero transition while balancing economic and environmental priorities.

In the sections below, we first present an overview of the calibration and validation conducted to improve the representation of Australia's agriculture and land systems in GLOBIOM-Australia. We then present an application of model coupling between GLOBIOM and GTEM that enables the simulation of emissions and the response to climate policy in all sectors of the economy with consistency between the two models. Finally, we explore a decarbonisation transition scenario in Australia and evaluate its implications for land use.

## 2. Methods

## 2.1. GLOBIOM-Australia parameterisation

GLOBIOM-Australia is a version of the GLOBIOM model (IBF-IIASA, 2023) parameterised and calibrated to reflect the distinct land and agricultural conditions of Australia. GLOBIOM is a PE model of agriculture and land use that simulates land-use change under competing demands for land. The model identifies optimal land use on simulations units recursively at a 10-year time step from 2000 to 2050 by maximising the sum of producer and consumer surplus, used as an indicator of economic welfare (IBF-IIASA, 2023). Simulation units represent the supply side of the model, i.e., land characteristics and productivity potential, based on 30-arcminutes (~50 km at the equator) grid resolution in Australia and 2 degrees (~200 km) in other countries. The simulation of demand and trade is based on 59 world regions, with Australia represented as a distinct region. GLOBIOM has been applied globally and parameterised for specific regions, including Brazil (Soterroni et al., 2018), China (Zhao et al., 2021), Europe (Frank et al., 2016) and West Africa (Palazzo et al., 2017), but has never been applied or parameterised specifically for Australia. The conceptual framework of the model is presented in Figure 1 and includes specific sections of the article where modifications to adapt the model to the Australian context are described.

The spatial distribution of crop harvested area and cropland (section 2.1.1) and livestock (section 2.1.2) was improved by using downscaled gridded national statistics, whereas grazing productivity was parameterised using the AussiGRASS pasture growth map (section 2.1.3). Emissions from agriculture were parameterised for the initial year of the model (2000) by substituting default emission factors from the Intergovernmental Panel on Climate Change (IPCC) with emission factors used by the national government to align with the Australian greenhouse gas (GHG) inventory (section 2.1.4). Given the importance of land-based carbon sequestration to achieve NZE, we also parameterised the carbon sequestration potential from environmental planting and human-induced regeneration (HIR) based on spatial layers from the Full Carbon Accounting Model (FullCAM) (section 2.1.4).

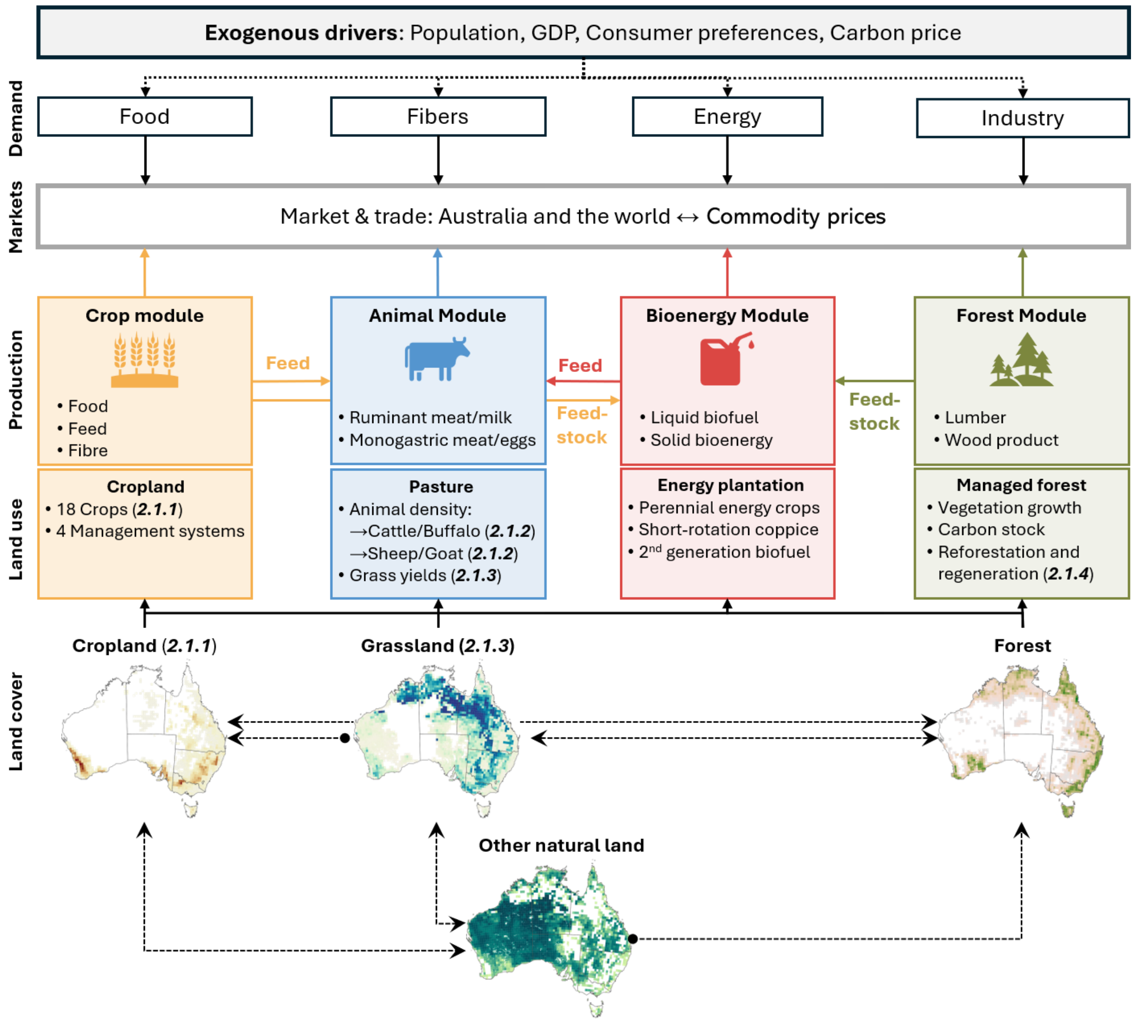


*Figure 1. Conceptual framework representing GLOBIOM-Australia, adapted from IBF-IIASA (2023). Potential conversion between each land cover is represented with dashed, two-away arrows. Arrows starting with a circle represent one-way conversion, e.g., grassland to cropland only. The top box indicates exogenous drivers of change, some of which are sourced from GTEM simulations, i.e., GDP and carbon price. Specific aspects of the model that were adapted for GLOBIOM-Australia are described in the section numbers appearing in parentheses.*

### *2.1.1. Crop distribution*

The spatial distribution of crop harvested area in Australia was parameterised using mapspamc package in R (van Dijk et al., 2023), an adaptation of the global Spatial Production Allocation Model (SPAM) (You and Wood, 2006). The mapspamc package was designed to facilitate data processing to allocate harvested areas across multiple crops within a specific country based on national statistics.

Data on harvested area of 40 crops were obtained by Statistical Area 2 (SA2) from the Agricultural Bureau of Statistics (ABS) for the year 2000, the initial year of the GLOBIOM model, as the main input for the spatial crop allocation. Other inputs to the model included potential yield and biophysical suitability of each crop under different production systems (i.e., irrigated, high input, low input) obtained from the Global Agroecological Zones database (FAO and IIASA, 2025) to estimate a suitability score for each grid cell.

Layers of cropland areas were used to create synergy maps and determine in which grid cells cropland can be allocated. The synergy map of cropland areas was generated by combining remote sensing information from Global Land Analysis and Discovery (GLAD) (Potapov et al., 2022) and European Space Agency Climate Change Initiative (ESA CCI) (ESA, 2017) with cropland from the national land use map (NLUM) for the year 2000 (ABARES, 2006).

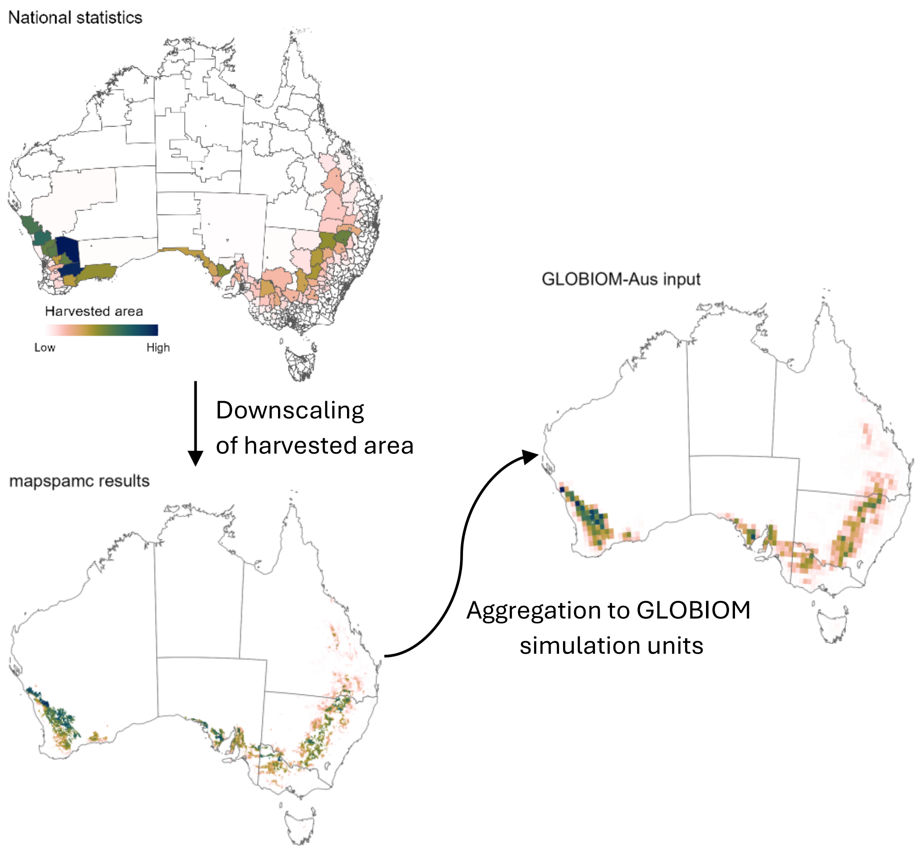


*Figure 2. Process to modify the distribution of harvested areas in GLOBIOM-Australia at year 2000 using mapspamc spatial allocation model. Wheat is used here as an example.*

In addition to general cropland, a synergy map of irrigated cropland was determined by combining the Global Map of Irrigation Areas (GMIA) (Siebert et al., 2005), Global Irrigated Areas (GIA) (Meier et al., 2018) and the irrigated areas from the NLUM. All gridded input layers were resampled to 5-arcminute (~10 km) resolution. The mapspamc model allocated harvested area for 25 crops present in Australia and three production systems (i.e., irrigated, rainfed high-input, rainfed low-input) from each SA2 region to 5-arcminutes grid cells using a cross-entropy optimisation (van Dijk et al., 2023). Detailed descriptions of the mapspamc and SPAM models can be found in van Dijk (2023) and Yu (2020), respectively.

Once all crops have been distributed across the grid covering Australia, harvested areas were then aggregated to 30-arcminutes grid cells (~50 km), the spatial resolution of simulation units in GLOBIOM-Australia. This step aimed to improve the spatial distribution of harvested areas for different production systems in Australia in the model. Information on harvested area in other countries was not modified.

*2.1.2. Livestock distribution*

The GLOBIOM model includes seven types of animal-source food: beef cattle, dairy cattle, sheep and goat meat, sheep and goat dairy, poultry meat and eggs, and pig meat. The main input dataset on the spatial distribution of livestock, the Gridded Livestock of the World (Wint and Robinson, 2007), only includes the distribution of animals, e.g., cattle, and does not differentiate between production types such as beef and dairy cattle. Given the particular Australian livestock systems, where dairy production is concentrated around major urban centres and along the coasts, while low-intensity beef grazing systems extend inland across dry rangelands, we incorporated this distinction by generating new distribution maps of beef cattle, dairy cattle, and sheep meat.

Following a procedure similar to the crop allocation described in section 2.1.1, we used layers of distributed animal numbers from SA2 regions to 30 arc-second (~1km) grid cells based on a range of predictor variables, such as grass productivity and distance to water bodies (Navarro et al., 2026). The new livestock distribution maps were then aggregated at the resolution of GLOBIOM simulation units (30 arcminutes).

#### *2.1.3. Grazing productivity and grassland distribution*

We updated grassland distribution in the model by using native and modified pastures from NLUM layer (ABARES, 2006) at year 2000. We then modified grass yields using the annual total pasture growth for year 2000 from the AussiGRASS pasture growth model (Queensland Government, 2025). Pasture utilisation rate was assumed to be 25% in native pastures or rangelands (Hunt, 2008; Walsh and Cowley, 2011) and 50% in modified pastures based on estimated sustainable utilisation targets in Australia (Meat and Livestock Australia, 2022).

#### *2.1.4. Emission accounting and carbon sequestration potential*

Emission factors for the agricultural sector were updated using data from the Australian National Greenhouse Accounts (ANGA) to align with the national emission inventory (Australian Government, 2023). This step was critical for adjusting emissions from manure left on pasture, for which ANGA emission factors are between 5 and 9 times lower than the IPCC emission factors included by default in GLOBIOM, depending on livestock types.

GLOBIOM has been linked in the past with the Global Forest Model (G4M) (Gusti and Kindermann, 2011) to simulate land-based climate change mitigation potentials (Frank et al., 2021). However, to limit the requirement for model coupling beyond the GTEM–GLOBIOM-Australia interactions, carbon sequestration through reforestation was implemented within GLOBIOM-Australia to enable its endogenous simulation. To do so, mechanisms from GLOBIOM-forest (Lauri et al., 2021), a separate version of the model that includes a forest sector in more detail, were incorporated into GLOBIOM-Australia, whereby revenue from carbon sequestration is included in the objective function that determines land-use change.

We considered two options for generating negative emissions through land-use change in the model: 1) human-induced regeneration (HIR), and 2) environmental planting. The HIR method consists in helping to regrow native vegetation previously suppressed through grazing, invasive species or suppression of regrowth, while environmental planting consists in establishing permanent forest without harvest through planting a mixture of native species (Department of Climate Change, Energy, the Environment and Water, 2011). Although the HIR method to obtain carbon credits officially expired in 2023, managed regeneration is expected to be included in the proposed Integrated Farm and Land Management (IFLM) method (Department of Climate Change, Energy, the Environment and Water, 2023).

Carbon sequestration potential was determined for the two land uses based on spatial layers of potential areas, maximum carbon density and age-class dynamics (Roxburgh et al., 2020). These layers were first obtained at 30 arc-second resolution and aggregated at the resolution of

GLOBIOM-Australia simulation units. To avoid double counting between existing (exogenous) and future simulated (endogenous) vegetation-based carbon sequestration projects, areas associated with existing ACCU projects (Clean Energy Regulator, 2026) were masked out from the suitable land extent when estimating the spatial suitability for future projects.

We assumed that HIR entails an establishment cost associated with exclusion fencing (Giumelli and White, 2016; Moravek et al., 2017) while environmental planting included costs associated with tubestock planting and direct seeding per area, based on data from Summers et al. (2015). These costs were adjusted to 2000 values using gross domestic product (GDP) implicit price deflator (Australian Bureau of Statistics, 2025a) for consistency with other costs in GLOBIOM-Australia.

Negative emissions from land-use change prior to 2020 were considered exogenously and taken from the National Greenhouse Gas Inventory (NGGI) (Australian Government, 2023) for projections in the modelling framework.

## 2.2. GLOBIOM-Australia calibration and validation

Since the GLOBIOM-Australia model is initialised for the year 2000, the model behaviour and outcomes can be verified by comparing different results with historical observations to ensure that the model properly represents Australian conditions over time and provides results consistent with historical outcomes. In this validation procedure, we compared 1) the modelled and observed production of four of the most valuable crops (i.e., wheat, canola, barley, cotton) and three livestock products (i.e., beef, sheep meat, milk); and 2) agricultural GHG emissions between 2000 and 2020.

We compared simulated production of commodities against ABS data for both crop and livestock products (Australian Bureau of Statistics, 2025b). Simulated emissions were compared with emissions from the NGGI (Australian Government, 2023). Since GLOBIOM-Australia has a 10-year time step, the number of time points is insufficient to conduct residual-based quantitative validation, such as regression analysis. Furthermore, crop production can exhibit high interannual variability depending on discrete climate events such as the Millenium Drought (Chambers et al., 2020). Therefore, we adopted an approach in which the trend in the national statistics data is first evaluated with a local regression analysis, which consists in locally fitting a polynomial trend to the historical time series from 2000 to 2024. We chose a polynomial fit to capture non-linear temporal dynamics that could be obscured by linear trends, for instance the impact of the Millennium Drought on agriculture from 2001-2009. In addition, we estimated 95% confidence intervals based on standard error calculations to determine a credible range of observations expected to align with model results. We then calibrated GLOBIOM-Australia so that key production and emission outputs fall within this confidence envelope for each variable compared for the 2000-2020 period.

Given the importance of exports in the Australian agricultural system and the inclusion of bilateral trade flows in GLOBIOM, calibration of production was mainly conducted by fine-tuning trade cost parameters to adjust exports and imports. In some cases, demand for commodities in other regions were also adjusted to affect trade flows with Australia based on food balance sheets representing trends in consumption and imports from Australia (FAO, 2025). The calibration of emissions over time, particularly from enteric fermentation, was undertaken by updating sheep and cattle numbers by adjusting trade flows and production.

Feed ratios were also updated based on food balance sheets (FAO, 2025) to improve the representation of crop demand for animal feed.

## 2.3. Economy-wide feedback with GTEM

The GTEM model is a multi-region, multi-sector dynamic CGE model that simulates market equilibrium in all sectors of the economy and runs at an annual time step. The model, along with its general details and mechanisms, has been described in previous publications (Cai et al., 2015). GTEM does not have an explicit and endogenous representation of land use and land-use change, although it does represent physical energy systems and emissions in some detail. As a result, the model is limited in its ability to simulate land-based carbon mitigation measures. Previous applications of the model have used land-based climate change mitigation potentials exogenously, for instance, using results from earlier versions of the GLOBIOM model without iterative convergence (i.e., one-way link) (Frank et al., 2021; Nong et al., 2025). Here, the model was coupled with GLOBIOM-Australia to incorporate carbon sequestration potential endogenously and therefore represent all major emission sources and sinks across all economic sectors.

## 2.4. Integrated modelling framework

The GTEM and GLOBIOM-Australia models were coupled (or linked) via a two-way interaction. There are two general approaches for such a coupling: hard or integration coupling, and soft or interaction coupling (OECD, 2024). Integration coupling requires hard linking the models into a single analytical tool. Technical barriers around programming languages and licenses complicate this approach, so instead we opted for an interaction coupling. Interaction coupling consists of running each model sequentially for the whole simulation period, exchanging key outputs to inform the other model, and repeating the procedure iteratively until convergence of critical model outputs is reached.

In the coupling process GTEM was first run until 2050 with an initial projection of LULUCF emissions, planting costs and population growth based on Australian emission pathways from a previous application of the model (Verikios et al., 2025). The resulting time series of GDP and a price applied to all GHG emissions (hereafter referred to as the carbon price) required under an NZE pathway (see section 2.5 for more detail) were then temporally aggregated from annual to 10-year time steps to be included as exogenous variables in GLOBIOM-Australia. Both GDP and carbon price were aggregated by averaging values for all years of a decade, for instance, 2020-2029 aggregated to the 2020 decade (Figure 3).

In the next step, land-use change, including the conversion of land to forests for carbon sequestration, was simulated endogenously within GLOBIOM-Australia based on the carbon price from GTEM and competing land demands. Once a GLOBIOM-Australia run was completed, the LULUCF emissions and the environmental planting costs were used as inputs into GTEM for the next iteration. To do so, areas converted to forests in GLOBIOM-Australia were temporally downscaled by allocating an equal amount of converted area to each year of a decade considering constraints on annual reforested areas (see section 2.5). This annual area was then used to calculate annual carbon sequestration based on vegetation growth information from the FullCAM model and planting costs. Since GTEM simulates agricultural production and emissions endogenously, only emissions from LULUCF, rather than the broader agriculture, forestry, and other land uses (AFOLU) sector, are transferred from GLOBIOM-Australia to GTEM.

This interaction between the two models was repeated iteratively until convergence was achieved, i.e., when the average difference in the annual carbon price for the last 10 years of an iteration reached a 10% difference compared to the previous iteration, in line with previous soft-linking applications (Fernandez Vazquez, 2026). Since iterations between the two models can exhibit oscillatory behaviour and slow convergence, we used a procedure with successive substitution to accelerate convergence. To do so, a weighted-relaxation approach was used, in which all carbon price time series from prior GTEM runs were used to calculate an exponentially-weighted moving average carbon price, with exponentially greater weights assigned to more recent runs, which are assumed to be closer to the convergence points (Roberts, 1959). The relaxed carbon price that is passed from GTEM to GLOBIOM-Australia reduces abrupt changes between iterations and therefore dampens oscillations and accelerates convergence.

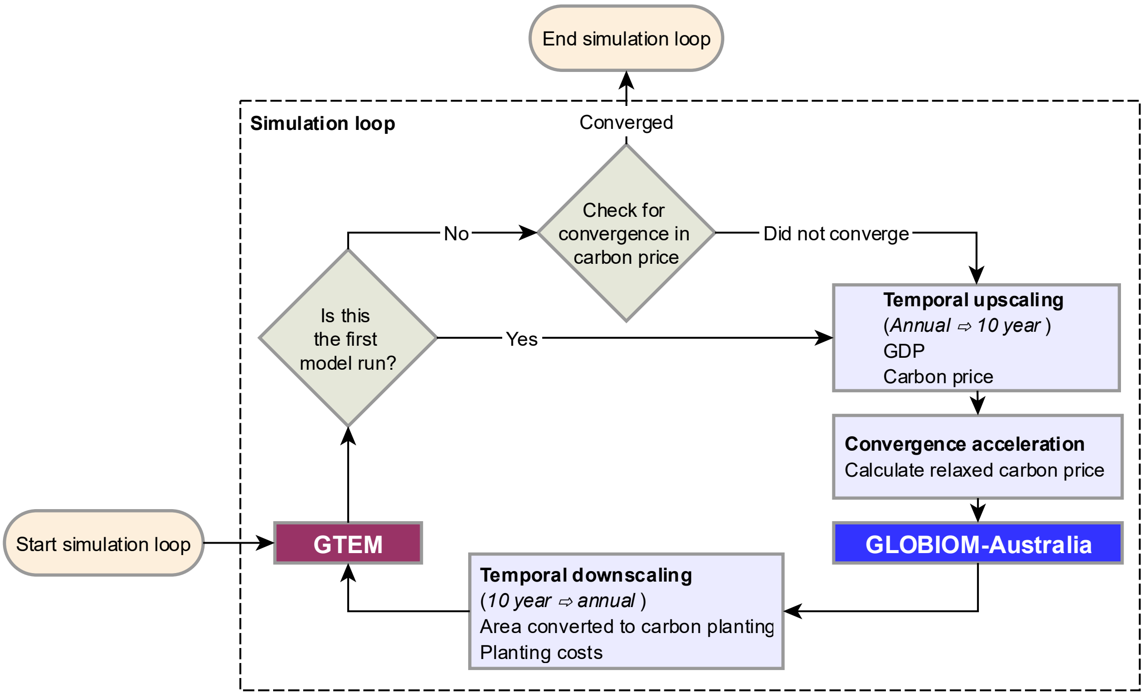


*Figure 3. Flow chart illustrating the approach used to couple GTEM and GLOBIOM-Australia models, and the underlying exchange of information between the two models*

Since convergence was determined using annual carbon price values from GTEM, the convergence assessment was conducted immediately after a GTEM model run, starting from the second iteration. Similar to other IAMs coupling partial and general equilibrium models (Humpenöder et al., 2024), the carbon price was selected as the key model result subject to convergence given its critical influence on driving land-use change in GLOBIOM-Australia and the economic structure and GHG mitigation costs in GTEM. This IAM framework was then applied to explore the contribution of the agriculture and land use sectors to achieving NZE in Australia.

## 2.5. Scenario design

We compared a policy scenario (*NZE*) designed to achieve NZE by 2050 through carbon pricing to a baseline scenario with no carbon price (*Baseline*). In the *NZE* scenario, GTEM takes a net emissions pathway for the whole economy as a constraint and a global carbon price is endogenously derived in the model to achieve this pathway. The emission trajectory was based on the IPCC AR6 Illustrative Mitigation Pathway with heavy reliance on renewables (IMP-Ren), which is consistent with a 1.5°C warming above pre-industrial levels (Riahi et al., 2023).

The *NZE* scenario limits the area of environmental plantings to 250,000 hectares per year to account for constraints on annual capacity for the supply of seedlings and labour required based on historical information on the maximum planting rates observed in Australia under government incentives (Verikios et al., 2025). For the *NZE* scenario, an exogenous time-series of LULUCF emissions (Verikios et al., 2025) was used for the initial GTEM simulation, and LULUCF emissions from GLOBIOM-Australia were used thereafter. In addition to emissions, the cost of environmental planting was estimated from the reforested areas in GLOBIOM-Australia and included in GTEM as an additional cost of reducing emissions (Figure 3).

For both scenarios, other exogenous variables, such as agricultural yields and food waste and loss, were aligned with the socio-economic pathway (SSP) 2 scenario (Fricko et al., 2017) in GLOBIOM-Australia and kept unchanged across iterations. No iterations between the two models were conducted for the *Baseline* scenario since no carbon price was implemented. The timeseries of GDP from the GTEM baseline simulation was also used in the GLOBIOM baseline simulation.

# 3. Results

## 3.1. GLOBIOM-Australia validation

### *3.1.1. Agricultural production*

The model was calibrated to replicate historical trends (2000-2020) and project baseline future (2020-2050) production of four of the major crop commodities in Australia, i.e., wheat, barley, canola, and cotton (Figure 4, left panels). The simulated production of these crops in Australia fell within the confidence ranges for the historical period. Production of canola (Figure 4B) and barley (Figure 4C) in particular, required more significant fine-tuning to align with the rapid increase in production observed after 2010, which was driven by rapidly growing exports. Further comparisons between production, harvested area and yield between 2000 and 2025 for six crops are presented in Figure S1.

The model was also able to replicate the temporal patterns in the production of the main animal-source foods in Australia during the validation period from 2000 to 2020. Beef production has remained at levels comparable to those in 2000, i.e., around 2 million tonnes of carcass weight per year (Figure 4E), with variability due to climate extremes, trade, and global prices. The general trend in sheep meat was also reproduced in the model, with a small decline in production between 2000 and 2010, followed by a growing production thereafter (Figure 4F). Mutton and lamb production experienced a clear drop in demand in China and the Middle East related to COVID-19, and impacts of the 2018–19 drought on the sheep flock. However, the rebuild of the national flock from 2021 led to a rapid increase in production in subsequent years. This long-term increase in production was reflected in the model with the increase in production after 2010. Both beef and sheep meat are expected to increase moderately until 2050.

Milk production has shown moderate but steady decline since 2000 due to falling exports and growing imports, particularly from New Zealand. The model was calibrated to reproduce this trend (Figure 4G) by adjusting Australian trade in milk. A comparison of results from GLOBIOM-Australia, the default version of the model, and national statistics is presented in Figure S2 to highlight improvements in projections, particularly for wheat, canola and milk production in GLOBIOM-Australia.

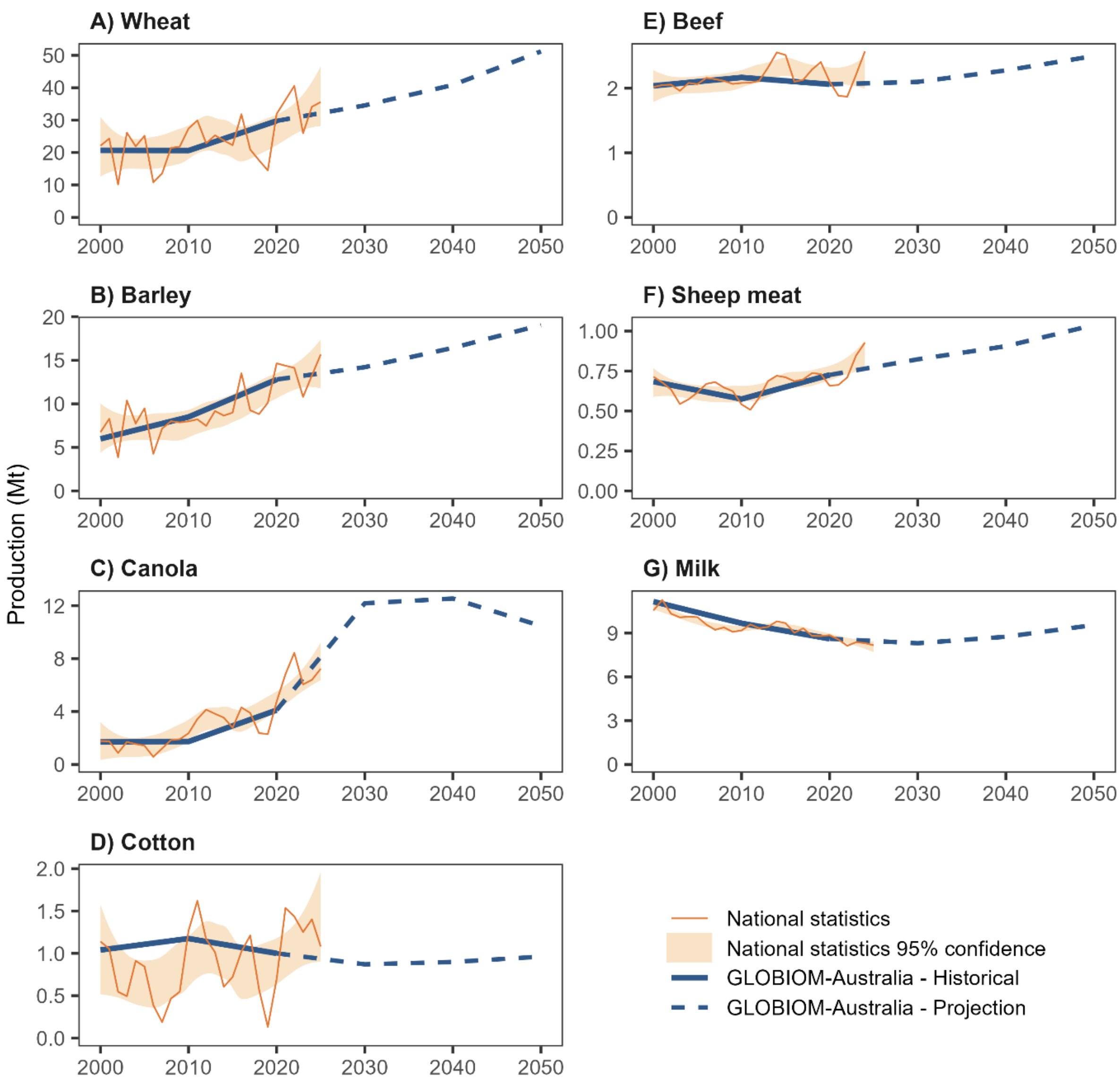


*Figure 4. Comparison of GLOBIOM-Australia results with national statistics on production of four major cropping commodities and the three most valuable livestock products.*

*3.1.2. GHG emissions*

As in most agricultural systems, methane emissions from enteric fermentation in ruminants dominate agricultural emissions. This pattern is also observed in Australia, where enteric fermentation accounted for approximately 73% of total agricultural emissions in 2000 and 78% in 2020 (Australian Government, 2023). The model reproduced the downward trend in emissions from enteric fermentation from 2000 to 2010 (Figure 5). This reduction was partly due to declines in milk production (as seen in Figure 4G), a decrease in animal numbers due to destocking during the Millenium Drought and falling exports of live sheep. However, total agricultural emissions from GLOBIOM-Australia displayed a stable trend from 2010 to 2020, which aligned with the NGGI.

Results from GLOBIOM-Australia are also compared with the default version of GLOBIOM and NGGI data to highlight improvement in the calibrated version of the model in Figure S3. Specifically, emissions from enteric fermentation and agricultural soils were substantially adjusted to better align with the NGGI dataset.

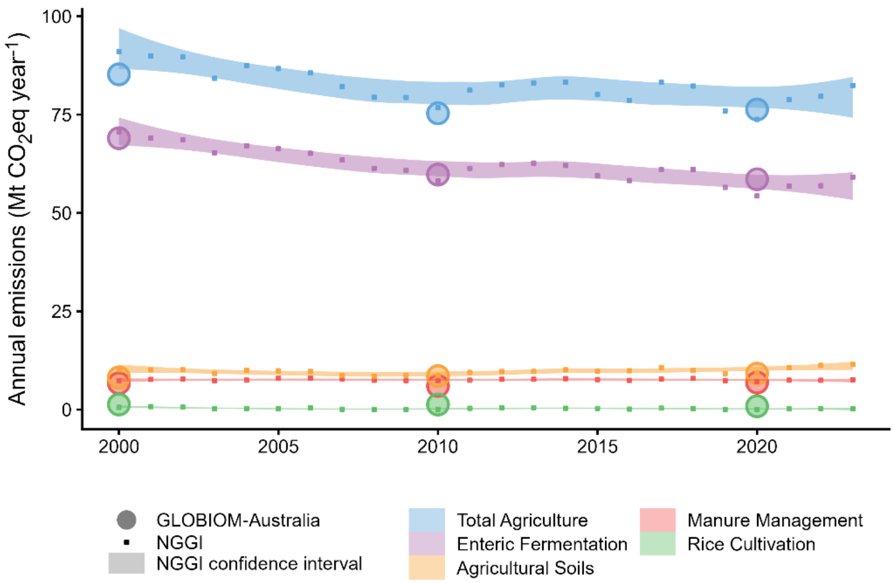


*Figure 5. Agricultural emissions from GLOBIOM-Australia in comparison with emissions from Australia's National Greenhouse Gas Inventory (NGGI).*

## 3.2. Convergence in model results

Following calibration and validation of GLOBIOM-Australia, the model was linked to GTEM to create an IAM able to reflect specific Australian economic and environmental conditions. The carbon price resulting from the model coupling under the *NZE* scenario stabilised at the tenth iteration, where the mean difference between the annual carbon price from GTEM for the last 10 years of the simulation (2041 to 2050) reached 7.7% compared to the previous iteration (Figure 6). At this converged carbon price, LULUCF emissions reached a total of -243Mt $CO_2$eq per year by 2050, with 1% difference over the last 10 years of the simulation compared with the previous iteration. Of this total sink, -187 Mt $CO_2$eq per year consists of the carbon sequestered in HIR and environmental plantings incentivised by carbon price and simulated endogenously in GLOBIOM-Australia, and 56 Mt $CO_2$eq per year represents carbon sequestered in past carbon storage projects included exogenously.

The large difference between the first and the subsequent iterations highlights the insufficient LULUCF emissions prior to 2040, which generate a drastic response in carbon pricing needed to achieve total emission reductions in earlier years. It also underscores the need for two-way interactions between such models, as a one-way link would result in outputs that are not consistent between the two models.

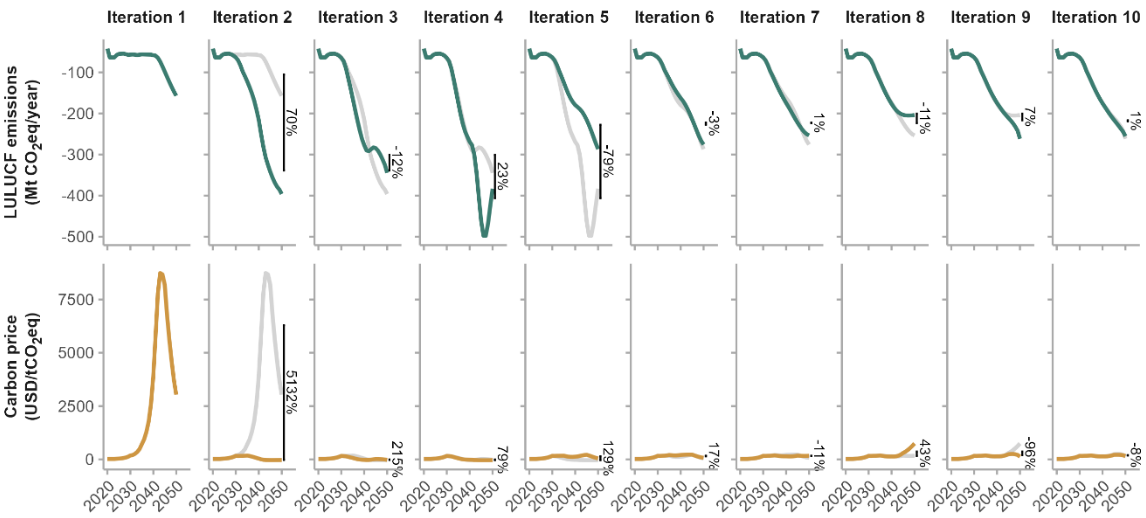


*Figure 6. Iteration results of the GTEM–GLOBIOM-Australia coupling for carbon price and LULUCF emissions. For both outputs, the grey line displays the resulting time series from the preceding iteration. Error bars indicate the difference between the mean values for the last ten years of the simulation (2041-2050) of the current timeseries and the time series of the previous iteration. The percentage change is shown next to the error bar.*

## 3.3. Net zero emissions in agriculture and land use

Under the *Baseline* scenario, most emissions from agriculture slightly increase over time, driven by growing agricultural production and culminating in 98.5 Mt $CO_2$eq per year, of which 81% would come from enteric fermentation (Figure 7). Net AFOLU emissions also increase, reaching 42.7 Mt $CO_2$eq per year by 2050.

Under the *NZE* scenario, land-based carbon sequestration, from existing and simulated HIR and environmental planting initiatives, is sufficient to offset total agricultural emissions and allow the country to reach *NZE* in the AFOLU sector by 2030, achieving net emissions of -43.2 Mt $CO_2$eq per year (Figure 7). Net zero would be achieved for the whole economy by 2050, and net emissions from AFOLU would decline to -175 Mt $CO_2$eq per year, extending a historical trend in declining AFOLU emissions observed since 2006 (Figure S4). In addition to the increasing carbon sink from land-based sequestration, agricultural emissions also decline in the *NZE* scenario compared to the *Baseline* scenario. Enteric fermentation would shrink to 53.3 Mt $CO_2$eq per year in 2050 due to declining animal numbers, while total agricultural emissions are limited to 68.3 Mt $CO_2$eq per year, approximately 30% lower compared to the *Baseline* scenario.

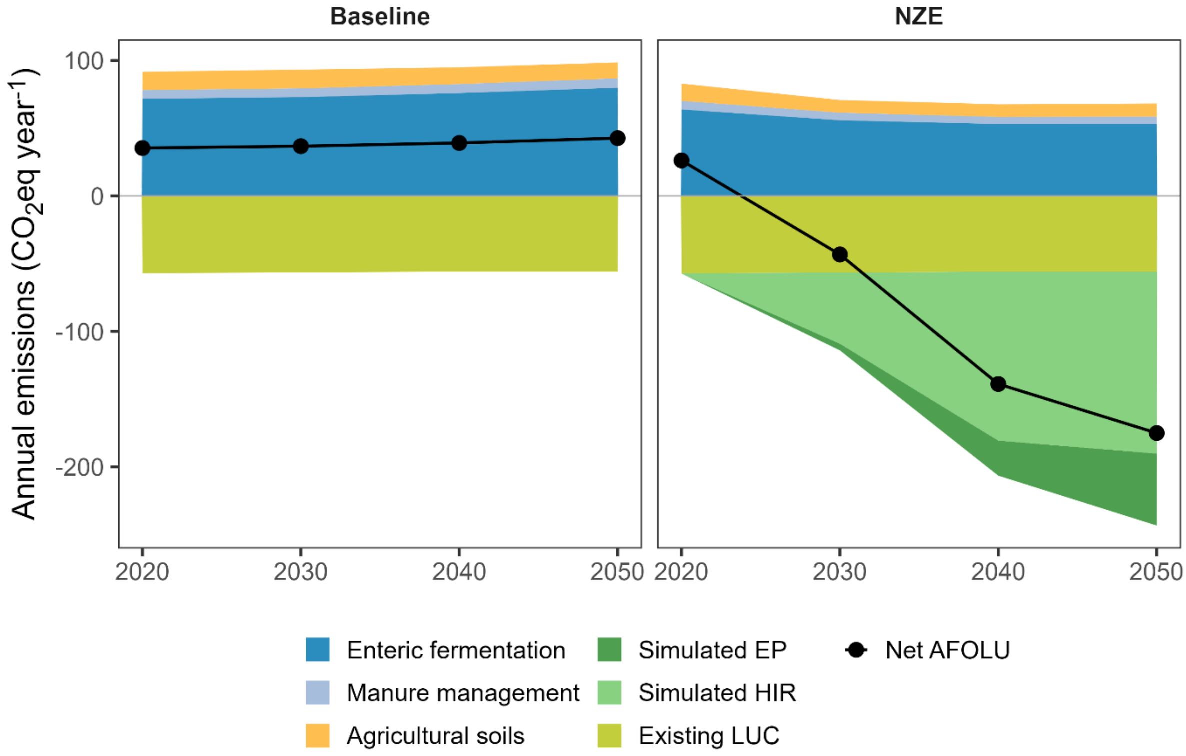


*Figure 7. Emission for the AFOLU sector in Australia from GLOBIOM-Australia, comparing the Baseline (left) and NZE (right) scenarios. EP refers to environmental planting, and HIR refers to human-induced regeneration.*

## 3.4. Land-use change required for NZE

The large carbon sink from HIR and environmental plantings observed under the *NZE* scenario would require an increase in environmental planting and HIR areas, in addition to existing projects, of 2 and 23.7 million hectares (Mha), respectively, across the country by 2050 compared to 2020. Most of the new environmental planting areas would occur in New South Wales (0.85 Mha), followed by Western Australia (0.5 Mha) and Victoria (0.4), whereas Queensland (13.3 Mha), New South Wales (4.8) and Northern Territory (4.1) would see the largest increases in land allocated to HIR (Table S1).

Cropland area is projected to decline compared to the *Baseline* scenario in Queensland (-2% in 2050), but increase in New South Wales (25%), Victoria (17%) and South Australia (4%), mainly driven by pasture conversion given the lower emission intensity of crop production. Furthermore, large areas of mostly extensive pasture in the states of Queensland, New South Wales, and Northern Territory are projected to revert to natural land (Table S2).

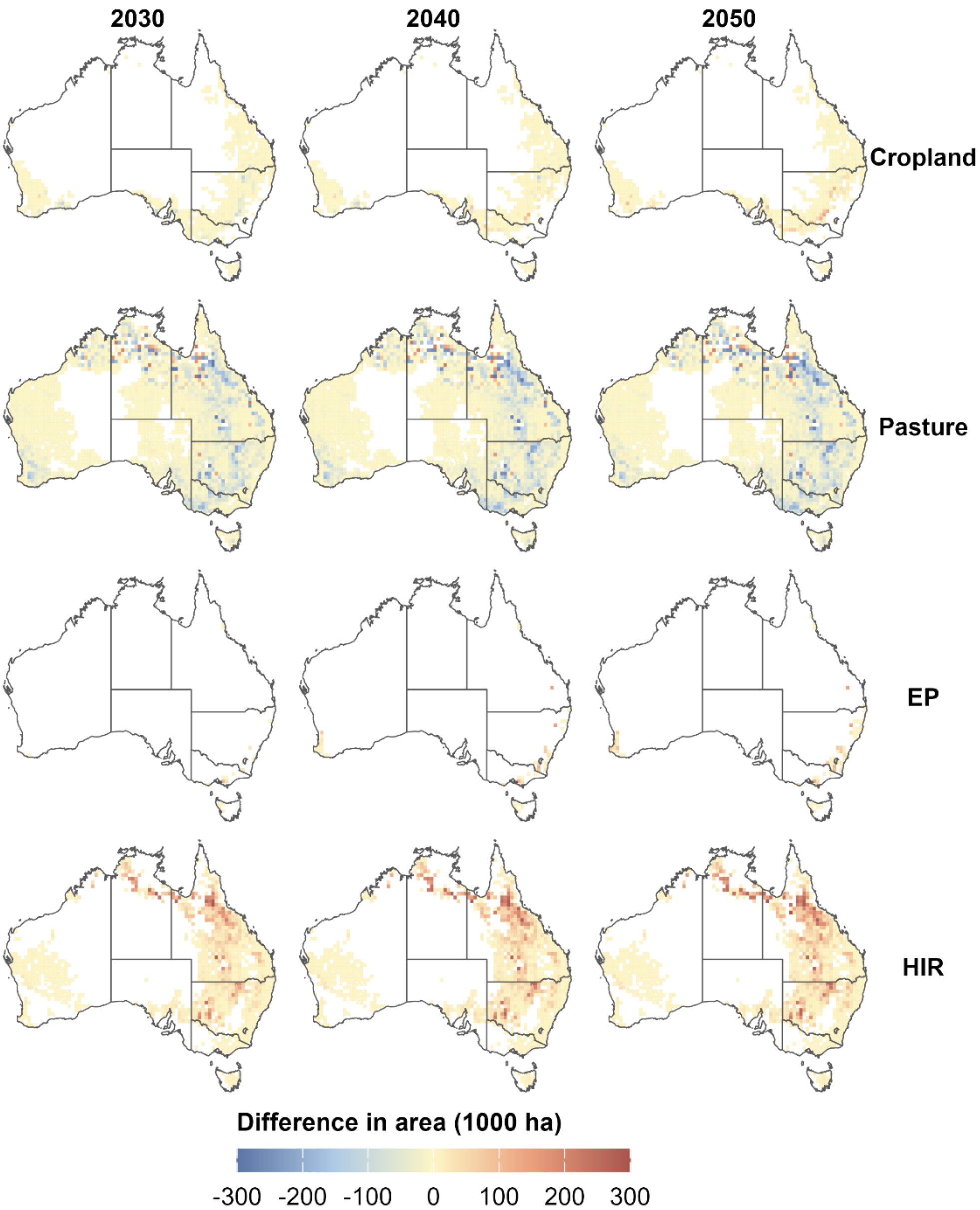


*Figure 8. Difference in area (1000 ha) for major land use classes under the NZE scenario compared to the Baseline scenario. EP refers to environmental planting.*

# 4. Discussion

In this study, we introduced an integrated modelling framework coupling two market equilibrium models with global scope calibrated for Australia. Through iterative information exchange, the modelling framework provides more consistent and robust results than if the models were used separately. Although this modelling framework can provide valuable insights on low-carbon transitions, some limitations should be considered when interpreting results. Below we discuss these challenges in more detail, along with future work that could help address these limitations. We conclude with the potential benefits of the framework to inform a rapidly evolving policy landscape supporting concurrent decarbonisation of multiple sectors of the Australian economy.

## 4.1. Validation of a partial equilibrium model

Verification and validation is a critical step to ensure reliability and credibility of results in any simulation model (Kleijnen, 1995). Most integrated assessment models, as well as land use models previously applied in Australia (Bryan et al., 2016; Morris et al., 2025), do not compare model results against historical data to test whether simulated and observed responses are correlated. While models that attempt to represent human decisions are typically challenging to validate, providing evidence that a model has the ability to replicate observed trend significantly enhances trust in model results and credibility. This is even more valuable when using global models in countries or regions with distinct land and agricultural conditions.

In this study, we presented an approach to parameterise a global model with national statistical data and calibrate processes in the model so that results align satisfactorily within an uncertainty envelope with observed trends over a 20-year period. This validation procedure was critical to appropriately represent trends in production, particularly dairy, wheat and barley, as well as emissions from enteric fermentation and manure left of pastures.

Future work should focus on validating land-use change processes. The current validation procedure centred around agricultural production and emissions, and historical land-use change emissions were treated exogenously rather than simulated. Extending validation to these processes would further build confidence in the modelling framework, particularly with respect to mechanisms underlying land-use change specifically for carbon sequestration.

## 4.2. Contributions to model coupling literature

The significant difference in carbon price and LULUCF emissions from the first to the second iteration illustrated in Figure 6 highlights the importance of a modelling framework that enables iterative coupling to reach consistency between models, as opposed to a one-way linkage. In this case, the latter approach would provide unrealistic assumption with respect to the ability of the carbon price to generate sufficient LULUCF to achieve the emission pathway in GTEM. While such model coupling is more frequent with energy system models, this novel framework adds to limited applications linking a detailed assessment of decarbonisation of the AFOLU sector with the rest of the economy, overcoming challenges on data exchange across platforms and temporal scales (Keppo et al., 2026).

In addition to carbon sequestration from LULUCF emissions, additional linkages between the GLOBIOM-Australia and GTEM models could include biofuels and bioenergy with carbon capture and storage (BECCS) for a more comprehensive inclusion of emission mitigation options from the AFOLU sector. Biomass demand and price are already considered in GLOBIOM as an exogenous variable, obtained in previous work from the MESSAGE model (Fricko et al., 2017), which drives the supply of feedstocks. A similar linkage could be implemented with GTEM, whereby GTEM provides demand and prices for bioenergy to GLOBIOM-Australia, which in turn, provides land-use change emissions and costs of biomass production.

The iterative coupling described in the study allowed to reach convergence in carbon price, a key variable driving emissions reduction. However, with greater complexity and sectoral detail, as well as multisectoral interactions, come a substantial computational burden, often including software licensing, different programming languages and computational resource requirements. These challenges hinder the flexibility of the modelling framework and ability to undertake uncertainty assessment, robustness analysis and explore a wide range of potential futures. For instance, in the case of this study, we illustrated the use of the modelling framework with one emission-reduction scenario along with a baseline scenario due to relatively high run time of iterating between two models.

This limitation could be addressed through the development of emulators or surrogate modelling, generating a much simpler and more flexible model which allows scaling of the number of simulations and enables ensemble scenario modelling (Guivarch et al., 2022; Moallemi et al., 2025). The GLOBIOM model is already used as an emulator of land-use dynamics in the IAM MESSAGEix-GLOBIOM (Fricko et al., 2017) and a similar approach could be followed for the GTEM–GLOBIOM-Australia modelling framework to allow faster and more efficient scenario analysis. Rapid developments in generative artificial intelligence could be leveraged to develop an emulator model based on deep learning (Holmes et al., 2026; Khan et al., 2024; Li et al., 2025; Shin et al., 2026), identify pathways to simplify models to optimise model parsimony through sensitivity analysis, or improving the parameterisation, calibration and performance evaluation of the models through human-AI collaboration and co-development (Muccione et al., 2024; Spillias, 2026).

## 4.3. Role of AFOLU in achieving NZE

We found that carbon sequestration through regeneration and reforestation play a critical role in achieving NZE by 2050. Under this scenario, 1.5 and 23.7 million hectares of land, in addition to existing projects, would be converted for carbon sequestration by 2050 through environmental plantings and HIR, respectively. This land conversion would generate a total of 190 Mt $CO_2$eq annually by 2050. This is higher than a previous study using the SAFE (Sequestration on Agricultural Land: Impacts and Policy Trade-offs) model, a spatial allocation model that also simulates carbon sequestration projects through HIR and environmental plantings under a carbon price (Morris et al., 2025). This study found that 18 million hectares of projects combining environmental plantings and HIR could sequester 119 Mt $CO_2$eq, driven by an exogenous linear carbon price path that was not obtained through iterative coupling with a CGE model. Therefore, the lack of interaction between emission reductions across multiple sectors of the economy could explain the difference in carbon sequestration.

Assisted vegetation regrowth is the dominant form of carbon sequestration in our results. While this form of carbon sequestration is expected to be included in the upcoming IFLM method to generate ACCUs, the specific HIR method expired in 2023 and can no longer be used to earn carbon credits. Furthermore, the effectiveness of HIR to increase forest cover and foster carbon sequestration has been questioned due to raised issues with non-compliance and under-performance (Macintosh et al., 2024a, 2024b). We included HIR in this study to allow for comparison with previous studies (Morris et al., 2025), however there could be a risk of overestimating carbon sequestration from this method if land-use change in practice does not align with simulated carbon sequestration (Roxburgh et al., 2020). Future work should focus on integrating uncertainties around the performance of different ACCU methods to generate carbon sequestration into economic models such as GLOBIOM-Australia.

In this study, we assessed the feasibility of achieving net zero in Australia by 2050 through reforestation and regeneration only. Agricultural demand, production, and emission intensity for different commodities are simulated in both GLOBIOM-Australia and GTEM, but only GTEM agricultural emissions are currently considered for the emission budget. Future work will consist in ensuring consistency in agricultural production and emissions across the two models. We did not consider strategies to mitigate emissions in the agricultural sector in GLOBIOM-Australia, for instance, through feed supplementation to mitigate enteric fermentation, or agricultural practices such as soil amendments with biochar. Given the high potential for trade-offs between agricultural productivity or cost of mitigation options and emissions reduction, finding solutions to reduce emissions without significantly increasing costs of production and affecting productivity will be critical to limit impacts on livelihoods in regional communities and food security. Future work will aim at improving the representation of agricultural practices and technologies with potential to improve emission intensity and suitable for the Australian context, particularly in the livestock sector. This will include both non-$CO_2$ (Frank et al., 2018) and $CO_2$ mitigation strategies on agricultural land (Frank et al., 2024) that can enable emission reductions without compromising agricultural livelihoods and food security. The mitigation of emissions in the agricultural sector could help reduce the conversion of agricultural land to reforestation and regeneration.

## 4.4. Land-use transitions and trade-offs

The land sector is subject to competition between various uses, including agriculture, carbon sequestration, biodiversity conservation and restoration, and bioenergy. In Australia, the bioenergy market is relatively small despite a high production and exports of feedstocks. For instance, the country is one of the largest producers of canola feedstock, which is mainly processed to produce biofuel in other countries (ABARES, 2025). However, with imminent international regulations on emissions from international aviation (Prussi et al., 2021), rising concerns around energy insecurity and a growing recognition that low carbon liquid fuels (LCLFs) can support Australia's nationally determined contributions and net zero targets, the government recently signalled a stronger interest in developing this industry (Department of Agriculture, Fisheries and Forestry, 2025). In light of these developments, biofuels are expected to represent a growing competing use for land over the next decades in Australia (O'Sullivan et al., 2025). While bioenergy can help reduce emissions in the transport sector, it can also have unintended consequences on land-use change and agricultural emissions (Searchinger et al., 2008).

Another competing use of land that could alter the dynamic of land-use change in the future is the Nature Repair market, an upcoming national, legislated biodiversity market (Department of Climate Change, Energy, the Environment and Water, 2026). The market will aim to provide incentives for nature restoration. Depending on the level and design of incentives for restoration, competition could occur between land use maximising carbon sequestration and land use maximising biodiversity restoration. GLOBIOM includes a measure of biodiversity, the biodiversity intactness index (BII), which varies through land use transition, in combination with a pixel-specific regional relative range rarity-weighted species richness score (Leclère et al., 2020). Land-use change can be affected by an incentive to maximise BII value, thereby increasing the biodiversity value over time. This existing mechanism could be adapted to the Australian context to better incorporate the potential competition, or synergies, between biodiversity enhancement, carbon sequestration, bioenergy, and food production. Accounting for biodiversity benefits could further increase the relative performance of assisted regeneration over environmental plantings given the superior potential for biodiversity restoration in agricultural landscapes (Evans et al., 2015).

### 4.5. Policy implications

In addition to Australia's economy-wide Net Zero Plan (Department of Climate Change, Energy, the Environment and Water, 2025), The Department of Agriculture, Fisheries and Forestry (DAFF) recently released the *Agriculture and Land Sector Plan* that establishes a framework for the sectors to contribute to Australia's net zero target (DAFF, 2025). Comprehensive decision-support tools that account for interactions between sectors will be needed to evaluate and minimise trade-offs among multiple priorities of the government, including reducing emissions and increasing agricultural productivity.

The results of this study provide several insights for the design of net-zero policies in Australia. For instance, the strong reliance on land-based carbon sequestration to achieve net-zero emissions highlights the critical role of the LULUCF sector in national mitigation strategies. This implies that policies that incentivise reforestation and regeneration should be coordinated with agricultural policy to manage increasing competition for land and limit disparity in the distribution of costs across regions. For instance, the NZE scenario entails conversion of pastures, particularly in Queensland. The transition of pastures to natural vegetation projected in this scenario would accelerate an observed trend in land-use transition Australia. Between 2010 to 2022, approximately 10 Mha of grassland were converted to forest land, and managed grassland experienced a net loss of 4 Mha, according to ANGA (Australian Government, 2023). Furthermore, a total of 1.9 Mha and 43.8 Mha of land have been converted to environmental plantings and HIR between 2014 and 2023, respectively (Clean Energy Regulator, 2026). Policy design will require measures to mitigate excessive agricultural land abandonment to safeguard food security and regional livelihoods during the low-carbon transition.

The findings also demonstrate that interactions between sectors significantly influence both emissions trajectories and carbon prices. In particular, constraints on land availability and the timing of sequestration incentives affect the cost of achieving net zero. This was illustrated through a high carbon price following late carbon sequestration in the first iteration of the model coupling in Figure 6. This highlights the importance of time-sensitive policy design and early climate action that considers cross-sectoral feedbacks over time rather than evaluating static mitigation options in sectoral silos.

## 5. Conclusion

We describe the development and present an initial application of the GLOBIOM-Australia model adapted to represent the unique agriculture and land system conditions in Australia. Results demonstrated that this model performed well in replicating temporal trends in production of the major agricultural commodities and emissions over the past two decades.

We also presented an approach to develop an integrated modelling framework linking GLOBIOM-Australia with GTEM, with an example to explore a net zero emissions pathway in Australia by 2050. This modelling framework is one of the few coupled CGE-PE models with global coverage that can simulate climate policy and GHG emissions endogenously in all sectors of the economy. Among these tools, it is the only one that includes Australia as a separate region, and parameterised and calibrated to reflect the distinct conditions of the country, and thus, making it particularly well suited to inform national climate-policy development and assessment. The integrated framework demonstrated stabilisation of the carbon price after ten iterations, ensuring consistency between the carbon price and LULUCF emissions. As such, this new modelling framework overcomes important challenges of coupling different types of models at varying spatial and temporal resolutions. Thus, it provides a potential template for other researchers wishing to couple CGE and PE models in this area.

Finally, the IAM framework was applied to explore a trajectory of the Australian economy toward NZE by 2050. Results show that net emissions from AFOLU would decline to -178 Mt $CO_2$eq per year to achieve this target. This would be realised largely through a combination of allocating 1.5 million hectares to environmental plantings and 23.7 million hectares to managed regeneration by mid-century.

Future work will focus on introducing bioenergy demand and supply as an additional driver of land-use change and emission mitigation measures. Information on the cost and performance of crop and livestock technologies and management practices to reduce GHG emissions will also be incorporated into GLOBIOM-Australia to explicitly capture the response of emission efficiency in agriculture to climate policies. These additions will further improve the representation of interactions between agriculture and land sectors with the rest of the economy, thereby strengthening the ability of the modelling framework to support sustainable multi-sectoral low-carbon transitions.

## List of acronyms

Computable General Equilibrium (CGE)
Partial Equilibrium (PE)
Integrated Assessment Models (IAMs)
Global Trade and Environment Model (GTEM)
Global Biosphere Management Model Australia (GLOBIOM Australia)
Land Use, Land Use Change, and Forestry (LULUCF)
Net zero emissions (NZE)
Integrated Farm and Land Management (IFLM)
Intergovernmental Panel on Climate Change (IPCC)
Full Carbon Accounting Model (FullCAM)
Spatial Production Allocation Model (SPAM)
Agricultural Bureau of Statistics (ABS)
Global Land Analysis and Discovery (GLAD)
European Space Agency Climate Change Initiative (ESA CCI)
National Land Use Map (NLUM)
Global Map of Irrigation Areas (GMIA)
Global Irrigated Areas (GIA)
Australian National Greenhouse Accounts (ANGA)
Human-Induced Regeneration (HIR)
Australian Carbon Credit Units (ACCUs)
Global Forest Model (G4M)
Gross Domestic Product (GDP)
Agriculture, Forestry, And Other Land Uses (AFOLU)
Low Carbon Liquid Fuels (LCLFs)
Department of Agriculture Fisheries and Forestry (DAFF)
Biodiversity Intactness Index (BII)

# Supplementary material

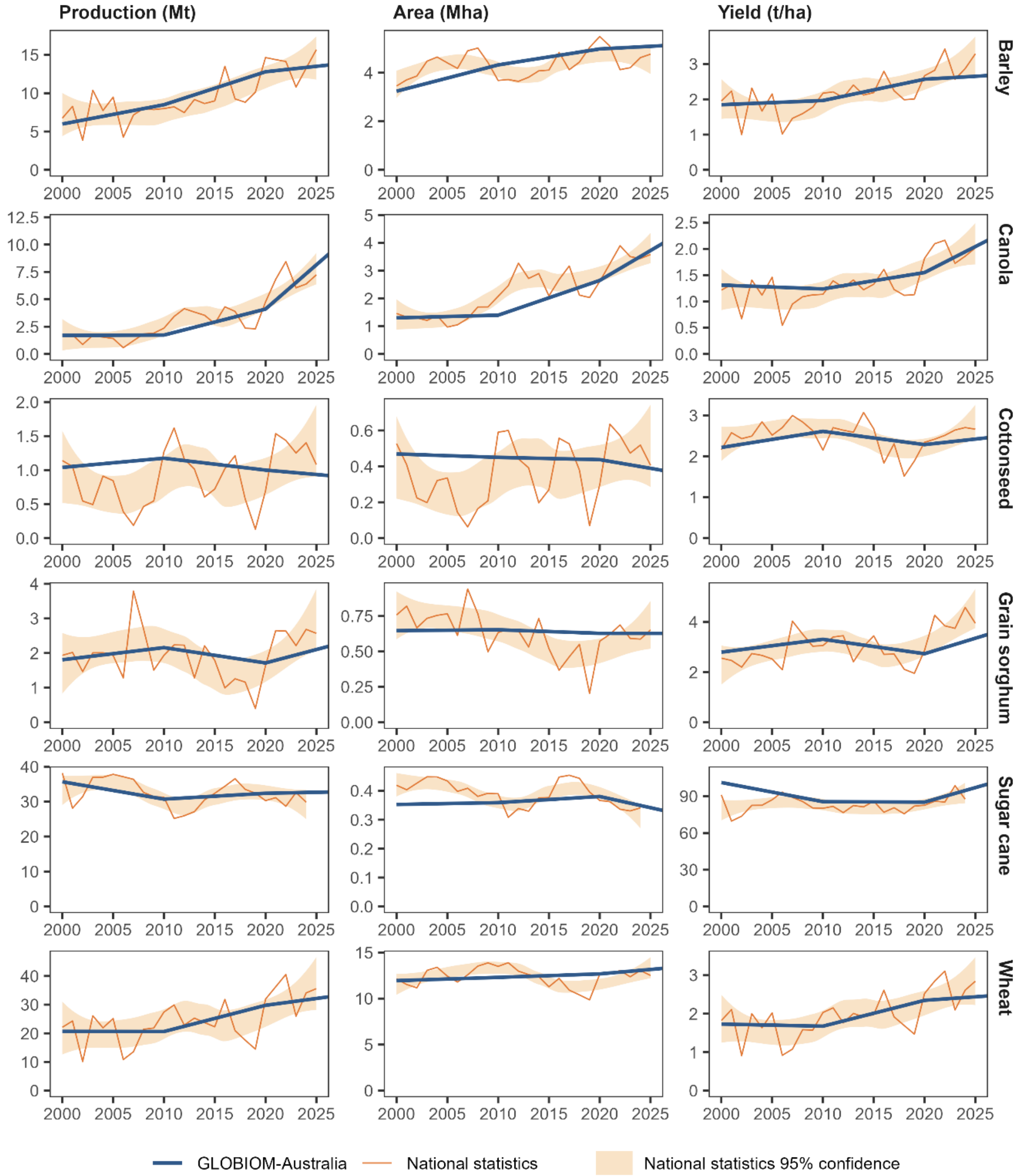


*Figure S1. Comparison of production, harvested area and yield for six crops in Australia for the historical period.*

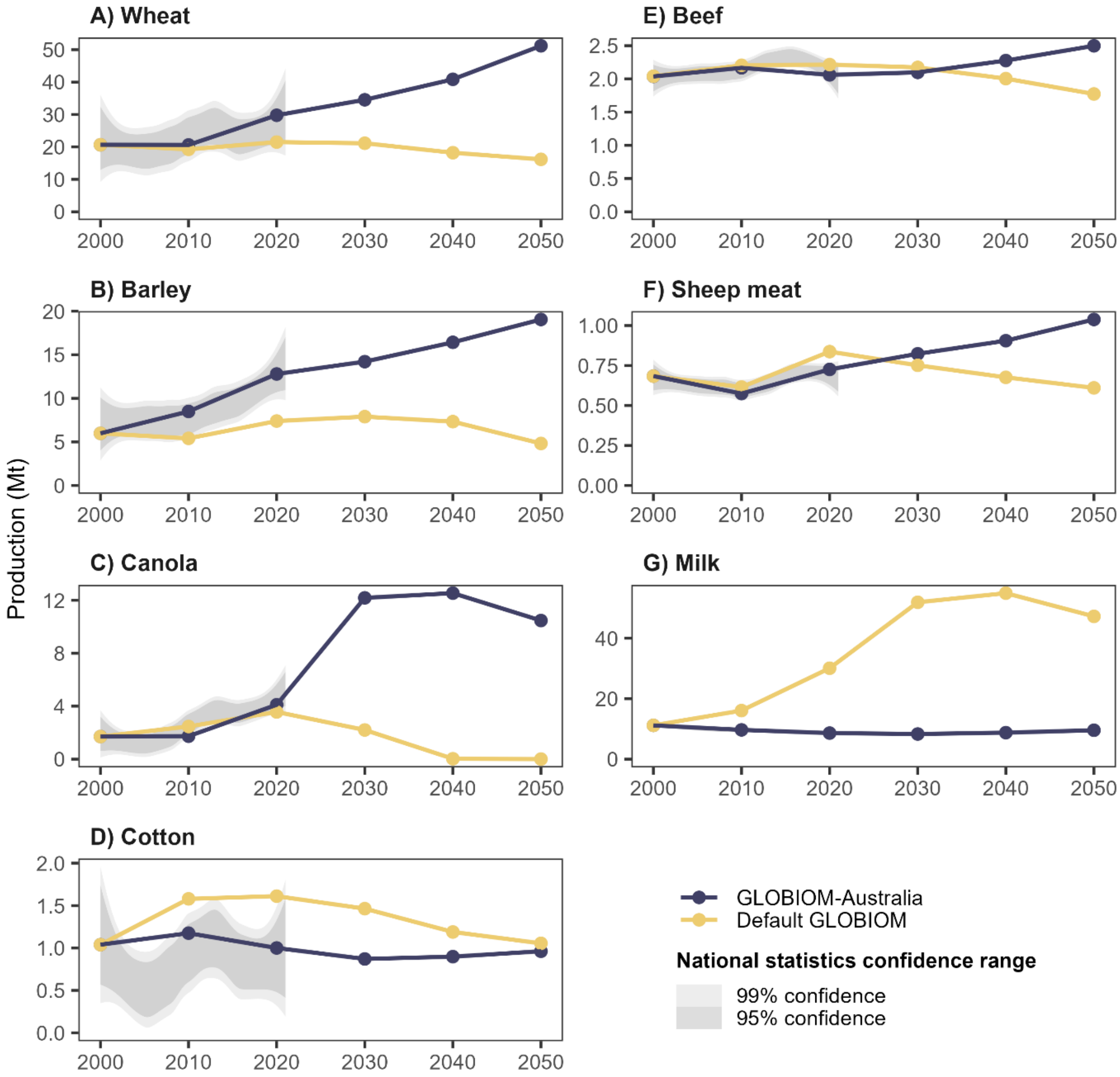


*Figure S2. Comparison in annual production between GLOBIOM-Australia, the default version of GLOBIOM and the confidence range from national statistics for nine of the most valuable agricultural commodities in Australia. Projections in production to 2050 are shown for the baseline scenario.*

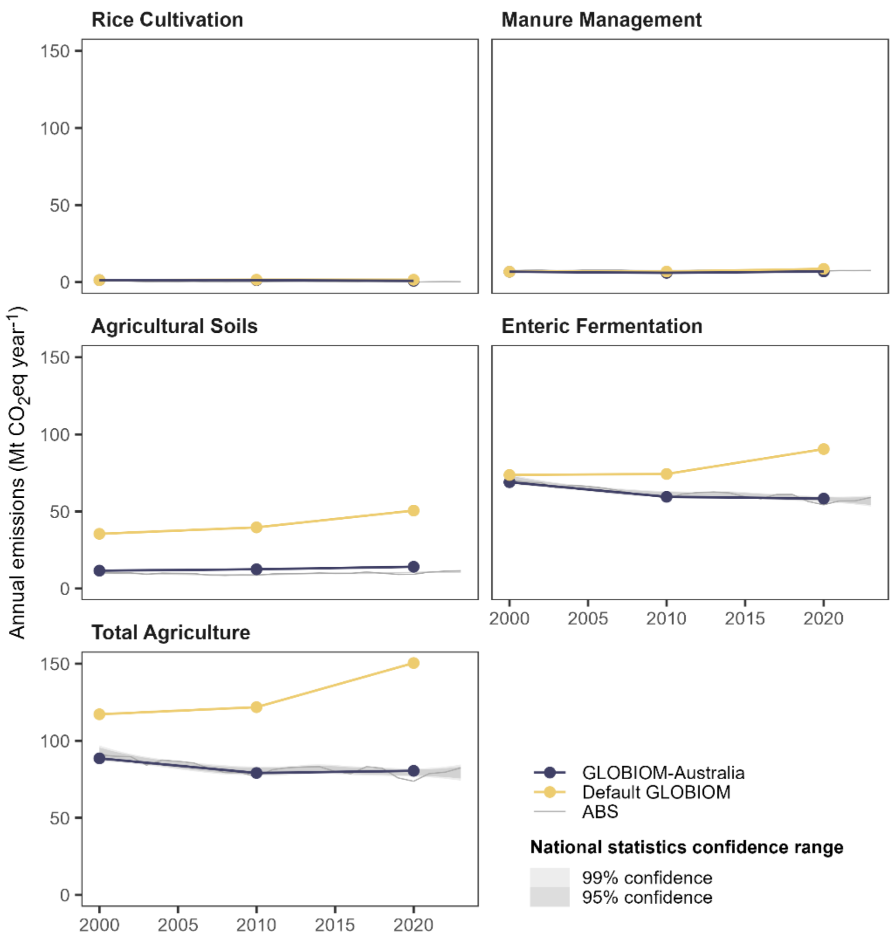


*Figure S3. Comparison in annual agricultural emissions between GLOBIOM-Australia, the default version of GLOBIOM and the confidence range from national statistics in Australia.*

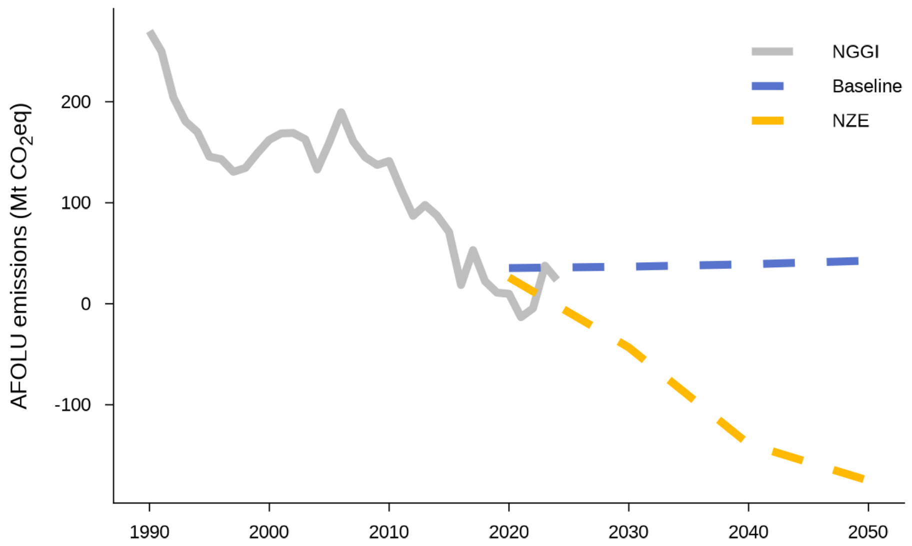


*Figure S4. Comparison of historical trend in AFOLU emissions from the Australian National Greenhouse Gas Inventory with simulated AFOLU emissions in the Baseline and NZE scenarios*

*Table S1. Total change in area in 1000 hectares for land use types for each state in 2050 compared to 2020 under the NZE scenario. Colour shading highlights the extent of increase (green) and decrease (red) in area of a land use. Natural land here combines Natural and Abandoned land from Table S1. EP refers to environmental planting.*

| State | Cropland | Pasture | Forest | EP | HIR | Natural land |
|---|---|---|---|---|---|---|
| Canberra | 0 | -24 | 0 | 24 | 0 | 0 |
| New South Wales | -1,113 | -8,694 | 0 | 850 | 4,799 | 4,158 |
| Northern Territory | 0 | -4,255 | 0 | 0 | 4,169 | 85 |
| Queensland | -346 | -15,128 | -13 | 166 | 13,368 | 1,952 |
| South Australia | -463 | -1,763 | 0 | 0 | 495 | 1,732 |
| Victoria | -375 | -3,400 | 0 | 410 | 98 | 3,267 |
| Western Australia | -520 | -2,203 | -2 | 518 | 853 | 1,354 |

*Table S2. Total land area for the main land use categories in GLOBIOM-Australia, in 1000 hectares*

| Land Cover | Scenario | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|
| Cropland | Baseline | 18 | 18 | 16 | 14 |
| | NZE | 19 | 16 | 16 | 16 |
| Grassland | Baseline | 170 | 171 | 171 | 172 |
| | NZE | 151 | 128 | 120 | 117 |
| Managed forest | Baseline | 7 | 7 | 7 | 7 |
| | NZE | 7 | 7 | 7 | 7 |
| Primary forest | Baseline | 93 | 93 | 93 | 93 |

| | | | | | |
|---|---|---|---|---|---|
| | NZE | 93 | 93 | 93 | 93 |
| HIR | Baseline | 0 | 0 | 0 | 0 |
| | NZE | 13 | 27 | 33 | 36 |
| Environmental planting | Baseline | 0 | 0 | 0 | 0 |
| | NZE | 0 | 0 | 1 | 2 |
| Natural land | Baseline | 387 | 387 | 387 | 387 |
| | NZE | 389 | 389 | 389 | 389 |
| Abandoned land | Baseline | 2 | 2 | 4 | 6 |
| | NZE | 7 | 19 | 19 | 18 |

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