Australia's National
Science Agency

Australian Grains Baseline and Mitigation Assessment

Main Report

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Glossary of terms and abbreviations

AER – Agro-ecological region

AEZ – Agro-ecological zone (grains specific)

AFOLU – Agriculture, Forestry and Other Land Use (Scope 1 emission category)

APSIM – Agricultural Production Systems Simulator

AusLCI – Australian Life Cycle Inventory

GHG – Greenhouse gas

GRDC - Grains Research and Development Corporation

IPCC – Intergovernmental Panel on Climate Change

LCA – Life Cycle Assessment

LCI – Life Cycle Inventory

MLA - Meat and Livestock Australia

NGLCI – National Grains Life Cycle Inventory

NGGI – National Greenhouse Gas Inventory (data underlying the NIR)

NIR – National Inventory Report (Australian Government Submission to the UNFCCC)

UNFCCC – United Nations Framework Convention on Climate Change

WFLDB – World Food LCA Database

Executive summary

With both climate adaptation and mitigation becoming increasingly urgent, there is a need to establish greenhouse-gas (GHG) baselines at sector level that can serve as a reference for monitoring of emission mitigation as well as for designing mitigation pathways. Australian agriculture has defined ambitious objectives, such as in the 2030 Roadmap of the National Farmers' Federation, which aim to contribute to Australia's emissions reduction but also to keep commodities competitive in export markets that increasingly require evidence of low-emissions credentials.

The Grains Research and Development Corporation commissioned this study to establish a detailed and robust GHG emissions baseline for the Australian grains sector and explore mitigation pathways that maintain or increase production.

An accounting methodology was specifically constructed to account for all GHG emissions associated with on-farm activities relating to the production of grains, including embedded emissions of inputs such as fertiliser. This methodology is described in detail in a separate Methodology Report. To align with the reference year for Australia's Nationally Determined Contribution under the Paris Agreement, 2005 was selected as the baseline year. Total GHG emissions associated with grains production in 2005 were found to be 13.75 Mtonne CO2-equivalent. The baseline GHG intensity was found to be 315 kg CO2-equivalent/tonne grain, which is low compared to other exporting countries.

On-farm emissions ("Scope 1") comprise 61% of emissions, dominated by emissions associated with application of fertiliser and lime (26%), denitrification of residue nitrogen (~20%) and fuel use (11%). Off-farm emissions ("Scope 3") are dominated by the embedded emissions in fertilisers (22.5%) and in crop-protection products (11%). All up, the use of fertilisers contributes ~38% of the total GHG baseline emissions and therefore is a key factor.

The year 2005 was found to be average in many of the relevant aspects, but the extreme weather variability in Australia will generally require the use of multi-year averages to assess mitigation or benchmarking. Simulations with APSIM, conducted for baseline conditions, show high annual variability of on-farm emissions, but average results for nitrous oxide emissions align well with those calculated using static emissions factors, for the West and South Regions.

A limited number of mitigation options was modelled using APSIM, varying rotations and nitrogen management compared to the baseline scenario. The results show that it is possible to increase overall production without significantly increasing overall on-farm emissions, by choosing locally productive and profitable rotations with low GHG emission intensity and optimizing nitrogen management. If nitrogen fertiliser could be supplied in such a way as to exactly meet crop demand, total fertiliser use is modelled to increase by a factor 3 compared to the 2005 baseline. Nevertheless, net on-farm emissions would slightly decrease on average because extra emissions are balanced by increased carbon sequestration in soils.

Off-farm emissions would increase, because of the additional fertiliser use. This increase could be mitigated by about 50% by using fertiliser produced with so-called green ammonia, but this is unlikely to be feasible before 2030. Further adoption of controlled traffic farming could reduce on-farm emissions and further increase yields, but more research is needed to establish its effects.

The key finding of this study is that improved fertiliser application can result in a decrease in GHG intensity per tonne grain of up to 20% while increasing production. Based on estimated uptake by 2030, an overall reduction in GHG intensity of ~15% may be feasible, while at the same time increasing production by 30-40%. In the longer term, GHG intensity is likely to decrease further, but to achieve reduction in overall absolute emissions, with increasing production, significant reduction of embedded emissions of fertilisers and other inputs will be needed.

The GHG intensity of Australian grains is already low compared to many other exporting countries, but it is important to stay competitive on a global market that increasingly focuses on sustainability credentials. This could be achieved while at the same time increasing production.

Offsetting of emissions via reforestation seems the most viable option to reduce absolute emissions. This would come at a cost to the sector, which could be compensated for by increased production.

The baseline and mitigation results provide a starting point for further research. This study had a limited scope and, amongst others, effects of ameliorating (sub) soil constraints or specific strategies to increase soil carbon could not be assessed. Details of current nitrogen management are not well known. Recommendations for further research also address better understanding of how system interactions influence GHG emissions but also on informing more localised low-emission farm management choices via modelling and/or technology development and testing.

Part I Baseline assessment

The GHG Balance of Australian Grain production systems in 2005.

1 Introduction

With both climate adaptation and mitigation becoming increasingly urgent, there is a need to establish greenhouse-gas (GHG) baselines at sector level that can serve as a reference for monitoring of emission mitigation as well as for designing mitigation pathways. Australian agriculture has defined ambitious objectives, such as in the 2030 Roadmap of the National Farmers' Federation (NFF 2019), which aim to contribute to Australia's emissions reduction but also to keep commodities competitive in export markets that increasingly require evidence of low-emissions credentials. Recent reports (e.g. EY 2021) describe high-level pathways to net zero emissions by 2050 for Australian agriculture. Agriculture is a highly diverse industry and, although most farms are involved in producing a range of commodities, it is useful to evaluate contribution to GHG emissions and potential mitigation strategies at sector level.

The Australian grain production sector is a large land use covering more than 20 Mha. The sector is very geared toward export markets, with wheat, barley and canola in the top 10 of agricultural commodities by export value. Therefore, understanding the total GHG emission balance of Australian grain is essential to inform grains GHG mitigation strategies as well as maintaining competitiveness in global markets into the future (see Greenville et al. 2020).

This study establishes a detailed and robust GHG emissions baseline for the Australian grains sector and explores mitigation pathways that maintain or increase production. The overall study evaluates a *historic baseline* for the year 2005 (using a *static* accounting approach), a *dynamic baseline* that models the emissions of the business-as-usual scenario over the period 1991-2019 (using APSIM) and *mitigation pathways*, modelling the effects of mitigation scenarios over the same period (using APSIM).

GHG accounting, also called carbon accounting, is a broad term that refers to the process to establish total amounts of GHG emitted directly or indirectly by an entity or emitted in a chain of processes resulting in a particular product. Different GHG can be added to yield a single result by using a metric that reflects their relative effect on climate change. The most common metric is the 100-year Global Warming Potential (GWP100) that is set by the IPCC (e.g. IPCC 2007).

A full GHG account for the Australian grains sector required definition of the system and methodology, building on previous work in National Grains Life Cycle Inventory (NGLCI; Simmons 2017; Simmons et al. 2019) and the Australian Life Cycle Inventory (AusLCI[1]). The system is defined by the production of all GRDC leviable crops in 2005. The leviable crops are:

- Wheat
- Coarse grains
    - barley, oats, sorghum, maize, triticale, millets/panicums, cereal rye, canary seed

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[1] http://www.auslci.com.au/

- Pulses
    - lupins, field peas, chickpeas, faba beans, vetch, peanuts, mungbeans, navy beans, pigeon peas, soybeans, cowpeas, lentils
- Oilseeds
    - canola, sunflower, safflower, linseed.

Data for the static accounting as well as for definitions of systems simulated in APSIM was collected and aggregated from a range of data sources to the level of those 25 crops and 24 grains subregions. Results of subsequent emission calculations are aggregated to totals for each of the three grains regions and reported as total emissions as well as GHG intensity, by total production.

This integrated approach using the static accounting approach as well as APSIM modelling to evaluate GHG emissions allows for capturing the seasonal variability of emissions and to cross check static emission factors with the results of simulations at this highly aggregated level. The dynamic baseline, based on APSIM, also provides the appropriate reference for APSIM-based mitigation scenarios given some differences found between APSIM-based emissions and results of the static baseline calculations, especially around soil carbon (see Chapter 3).

The first part of this report focuses on the results of the historic baseline calculations as well as the APSIM-based dynamic baseline. The second part describes a limited number of mitigation options that were selected for evaluation of effects on GHG emissions, either via adjustment in emission factors or via APSIM simulations. Results are presented and compared to the relevant baseline result. A discussion of adoption in the short term is included to assess what mitigation may be feasible to achieve by 2030. The third part of the report puts the results in broader context and discusses limitations, recommendations and conclusions.

2 Historic Baseline 2005

2.1 Introduction

The historic or “static” baseline gives a snapshot of greenhouse gas (GHG) emissions associated with Australian grains production in 2005 (financial year July 2005 to June 2006), based on areas and yields reported for that year for the 25 Grains Research and Development Corporation (GRDC) leviable crops.

The system boundary used for the baseline assessment is “cradle-to-farm-gate” with a full life-cycle or footprint approach, i.e. including Scope 1,2 and 3. Scope 1 emissions occur on farm, Scope 2 emissions are associated with the production of electricity that is used on farm, and Scope 3 emissions are associated with other activities outside farm boundaries, such as the production of fertilisers. Data on use of fertilisers, lime and chemicals as well as fuel use for operations were derived from the NGLCI when possible, with gaps filled in with other sources, and adjusted for 2005 yields. Data on drying and storage was sourced from industry.

On-farm emissions were derived from the activity data using methodology and emissions factors from the National Inventory Report for 2018 (NIR 2018), including nitrous oxide emissions due to fertiliser use and residue management, carbon dioxide emissions of application of urea and lime, and emissions due to changes in soil organic carbon. Off-farm emissions and emissions of fuel use were calculated using data from the AusLCI database.

In practice, data sources had varying spatial resolution, ranging from state-level data to agro-ecological regions to grains subregions and level-2 statistical areas (SA2), combined with some emission factors defined by local climate conditions. The resulting activity data set and emission inventory was built at the level of SA2 and crop, using correspondence tables to match the various region definitions, and then re-aggregated using consistent definitions of the 24 subregions and 3 regions that are commonly used when discussing the Australian grains sector (see Figure 2).

Full details are available in the Methodology Report (Sevenster et al. 2022).

2.2 National GHG emissions and intensity

Total GHG emissions associated with grains production in 2005 were found to be 13.75 Mtonne CO_2-equivalent. The contributions to the total of Scope 1,2 and 3 emissions is 61.3%, 0.1% and 38.6% respectively. A more detailed split is shown in Figure 1.

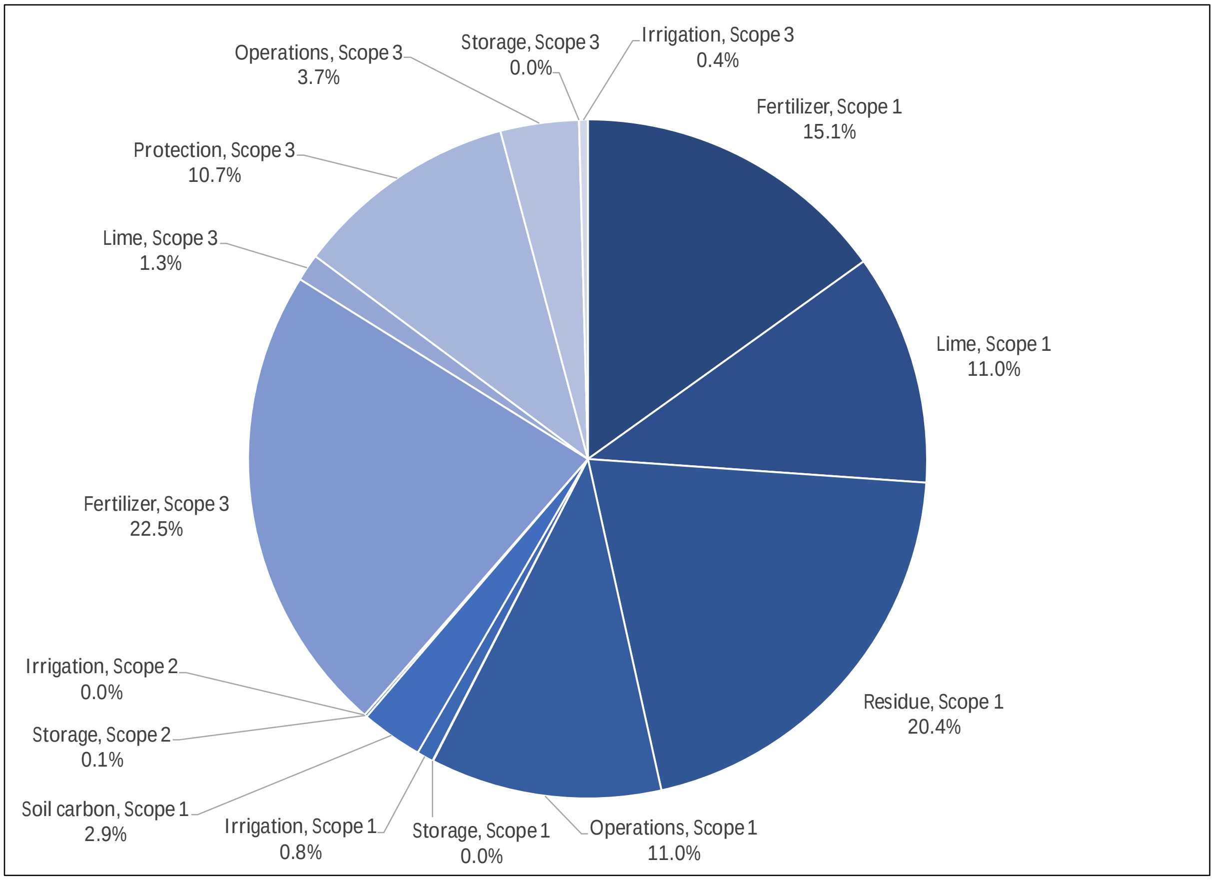

Figure 1 Contributions of emission source categories to the total GHG emissions baseline. The contribution of Residue combines emissions from burning and from decomposition of crop residue.

The contributions show that the AFOLU (agriculture, forestry and other land use) emissions account for almost exactly 50% of the total. AFOLU includes the Scope 1 emissions of fertilizer and lime application, residue burning and decomposition and changes in soil carbon. Of the Scope 1 fertilizer emissions, 45% (6.8% of the total) is due to re-emission of the CO_2 contained in urea upon application. This CO_2 is removed from the atmosphere during the production of urea, and therefore the net effect over the cycle of urea of production and application of urea is zero. However, because production and application occur in different sectors and potentially in different countries, removal and re-emission are counted explicitly in the national inventory. For the grains GHG baseline, it means the Scope 1 emissions are higher, but the Scope 3 emissions are lower than they would be if this short-cycle CO_2 was excluded from the assessment. The net GHG balance would not be different. Of the Residue emissions, 11% (in CO_2-equivalent) arise from burning of residue (N_2O and CH_4) and 89% from decomposition of residue left in the field (N_2O).

Scope 1 emissions of fuel use for operations (spraying, harvesting, etc), irrigation and storage, including drying and loading, account for about 12% of the total. Scope 2 emissions are negligible, given that irrigation was assumed to be 100% diesel based (i.e. no electricity) and electricity use for storage (aeration) is minimal. Embedded emissions in fertilizer supply account for most of the remaining 38% Scope 3 emissions.

GHG emission intensity results are 618 kg CO_2-equivalent/ha, 315 kg CO_2-equivalent/tonne harvested, 2.63 kg CO_2-equivalent/kg protein, 19.2 kg CO_2-equivalent/GJ calorific value and 1.48 kg CO_2-equivalent/AUD revenue (see 0). These values all include emissions due to change in soil organic carbon in the absence of land use change (see Methodology Report) which account for 3% of the total emissions (Figure 1).

2.3 Regional results

Results were calculated separately for the main GRDC North, South and West regions (see Figure 2). Values for production metrics such as total area and total production are listed in 0, and resulting total production metrics for each of the regions are listed in Table 1.

Table 1 Production metrics for the three Regions (see Appendix A.2 for values used by commodity)

Region	Area (kha)	Production (ktonne)	Protein (ktonne)	Energy (PJ)	Value of crops (million AUD)
North	7931	16075	1799	262	3445
South	6913	14010	1682	229	2944
West	7410	13526	1748	224	2887

Figure 2 The GRDC North, South and West regions as used in the baseline assessment. Tasmania is part of the South region.

Total GHG emissions associated with grains production in 2005 by Region are shown in Figure 3. The South has the smallest contribution to the total, which reflects the smaller total area and output. The contributions of each of the emission sources are similar across the Regions, with the exception of Scope 1 and 3 emissions of lime which are considerably higher in the West, and Scope 1 and 3 emissions of irrigation (pumping) which are higher in the North. Scope 1 emissions associated with (nitrogen) fertilizer application are higher in the North than in the West, due to higher emission factors in higher rainfall areas. This is despite a somewhat higher application rate in the West which results in higher fertilizer Scope 3 emissions.

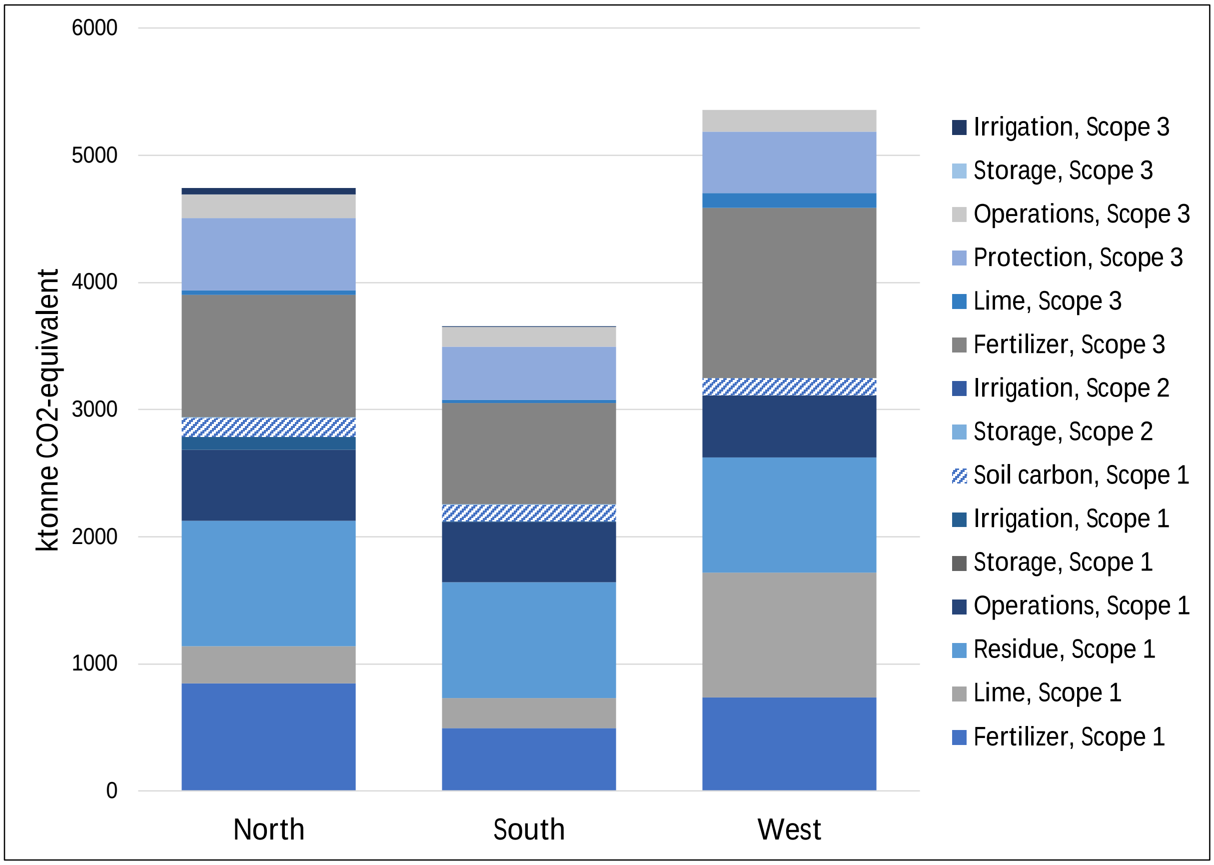

Figure 3 Total GHG emissions in 2005 by GRDC region.

GHG emission intensity results vary across the Regions (Figure 4) with values of 261, 295 and 396 kg CO_2-equivalent/tonne harvested for South, North and West, respectively. The higher intensity in the West is partly reflecting a higher fraction of legumes, as is clear from the GHG intensity per kg protein (Figure 5).

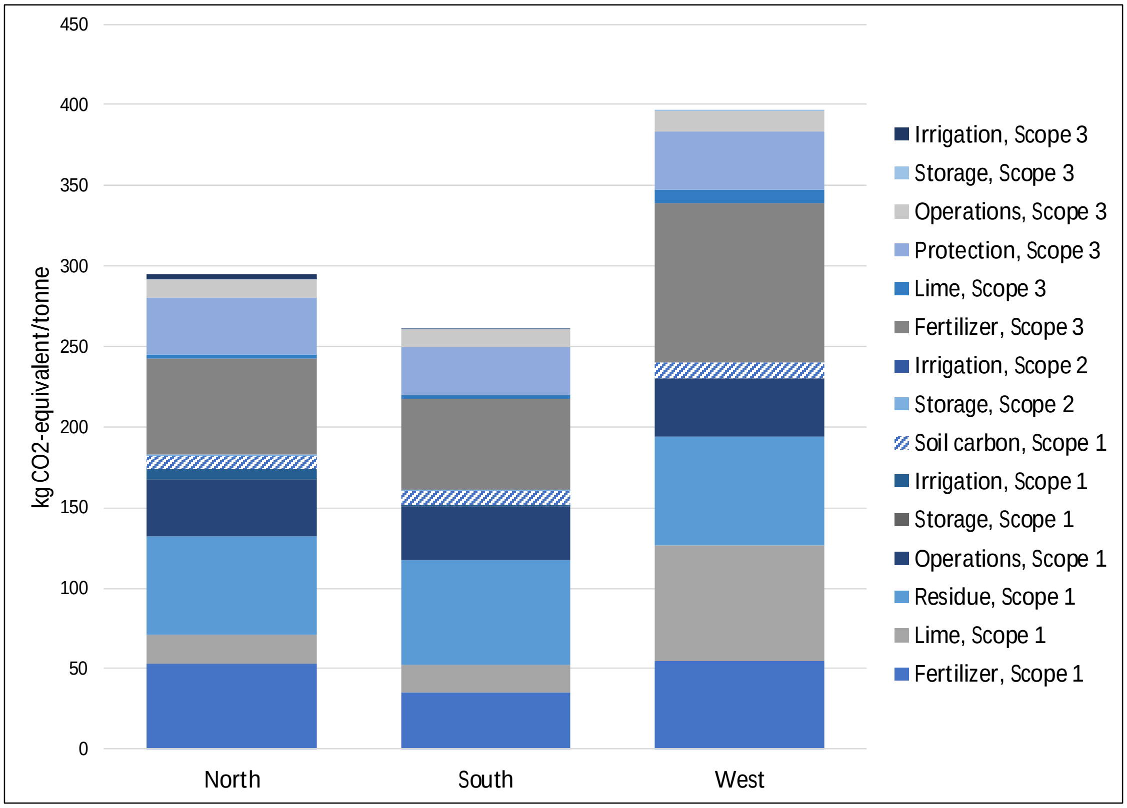

Figure 4 GHG intensity per tonne harvested in 2005 by GRDC region.

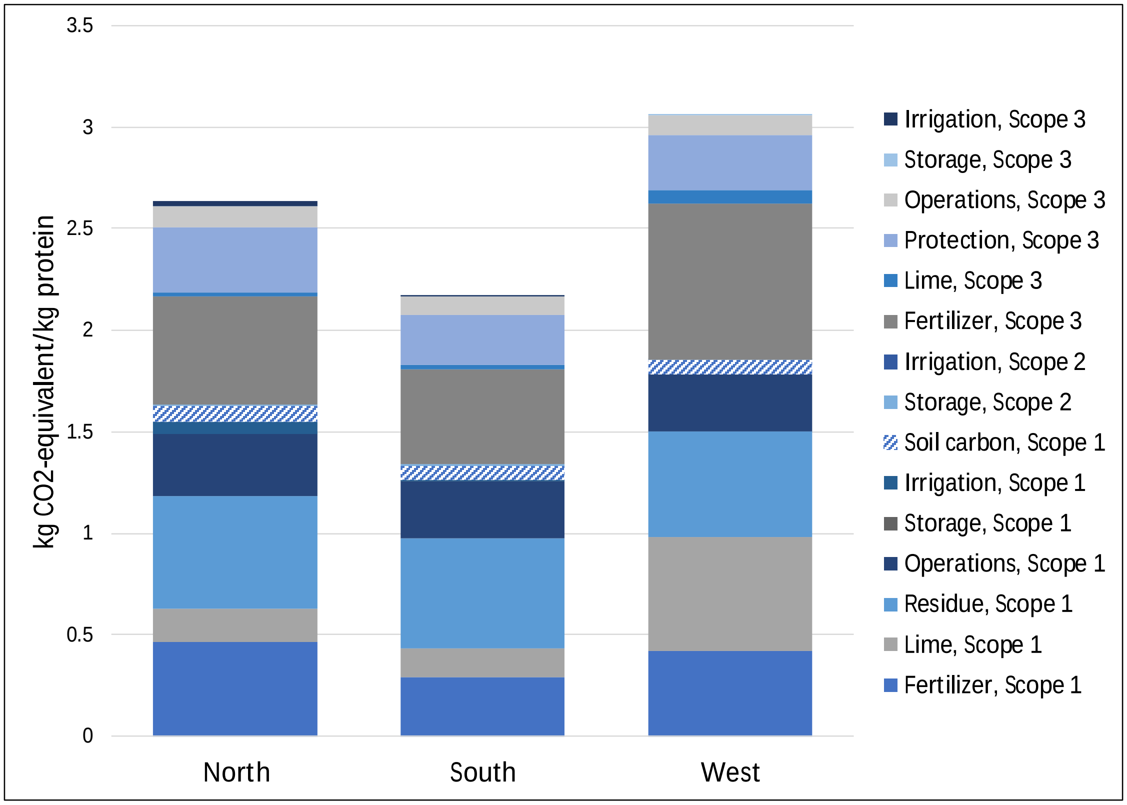

Figure 5 GHG intensity per kg protein produced in 2005 by GRDC region

2.4 Comparison with other sources

The intensity baseline result can be compared to life-cycle assessment results for core commodities such as wheat and barley (75% of total production by area in 2005). For cereals, the baseline assessment indicates an emissions intensity of 294 kg CO_2-equivalent/tonne when excluding emissions from change of soil carbon. As expected, given the similarity in approach, this is very similar to the values of 307 kg CO_2-equivalent/tonne wheat and 265 kg CO_2-equivalent/tonne barley, according to AusLCI[2].

The international World Food LCA Database (WFLDB), on the other hand, gives values of 498 kg CO_2-equivalent/tonne Australian wheat and 426 kg CO_2-equivalent/tonne Australian barley (excluding their values for emissions from land use change). Figure 6 shows GHG intensities for a number of exporting countries derived from the WFLDB, compared to the result for cereals found in this study.

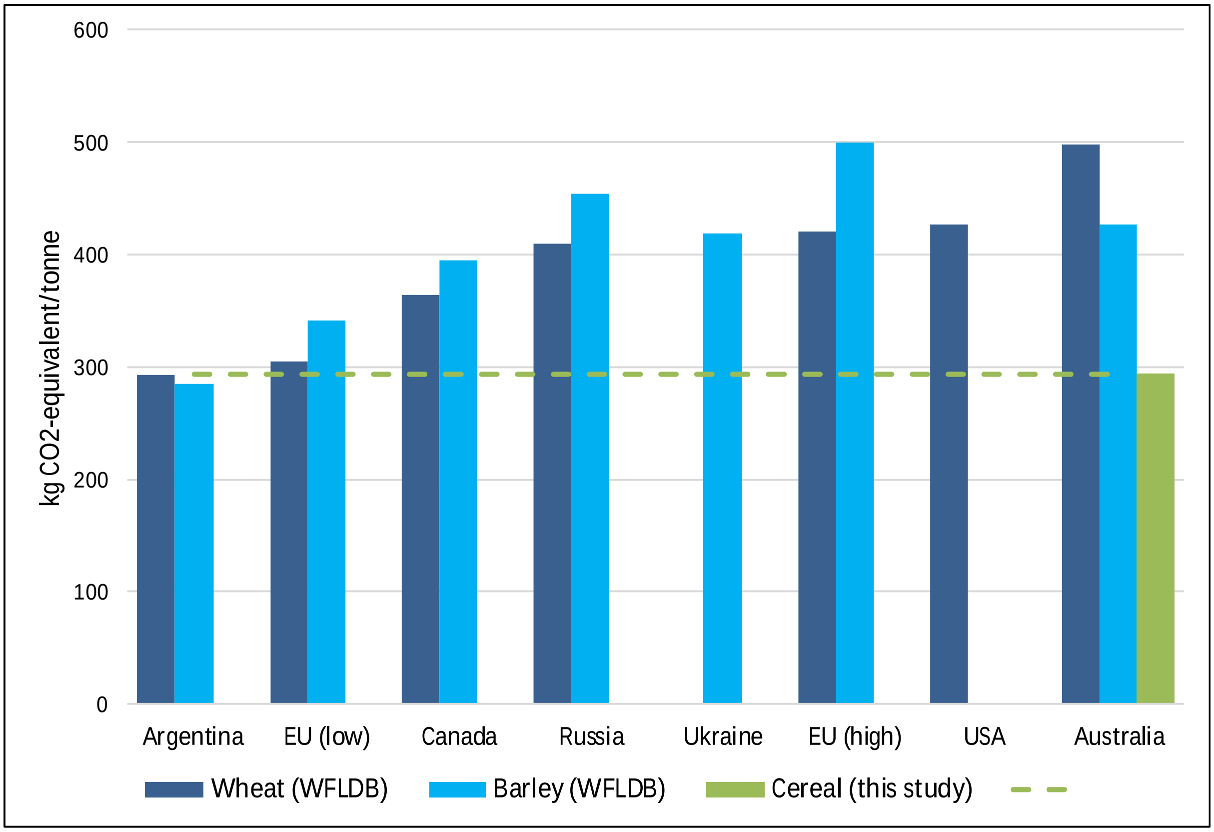

Figure 6 Comparison of GHG intensity results for wheat and barley, by country as available in the WFLDB, with the result from this baseline assessment. All data exclude emissions from soil carbon change and land use change.

When including the emissions from land use change in the comparison (Figure 7) the contrast between international sources and the Australia-specific baseline is even clearer.

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[2] http://www.auslci.com.au/

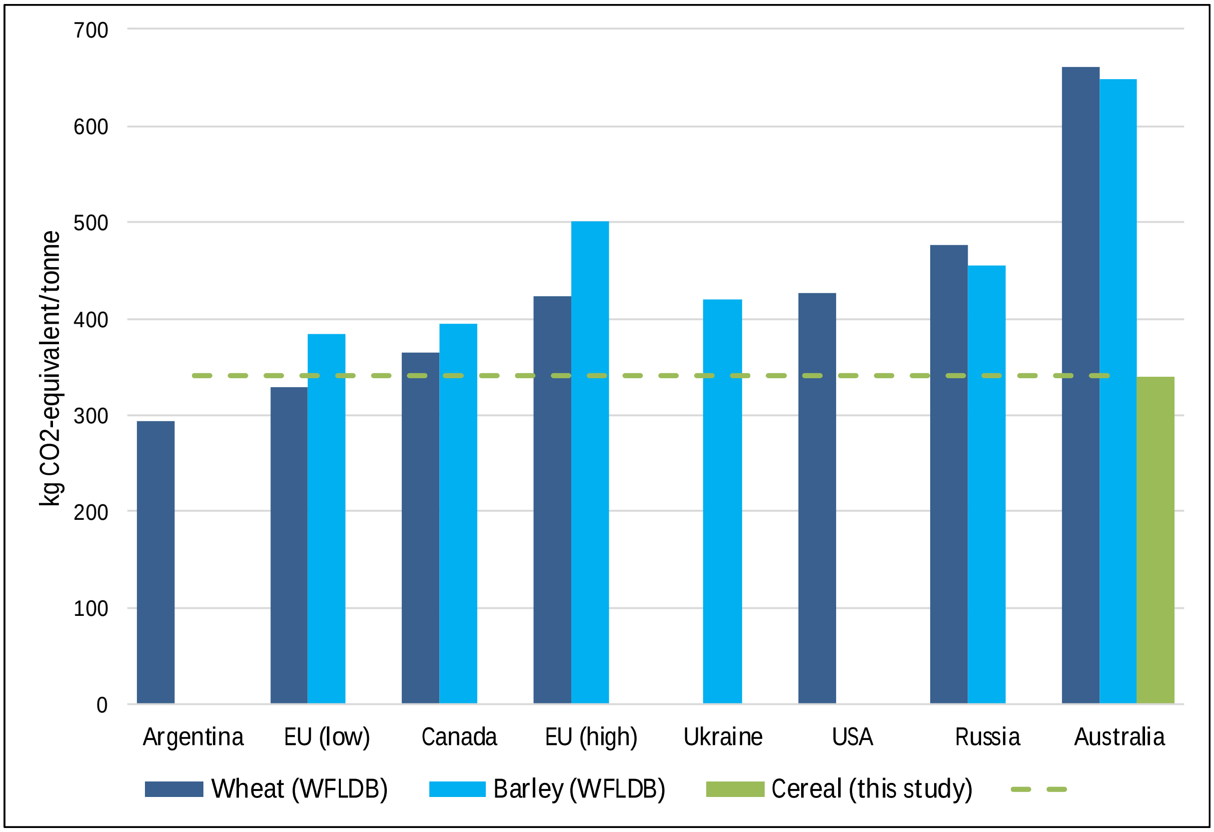

Figure 7 Comparison of GHG intensity results for wheat and barley, by country as available in the WFLDB, with the result from this baseline assessment. All data include emissions from land use change.

According to the WFLDB as well as similar international databases, the GHG intensity of Australian wheat and barley is at the high end of the range compared to other countries, and the highest when including land use change emissions. This is partly explained by the use of tier-1 emission factors (Nemecek et al. 2019) which are too high for Australian conditions (NIR 2018), but also because methods for estimating emissions from land use change result in values that are too high for Australia (Bontinck et al. 2020).

In the ABARES Insights of December 2020 (Greenville et al. 2020), the GHG intensity of Australian cereal production was compared to other major exporting countries based on AFOLU emissions as reported by FAO. For 2005, the FAO gives a value of 217 kg CO_2-equivalent/tonne for Australian cereal production. The equivalent in this study is found to be 142 kg CO_2-equivalent/tonne (excluding emissions from change of soil carbon to align with FAO). This value would put Australia well below the average emissions intensity of major cereal exporters (see Figure 7 in Greenville et al. 2020). Similar corrections apply to the other countries, but for most countries included in Figure 6 and Figure 7 UNFCCC[3] reporting suggests emission factors that are equal or higher rather than lower than the tier-1 emission factor. Australia has the lowest UNFCCC reported emission factor for direct nitrous oxide emissions. The emission factor reported by Canada is slightly lower

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[3] United Nations Framework Convention on Climate Change, see https://di.unfccc.int/flex_annex1

than the tier-1 factor; the USA and Russia report factors that are well above tier-1. Most countries are using the tier-1 factor or similar.

The above comparisons underline the importance of using representative emission factors, as opposed to default global tier-1 emission factors that underly both the FAO and WFLDB data. As is highlighted by Greenville et al. (2020), GHG emissions intensity is increasingly becoming a factor in competitiveness and therefore transparent and accurate GHG accounting can support continued market access. The AusLCI database, which uses a methodology very similar to the one applied in this study, is freely available to anyone, in several common formats. In addition, the Australian LCA Society[4] is discussing possible integration within international databases.

2.5 Sensitivity assessments

2.5.1 Cotton-wheat rotation

Actual data on the area of grains in rotation with cotton in 2005 could not be found. This means that the explicit allocation of fertilizer application in cotton-grain rotations could not be applied (see Methodology Report). To estimate the potential effect of such allocation, results were adjusted for the following assumptions:

- The area of grains in rotation with cotton in 2005 equals the area under cotton in that year
- No nitrogen is applied to the grain when in rotation with cotton
- Average yields are the same for grain in rotation with cotton

In practice, rotations with cotton would involve wheat primarily, so these assumptions are a simplification, but wheat is by far the dominant crop in the baseline. The estimate is that if cotton-wheat rotations could be taken into account accurately the total baseline emissions would be less than 1% lower. As cotton is predominantly grown in the North Region, the total emissions for that region would be approximately 2% lower.

2.5.2 Land use change

As outlined in the Methodology Report, emissions due to land use change are evaluated as a sensitivity assessment, based on the emissions reported under Forest land converted to cropland in NGGI (NIR 2018). These emissions are estimated to add 17% to the national baseline and 21%, 6% and 22% for the North, South and West Regions, respectively. This indicates that deforestation still had a significant effect on emissions in 2005.

In the baseline year, approximately 5% of cropland[5] area is associated with cumulative (legacy) land conversion, and approximately 0.03% with net conversion in the same year (NIR 2018). Since 2015, net annual change in Forest land converted to cropland has been negative. The emissions reported under this category have also halved compared to the baseline year.

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[4] www.alcas.asn.au

[5] Including temporary pastures

2.5.3 Choice of baseline year

The year 2005 was chosen for the baseline assessment to align with the Paris Agreement. A single reference year is not so appropriate for agriculture, however, given the large intrinsic variability. Nevertheless, even though 2005 was in the middle of the Millennium Drought it was a relatively normal year in terms yields in broad acre cropping.

As shown in Figure 8, for the major crops, wheat and barley, there is some variation in area cultivated over the period 1999-2016. The variability mainly shows in production and hence in yield. The year 2005 was in upper-middle quartile for the three parameters. For production and yield, this is largely due to the severely drought-affected harvest years 2002, 2006 and 2007. When excluding those from the range, 2005 is in fact very close to the median for all three parameters.

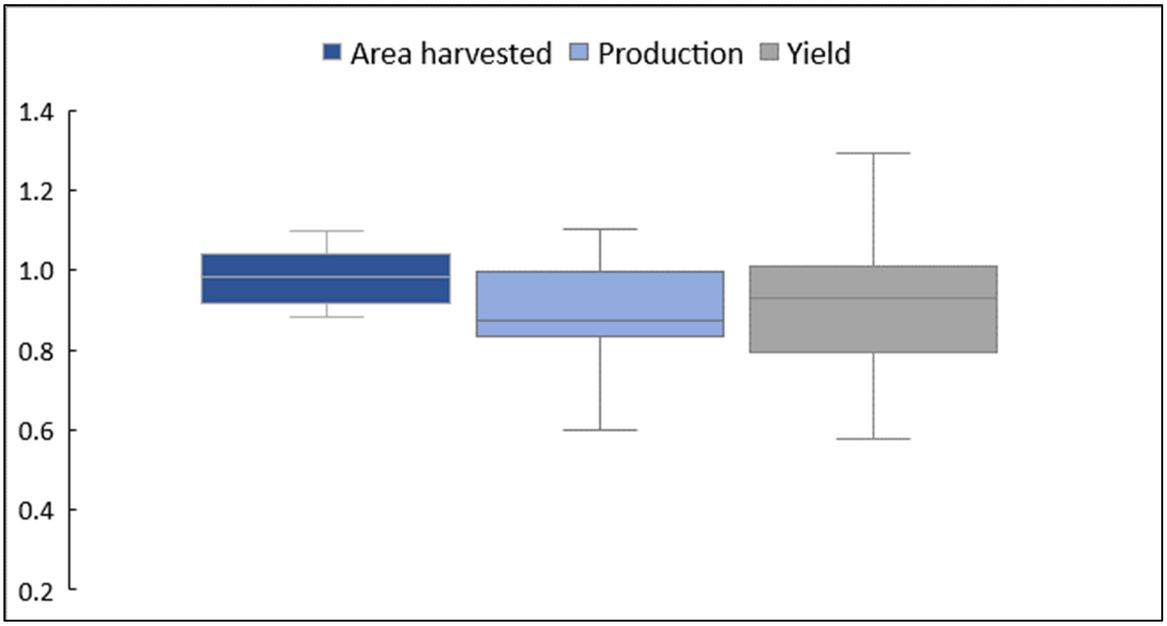

Figure 8 Variability in area, production, and yield for wheat plus barley over the period 1999 – 2016 (harvest year), relative to 2005 (ratio). This means 2005 is represented by the value 1 in this graph. Source: FAO

Given that many emission sources scale with production (see Methodology Report) the total GHG emissions baseline can therefore be expected to be close to the median in 2005. The GHG emissions intensity in fact shows much less variability for the same reason. The emission sources that scale with area are irrigation, liming, tractor operations and soil carbon change. It is the latter that would cause most variability in the historic baseline by year, both for total emissions and for emissions intensity. As shown in Figure 9, the year 2005 is very close to the median regarding soil carbon change emissions.

The second-strongest factor in causing variability in the emissions intensity baseline is liming, which would affect the West primarily. To conclude, the harvest year 2005 (FY 2005-2006) appears to be representative of longer-term average grains production, but annual variability should be expected to be large for absolute GHG emissions. This is addressed in Chapter 3.

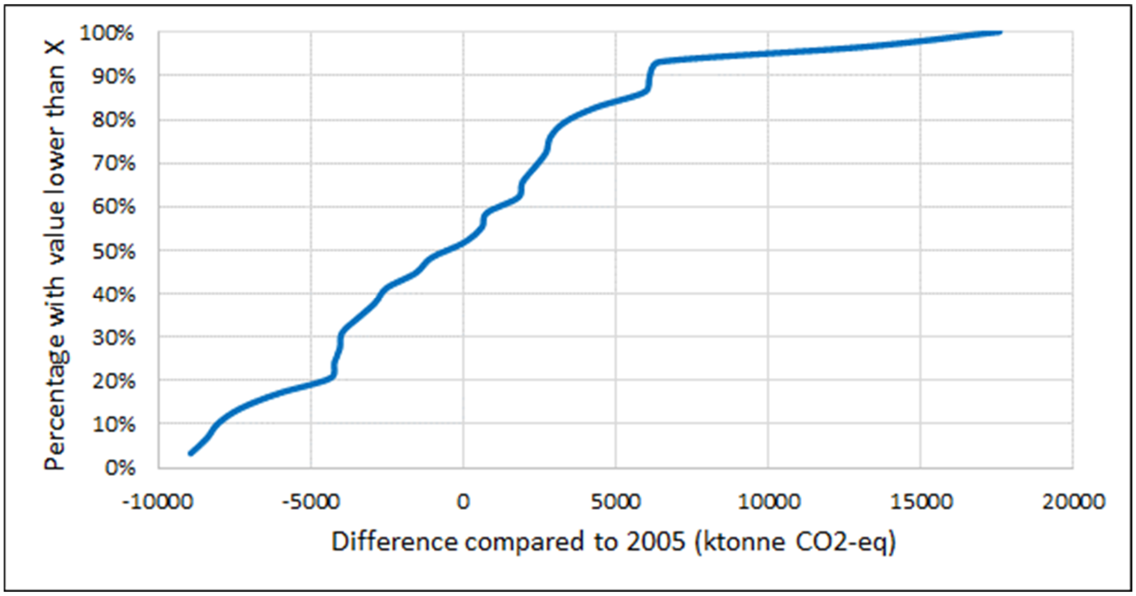

Figure 9 Variability in emissions due to soil carbon change (Cropland remaining cropland) nationally relative to 2005 (difference) over the period 1990 – 2016. The year 2005 is represented by the value 0 in this graph. Source: NIR 2018

2.5.4 Embodied carbon

Embodied carbon refers to the carbon atoms that are actually part of products, in whatever molecular form. In crops, this carbon is temporarily stored after the plant sequesters carbon dioxide from the atmosphere via photo synthesis and the total amount of CO_2 thus removed from the atmosphere even for the harvested products only is considerably larger than the total GHG emissions established for the 2005 baseline in this study. With a production of around 44 Mtonne of grain, the embodied carbon can be estimated to represent the equivalent of 80 Mtonne CO_2 removed from the atmosphere.

However, for annual crops, this is CO_2 considered “short cycle” and therefore it is not included in GHG inventories (e.g. NGGI). The carbon will be released again upon consumption (or other decomposition) of the food product and this is typically well within a timescale of a few years. There is therefore no net effect on future global warming. The same is true for the carbon embodied in crop residue. Carbon dioxide emissions from residue burning or decomposition are not included in GHG inventories.

In some product-level carbon footprint protocols (ISO 14067) it is prescribed to keep track of embodied carbon separately, but again, the net effect over the full product life cycle is considered zero. Additional calculations are allowed for long-lived products. For food, some protocols make an exception to the rule to track embodied carbon (PAS2050:2011). It is worth noting that the carbon embodied in annual crops is considered by some as more truly climate neutral than e.g. wood (Guest et al. 2012) because wood has longer growth cycles. In practice, however, embodied carbon in trees is, just like embodied carbon in crops, not considered to have climate benefits unless the total stock is increasing (e.g. reforestation). Soil carbon could be seen as the equivalent for cropping systems, with increases in biomass production typically enhancing soil carbon stock.

3 Dynamic Baseline

3.1 Introduction

While single year GHG accounting is often used to benchmark emissions nationally at particular times, this is problematic in agricultural systems, particularly in Australia, where large variations in climate can induce large year-on-year variation in production and GHG emissions. For this reason, we calculated a dynamic baseline assessment using practices analogous with those in 2005 but that accounts for annual variability. This was done by combining results from APSIM, a farming systems simulation model, with emissions as calculated for the static baseline for sources that are not modelled by APSIM. APSIM was characterised using the activity data for 2005 to simulate the 30-year period from 1990-2019 across a diversity of locations spanning the grain production regions of Australia. APSIM has been demonstrated to accurately simulate the key GHG emissions and balances that were used as inputs into the LCA. APSIM generates predictions of direct nitrous oxide emissions, nitrate leaching, and carbon dioxide from changes in soil organic carbon (see Appendix C for details on APSIM's capacity to simulate these processes). To calculate a dynamic baseline result that covers all the same emission sources as the historic baseline, indirect nitrous oxide emissions from volatilization are derived from the direct emissions and indirect nitrous oxide emissions from leaching are calculated by multiplying the APSIM results with the NGGI emission factor (see Methodology Report). All other emission sources, such as fuel use, carbon dioxide emissions of urea and lime application, and all embedded emissions, are copied from the static baseline and therefore do not contribute to variability. For an overview of the integration of APSIM results and elements from the static baseline, see Table 3 in 5.2.

3.2 Methodology

Simulations were conducted using the Agricultural Production Systems sIMulator (APSIM Version 7.10; Holzworth et al. 2014) using historical daily temperature, rainfall and solar radiation data from 50 high quality weather stations (Figure 10). The 50 stations were selected based on their representation of production districts so that each equally covered a similar cropping area within a 50 km radius of each station. It was considered that these stations give a good representation of sub-regional and national grain cropping areas (Hochman et al. 2016). At each site, simulations were conducted on the three most common soil types found within the 50 km radius and the characterisation of these soil types were derived from the median value for all similar soils found within the APSoil database. Simulations were run for at least 15 years prior to the 30-year analysis period (1991-2019) to allow the attributes of the model to come to a (dynamic) equilibrium and reduce the influence of model initialisation on simulated outputs. In each subregion, crop area data from 2005 (ABS 7121), together with expert knowledge of commonly used crop rotations were used to develop a list of crop rotations and their proportional areas that matched the land allocated to each crop type (Appendix A.1). Each of these rotations were simulated in APSIM, along with crop agronomic management known to well represent that used across the country.

Simulations used fertiliser application rates as determined for the historic baseline (for details see Methodology Report). Further details on the simulations can be found in Appendix A.1.

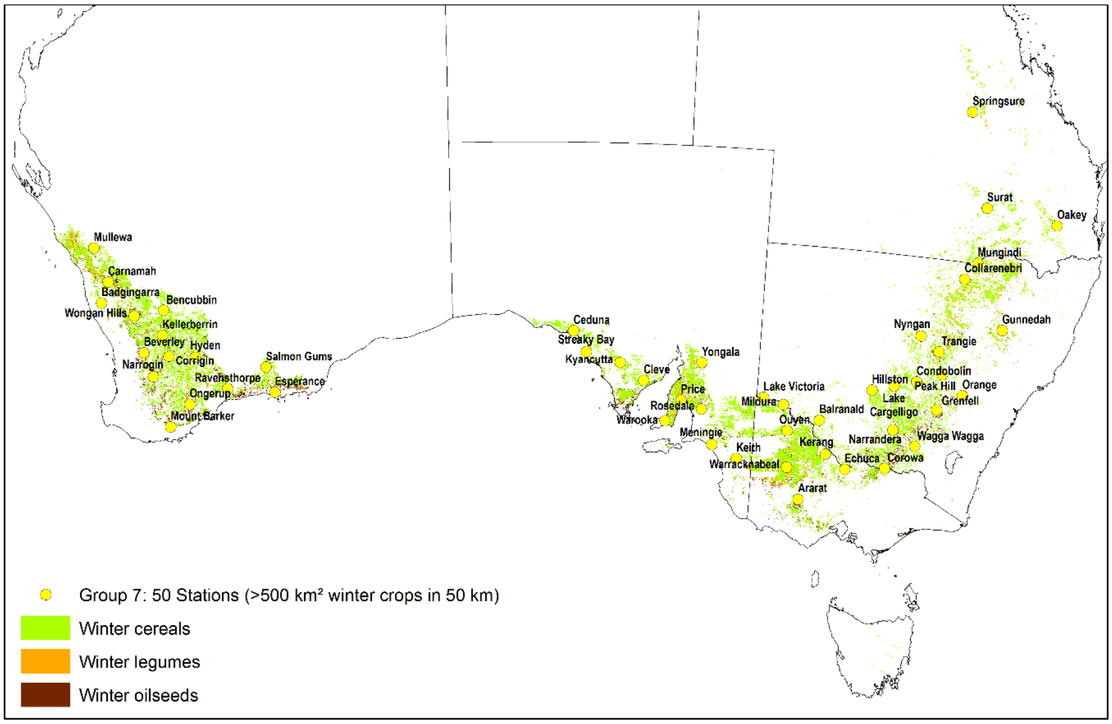

Figure 10 Location of 50 weather stations used in simulations. These were selected to represent the cropping area by district across Australia (see Hochman et al. 2016).

APSIM results were aggregated to subregion, region and national scale based on the proportional area that each rotation and soil type represented.

3.3 Regional results

The results for the two main sources of annual variability in emissions, direct nitrous oxide and indirect nitrous oxide from leaching, are compared in Figure 11 to the results found for the static baseline. For the South and the West regions, the long-term average of the simulation results is very well aligned with the 2005 baseline result. This indicates that the NGGI emission factors used do reflect the long-term average emissions at that regional scale.

For the North, however, APSIM results are considerably higher than those derived with the static emission factors. This effect is seen across all northern subregions, and more research is needed to understand what underlies this discrepancy.

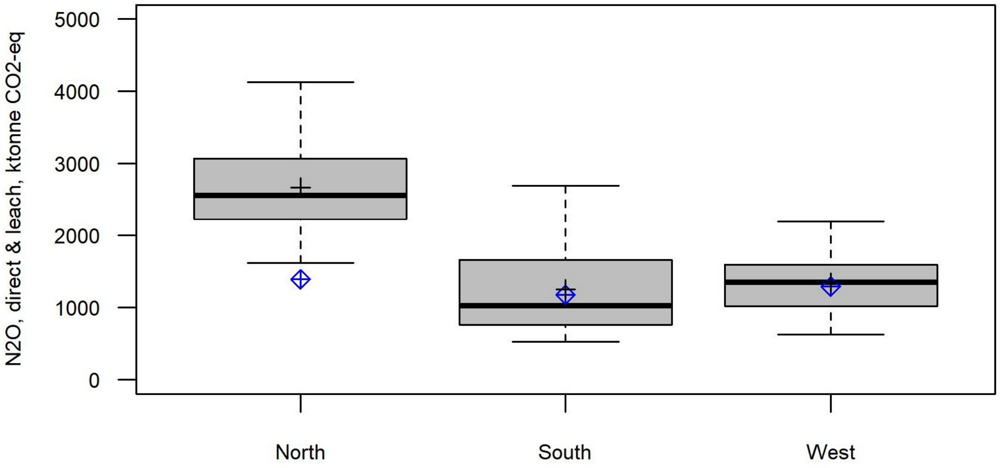

Figure 11 Boxplot showing the range of APSIM annual results for direct and indirect (leaching) N_2O for 1990-2019 by Region. The + indicates the mean value of the APSIM annual results. The blue diamond indicates the equivalent result for 2005 in the historic baseline. The outer quantiles are limited to 1.5 times the inner quantile range.

Adding volatilization, which is estimated based on the direct nitrous oxide emissions for APSIM (not separately modelled), as well as all other baseline emissions sources copied from the historic baseline, an indication of the effect of the variability in the nitrous oxide emissions on the overall result is obtained (Figure 12). For all regions, the variability (outer quantile range) ranges from about 20% to 40%. For the South, the distribution is asymmetric, with values skewed toward the high end.

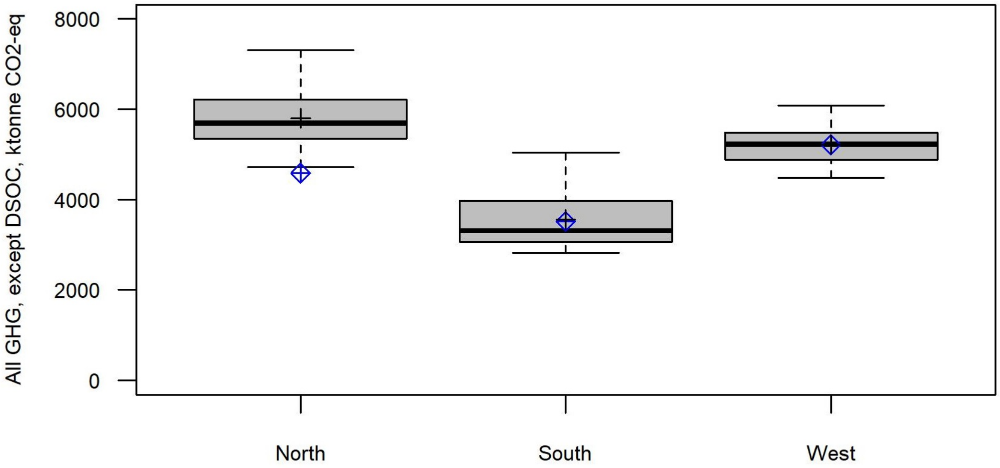

Figure 12 As Figure 11, for all emissions except those from soil organic carbon change and land use change

With the nitrous oxide emissions (Figure 11) representing approximately 28% of the baseline emissions, the discrepancy in that emission source contributes significantly to the discrepancy in the total emissions (Figure 12).

The emissions from soil organic carbon change in the static 2005 baseline are based on a single national value per hectare. In APSIM, soil organic carbon varies through time, driven by cropping practices, climate and soil properties. Therefore, the results of the APSIM simulations are likely to give a better reflection of the regional differences. The simulations clearly show the variation between regions in this emission source (Figure 13), with the mean value for the West below zero, indicating net uptake into soils of around 26 kg CO_2-equivalent/ha, and the mean value for the North ~2100 ktonne CO_2-equivalent or 268 kg CO_2-equivalent/ha. It is interesting to note that there are years with CO_2 uptake (negative emission) into the cropping soils in all regions. In practice, soil carbon changes are monitored as averages over several years which would smooth out some of the variability.

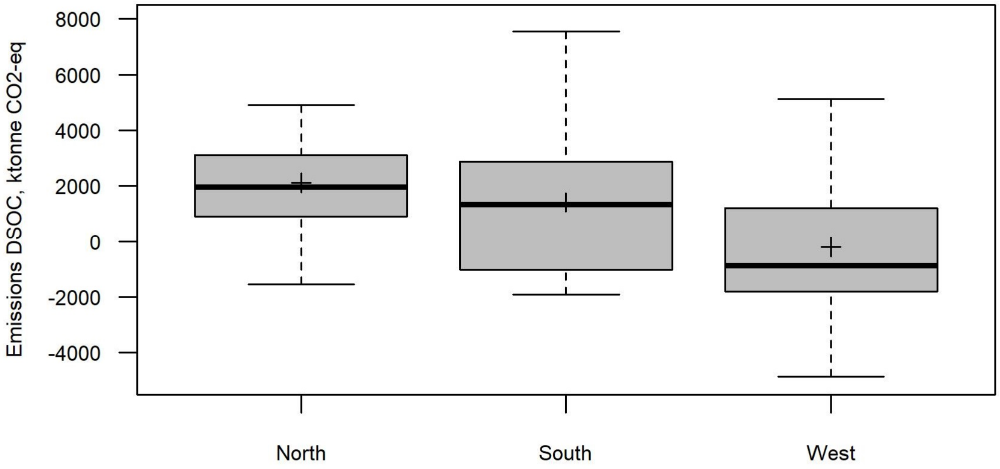

Figure 13 Boxplot showing the range of APSIM annual results for emissions due to soil carbon change for 1990-2019 by Region. The outer quantiles are limited to 1.5 times the inner quantile range. The + indicates the mean value of the APSIM annual results.

The results for soil carbon change in APSIM cannot be separated into effects of (historic) land use change and effects of current land use management. The results in Figure 13 can be interpreted as a combination of the two, to some extent, although the APSIM modelling is set up to exclude any recent land use change (see Appendix A.1). In the static baseline the NGGI approach is adopted to calculate the two effects separately. When combining the total emissions of Cropland remaining cropland and Forest land converted to cropland (see Chapter 2) for the static baseline, the result is 2.8 Mtonne CO_2-equivalent, compared to 3.3 Mtonne CO_2-equivalent as the mean of the APSIM annual results. It should be noted that results of simulations of soil carbon changes are uncertain, regardless of the model used, and that the emissions of Cropland remaining cropland and Forest land converted to cropland are frequently revised (retrospectively) in the NGGI.

4 Discussion of Baseline Results

The historic baseline assessment successfully pulls together data from a wide range of sources with varying levels of spatial resolution. Leviable crops with lower data availability are included by applying a set of rules to establish most suitable proxy data (see Methodology Report) with national area and yield data specific for each crop. Production of cow peas and pigeon peas is reported to be zero in 2005.

The total contribution of fertilizer and lime application to the GHG emissions, including Scope 1 and Scope 3 emissions, is 50%. Other large contributing sources are fuel use for tractor operations and supply of crop protection products. The combined Scope 3 emissions contribute just under 40% to the total baseline. Including these emissions can provide additional scope for mitigation and should therefore not be seen as an unfair extra burden but an opportunity to achieve mitigation together with the supply chain. It is important to note that many GHG reporting frameworks take a Scope 3 (full life cycle) approach. It could be a risk not to have visibility of Scope 3 emissions.

For the first time, the GHG emission effects of irrigation and storage are included in a large-scale GHG assessment of Australian grains. While activity data for these two categories are not readily available on an annual basis at this point, the data collected is of appropriate quality to assess the significance of emissions associated to energy use. Emissions of storage, including drying, aeration and loading, are found to be negligible at 0.1% of the total. Irrigation pumping and infrastructure contributes a little over 1% of total emissions. Irrigation also increases the emission factors for nitrous oxide from nitrogen fertilizer application by an estimated 5% but this effect is included in the overall nitrous oxide emissions.

Ongoing emissions from historic land use change are not considered part of the main baseline assessment, because they are not influenced by current management and thus not actionable for mitigation. Sensitivity assessment indicates that those emissions would constitute 17% of the national baseline. This is close to the contribution of land use change emissions to carbon footprints of Australian wheat and barley found via an entirely different method. Bontinck et al. (2020) find values of 22% and 25%, respectively, on top of a carbon footprint of approximately 300 kg CO_2-equivalent/tonne. This reinforces the message of those authors that values used for land use change in Australian crops in the international life cycle assessment community are far too high (see Figure 7).

Emissions due to changes in soil organic carbon under cropland management (*Cropland remaining cropland* in NGGI) are considered part of the baseline. In 2005, these emissions were average at the national level. However, the simulations performed as part of this study indicate that there is extreme variability in this emission source. Contrary to nitrous oxide emissions, which are also variable but can be captured by appropriate long-term average emission factors that reduce variability in the resulting GHG accounting, it should be expected that soil carbon emissions will strongly influence annual GHG balances. This can complicate tracking of progress to a mitigation target.

The year 2005 is found to be a reasonably average year to assess a representative baseline despite being in the middle of the Millennium Drought. Australian grains have a relatively low emissions intensity compared to other exporting countries (Figure 6, Figure 7). The established GHG baseline with a high degree of completeness puts the sector in an even better position to track mitigation and use this to competitive advantage. There is some variation in GHG intensity between the three GRDC regions, but this does not reflect regional differences in soil carbon change that may be considerable (Figure 13).

Part II Mitigation analysis

How much can GHG emission intensity be improved?

5 Mitigation Scenarios

Knowing the major sources of emissions associated with grain production across Australia, this section sets out to quantify the potential reductions in GHG emissions or improvements in GHG intensity that might be achieved via several prioritised mitigation scenarios that might be achievable on-farm in the next 10-20 years. Hence, this does not include any ‘blue sky’ or highly prospective technologies and focusses on those practices which are considered plausible adaptations to current production practices. These scenarios were designed to reflect consequences associated with a range of potential changes to the grain production system that could be achieved via several technologies or practices, rather than individual practices themselves. This was done to avoid focussing on one or two practices alone, because it was clear that a diversity of different farm practices was essentially targeting similar outcomes. This also meant that the analysis would have wider reaching application across the broad range of farming systems and environments found nationally across Australia, and hence allowing for potential diversity of practices that may be better or less suited to certain situations or contexts. Identification and implementation of scenario predictions

A range of potential mitigation pathways were identified and prioritised through advice from a variety of stakeholders to short-list a set of scenarios that could influence the GHG emission intensity of grain production systems across Australia over the coming 10-15 years. Using a cohort of 20 CSIRO scientists from diverse disciplines (soil science, agronomy, ecology) we collected a wide range of probable and possible mitigation options. Information or guidelines about how these would influence aspects of the production system were also discussed. These options were then grouped and prioritized after several further consultations with industry and stakeholder groups (e.g. GRDC managers and regional panels, Grain Growers, Grain Producers Australia). From this exercise we arrived at a set of 6 mitigation scenarios to be examined further (see below section 5.1). These were chosen to target the larger sources of emissions identified in grains production systems.

The impact of each of these scenarios were simulated using the cropping systems simulation model APSIM or via changes to calculations of emissions factors used in the static assessment. The general approach employed involved using the model to predict a baseline scenario, and then altering aspects of the simulated system to compare how much this change would alter the GHG emissions and the production intensity (i.e. crop production per unit GHG emitted). For all simulated scenarios, we again simulated 30 years (1991-2019) of phased crop rotations (i.e. every crop in the rotation grown in each year) for 50 representative climate locations and 3 soil types that cover the diversity of the Australian grain growing zone. This generated data on differences in potential grain production, N_2O emissions and changes in soil C that were induced by the different mitigation scenarios. These model outputs were used in combination with information on other production inputs to calculate the relative GHG emissions, and production and economic outcomes from the different scenarios. Specific details on the crop management assumptions implemented in APSIM can be found in Appendix A.1.

5.1 Scenario definitions

Six mitigation scenarios were examined, with specific aspects altered from the Baseline (Scenario 0). This involved stepwise changes to either factors used in static calculations or simulated changes in agronomic management. The relationships of these comparisons are depicted in Figure 14, with each box indicating a scenario combination for which the mitigation potential is calculated. Explanation of the scenario names and numbering is given in the sections below.

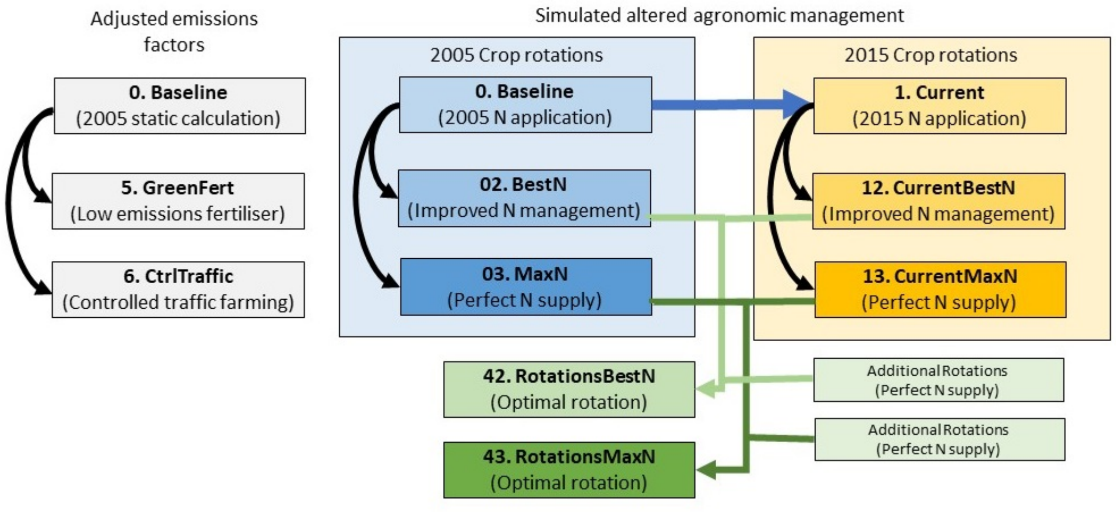

Figure 14 Diagram of the scenarios and relationships between them

5.1.0 Baseline (scenario 0)

The baseline scenario reflected crop management and crop rotations aligned with statistical information from 2005. This is the same scenario as the dynamic baseline described in Chapter 3. The crop rotations simulated were chosen to reflect the ratio of winter cereals, oilseeds, legumes and summer cereals grown in each sub-region of the grains zone (Appendix A.1). Fertiliser and pesticide applications reflect the 2005 baseline practice.

5.1.1 Current rotations and N rate (scenario 1)

This scenario is called “Current”. Recognising that the mix of crops grown and fertiliser inputs within Australian cropping systems has changed significantly since 2005, this scenario compared rotations that now matched the ratios of crops and N application rates using 2015/16 crop statistics. While systems were still largely dominated by winter cereals, this saw the proportion of oilseeds in cropping systems increase nationally at the expense of cereals. The proportion of legumes increased in some subregions but decrease in others. Details on the altered crop rotations used in this scenario compared to the baseline can be found in Table A2 in Appendix A.

Changes in N fertiliser application were estimated by applying a multiplier to the baseline N rates by crop (cereals and oilseeds only) and subregion, derived using a range of evidence around increased N application per tonne grain produced. For details on the derivation of the multiplier see A.4.

Details of the fertiliser N applications applied to each crop in each sub-region can be found in Appendix A.1.

5.1.2 Best practical N application (scenario *2)

Scenarios using this N application model are indicated by "BestN". These scenarios simulate systems where fertiliser applications reflect current best management guidelines. Significantly higher fertiliser applications were implemented for all non-legume crops. This was done by ensuring adequate N was available in the soil profile at sowing and topping this up as needed to reach critical base levels. Then between floral initiation and flowering, additional N fertiliser was applied when soil water conditions were sufficiently high to indicate that a further fertiliser response might occur. In this way, top-up applications in crop were sensitive to climatic conditions and additions were only made when a positive outlook for that crop was expected, otherwise no additional N was provided. However, the top-up amounts were predetermined and were not adjusted in any way to the seasonal outlook or other crop conditions. All other simulation initialisation, production inputs and emission factors were held constant. Details of the implementation of simulations are provided in Appendix A.1.

5.1.3 Perfect N management – Max N (scenario *3)

Scenarios using this N application model are indicated by "MaxN". These scenarios simulate systems where fertiliser applications 'perfectly' matched crop demand to maximise yield for rainfall conditions in the year simulated, so avoiding over and under application. Hence, this simulated a situation where N was not limiting for crop growth, but at the same time surplus levels were not allowed to accumulate in the soil and be prone to losses to the atmosphere. All other simulation initialisation, production inputs and emission factors were held constant. Details of the implementation of simulations are provided in Appendix A.1.

This scenario represents a situation where N can be provided in a way that best meets crop demand through a combination of improved N fertiliser practices and/or technologies which may include variable rate fertiliser applications, improved N fertiliser budgeting and application timings, slow or controlled release fertilisers (e.g. organic or enzyme modified). It is unclear how close these technologies or practices may get to this perfect N supply scenario, but this scenario provides an indication of how much further production and GHG emissions might be improved.

This scenario was applied to both the Baseline crop rotations (i.e. Scenario 03) and also to the crop rotations associated with the Current system in 2015 (i.e. Scenario 13).

5.1.4 Optimised rotation (scenario 4)

Scenarios using this rotation selection are indicated by "Rotations". This scenario considered the potential for alternative crop rotations to optimise the GHG intensity of grain systems. This was done by simulating 7-10 diverse rotations relevant in each region that vary in their frequency of cereal, legume and oilseed crops. The rotations considered included those crop rotations already simulated at each location in the Baseline and Current system scenarios but to capture additional diversity of crop rotations, others from nearby regions were also simulated. This set of rotations were simulated using both the Best Practical (BestN) and Perfect N management (MaxN) options described above. From these simulations, the optimum rotation was identified for each soil type and met station combination (Figure 15) and this was scaled according to proportional contribution of this soil-location to each sub-region. The selected rotations were then combined into the “RotationsBestN” scenario (42) and the “RotationsMaxN” scenario (43).

To select the optimum rotation, the ratio of revenue to CO2-e emission was calculated and the rotations along a frontier that with the highest GHG intensity were identified (i.e. maximum income per kg of CO2-e emitted). Using rotations positioned along this frontier, we calculated the potential income for each rotation at a common CO2-e emission value (lowest CO2-e emission recorded for high performing rotations), assuming a carbon price of $16 per tonne. By scaling the highest performing rotations to the lowest CO2-e emission value on the frontier, we calculated the potential income assuming foregone emissions would be compensated at the carbon price (equation 1). Using this calculation, the rotation which optimised potential income per tonne of CO2-e emitted was selected as the optimum rotation. Some sensitivity analysis with different carbon prices was also performed to see if this altered the optimum rotation that was selected.

Equation 1.

$$potential\ income = income + carbon\ price\ \times (CO_2e_{actual} - CO_2e_{minimum})$$

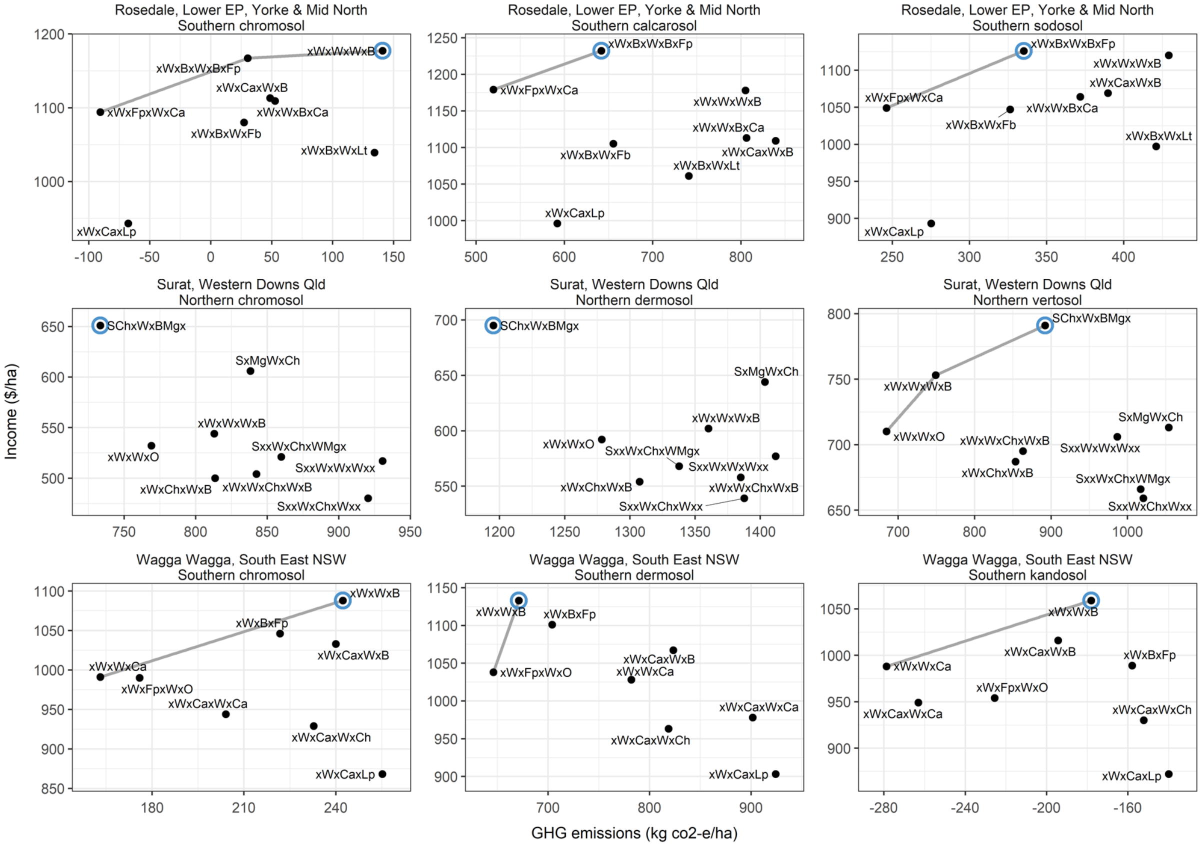

Figure 15 Examples of optimal rotation selection on different soil types at a selection of locations. The modelled income and GHG for each of 7-10 rotations for each soil – climate station were plotted to identify those rotations defining the frontier between income and GHG emissions (indicated with the grey line). The crop rotation achieving

the highest ratio of income per unit of GHG emissions after accounting for a carbon price ($16/t) are highlighted with a blue circle.

5.1.5 Green ammonia fertiliser (scenario 5)

This scenario is called “GreenFert”. This scenario examined the GHG emissions benefits of alternative fertiliser products with reduced embedded emissions. Production of hydrogen using renewable energy and feedstock sources links into fertiliser production via the production of ammonia. In the literature, “blue hydrogen” and “green hydrogen” are distinguished, with green production using renewable inputs and blue production using carbon capture and storage technology with the conventional process (e.g. Hydrogen Council, 2021). Similarly, there is blue and green ammonia.

Production of green ammonia was modelled by replacing natural gas as a feedstock and replacing electricity use with renewable energy, which resulted in a 90% reduction of embedded emissions of ammonia (see Table 2). This is an estimate only, but it aligns with projections for 2030 (Hydrogen Council, 2021).

It should be noted that the use of blue instead of green hydrogen could result in smaller net reduction of embedded emissions. Several recent sources show lower average reduction for blue hydrogen (Advisian 2021, Longden et al. 2022; Howarth and Jacobson 2021). Advisian (2021) report that where carbon sequestration is possible, blue hydrogen can currently be produced more cheaply and therefore may be a transition option but by 2030, green hydrogen is likely to be cheaper.

Table 2 Embedded emissions in kg CO_2-equivalent per kg product for conventional production (source AusLCI) and for ammonia produced using green hydrogen (model assumptions). The values for Urea (*) are implemented in this study. A correction for the uptake of CO_2 in the urea production process is needed to balance the re-emission of that same CO_2 when urea is applied in field to align with NGGI accounting

	Conventional	Green	Reduction
Ammonia	1.82	0.18	90%
Urea	1.51	0.60	60%
Urea (*)	0.80	-0.11	*(114%)*
AN	3.10	2.75	11%
MAP	1.24	1.03	17%
DAP	1.36	1.01	26%

Table 2 also lists the reduction of embedded emissions when green ammonia is used in the production of the different fertilisers. The effect is largest for urea. When assuming 100% replacement of ammonia by 2030, the overall reduction in Scope 3 emissions of all fertiliser production as modelled for the baseline is 50%.

This scenario is a static scenario, implemented by applying a correction factor to Scope 3 emissions based on the fertiliser mix by region.

5.1.6 Controlled traffic farming (scenario 6)

This scenario is called “CtrlTraffic”. Emissions associated with fuel use are found to contribute just under 15% to the GHG baseline (Chapter 2). Improvements in fuel efficiency of equipment and operations can be translated into emission reduction directly. Several technologies or practices are available now that can reduce fuel use, and further technological advancements are likely to emerge into the future that replace fossil fuels (e.g. electric or hydrogen tractors). Fuel replacement cannot be directly translated to emission reduction, as there may be residual embedded emissions from the production of alternative energy sources. Information on future adoption of electric or hydrogen tractors in Australian farming is still largely qualitative.

A practice that has been demonstrated to reduce fuel use via operational efficiency and is already widely adopted is controlled traffic farming (CTF). CTF is a system of restricting soil compaction and crop damage to permanent tramlines or wheel-ways enabling improved crop yields and quality (Blackwell et al. 2013). Blackwell et al. (2013) mention a 5% reduction in fuel use and a 5-10% increase in cereal yield as some of the benefits of CTF in WA. For Queensland, an older paper reports a ~10% increase in yield (Li et al. 2007) and Hussein et al. (2021) report 50% and higher increases in yield under high N rates for sorghum.

For GHG mitigation, CTF has additional interest as it may increase nitrogen use efficiency and decrease nitrous oxide emissions relative to non-CTF systems. Based on a literature review, Antille et al. (2015) conclude there is evidence to suggest that improved soil structural conditions and aeration offered by CTF can reduce N_2O emissions by 20% to 50% compared with non-CTF. Tullberg et al. (2018) find that adoption of CTF could reduce total soil emissions by 30% to 50%, with soil emissions referring to direct N_2O as well as net CH_4. Hussein et al. (2021) conducted a single-season experiment growing sorghum in SE Queensland. The results confirm that nitrogen use efficiency is higher in CTF systems than in non-CTF when N inputs are optimised in both. Rainfall-use efficiency was also found to be higher in the CTF system, reducing the amount of runoff compared with non-CTF. Hussein et al. (2021) find that under optimised N application rates in both CTF and non-CTF, a 44% higher N input in CTF would result in 90% higher yield.

Based on these literature sources, a simple scenario was defined to estimate the mitigation potential of CTF, assuming a yield increase of 5%, fuel use reduced by 5% and N_2O emissions reduced by 20%. No changes in leaching and run-off were assumed, nor any potential changes in soil carbon sequestration due to increased biomass and nitrogen use efficiency. Adjustment factors were applied to the static baseline values for production, operations (Scope 1 and 3) and direct N_2O emissions.

5.2 Total emission calculations

For each of the APSIM simulations, values are generated for yield, applied nitrogen (in the case of maximized yields), direct nitrous oxide emissions, leached nitrogen, soil carbon stock (0-30cm) and changes in soil carbon stock. Indirect nitrous oxide emissions from leaching and from volatilisation are derived from these values using the same approach as for the dynamic baseline (see Methodology Report). Additional scope 1 emissions (carbon dioxide from application of lime and urea, fuel combustion) and scope 2 and 3 emissions are added using the values from the static baseline, adjusted for increased nitrogen application when relevant (Table 3).

Table 3 Approach to combine APSIM results with elements of the static baseline to achieve total GHG balance for the dynamic scenarios. The last column shows which static elements were corrected to reflect a change in N applied compared to the baseline. The correction is by the ratio of N applied : N applied baseline.

Emission category	Scope	APSIM	Static	Correction
Direct N_2O	Scope 1	Modelled (A)		
Indirect N_2O, leaching	Scope 1	Modelled (B)		
Indirect N_2O, volatilisation	Scope 1	Derived		
Direct CO_2, lime	Scope 1		x	
Direct CO_2, urea	Scope 1		x	N applied
Residue N_2O	Scope 1	in A & B		
Operations	Scope 1		x	
Storage	Scope 1		x	
Irrigation	Scope 1		x	
Soil carbon change (DSOC)	Scope 1	Modelled		
Storage	Scope 2		x	
Irrigation	Scope 2		x	
Fertiliser, embedded emissions	Scope 3		x	N applied
Lime, embedded emissions	Scope 3		x	
Crop protection, embedded emissions	Scope 3		x	
Fuel, embedded emissions	Scope 3		x	
Storage	Scope 3		x	
Irrigation	Scope 3		x	

The simulations underlying the dynamic scenarios are averaged over the locations (representing weather stations), soil types and rotations within a GRDC Subregion and multiplied by the area of grain cropping in each Subregion as established for the 2005 baseline. This eliminates a change in cropped area[6] as a factor influencing GHG emissions. For the static mitigation scenarios (5,6), correction factors as outlined in 5.1 are applied directly to the scope 1,2 and 3 emissions of the static baseline at the level of Subregions. Results are then aggregated to the three Regions (see Methodology Report for more details).

Note that the considerable additional demand for nitrogen fertiliser in the high-N scenarios could be expected to influence supply. In life cycle assessment that would be assessed for changes in the expected marginal – and hence average – embedded emissions associated with supply. Given the current direction of the market, this could potentially accelerate the production of fertilisers using green or blue ammonia and hence reduce fertiliser embedded emissions, especially when those options become cheaper than traditional production. This 'accelerated' change in embedded emissions is not modelled separately, but assessed by combining a high-N scenario with the findings for the green fertiliser scenario in Chapter 7.

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[6] . In practice, for the 2015 cropping season, the area under grains was 95% of the baseline area.

5.3 Reforestation of cropland

Environmental plantings sequester carbon and hence can offset some of the yearly emissions from grains cultivation in Australia. This analysis looks at the conditions under which this may be feasible, building on over ten years of scientific work undertaken over a range of projects within CSIRO. Results are derived from the work by Roxburgh et al. (2020) which incorporated aspects of CSIRO's Land Use Tradeoffs (LUTO) model (Connor et al. 2015; Bryan et al. 2014).

The basis of the assessment of agriculture's capacity to offset emissions is whether carbon/environmental plantings, as a land use, prove more profitable than current land uses (here restricted to land uses related to crop land in the broadacre zone: cereals (excluding rice), legumes and oilseeds). The model looks at every 250m^2 agricultural pixel in the landscape (ABARES 2016) and makes a decision regarding whether the current land use is more or less profitable than switching to carbon or environmental plantings. That choice is not simple, as it depends on a number of factors:

1. Agricultural profitability as the net present value of agriculture over 100 years, given:
    a. Long term yields
    b. Long term commodity prices
    c. Typical production costs
2. Profitability of carbon sequestration as the net present value (NPV) over 25 years given:
    a. Carbon price
    b. Production costs: Establishment, transaction and annual management
    c. Hurdle rate: The difference in profitability (NPV) that is required for adoption. Increasing hurdle rates assume that landowners are more risk averse and would require a greater incentive to switch land use even if the new land use is more profitable.
3. NPV periods of agriculture and carbon plantings are different because carbon sequestration has a permanence requirement of 100 years.

The analysis compares the capacity to generate value from carbon sequestration in the Australian agricultural landscape under different types of Emissions Reduction Fund (ERF) methods, carbon prices, current land use (cropping or mixed crop/livestock) and hurdle rates. The goal is to determine the conditions under which yearly grains emissions, as determined in Chapter 2, could be offset in the next 10 or 25 years.

Evaluation of the six relevant ERF methods (see Annex A.3) indicates that the Environmental Plantings Block Environmental Services method is the most effective one in the context of reforestation of cropland. It should be noted that other types, such as belt plantings, are likely to have higher co-benefits.

As annual sequestration varies from year to year, results for this method are presented in Table 4 for both the 10-year and 25-year annual average. More carbon sequestration occurs in the first 10 years and so this amount is greater than for the 25-year average for the same carbon price point.

For the 25-year average to achieve a 0.7 MtCO2 abatement goal (5% of the GHG baseline determined in Chapter 2) a carbon price of between 45-50 \$/tCO$_2$ is required for the environmental plantings block method on crop land (Table 1) assuming a hurdle rate of 1. For a hurdle rate of 2, this rises to 60-65 \$/tCO$_2$.

Table 4 Carbon sequestration in Mtonne CO_2 per year, by carbon price, hurdle rate, for Environmental Plantings Block Environmental Services in cropland

	10-year average Mtonne CO2/yr				25-year average Mtonne CO2/yr			
Carbon price ($/tCO2)	**Hurdle rate 1**	**Hurdle rate 1.2**	**Hurdle rate 1.5**	**Hurdle rate 2**	**Hurdle rate 1**	**Hurdle rate 1.2**	**Hurdle rate 1.5**	**Hurdle rate 2**
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	0.04	0.01	0.01	0.00	0.03	0.01	0.01	0.00
35	0.22	0.12	0.03	0.01	0.18	0.10	0.02	0.01
40	0.44	0.30	0.15	0.02	0.36	0.25	0.13	0.02
45	0.88	0.54	0.31	0.10	0.74	0.45	0.26	0.08
50	1.56	0.96	0.54	0.25	1.31	0.80	0.45	0.21
55	2.59	1.65	0.88	0.41	2.16	1.37	0.73	0.34
60	3.98	2.62	1.42	0.63	3.32	2.19	1.18	0.53
65	5.54	3.88	2.20	0.95	4.61	3.23	1.83	0.79
70	7.43	5.28	3.20	1.37	6.19	4.40	2.67	1.14
75	10.11	7.04	4.43	1.98	8.42	5.86	3.69	1.65
80	13.31	9.41	5.73	2.79	11.09	7.84	4.78	2.33
85	16.54	12.39	7.55	3.76	13.77	10.32	6.29	3.14
90	20.03	15.40	9.91	4.85	16.67	12.82	8.25	4.05
95	23.93	18.40	12.61	6.14	19.92	15.32	10.51	5.12
100	28.29	21.77	15.36	7.86	23.56	18.13	12.79	6.55
125	52.13	43.18	31.68	19.38	43.41	35.96	26.38	16.13
150	73.05	63.58	51.17	34.64	60.83	52.95	42.61	28.84
200	101.61	93.20	81.26	63.98	84.64	77.63	67.68	53.28
250	117.57	111.68	102.39	86.62	97.95	93.05	85.29	72.15

To offset the full GHG baseline for grains with 25-year average sequestration, carbon prices of 85-120 $/t$CO_2$ would be required and this would involve approximately 5.5% of the current area used for grains cultivation (Figure 16).

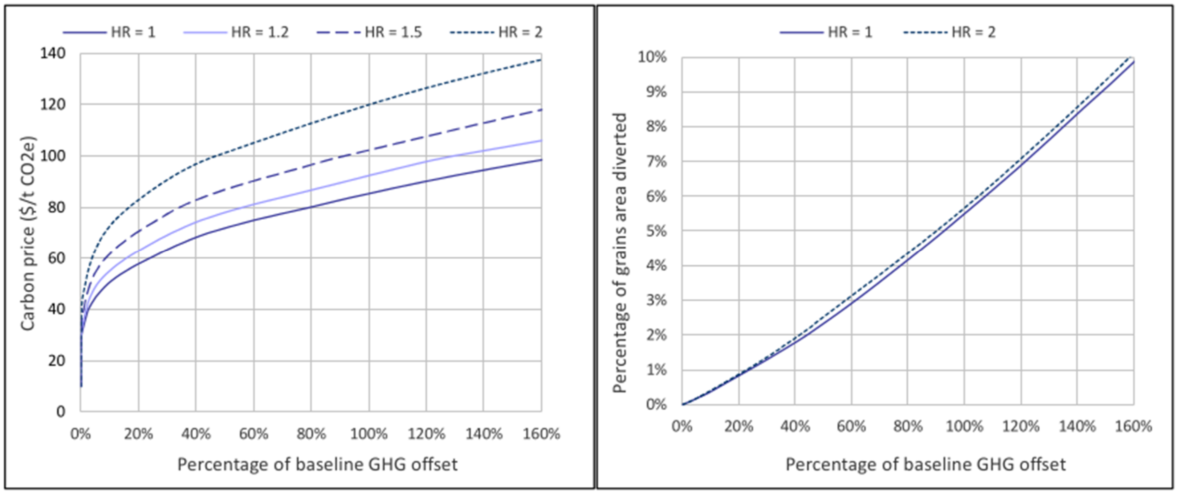

Figure 16 Carbon price required to achieve reforestation to offset a certain percentage of the grains baseline emissions (left) and associated percentage of area under grain cultivation diverted (right).

Offsetting grains emissions would be more affordable if plantings occurred on the livestock portion of mixed farms because currently the net present value of pasture lands tends to be lower than that of croplands and therefore adoption makes economic sense at lower carbon prices. In a study for West Australia, Kingwell (2021a) finds that all agricultural emissions (including livestock) in that region could be offset locally at prices no more than 35$/tCO2 but this would lead to a decrease in farm business profit. The question addressed in Kingwell (2021a) is “how much would it cost to offset all emissions locally now” whereas the question addressed in this section is “what carbon price would be required to generate carbon offsets within the grains system without a loss of farm income”. Note that to keep those carbon offsets within the sector, the cost to the sector would be considerable at about 10% of current gross value of production for grains.

6 Results

6.1 Comparison of scenarios

The baseline scenarios (scenario 0) are compared to mitigation scenarios by either a direct comparison to the static baseline (left side) or for modelled scenarios with the dynamic baseline (right side). The results for the modelled scenarios report the mean result over the 29-year time series.

Figure 17 shows the mean simulated annual production in ktonne grain nationally for each of the scenarios. Total modelled grain production in the Current scenario (scenario 1) is 8% higher than that of the Baseline scenario; the same is true for protein and energy yield, as well as estimated value of the grain crops. This result is primarily attributable to the higher N inputs minimising N limitations to yield. All production metrics (protein, energy, value) are considerably higher for all scenarios with best-practice (BestN) and perfect nitrogen (MaxN) management. Total production was increased by 10-15% for selected optimal rotations, when comparing scenarios 42 and 43 with baseline scenarios 02 and 03, respectively. Net production was maintained in the Green Fertiliser scenario (5) but was increased in line with assumed yield increases in the Controlled Traffic Farming scenario (6).

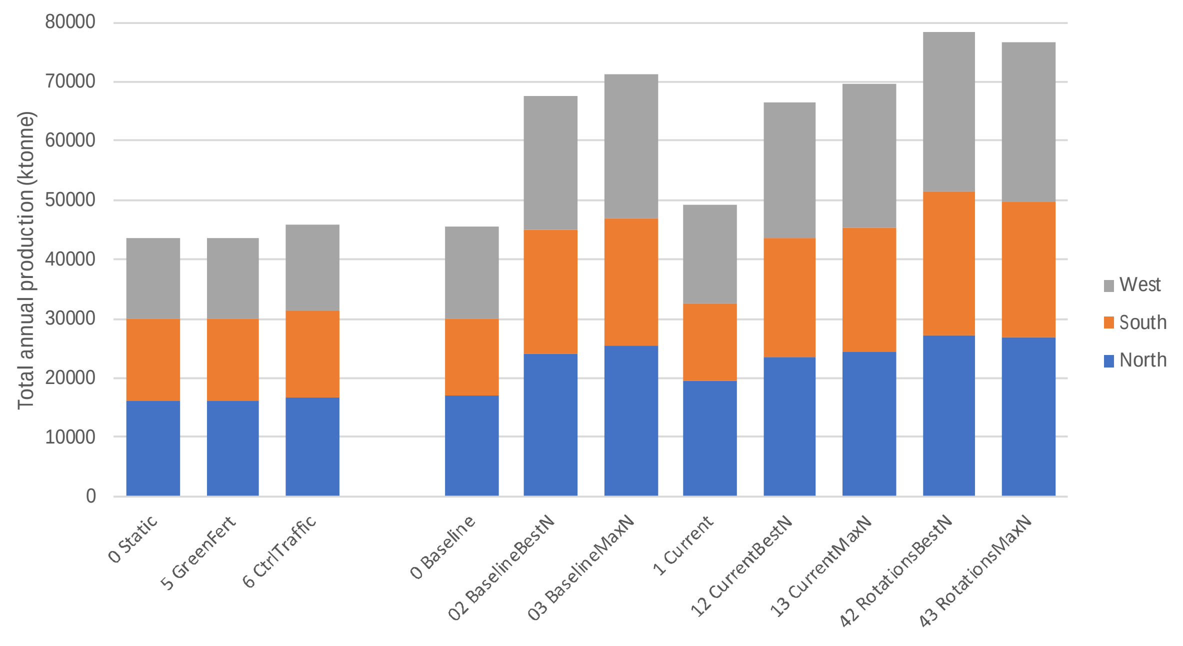

Figure 17 Total production in ktonne grain by Region and by scenario. Values for the dynamic scenarios are the mean over the time series.

Figure 18 shows the total mean annual emissions in Mtonne CO_2-equivalent for each of the scenarios analysed.

Please note that the discrepancy between the static and dynamic baseline scenarios in this respect can be attributed to differences in accounting for soil carbon changes as well as a difference in calculated nitrous oxide emissions in the North Region. For more details on the comparison between static and dynamic baseline, see Chapter 3.3. Hence, comparisons for the simulated mitigation scenarios should only be drawn with the dynamic baseline.

Compared to the dynamic baseline, all scenarios result in higher total emissions due to increases in fertiliser inputs. For example, the current production systems with higher fertiliser inputs were estimated to generate about 14% higher emissions than the 2005 baseline. Scenarios involving higher N inputs (BestN and MaxN) increased net emissions further. Only the static scenarios 5 and 6 were found to reduce total net emissions of the system.

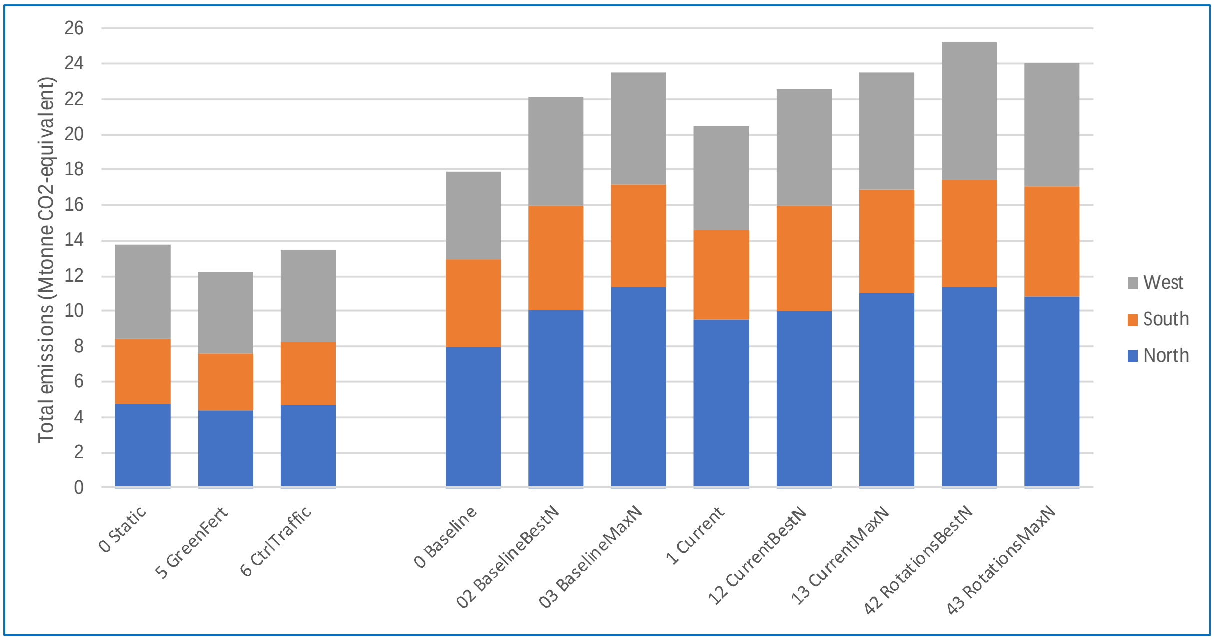

Figure 18 Total emissions in Mtonne CO_2-equivalent by Region and by scenario. Values for the dynamic scenarios are the mean over the time series. The difference between static and dynamic baseline are caused by using the modelled emissions from APSIM in the dynamic baseline compared to emissions factors in the static baseline.

The increase in emissions is largely associated with the embedded emissions in (additional) fertiliser. Figure 19 shows that the Scope 1 emissions vary only very little between the dynamic scenarios (as well as between the static scenarios) and the net Scope 1 emissions are in fact slightly lower for most scenarios with best-practice and perfect nitrogen management (BestN and MaxN). The higher N_2O emissions in these scenarios are more than offset by reduced losses or increased gains of soil organic carbon in the South and West, while in the North net Scope 1 emissions are somewhat higher for those scenarios. On average, Scope 1 emissions contribute only just over 50% of the total for scenario 43, compared to 61% in the static baseline (Figure 1). The highest increase in Scope 1 emissions is 8%, in the Current scenario (1).

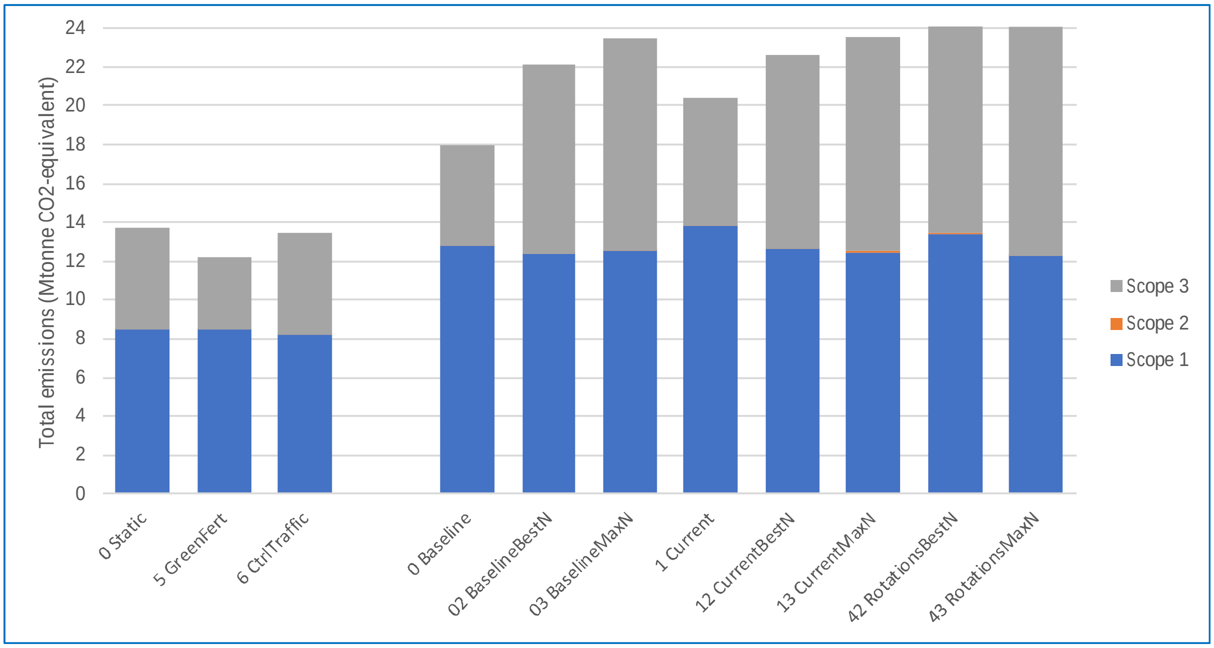

Figure 19 As Figure 18, but showing contributions of emissions by scope.

Given that most scenarios increased both production and total GHG emissions, it is critical that they are compared in terms of their emissions intensity, that is, emissions produced per tonne grain (or other production metric). Figure 20 compares the emission intensity per tonne grain for all scenarios, including static and dynamic baselines, across the three grain production regions of Australia.

All scenarios except the Current systems show improved (lower) emissions intensity compared to the baseline for each grain production region; however, there are significant regional differences in how much improvement was predicted. The increase in current systems compared to the baseline is largest for the West Region in the Current scenario, which is due to the increased production of canola in that region (from 6% of area in the Baseline to 14% in the Current scenarios) at the expense of legumes.

In all regions, improved N management is seen to bring about lower emissions intensity because the increases in grain production exceed the increases in the associated GHG emissions. However, in the North region, the intensity in the MaxN scenarios is slightly higher than in the BestN scenarios. Emissions in response to the even higher N application outweigh the increase production in these cases.

Compared to the BestN scenarios 02 and 12, changing the system to optimal rotations (scenario 42) achieved further reductions in the emissions intensity in the northern and southern regions, but not in the western region. Under 'perfect' N management (scenario 43) there is some reduction in the northern region, compared to scenarios 03 and 13, but only very small difference in the southern and western regions.

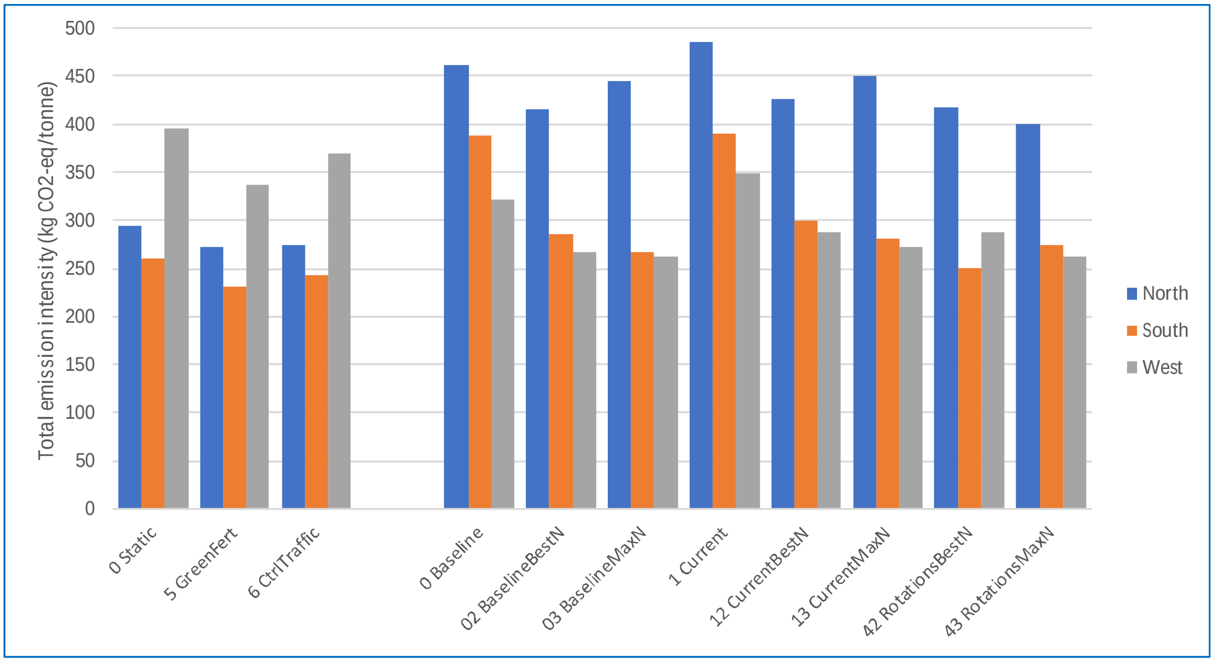

Figure 20 Total emission intensity in kg CO$_2$-equivalent per tonne grain, by Region and by scenario. Values for the dynamic scenarios are the mean over the time series. See text for information.

Nationally, the various mitigation scenarios showed that reductions in emissions intensity of up to 20% were possible in grain production systems (Figure 21). The Current scenario (1) was estimated to somewhat increase emission intensity (+7%) overall. All BestN and MaxN scenarios result in a decreased emission intensity (-13% to -20%) compared to the dynamic Baseline.

The national average results for the two scenarios employing optimised crop rotations are similar, reducing emissions intensity by about 18%, even though this is not the case for each of the regions separately (Figure 20). Combining the best scenarios for each Region (ie. applying mitigation scenarios 43 for North, 42 for South and 03 for West) results in a reduction of almost 22% in the average emissions intensity nationally (shown in green in Figure 21).

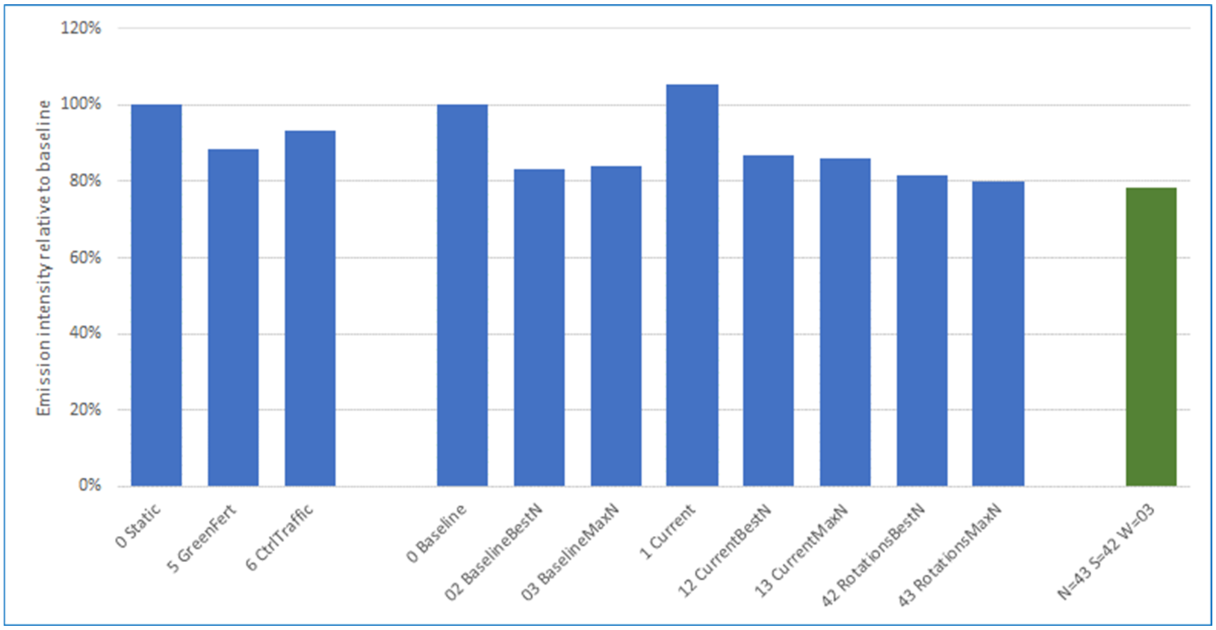

Figure 21 As Figure 20, showing weighted averages for national production compared to the static and dynamic baseline result, respectively. A combination of best scenario results for each region is shown on the right. See text for information.

Comparing the emission intensities for Scope 1 emissions only, reductions of up to ~40% are achieved and the intensity for the Current scenario is found to be the same the same as for the Baseline (Figure 22).

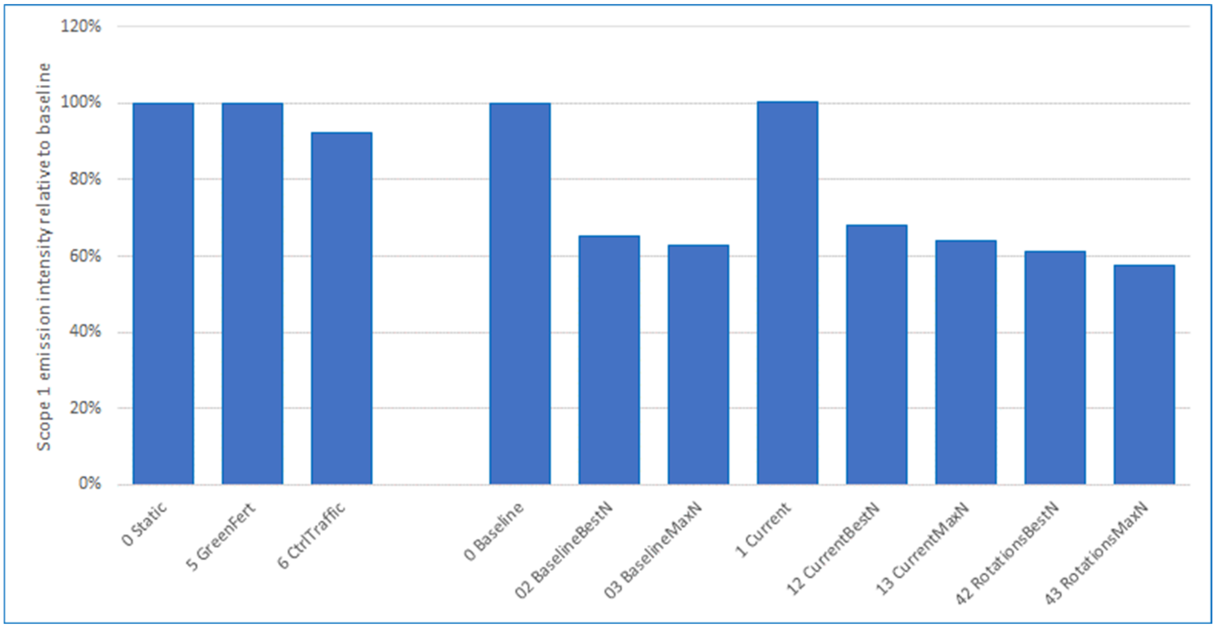

Figure 22 As Figure 21, for Scope 1 emissions only (see also Figure 19).

It is worth noting that here we are referring to the mean emissions generated over the 29-year analysis period (1991-2019) and that there is extreme interannual variation in the emissions and emission intensities achieved between years, as driven by varying weather conditions. The influence of this variability on the consistency of the differences between scenarios is discussed in Annex Appendix B .

6.2 Effect of nitrogen application

The effect of higher nitrogen application is clear in the results presented in 6.1. On average, scenarios with higher N application result in higher absolute average N_2O emissions but lower emissions due to soil carbon change, within each Region (see Appendix B). Between Regions as well as between years, however, soil carbon emissions increase with increasing N_2O emissions. This effect is likely driven by weather and soil properties.

In terms of long-term effects of management, higher and more efficient N application is associated with lower emission intensity across all Regions and most years. Figure 23 shows how the GHG intensity decreases with increased nitrogen application per tonne production. Only four scenarios are shown for clarity, but the trends are very similar for other scenarios.

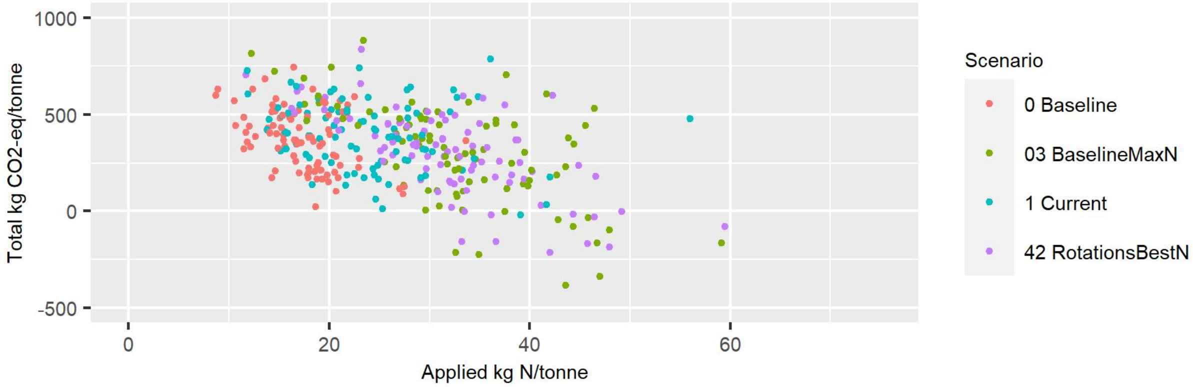

Figure 23 Total GHG intensity compared to applied nitrogen per tonne for selected scenarios. Each point represents one region (West, South, North) and one year of the simulations.

The Current scenario (1) demonstrates that just applying more fertilizer N does not necessarily achieve lower emission intensity. The modelling underlying the Current scenario involves higher N rates than the Baseline (Figure 24), but timing of application is assumed to be the same (see A.1). The more targeted timing of application as in the BestN and MaxN scenarios is likely what results in an increase of production that generally outweighs the increase in net emissions, despite much higher N application.

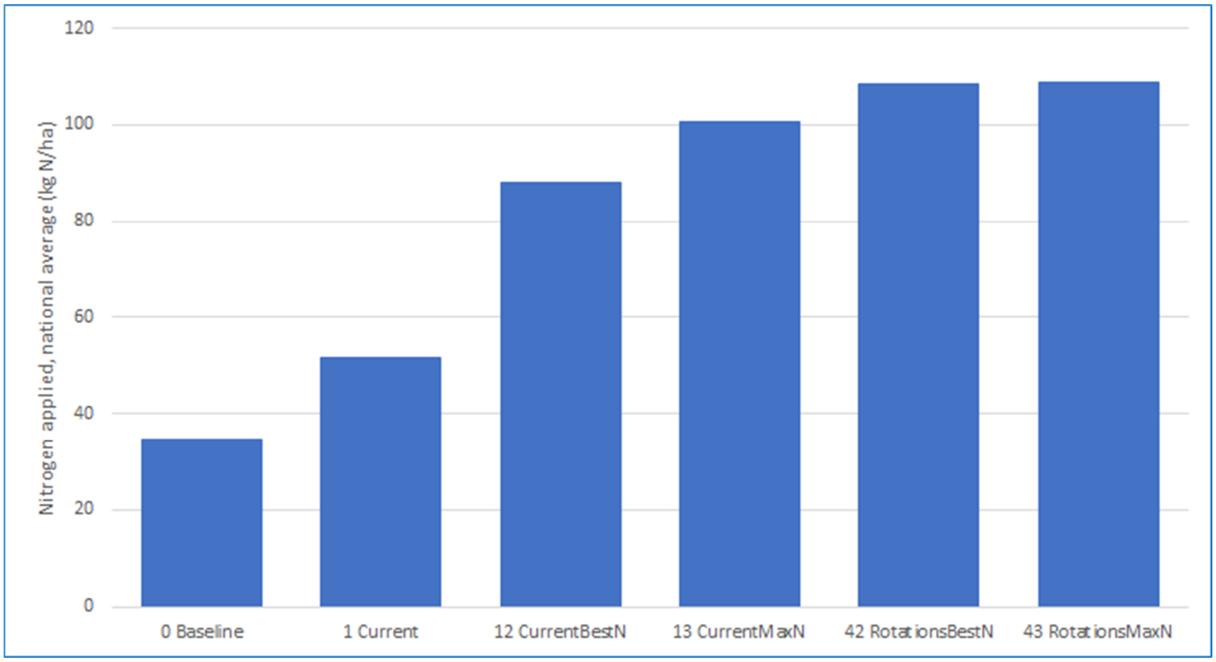

Figure 24 Area-weighted average N rate by scenario, over all crops

As noted in 6.1, in the high-N scenarios higher N_2O emissions are largely offset by reduced losses or increased gains of soil organic carbon (see also Appendix B). One effect that contributes to this is that the N_2O emissions relative to N applied appear to be lower in the higher N regimes, especially in the South. This effect requires more investigation, but potentially indicates that the direct N_2O emission factor of either fertiliser application or residue decomposition is lower in those optimized N regimes.

6.3 Effect of rotations

The effect of different assumptions around rotations on GHG emissions is much smaller than for assumptions on nitrogen application. Comparing scenarios 42 and 43 to scenarios 02 and 03 respectively, improvement is 1.5-4.5% in GHG intensity. For scenario 42, this difference is dominated by intensity reduction in the South, whereas the North shows a bigger difference between 03 and 43 partly because the GHG intensity in the North is higher in scenario 03.

The selection of optimum rotations (see 5.1.4) had different results under the BestN and MaxN scenarios. Under the MaxN scenario, there is an increase in cereal dominated crop sequences (Table 5). That is, under a higher N management scenario the cereal crops frequently generated a higher return sufficient to offset any increase in emissions, and in some subregions especially in the North there were reduced net emissions (Table 6).

Under the BestN scenario, GHG emissions were reduced in all Southern subregions at the same time as income was increased, through the choice of the optimal rotation which reduced though not completely eliminated the fraction of legumes. As shown in Figure 20, the RotationsBestN scenario (42) gives the best results for GHG intensity in the South.

At the assumed carbon price of 16\$/tCO_2, it was optimal in almost all situations to select the rotation that generated the highest income rather than rotations that reduced GHG emissions. We did not conduct simulations required to complete the optimisation analysis of crop rotations under lower N application scenarios, which would have likely seen a different mix of optimal rotations selected.

Table 5. Rotations and their relative areas across each subregion in the Baseline scenarios compared to the rotations achieving the optimal emissions intensity under the BestN (42) and MaxN (43) scenarios. For some subregions, more than one rotation was selected if a different option was found for different soil types.

	Baseline		BestN optimal		MaxN optimal	
Subregions	Rotation	% area	Rotation	% area	Rotation	% area
NORTHERN REGION						
Central Qld	SxSxxWxChxWxx	50	SxSChxWxBxx	100	SxSChxWxBxx	100
	SxSxxWxWxWxx	50				
Eastern Downs Qld	SxSxSBxWxx	60	SxSxSBxWxx	100	SxSxSBxWxx	100
	MzxSxSBxWxx	25				
	SxSxSChxWxx	15				
North East NSW	SBxWxx	80	SxSChxWxBMgx	100	SxSChxWxBMgx	100
	xWxChxBxO	20				
Liverpool Plains NSW	SBxWxx	60	BxWx	100	xWxWxO	95
	SxSfxSx	15			BxWx	5
	SxSxxWxCaxWxx	15				
	xWxWxO	10				
Western Downs Qld	SxxWxWxWxx	60	SChxWxBMgx	100	SChxWxBMgx	100
	xWxChxWxB	15				
	xWxWxWxB	25				
North West NSW	xWxWxB	50	xWxWxB	93	xWxWxB	93
	SxxWxWxx	30	SxMgWxCh	7	SxMgWxCh	7
	SxxWxChxWxx	20				
Central East NSW	xWxWxB	50	xWxWxB	65	xWxWxB	100
	xWxWxO	35	xWxBxFp	13		
	xWxFpxWxCa	15	SChxWxBMgx	22		
South East NSW	xWxWxB	45	xWxWxB	97	xWxWxB	100
	xWxWxCa	30	xWxBxFp	3		
	xWxFpxWxO	25				
Central West NSW	xWxWxB	65	xWxWxB	100	xWxWxB	100
	xWxWxO	35				
South West NSW	xWxWxB	70	xWxWxB	100	xWxWxB	100
	xWxFpxWxCa	15				
	xWxWxO	15				
SOUTHERN REGION						
Wimmera and Central Vic	xWxWxB	35	xWxWxB	100	xWxWxB	100
	xWxBxCa	20				
	xWxBxFp	15				

Subregions	Baseline		BestN optimal		MaxN optimal	
	Rotation	% area	Rotation	% area	Rotation	% area
	xWxBxLt	15				
	xWxWxCh	15				
Southern High Rainfall	xWxBxCa	60	xWxWxWxB	52	xWxWxWxB	100
	xWxWxBxOxFp	40	xWxBxFp	48		
Lower EP, Yorke and Mid North	xWxBxWxBxFp	70	xWxWxWxB	58	xWxWxWxB	100
	xWxWxBxCa	30	xWxFpxWxCa	22		
			xWxBxWxBxFp	20		
SA Vic Mallee	xWxWxB	85	xWxWxB	63	xWxWxB	100
	xWxBxCaxWxLt	15	xWxWxCa	37		
Upper EP and Upper North	xWxWxWxB	85	xWxWxWxB	78	xWxWxWxB	100
	xWxWxBxFp	15	xWxWxBxFp	22		
WESTERN REGION						
Geraldton	xWxWxWxLp	80	xWxWxWxB	100	xWxWxWxB	100
	xWxWxBxCa	20				
Kwinana East	xW	40			Wx	24
	xWxWxWxB	40	xWxWxWxB	63	xWxWxWxB	33
	xWxWxWxLp	20	xWxWxBxO	37	xWxWxBxO	43
Kwinana West	xWxWxWxLp	50	xWxWxWxB	82	xWxWxWxB	100
	xWxWxBxO	25	xWxWxWxCa	18		
	xWxWxBxWxCa	25				
Albany	xWxWxBxCa	40	xWxWxWxB	99	xWxWxWxB	100
	xWxWxBxLp	40	xWxWxCa	1		
	xWxWxBxO	20				
Esperance	xWxWxBxCa	60	xWxWxWxB	67	xWxWxWxB	67
	xWxWxBxFp	40	xWxWxBxFp	33	xWxWxBxFp	33

Table 6. Change in revenue and GHG emissions as modelled by APSIM (direct and indirect (leaching and run off) emissions of N2O plus changes in soil carbon), between the Baseline mix of crop rotations and the optimised crop rotation choice under both the Best Practical management (BestN, scenario 42) and the perfect N application (MaxN, scenario 43) scenarios.

GRDC Region	GRDC Subregion	Change in estimated revenue ($/ha/yr)		Change in APSIM emissions (kg CO2-eq/ha/yr)	
		BestN	MaxN	BestN	MaxN
North	Central East NSW	299	69	789	42
	Central Qld	168	179	148	-82
	Central West NSW	38	16	-20	21
	Eastern Downs Qld	45	35	93	-1
	Liverpool Plains NSW	141	-1	107	-498
	North East NSW	108	23	15	-121

	North West NSW	-11	-11	-7	-267
	South East NSW	218	93	126	25
	South West NSW	17	22	-3	13
	Western Downs Qld	93	105	-93	-229
South	Lower EP, Yorke and Mid North	164	69	-102	51
	SA Vic Mallee	218	19	-174	-4
	Southern High Rainfall	221	140	-200	141
	Upper EP and Upper North	88	6	-54	4
	Wimmera and Central Vic	80	75	-93	-34
West	Albany	224	113	344	15
	Esperance	125	88	-43	9
	Geraldton	97	104	24	-1
	Kwinana East	-35	27	-23	45
	Kwinana West	253	113	-96	25

6.4 Adoption by 2030

The results presented in 6.1 all reflect full implementation of the scenario assumptions across the entire grains system. To estimate potential GHG reduction in 2030 compared to the 2005 baseline, those results need to be adjusted to reflect the likely (change in) adoption of practices between 2005 and 2030.

6.4.1 Nitrogen application rates

The Current scenario gives a snapshot of the influence of some changes in the system between 2005 and 2015, but it doesn't incorporate all effects such as increased adoption of controlled traffic farming or changes in timing of fertiliser application. Nationally, the estimated average N rate (see Annex A.4) has increased from 36 kg N/ha to 51 kg N/ha across all grains, including legumes. For the best practical N and maximum N scenarios under current rotation (scenarios 12 and 13) the rates are 88 kg N/ha and 101 kg N/ha, respectively.

Using a price of urea of AU$400/tonne for urea[7] which is at the higher end of the range over the period 2015-2020 but excludes the global price hikes since late 2020, as well as average crop prices (see A.2), an estimated return ratio can be calculated for revenue per kg N applied. Table 7 shows that as expected the return ratio is highest for lower N rates (Baseline, Current) and it is almost the same for all higher-N-input scenarios (BestN, MaxN). These estimates are rough, and don't reflect any of the market mechanisms that would normally inform a farmer's decisions, nor the cost of additional operations. While the cost efficiency of N use is lower for the BestN and

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[7] https://fertilizer.org.au/Fertilizer-Industry/Global-Fertilizer-Prices

MaxN scenarios, the higher production (Figure 17) means that there is still an increase in margin compared to the Baseline.

Table 7 Estimated revenue per cost of nitrogen, using average 2007-2017 prices for crops and a price of $0.87/kg N (see text), as well as the resulting relative increase in partial margin compared to the Baseline scenario. All values reflect national averages.

Scenario	Estimated revenue per cost of nitrogen (AU$/$)	Estimated increase in margin (revenue minus cost of N only) for total production compared to the Baseline
0 Baseline	18	
02 BaselineBestN	11	43%
03 BaselineMaxN	10	48%
1 Current	13	6%
12 CurrentBestN	10	39%
13 CurrentMaxN	10	45%
42 RotationsBestN	10	64%
43 RotationsMaxN	10	59%

These results reflect national averages. In practice, the value proposition of optimizing N application will vary depending on local conditions, as also discussed in 6.3. In addition, additional costs should be expected, whether the “perfect” N application is achieved via use of slow-release fertilisers or urease/nitrification inhibitors, or via precision agriculture tools. The current rise in the prices of fertiliser also counteracts the value proposition of the improved nitrogen management scenarios.

More research is needed to estimate what the level of adoption by 2030 could be, based on cost and technology projections.

6.4.2 Rotations

Adoption of rotations that are more profitable but reduce GHG emissions in the short term is realistic, if more information is available to growers what optimum rotations are at a local level. Detailed analysis has been done for some regions (Hochman et al. 2021). For 2030, it can be assumed that the results of the optimum-rotation scenarios are achievable, but at reduced nitrogen levels compared to scenarios 42 and 43.

6.4.3 Green ammonia fertilizer

Green hydrogen and ammonia, and consequently green N fertiliser, are emerging technologies. Timescales for adoption are currently primarily determined by production capacity. Most planned production of green hydrogen and ammonia in Australia is expected to become (fully) operational around 2030. Estimates suggest that globally green ammonia could become cost-competitive in niche markets around 2030 (Fasihi et al. 2021) but more general cost competitiveness may take as long as 2050 to achieve (Advisian 2021).

Therefore, adoption before 2030 is expected to be negligible.

There may be a role for ammonia based on blue hydrogen before that, but currently this is estimated to be ~35% more expensive than grey hydrogen (Advisian 2021) and it has lower mitigation benefits than green hydrogen. On the other hand, there is significant current investment in blue and green hydrogen research and development which may lead to faster development of low emission and cost-effective options.

With 100% adoption, the green fertiliser scenario gives an 11% reduction in GHG emissions as well as emission intensity. The reduction of Scope 3 emissions of the modelled fertiliser production compared to the baseline is 50%, based on the relative contribution of ammonia in the overall embedded emissions of fertiliser (5.1.5), and with future technologies this reduction could become higher. This means that in the longer term, some or most of the additional Scope 3 emissions associated with the BestN and MaxN scenarios may be mitigated.

6.4.4 Controlled traffic farming

Current adoption of CTF in broad-acre farming is 38% nationally (ABARES 2021b), ranging from a low 22% in South Australia to 60% in Queensland. Implementation by 2030 is estimated to be around 50% nationally (D. Antille, J. Tullberg, private communication). Uptake is likely to be influenced by the pay-back time of required investment which depends on the expected increase in yield and hence varies by region (Blackwell et al. 2013). A lack of more comprehensive information on, and hence potential benefits of, GHG reduction as described in 5.1.6 may also influence adoption.

Full implementation of the CTF scenario (6) gives a reduction of 2% in total emissions and 7% in emission intensity (Figure 18, Figure 21). Therefore, estimated mitigation potential by 2030 would be ~3.5% of GHG intensity compared to 2005.

Note that this would not current be captured in most static GHG accounting approaches. Additional investigation is needed, as flagged in Chapter 8.

6.4.5 Reforestation

The average price for ERF carbon credits in the October 2021 auction was 17\$/tCO_2 (Clean Energy Regulator[8]) but spot prices for ACCU were reportedly as high as 33\$/tCO_2[9]. The latter represents an unprecedented doubling within the 2021 calendar year. Reputex (2021) forecast that prices for Australian Carbon Credit Units (ACCUs) could more than double by 2030, rising to a range of 20-45\$/tCO_2.

At this higher price, using the results for low hurdle rate and 25-year average sequestration (Table 4), about 5% of the baseline emissions could be offset within the grains system, while maintaining or increasing farm profitability.

It is interesting to consider offsetting emissions for the highest emission scenarios (42 and 43). The increase in emissions compared to the dynamic baseline is 33% (Figure 18) which would require a

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[8] http://www.cleanenergyregulator.gov.au

[9] https://www.reputex.com/research-insights/accu-spot-price-rally-continues-up-103-year-to-date/

carbon price of at least 100 $/tCO_2$ and 8% of the current area under grains (Figure 16). Assuming that the reforestation would occur across the system[10], an 8% reduction of production for those scenarios would still result in an increase in production of 60% compared to the baseline (Figure 17). However, this option is likely to be expensive compared to other options to offset emissions and the mitigation potential by 2030 using reforestation of current (grains) cropland is expected to be very small. Reforestation on other land (marginal cropland, non-arable land, rangeland) can be more cost-effective and provide a feasible alternative to offset emissions (e.g. Kingwell 2021a).

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[10] Reforestation would not necessarily occur on more marginal cropland, because the production of tree biomass and hence carbon credits is also likely to be lower on such land

Part III Integration

Putting the results in context

7 Discussion

7.1 Interpretation

7.1.1 Main findings

The results in Chapter 6 show that increasing production while reducing GHG intensity of grains is possible. Better nitrogen management could lead to significantly increased production and lower relative losses of N. On average, scenarios with higher N application do result in higher absolute N_2O emissions but lower emissions due to soil carbon change, within each Region. The N_2O emissions relative to N applied also appear to be lower in the higher N regimes. Those effects result in only very small increases, or even decreases, in total on-farm emissions (Scope 1) although it should be noted that annual variability is high (Appendix B).

The increase in total emissions in the higher N scenarios occurs almost entirely in the embedded emissions in fertilisers (Scope 3) that were already found to be a significant contributor to the Baseline emissions (see Chapter 2). Forecast technology for the use of green ammonia in nitrogen fertilisers will not be able to reduce those emissions in the short term (i.e. before 2030) and moreover is estimated to reduce embedded emissions of the full fertiliser mix by only about 50% (5.1.5) based on current information. In the shorter term, an option to reduce Scope 3 emissions could be a more efficient use of crop protection products. The embedded emissions of chemicals were found to contribute ~11% to the baseline (Figure 1) and increased efficiency of chemical use is already something many farmers focus on (ABARES 2021b). In addition, embedded emissions of all inputs are likely to decrease with increasing decarbonisation of energy supply around the world.

To judge current emissions and emission intensity compared to the Baseline, more information is needed on real on-farm activity data. With the increase in use of AgTech and farm management software, as well as increased cover of the GRDC farm practices survey, it is becoming feasible to do regular GHG accounts for the grains sector for comparison with the Baseline. Some of the changes that are (like to have) occurred since 2005 are modelled in the Current scenario. The increase in canola production along with increase N rates across the system result in higher emissions and emission intensity. The increase in N rates was based on a meta-analysis (see A.4) resulting in an estimate of how the partial productivity factor of N fertiliser (PPFN, tonne crop/tonne N) has decreased on average across the system. Changes in timing of applications were not modelled. As demonstrated by the BestN and MaxN scenarios, improved timing of nitrogen application is likely to allow for increasing nitrogen use without increasing net emissions. The ABS Land Management survey (ABS 4627) does include some data on timing but information on real practice around timing could be used to assess this in more detail.

There are no easy wins in term of absolute GHG mitigation in grain cropping. Trade-offs between yield (desired increase) and emissions (desired decrease) may be inherent to the system, but it is very important to note that the high-N models do show a considerable decrease of net Scope 1 emissions as well as an increase in production in the South and West regions. In a recent paper, Chai et al. (2021) investigate crop management practices, such as intensified cropping through relay planting or intercropping, in China. They find that yield is increased, with reduced GHG intensity, but total emissions also increase. Research by Meier et al. (2022) suggests that total emissions decrease significantly when implementing short-term cover crop options, but at the expense of yield.

Assuming that half of the estimated benefits of the scenarios with most improved GHG intensity can be achieved by 2030, combined with an expected 50% uptake of controlled traffic farming, a total reduction of ~15% in GHG intensity per tonne grain might be achieved compared to the Baseline. Scope 1 emissions would remain almost constant nationally, but total emissions increase by about 20%.

Assuming that all estimated benefits of Scenario 43 (see 5.1.4) could be achieved in the longer term, together with full uptake of green-ammonia fertilisers, a total reduction of ~35% in GHG intensity is estimated based on the results in Chapter 6. This would involve a decrease of Scope 1 emissions (~3.5%) but total emissions would still be up by ~7%. However, as noted earlier, Scope 3 emissions are likely to reduce as the world moves to a decarbonised energy supply and current activities around green and blue hydrogen in the fertiliser supply chain are likely to only be a start. Also, under optimised nitrogen conditions, the effect of controlled traffic farming could be considerable (see 5.1.6; Hussein et al. 2021) but more research is needed to establish under which conditions this applies.

Offsetting of emissions via reforestation seems the most likely option to reduce absolute emissions. Using cropping land for reforestation could reduce crop production but this could potentially be compensated for by increasing production on remaining land, as demonstrated by the results of the high-nitrogen scenarios. Soil carbon sequestration was not explicitly targeted in this study but was found to be a potential benefit of the improved nitrogen application scenarios. The associated CO_2 removals are found to offset the higher N_2O emissions to a large extent. If carbon credits generated by such practice change, or by reforestation, in the grain sector were sold as offsets for emissions in other sectors, they could no longer be used to make a claim for low-GHG or carbon-neutral grains as this would constitute double counting. Growers need to weigh up the benefits of selling carbon credits against the use of these credits to maintain or increase market access. A sector-level approach to the generation and utilisation of carbon credits could ensure that the grains sector as well as individual growers obtain maximum benefit from carbon sequestration strategies.

The MaxN scenarios simulate a ‘perfect’ scenario where crops are fertilised optimally to meet their nitrogen demand throughout the growing season. As demonstrated by the results, this has the potential to increase yields considerable while also reducing relative losses of N as well as of soil carbon. In practice, this is not easy to achieve, and as recently addressed by Hochman and Waldner (2020), even more difficult in an increasingly variable rainfall environment. A range of technologies is likely to be required, from slow-release or stabilised fertilisers to better decision-making tools (Hochman and Waldner, 2020) to strategies like N banking, top-up or seasonal budgeting, and precision agriculture and AgTech.

In addition to nitrogen management, there is scope to improve the emission intensity of grain production systems if the most optimal rotations could be utilised across the country. These are likely to differ significantly based on soil and location characteristics. More regionalised assessments are needed to understand if there are specific attributes of the rotations that are optimal across locations or groups of similar agri-environments.

7.1.2 Markets versus domestic targets

GHG accounting in Australian agriculture serves two purposes: one is to contribute to Australia's emissions reduction targets, the other to keep commodities competitive in export markets that increasingly require evidence of low-emissions credentials. The results suggest that it is very difficult to achieve both.

However, if Scope 1 emissions can be kept more or less constant with increased production, this would still constitute a relative decrease compared to projections. Emissions associated with cropping are modelled to grow by about 25% between 2005 and 2030 in the national emission projections (DISER, 2021). Moreover, Scope 1 emissions as established[11] in Chapter 2 add up to only 1.7% of all national emissions reported in 2005-06.

It is the embedded emissions of fertiliser that are expected to increase with the modelled scenarios. As urea and other ammonia-based fertilisers are currently largely imported, these embedded emissions largely take place outside the national boundaries and as such do not contribute to Australia's emission inventory. However, decisions around use inextricably linked with farm management and from the perspective of markets the "footprint" approach, or GHG intensity, includes Scope 3 or embedded emissions. As shown in 2.4, Australian cereals have low GHG intensity compared to other exporting countries. Further improvement is likely to increase competitive advantage in future (Greenville et al. 2020).

This tension between total emission reduction and desire to increase production and export value has also been noted by the National Farmers' Federation in their Climate Change Policy (NFF 2020): "balance production and emissions policies, by adopting the principle of emissions intensity for agricultural emissions".

7.1.3 Differentiated emission factors

The APSIM results indicate that direct emissions of nitrous oxide may be lower under BestN and MaxN application relative to N applied, especially in the South. Interaction with soil carbon may play a role in this, with higher soil carbon sequestration (or lower losses) either using some of the nitrogen without resulting in net loss of yield or leading to different soil qualities which influence denitrification. Preliminary results from APSIM simulations not presented in this report also suggest that the emission factor for nitrous oxide emissions may be lower in conditions with high soil carbon content, although this is not in line with results reported by e.g. Barton et al. (2016). Further investigation into this is warranted.

APSIM nitrous oxide emissions include those associated with residue nitrogen, so it is not possible to compare modelled emission factors directly to those used in the NGGI. Nevertheless, the results suggest that emission factors – for N applied and/or residue N – are lower in systems with higher,

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[11] Including direct land use change to align with the total national emissions

efficient N input. The same may be true for emissions in systems using controlled traffic farming (see 5.1.6 and references there) and for differences in emissions due to different timing of application of fertiliser. Current emission factors do not capture any of these effects, largely because they have not been well established across crops, regions, soil- and weather conditions.

To monitor GHG mitigation or GHG intensity reduction in the sector going forward, differentiation in emission factors by practice is needed. This is also needed for farm-level GHG assessments, where currently the only effects of e.g. controlled traffic farming accounted for would be increased yield and reduced fuel use.

7.1.4 Indirect effects

It is important to consider the impacts of production changes on global markets when dealing with a globally traded commodity such as grains. Emission mitigation in Australian grain production that would result in a decline in overall grain production could lead to indirect effects that effectively increase global GHG emissions. This is because implementing activities that result in a decline in production is likely to shift production elsewhere to ensure global demand for a commodity continues to be supplied. Market-mediated effects occur because agricultural land is constrained at a global scale so shifting crop production elsewhere results in forestland or grassland being transformed to ensure global supplies of commodities are maintained.

There is a high degree of confidence that market-mediated effects shift the burdens of production in response to change in supply. For example, Meyfroidt et al. (2013) demonstrated that reforesting agricultural land and reducing agricultural outputs reduced the global benefit of reforestation activities by 50% when the shifted burdens of agricultural production were included in the assessment. Thus, implementing changes that maintain production is a key attribute of robust GHG emissions reductions strategy.

Therefore, a minimum requirement was identified (see Methodology Report) that Australian production should not decline compared to global production and consumption (forecasts) in achieving emission mitigation. The OECD-FAO Agricultural Outlook 2021-2030 (OECD/FAO 2021) forecasts a growth in demand for cereals and oilseeds of a little over 1% per year, which indicates a flattening of the growth curve compared to the previous decade. Over the coming (current) decade, the expansion of area for agriculture is also forecast to be considerably lower than over 2011-2020. This suggests that global indirect land use change pressure associated will reduce. For wheat, the increase in production and consumption is forecast to be 8.2% between 2021 and 2030, with 7.6% increase of average yield and only a slight increase in area. Total global demand for calories has grown by about 23% between 2005 and 2018 (van Dijk et al. 2021). Based on those sources, an increase in global demand for grains of ~35% is estimated for the period between 2005 and 2030. The increases in production modelled in the high-N application scenarios (see 6.1) are considerably larger than that, although unlikely to be achieved fully by 2030. Australian production trends and forecasts discussed by Kingwell (2021b) are also in line with the global percentages discussed, including a growth of 1% per year over the current decade.

If production increases more than those trends, e.g. due to optimisation of fertiliser application, there may be additional positive indirect effects. Intensifying agriculture can provide net global climate change mitigation even when it increases GHG emissions on an area basis because it avoids land use change elsewhere to ensure commodity production is maintained. Historically, intensifying global agriculture between 1961 and 2005 avoided the emission of up to 161 Gt C, despite increasing emissions from agricultural production, because less land had to be put into agricultural production to meet global demands for agricultural commodities (Burney et al., 2010). More relevant to the Australian grains sector, Simmons et al. (2020) found that intensifying Australian wheat production by increasing N application rates provided climate change mitigation at a global scale. This result demonstrates that meeting growing global demand for wheat by intensifying Australian production is less GHG intensive than expanding wheat production in other parts of the world (see also 2.4).

A different indirect effect is associated with the increase in canola production, especially in the West. Along with increased nitrogen inputs nationally, this has led to increased emissions and emission intensity for the grains system as a whole, under otherwise constant modelling assumptions, although total production and revenue have also increased. The increased demand for canola is driven by the European biofuel market, which suggests that this shift contributes to emission reduction globally. The European market requirements are such that biofuel feedstocks with low embedded emissions are sought after and Australian canola meets those requirements (Eady 2017).

7.2 APSIM as a modelling tool

APSIM is one of few models capable of predicting growth and productivity of a diversity of crops, rotations of these over time, and the underlying soil processes driving water and nitrogen availability that influence crop productivity. It is also the only such model that has been widely tested and applied in the Australian grains industry. These capabilities are critical for assessing multiple consequences of different practices in grain production systems and their concurrent impacts on GHG emissions such as soil N and C. To build such broad capability often requires simplifications of some processes. Many other models are available that may deal in more detail with sub-components of the farming system (e.g. specific aspects of soil C or N dynamics, soil water processes, plant growth), but these usually have greater simplifications in other process such as crop growth, and simple representation of farmer management. Thus, they often lack the capabilities to fully understand the trade-offs or interactions with other system elements.

Models such as APSIM provide a rigorous but not always exact representations of observed data. Hence, there can often be some difference between a model prediction and observations in a particular situation because there are insufficient data or information upon which to calibrate the model. For more details see also Appendix C .

However, the model is still helpful to understand the relative outcomes between different management options across a wide range of situations. Because APSIM is a process-based model this can be done without the need to site-specific parameterisation which enables common approaches to be applied across a wide range of environments and production systems. Therefore, the dynamic scenarios are all interpreted relative to the dynamic baseline.

7.3 Limitations and uncertainties

7.3.1 Static accounting

For the historic baseline as well as the two static mitigation scenarios, uncertainties are associated primarily with the activity data that are required to construct the GHG accounts. The following sources of bias were identified in the Methodology Report:

- The use of nitrogen rates based on AusLCI for some of the crops, which results in an overestimate of emissions associated with fertiliser. This effect is judged to be negligible.
- The use of proxy values for some of the small crops. These crops account for 1.5% of the area and 0.4% of production (by mass) so the uncertainty introduced is judged to be less than 1%.
- Lack of data for irrigated crops which means emission factors were adjusted for irrigation by area rather than by nitrogen applied which is expected to be higher in irrigated grains. This results in an underestimate of emissions associated with fertiliser. This effect is estimated to be small (~1% of total baseline).
- Allocation of Cropland-remaining-cropland emissions (NIR 2018) to crops only, i.e. not including temporary pastures which are also defined as cropland in the NIR. This was adopted as a conservative approach. It is likely to result in an overestimate, but the magnitude is unknown.

Overall, the nitrogen application rates determined for the calculation of the historic baseline are deemed to be robust for the purpose of determining GHG emissions at a high aggregation level. The assumption of constant crop production per unit of nitrogen, applied between the baseline year and the period around 2012 when nitrogen rates were determined in detail as part of the NGLCI, aligns with data on national fertiliser use (see A.4) and the average production modelled with APSIM also aligns well with the historic baseline production, supporting that the nitrogen rates are realistic.

In addition to the limitations in activity data, the use of emission factors, as well as emissions of land use and land use change, as defined in the NGGI has limitations because they do not take into account details on practice in cropping systems, let alone for grains. Also, regular updates based on new research or modelling are applied retrospectively which means that data for the baseline year are also revised. The use of the most recent emission factors and data available at the time of the baseline assessment was defined as best practice. However, the NIR 2019 which has become available since has significantly revised Cropland-remaining-cropland emissions for the baseline year. This should be taken as an indication of uncertainty in that emission source, which is also supported by the dynamic baseline assessment. Although, as noted in 3.3, the emissions due to soil carbon change as modelled by APSIM may include some historic land-use change effects. In the NIR (2018, 2019), a comparison is presented between results for soil carbon using FullCAM (the tool used to calculate the national inventory) and APSIM. The results show a high degree of correlation and good reproduction of trends, but they only cover a few sites and rotations.

As for the Cropland-remaining-cropland emissions, there are uncertainties associated with the emissions associated with Forest converted to cropland, which are evaluated as a sensitivity assessment (2.5.2). These emissions were attributed equally to all crops and temporary pasture by relative area at the national level, and hence do not reflect the full extent of regional variation. These emissions have also been revised in the NIR 2019.

7.3.2 Dynamic modelling

Results of APSIM modelling reflect by necessity the data that were used to define the simulation set up and crop management assumptions. For example, in the Current scenario, there is considerable uncertainty about nitrogen use in grain production systems, both in terms of quantities and timing of application. Similarly, APSIM simulations only included rainfed cropping systems, because of the small areas of irrigated grains which were excluded for simplicity.More in general, the APSIM modelling is based on generic approaches to allow for a common model application nationally, but that don't necessarily reflect detailed practices in each environment or location. Coarse crop management rules were applied across the country which were tailored to each broad region, but these may not reflect exactly the management in each location. Such assumptions are likely to introduce errors in specifying the agronomic management to fit different production environments (soil & climate).

Initial soil C status is critical for predicting potential soil C balance, and interacts with processes such as N cycling, and hence the propensity for N2O losses and the need for fertiliser N inputs. It is well established that initialisation of C pools in APSIM is critical for simulating GHG emissions from systems. Here we have used 'generic' soils in simulations based on data in soil databases, but clearly there is large variability across the landscape and historical management. Hence, sensitivity of results to different soil C states is unclear and may not reflect specific locations or situations.

While APSIM or modelling approaches can be good for testing the changes that could be achieved though alternative crop management practices, APSIM simulations here were not limited by biotic constraints (e.g. weeds, pests, diseases) or soil constraints other than water and N availability (e.g. other nutrients, soil acidity). Hence, the dynamic baseline simulation is likely to generate yield potential and response rates to inputs that may not be achieved by farmers under their real-world management practices. This is likely to further soften potential productivity gains per unit of inputs that are achievable on farm, and hence the capacity to further enhance GHG emission intensity compared to the simulated scenarios.

Sensitivity of optimal rotation selection to input and carbon price was not explored in depth, although initial testings suggest carbon prices need to be very high to result in different selections. Similarly, as above, the biotic constraints of rotations are not considered so this may alter the relative productivity or profitability of certain crop sequences. Further, some minor crops are not well characterised in APSIM (e.g. fababeans and lentils) which introduces some uncertainty about the precision of their yield predictions which may influence the relative productivity or profitability of rotations involving these crops - though this was typically only a small proportion of land in only a couple of regions. The sensitivity of rotation optimality to commodity prices is also important – we used long-term average prices (and these were not specified for individual regions). Small shifts in relative prices of some crops may indeed result in a lower emitting crop rotation being more profitable and *vice versa*.

Finally, the APSIM simulations were conducted using recent historical weather conditions (1990-2020). This is likely to be representative for the decade to 2030 but in the longer term, climate change may influence productivity and emissions of both nitrous oxide and soil carbon change into the future.

8 Recommendations RD&E

Based on the findings as well as the limitations of this study, a number of recommendations for further research, development and extension are made. The recommendations address the following main topics:

1. Assessing interventions and interactions that this study was unable to address;
2. Improvements to GHG accounting and modelling practices;
3. Localised decision making.

In addition, it is recommended to try to integrate GHG accounting in relevant investments. GRDC is investing in a lot of relevant RD&E already but ex-post evaluation of the effect of certain practices in terms of GHG emissions is often limited by lack of some key data, if GHG mitigation was not an explicit objective. Projects could be screened ex-ante and if found to be relevant, the necessary data may be collected at little extra effort.

It should also be kept in mind that GHG emissions are only one dimension of sustainability. It is important to continue to evaluate co-benefits as well as costs in other environmental domains.

8.1 Interventions

There are many measures that could potentially influence yield and/or GHG emissions that were not addressed in this study. An important one is amelioration of (sub)soil constraints such as e.g. optimised lime application. Any subsoil constraints that influence yields and soil chemistry may also influence GHG emissions and intensity. Lime application, both in amount and strategy, is likely to influence yields as well as nitrous oxide emissions and soil carbon. The GRDC investment portfolio already has many projects around this. It is important to know more about how constraints such as acidity may interact with yield, carbon and nitrogen cycling, and what options there are for improving overall efficiency of the system. In addition to field data, it could be valuable to further improve representation of these processes in APSIM to allow for modelling these effects.

More research is needed to understand options to increase soil carbon in cropping systems, as well as the effects of increased soil carbon on the nitrogen cycle. This could involve a range of organic amendments but also pasture phases or systems like dual-purpose or pasture cropping, expanding the system to a whole-of-farm perspective and including effects on production. There is also a need to further explore simulations of transition to high soil carbon states as well as potential effects of high soil carbon state such as changes in the nitrogen cycle, as well as the influence of climate change on the potential to maintain high soil carbon states.

Based on the available literature, controlled traffic farming could have considerable benefits in a low-rainfall and optimized-nitrogen environment, but evidence is currently limited to only a few climatic zones, crops and soil types. More comprehensive research in this area could inform more accurate assessment of overall mitigation potential across the system and emission factors that take effects of CTF into account. If mitigation potential turns out to be significant, there might be scope for development of an ERF[12] methodology. The development of an 'integrated farm method' has been prioritised for 2022[13] and this may provide a framework for additional mitigation options in future.

Integrated pest management is another topic that has potential GHG benefits. More research is needed to establish realistic mitigation potential as well as trade-offs and co-benefits, especially in light of threats to mitigation such as herbicide resistance or new diseases.

Investment in reducing 'upstream' embedded emissions of fertilisers is already ongoing. GRDC has partnered with CSIRO, the Australian Renewable Energy Agency (ARENA) and Orica on the Hydrogen to Ammonia project[14]. More detailed information on timelines and effective mitigation potential should be assessed against the overall GHG account of the grains sector as it becomes available.

8.2 GHG accounting and modelling

Regular GHG accounting to monitor changes in the system is only possible when the effects of changed practice can be captured. To facilitate this, more differentiated emission factors are required. As discussed in this report, this is the case for e.g. N_2O emissions in high soil carbon environment, N_2O emissions for varying N application rates as well as timing, and effects of controlled traffic farming. Establishing more differentiated emission factors is likely to require more field research as well as modelling, but also consensus building across relevant stakeholders.

In addition to emission factors, more effort is also required in data collection. The farm practices survey can be extended – as is already happening – to include more information on key factors for GHG accounting such as nitrogen rates and application practices. However, there is also a need for levels of disaggregation (by crop, region, soil type) that may be better met by using data that is available in existing data bases and farm management tools. With appropriate measures to ensure confidentiality, this could provide data that allow for regular GHG monitoring as well as benchmarking. As discussed in Appendix A.4, there is a large discrepancy between N rates assumed in the NGGI (AGEIS 2021) and bottom-up data such as used to establish N rates for the Baseline and Current scenarios in this study.

The NGGI emission factor for residue nitrogen is high and this source of emissions has a high contribution to the baseline with just over 20%. While the results of the dynamic baseline don't provide evidence that the static emission factor may be too high, it is not possible to distinguish between N_2O emissions from fertiliser and residue in APSIM results. A more in-depth assessment of this is recommended so that the emission factor may be improved if necessary. Similarly, the finding that average N_2O emissions in the North region as modelled by APSIM are higher than those calculated using the NGGI emission factor should be further explored.

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[12] Emissions Reduction Fund; http://www.cleanenergyregulator.gov.au/ERF

[13] http://www.cleanenergyregulator.gov.au/ERF/Pages/Method-development.aspx

[14] https://arena.gov.au/projects/hydrogen-to-ammonia/

An industry-wide agreement on best-practice in agriculture GHG modelling could also add considerable trust in modelling results, that will continue to play an important role in research and informing practice. More validation against measurements as well as between models could contribute to this. A project is about to get underway under auspices of Agricultural Innovation Australia to build consensus on static GHG accounting across agricultural sectors; a similar activity around GHG modelling could be initiated.

8.3 Localised decision making

In order to turn scenarios into reality, more localised information needs to be available for decision making on farms. There are large regional differences mitigation potential and in effects of actual practices, based on weather conditions and soil types. Finer scale information on optimal rotations, nitrogen management, soil carbon management, reforestation choices and benefits of windbreaks, et cetera, would provide insight into what is achievable. Given that most Australian grain growers are mixed farmers, practices need to be considered holistically at the farm scale.

Specifically, as discussed in 7.1, the MaxN scenarios simulate a ‘perfect’ situation where crops are fertilised optimally to meet nitrogen demand. To approximate this in practice, a range of technologies will be required, from slow-release or stabilised fertilisers to decision-making tools to strategies like N banking, top-up or seasonal budgeting, and precision agriculture and AgTech. More investigation is required to establish what is feasible locally.

A combination of grass roots knowledge, existing localised research and new research and modelling could build the required knowledge base.

9 Conclusions

The historic baseline assessment successfully pulls together data from a wide range of sources with varying levels of spatial resolution into a very detailed GHG inventory for grains. Leviable crops with lower data availability are included by applying a set of rules to establish most suitable proxy data with national area and yield data specific for each crop, resulting in high level of completeness. There are uncertainties at the detailed level but those are mostly associated with small emission sources.

Total GHG baseline emissions associated with grains production in 2005 were found to be 13.75 Mtonne CO_2-equivalent. The contributions to the total of Scope 1,2 and 3 emissions are 61.3%, 0.1% and 38.6% respectively. The total contribution of fertiliser Scope 1 and Scope 3 emissions is 38%. GHG baseline emission intensity was found to be 315 kg CO_2-equivalent/tonne grain, which is low by international standards.

Despite the high contribution of fertiliser use to baseline emissions, GHG intensity was found to decrease with increasing fertiliser application, under best-practice or ‘perfect’ application management scenarios. This reduction in GHG intensity is associated with a considerable increase in production. Total emissions increase in these models, but this increase is primarily in Scope 3 or embedded emissions associated with fertiliser production. Significant reduction of those emissions can be expected in the longer term via the production of green fertilisers and (other) decarbonisation of energy supply.

Offsetting of emissions via reforestation seems the most likely option to reduce absolute emissions. Using cropping land for reforestation could reduce crop production, and thus come at a cost to the sector, but this could potentially be compensated for by increasing production on remaining land.

Further research and development are needed to understand other mitigation options, across the range of environments that grain growers operate in. More localised information for decision making on farm will help turn scenarios into reality. In addition, development of more detailed emission factors as well as data collection is required for regular monitoring of GHG accounts.

Absolute GHG mitigation potential in the Australian grains sector is limited due to an intrinsic trade-off between total emissions and production. Given widely supported goals to increase production, it is unrealistic to expect significantly reduced absolute total emissions, given the essential role that carbon and nitrogen play in plant growth, but Scope 1 emissions are shown to reduce in the high-nitrogen scenarios in some regions. Setting targets in terms of average or progressive GHG intensity, combined with minimum conditions around Scope 1 emissions and production, is the most realistic and in line with recommendations made by the National Farmers’ Federation (NFF 2020).

Appendix A Methodology details

A.1 APSIM simulation set-up

Simulations were conducted using the Agricultural Production Systems sIMulator (APSIM Version 7.10; Holzworth et al., 2014) with at least 30 years of historical daily temperature, rainfall and solar radiation data from 50 high quality weather stations (map shown in 3.2). The temperature and rainfall data were sourced from the SILO database (Jeffrey et al., 2001) and the solar radiation data was derived from satellite imagery processed by the Australian Bureau of Meteorology from the Himawari series operated by Japan Meteorological Agency and from GOES-9 operated by the National Oceanographic & Atmospheric Administration (NOAA) for the Japan Meteorological Agency. The 50 stations were selected based on the areas of winter commodities (cereals, legumes and oilseeds) grown within a 50 km radius of each station and to be representative of the regional (Table A1) and national grain cropping areas. Several crop and fertiliser management rules were implemented differently for northern and southern regions, in line with local practices. Hence, all Qld and NSW sites above a latitude of 32.243815 (aligned with Dubbo) were classed as northern sites and sites with a higher latitude classified as southern sites.

The three most common soil types within a 50 km radius of each station were used in simulations. These were selected using the Australian Soil Resource Information System (ASRIS) soil maps (Johnston et al., 2003) in the cropping land use class. Soil profile characteristics for simulation of each soil type were determined (as described by Hochman et al., 2016) by taking the median value of the parameters of the same soil type from 434 deep soil profiles characterised in the APSoil database (APSIM Initiative, 2016). As initial soil moisture and nitrogen values were unknown, all simulations were run for at least 15 years prior to the thirty-year analysis period (1991-2019) to allow soil conditions to self-calibrate. These 15 years were used only to define the simulation starting conditions and results from this period were not included in the analyses. Soil organic carbon was set to default values for that soil type from the soil databases at the start of the 15-year initialisation. This was not reset at the start of the thirty-year simulation period to avoid the rapid changes in soil C that can occur during the first 5-10 years after the initiation of simulations. Hence, every combination of site-soil and crop rotation will have differing in the starting soil C states at the beginning of the simulation period, after which changes in these values were reported.

Simulation outputs generated annually included: grain yield, crop biomass, N fertilizer applied, runoff, deep drainage beyond the root zone, NO_3 leached beyond the root zone, number of fallow herbicide applications, change in soil C, and greenhouse gas emissions (i.e. N_2O and CO_2 emissions as CO_2 equivalents from the 0-30 cm layers as described in Hochman et al. (2017) and based on Huth et al. (2010)). The number of fallow herbicide applications was calculated by assuming spraying occurs 10 days after 30mm of rain is accumulated in 5 days with a minimum of 20 days between spray events.

Table A1. List of 50 locations used to simulate regional and national GHG emissions from the Australian grain industry.

Subregions	Weather Station
NORTHERN REGION	
Central Qld	Springsure
Eastern Downs Qld	Oakey
Liverpool Plains & NE NSW	Quirindi
Western Downs Qld	Surat
North West NSW	Collarenebri
	Mungindi
Central East NSW	Peak Hill
	Trangie RS
	Orange
Central West NSW	Condobolin
	Nyngan
	Lake Cargelligo
South East NSW	Corowa
	Wagga Wagga
	Narrandera
	Grenfell
South West NSW	Lake Victoria
	Balranald
	Hillston

Subregions	Weather Station
SOUTHERN REGION	
Wimmera and Central Vic	Ouyen
	Warracknabeal
	Echuca
	Kerang
Southern Vic SA	Keith
	Ararat
SA Vic Mallee	Meningie
	Mildura
Lower EP, Yorke and Mid North	Yongala
	Price
	Warooka
	Rosedale
Upper EP and Upper North	Ceduna
	Cleve
	Kyancutta
	Streaky Bay
WESTERN REGION	
Geraldton	Carnamah
	Mullewa
Kwinana East	Wongan Hills
	Bencubbin
	Kellerberrin
Kwinana West	Badgingarra RS
	Beverley
	Corrigin
	Narrogin
Albany	Mt Barker
	Hyden
	Ongerup
Esperance	Esperance
	Ravensthorpe
	Salmon Gums RS

Crop management rules

Sowing rules and agronomic management simulated for all crops were based on expert knowledge, GRDC GrowNotes and Pulse Australia recommendations. If the sowing criteria for any crop was not met during the sowing window, the crop was sown on the last day of the sowing window. The following rules were used to initiate sowing based on rainfall and available soil water (ESW) for each of the crops throughout all simulations (note: in some cases differences in crop management were applied for different regions):

WINTER CEREALS

<u>Wheat</u>: Different sowing rules based on northern/southern locations

- Northern sites: Sow if rain >=15mm over 3 days and ESW>=50mm
- Southern sites: Sow if rain >=15mm over 3 days regardless of soil moisture
- Three different cultivars could be sown depending on time of sowing:
    - 15 Apr – 1 May: sow Bolac
    - 2 May – 20 May: sow Gregory
    - 21 May – 1 Jul: sow Spitfire
- Sowing density = 150 plants/m^2, row spacing =250mm, sowing depth = 30mm

<u>Barley</u>: Different sowing rules based on northern/southern locations

- Northern sites: Sow if rain >=15mm over 3 days and ESW>=50mm from 26 April-15 July
- Southern sites: Sow if rain >=15mm over 3 days regardless of soil moisture from 26 April-15 July
- Variety=Hindmarsh, sowing density=150 plants/m^2, row spacing=250mm, sowing depth=30mm

<u>Oats</u>: Different sowing rules based on northern/southern locations

- Northern sites: Sow if rain >=15mm over 3 days and ESW>=50mm from 26 April-15 July
- Southern sites: Sow if rain >=15mm over 3 days regardless of soil moisture from 26 April-15 July
- Variety=Williams, sowing density=150 plants/m^2, row spacing=250mm, sowing depth=30mm

OILSEEDS

<u>Canola</u>: Different sowing rules based on northern/southern locations

- Northern sites: Sow if rain >=15mm over 3 days and ESW>=50mm from 20 April-15 Jun
- Southern sites: Sow if rain >=15mm over 3 days regardless of soil moisture from 20 April-15 Jun
- Variety=new_H46y78, sowing density=30 plants/m^2, row spacing=300mm, sowing depth=10mm

<u>Sunflower</u>: Only grown in northern regions

- All Sites: Sow if rain >=30mm over 5 days and ESW>=100mm from 15 Sep-21 Oct
- Variety=Medium, sowing density=3 plants/m2, row spacing=750mm, sowing depth=40mm

GRAIN LEGUMES

<u>Chickpea</u>: Sowing windows used were based on location.

- CQ (Latitude >= -24.5): Sow if rain>=15mm over 3 days from 15 Apr – 7 Jun
- SEQ NNSW (Latitude >= -32.2 and < -24.5): Sow if rain>=15mm over 3 days from 15 May – 7 Jul
- Southern (Latitude < -32.2) and WA: Sow if rain>=15mm over 3 days from 7 May – 7 Jul
- Variety=Amethyst, sowing density=30 plants/m2, row spacing=500mm, sowing depth=30mm

<u>Field pea</u>: Only grown in southern regions

- All sites: Sow if rain>=15mm over 3 days from 15 May – 30 Jun
- Variety=Kaspa, sowing density=60 plants/m2, row spacing=150mm, sowing depth=30mm

<u>Lentil</u>: Only grown in southern regions

- All sites: Sow if rain>=15mm over 3 days from 15 May – 15 Jul
- Variety=Jumbo, sowing density=120 plants/m2, row spacing=500mm, sowing depth=50mm

Lupin: Sowing windows and agronomic management varied based on location.
- WA, SA and Vic: Sow if rain>=15mm over 3 days from 1 May – 7 Jun
- NSW: Sow if rain>=15mm over 3 days from 25 Apr – 15 May
- WA: Variety=Mandelup, sowing density=40 plants/m2, row spacing=300mm, sowing depth=30mm
- SA, Vic and NSW: Variety=Mandelup , sowing density = 40 plants/m^2, row spacing = 150mm, sowing depth = 30mm

Faba bean: same management across all sites
- All Sites: Sow if rain>=15mm over 3 days from 7 May – 7 Jun
- Variety=Fiord, sowing density=15 plants/m2, row spacing=300mm, sowing depth=50mm

Mungbean: Sowing rules different depending on position in crop sequence
- After winter fallow: Sow if rain>=30mm over 3 days and ESW>=30mm from 1 Oct – 1 Dec
- Double-crop: Sow if rain>=30mm over 3 days and ESW>=30mm from 15 Nov – 15 Jan
- Variety=Green Diamond, sowing density=30 plants/m2, row spacing=500mm, sowing depth=30mm

SUMMER CEREALS

Maize: Only grown in northern regions
- All sites: Sow if rain >=30mm over 5 days and ESW>=100mm from 1 Sep - 15 Jan
- Variety=SC401, sowing density=5 plants/m2, row spacing=1000mm, sowing depth=45mm

Sorghum: Sowing windows used were based on location.
- Latitude >= -29: Sow if rain>=20mm over 5 days and ESW>=100mm from 15 Sep – 15 Jan
- Latitude < -29: Sow if rain>=20mm over 5 days and ESW>=100mm from 15 Oct – 15 Jan
- Variety=Buster, sowing density=7 plants/m2, row spacing=1000mm, sowing depth=30mm, skip solid

Dynamic Baseline Simulations (Scenario 0)

Crop area sowing data from 2005-06 (ABS 7121) together with expert knowledge of rotations in practice, was used to develop a list of crop rotations that were simulated in each sub-region for the baseline scenario (Table A2). These crop rotations simulated at all locations were proportionally weighted within a sub-region to match the statistical information available (Table A3). The simulations of all rotations were phased, so that each field and year of the rotation was used in each year of the climate record. For example, a rotation with four crops and four fallow periods was represented by a farm with four fields and requires four years to complete a cropping sequence. Ensuring that cropping cycles were completed required some systems to run for extra years (e.g. a four-year rotation was repeated eight times requiring 32 years to complete). The CO_2 concentration for 2005 (378.81 ppm) was used in all the simulations.

Actual fertiliser N rates from 2005 (Table A4) for each subregion were used in the simulations. All N was applied at sowing to all legumes and other crops simulated in the Northern region. For cereals and canola in Southern and Western regions, 10 kg N/ha was applied at sowing and the rest was applied on 10 August. Nitrogen applications to legumes was associated with starter fertilisers.

Table A2. Crop rotations simulated for each sub-region in the baseline (2005) and current (2015) scenarios, and their associated proportional area based on crop sowing data reported by ABARES. The sequence of crops are denoted: W – wheat, S – sorghum, B – barley, Ca – canola, Ch – chickpea, O – oats, Fp – fieldpea, Lt – lentil, Lp – lupin, Sf – sunflower, Mz – maize, x – 6-month fallow. Note: the dominant grain legume in each region is used in the simulation unless the area of each crop is >5%.

Sub-region	2005 Baseline		2015 Rotations	
	Rotation	% area	Rotation	% area
South East NSW	WxWxBx	0.45	WxCaxWxBx	0.60
	WxWxCax	0.3	WxCaxWxCax	0.25
	WxFpxWxOx	0.25	WxFpxWxOx	0.15
Central West NSW	WxWxBx	0.65	WxWxBx	0.42
	WxWxOx	0.35	WxWxOx	0.25
			WxCaxWxChx	0.33
Central East NSW	WxWxOx	0.35	WxFpxWxOx	0.35
	WxFpxWxCax	0.15	WxBxWxCax	0.50
	WxWxBx	0.5	WxWxBx	0.15
North West NSW	SxxWxChxWxx	0.2	SxxWxChxWxx	0.30
	SxxWxWxx	0.3		
	WxWxBx	0.5	WxChxWxBx	0.70
South West NSW	WxWxBx	0.7	WxWxBx	0.60
	WxFpxWxCax	0.15	WxWxCax	0.25
	WxWxOx	0.15	WxChxWxOx	0.15
North East NSW	SBxWxx	0.8	WxWxBx	0.60
	WxChxBxOx	0.2	WxWxCax	0.25
			WxChxWxOx	0.15
			WxWxBx	0.60
Liverpool Plains NSW	WxWxOx	0.1	WxCaxWxOx	0.20
	SBxWxx	0.6	SBxWxx	0.45
	SxSxxWxCaxWxx	0.15	SxSxxWMgx	0.10
	SxSfxSx	0.15	SxSChxWxBxx	0.25
Southern High Rainfall	WxBxCax	0.6	WxCaxWxBx	0.65
	WxWxBxOxFp	0.4	WxFpxOxCax	0.35
Wimmera and Central Vic	WxBxCa	0.2	WxBxCax	0.26
	WxBxCpx	0.15	WxBxFbx	0.15
	WxBxLtx	0.15	WxBxLtx	0.25
	WxBxFpx	0.15	WxBxOx	0.15
	WxWxBx	0.35	WxWxBx	0.19
SA Vic Mallee	WxWxBx	0.85	WxWxBx	0.70
	WxLtxWxBxCax	0.15	WxLtxWxBxCax	0.15
			WxLtxWxBx	0.15
Western Downs Qld	WxChxWxBx	0.15	WxWxChxWxBx	0.45
	WxWxWxBx	0.25	WxWxOx	0.10
	SxxWxWxWxx	0.6	SxxWxChxWxx	0.35
Eastern Downs Qld	SxSxSBxWxx	0.6	SxSxxWMgx	0.15
	MzxSxSBxWxx	0.25	MzxSxSChxWxBxx	0.35
	SxSxSChxWxx	0.15	SxSChxWxBMgx	0.50
Central Qld	SxSxxWxChxWxx	0.50	SxSxxChxWxx	0.40
	SxSxxWxWxWxx	0.50	SxSxxChxWMgx	0.60
Lower EP, Yorke and Mid North	WxBxWxBxFp	0.7	WxBxWxFbx	0.35
	WxWxBxCa	0.3	WxBxWxLtx	0.35
			WxCaxWxBx	0.30
Upper EP and Upper North	WxWxWxBx	0.85	WxWxWxBx	0.85
	WxWxBxFpx	0.15	WxCaxWxOxFbx	0.15
Albany	WxWxBxCax	0.4	WxWxBxCax	0.60
	WxWxBxLpx	0.4	WxCaxWxLpx	0.15
	WxWxBxOx	0.2	WxBxOx	0.25

Sub-region	**2005 Baseline**		**2015 Rotations**	
	Rotation	**% area**	**Rotation**	**% area**
Esperance	WxWxBxFpx	0.4	WxCaxBxLpx	0.20
	WxWxBxCax	0.6	WxWxBxCax	0.80
Geraldton	WxWxWxLp	0.8	WxWxWxLp	0.40
	WxWxBxCax	0.2	WxWxWxCax	0.40
			WxWxWxBx	0.20
Kwinana West	WxWxWxLpx	0.5	WxWxWxLpx	0.10
	WxWxBxWxCax	0.25	WxWxWxCax	0.20
	WxWxBxOx	0.25	WxWxWxBx	0.70
Kwinana East	WxWxWxLpx	0.2	WxWxWxLpx	0.25
	WxWxWxBx	0.4	WxCaxWxBx	0.50
			WxWxBxOx	0.25

Table A3. Percentage of crop type sown in each region from statistical data (stat) compared with the weighted proportions assumed from simulated crop rotations (sim) for the 2005 baseline (shown in Table A2). Where less than 3% of area occurred in the statistical information this crop was ignored in simulations.

Region	Wheat or Triticale		Barley		Oats		Grain legumes		Canola		Sorghum		Sunflower	
	Sim	Stat	Sim	Stat	Sim	Stat	Sim	Stat	Sim	Stat	Sim	Stat	Sim	Stat
Geraldton	70	69	5	6	-	1	20	19	5	4				
Kwinana East	85	82	10	9	-	2	5	6	-	1				
Kwinana West	65	66	11	12	6	6	13	12	5	4				
Albany	50	54	25	25	5	5	10	8	10	9				
Esperance	50	46	25	30	-	1	10	8	15	15				
Upper EP and Upper North	71	74	25	21	-	2	4	3	-	1				
SA Vic Mallee	63	64	31	30	-	2	3	3	3	2				
Lower EP, Yorke and Mid North	43	42	36	35	-	2	14	15	8	6				
Wimmera and Central Vic	45	42	33	32	-	5	15	15	7	7				
Southern High Rainfall	36	36	28	26	-	12	8	7	20	19				
South East NSW	66	66	11	14	6	6	6	3	10	10				
Central East NSW	64	62	17	17	12	14	4	2	4	3	-	1		
South West NSW	64	63	23	24	5	5	4	2	4	3	-	2		
Central West NSW	67	66	22	21	12	10	0	2	-	1	-	1		
Liverpool Plains NSW	33	37	20	19	3	3	0	1	3	2	36	33	5	4
North East NSW	32	32	32	33	5	4	5	4			27	24	-	2
North West NSW	63	60	17	16	-	1	5	5			15	14	-	4
Western Downs Qld	71	72	10	9	-	1	4	3			15	14		
Eastern Downs Qld	20	21	17	15	-	1	3	3			60	58	-	1
Central Qld	50	48	-	2	-	-	10	8			40	41	-	1

Table A4. Fertiliser N (kg N/ha) rates applied to each crop in each region assumed in Baseline simulations. This was calculated based on statistical data on N use from 2005 and relative yields across regions. Note N fertiliser applications to legumes are associated with starter fertilisers which have some associated N with their main nutrients (P, S, Zn).

Subregion	Barley	Canola	Chickpea	Field Pea	Lentil	Lupin	Maize	Oats	Sorghum	Sunflower	Wheat
Central Qld			11						26		38
Eastern Downs Qld	33		4				93		90		47
North East NSW	64		6					27	61		72
Liverpool Plains NSW	81	69						29	97	53	98
Western Downs Qld	4		8						21		48
North West NSW	6		5						38		53
Central East NSW	9	57		8				33			65
South East NSW	9	61		5				48			49
Central West NSW	5							25			23
South West NSW	6	67		6				38			30
Wimmera and Central Vic	6	46	7	10	5						40
Southern High Rainfall	56	55		12				67			59
Lower EP, Yorke and Mid North	7	58		6							57
SA Vic Mallee	4	31			4						27
Upper EP and Upper North	3			3							29
Geraldton	38	90				0					46
Kwinana East	16					4					18
Kwinana West	46	57				7		57			50
Albany	48	56				6		48			44
Esperance	37	87		8							80

Current System Simulations (Scenario 1)

Crop sowing data for 2015-16 (ABS 7121) was used to develop the crop rotations for the Current rotation simulations (Table A2). As with the baseline simulations, these crop rotations simulated at all locations were proportionally weighted within a sub-region to match the statistical information available for 2015 (Table A5). As with the baseline simulations, all rotations were phased, so that each field and year of the rotation used each year of the climate record and 2005 CO_2 concentration was used. Crop sowing and management rules were also consistent with the baseline scenario.

Estimated fertiliser N rates were updated for 2015 (Table A6) for each subregion were used in the simulations corrected for 2015 yield as well as increased fertiliser application per tonne grain (see A.4). All N was applied at sowing to all legumes and other crops simulated in the Northern region. For cereals and canola in Southern and Western regions, 10 kgN/ha was applied at sowing and the rest was applied on 10 August. Nitrogen applications to legumes was associated with starter fertilisers.

Table A5. Percentage of crop type sown in each region from statistical data (stat) with the weighted proportions assumed from simulated crop rotations (sim) for the 2015 scenario.

Region	Wheat or Triticale		Barley		Oats		Grain legumes		Canola		Sorghum		Mungbean	
	Sim	Stat	Sim	Stat	Sim	Stat	Sim	Stat	Sim	Stat	Sim	Stat	Sim	Stat
Geraldton	75	74	5	4	-	1	10	11	10	11				
Kwinana East	75	78	18	12	-	3	3	2	5	5				
Kwinana West	56	58	19	18	6	6	6	4	13	13				
Albany	46	45	23	28	8	5	4	4	19	18				
Esperance	45	45	25	26	-	1	5	3	25	25				
Upper EP and Upper North	70	73	21	18	3	2	3	4	3	2				
SA Vic Mallee	60	60	30	29	-	1	7	7	3	3				
Lower EP, Yorke and Mid North	50	50	25	26	-	2	18	16	8	7				
Wimmera and Central Vic	40	41	33	31	5	5	13	13	9	9				
Southern High Rainfall	41	41	16	17	9	9	9	8	25	24				
South East NSW	50	51	15	16	4	3	4	4	28	25				
Central East NSW	53	52	18	15	9	9	9	9	13	13	-	1		
South West NSW	64	64	20	20	4	3	4	4	8	8	-	1		
Central West NSW	61	59	14	18	8	8	8	7	8	8				
Liverpool Plains NSW	33	36	20	18	5	5	5	5	5	5	30	29	3	2
North East NSW	23	21	32	32	9	11	19	18	4	3	10	11	4	4
North West NSW	50	49	18	17	-	1	25	25	-	1	8	6	-	1
Western Downs Qld	55	57	9	9	3	3	20	19	0	0	11	10	2	2
Eastern Downs Qld	18	18	14	15	-	1	14	12	-	1	42	42	12	11
Central Qld	22	20	0	1	-	1	22	18	-	1	44	46	12	12

Table A6. Fertiliser N (kg N/ha) rates applied to each crop in each region assumed in Current simulations. This was calculated based on statistical data on N use from 2015 and relative yields across regions. Note N fertiliser applications to legumes are associated with starter fertilisers which have some associated N with their main nutrients (P, S, Zn).

Subregion	Barley	Canola	Chickpea	Faba Bean	Field Pea	Lentil	Lupin	Maize	Mungbean	Oats	Sorghum	Wheat
Central Qld			7						5		68	57
Eastern Downs Qld	140		8					150	6		142	132
North East NSW	138	103	6						5	24	107	138
Liverpool Plains NSW	127	106	7						5	39	154	139
Western Downs Qld	13		6						5	18	79	101
North West NSW	16		6								88	98
Central East NSW	13	83			9					40		81
South East NSW	13	93			6					58		63
Central West NSW	10	76	4							43		38
South West NSW	9	75	3							51		44
Wimmera and Central Vic	4	44		4		1				33		26
Southern High Rainfall	63	71			47					62		71
Lower EP, Yorke and Mid North	10	93		4		4						76
SA Vic Mallee	5	49				2						31
Upper EP and Upper North	8	72		4						34		61
Geraldton	73	128					0					62
Kwinana East	37	25					5			53		29
Kwinana West	74	65					6					62
Albany	78	71					6			71		63
Esperance	60	118					5					119

Best practical N application (Scenario 2)

In these scenarios the N fertiliser management rules applied in APSIM were altered to increase fertiliser application to levels and timings currently recommended to be implemented by farmers. Fertiliser was applied at sowing to meet critical soil mineral N levels and then subsequent top-up applications were made during key crop growth stages to replenish soil N when soil water levels indicated there was a likelihood of a response to additional N application. This N application management was applied to both the Baseline crop rotations (Scenario 02) as well as the Current crop rotations (Scenario 12). The specific fertiliser management rules for each crop were:

Winter Cereals (Wheat, Barley, & Oats)

- Sowing: Top-up to ensure 80 kg N/ha in top 60 cm of soil.
- Zadoks stages 30-45: If N < 80 kg/ha in top 60 cm of soil, and ESW>=50mm then add 70 kg N/ha.

Sorghum, sunflower and maize

- Sowing: Top-up to ensure 100 kg N/ha in top 60 cm of soil.
- Growth floral initiation-flag leaf: If N < 80 kg/ha in top 60 cm of soil, and ESW>=50mm then add 70 kg N/ha.

Canola

- Sowing: Top-up to ensure 150 kg N/ha in top 60 cm of soil.
- Growth stages 4.5-5.5: If N < 200 kg/ha in top 60 cm of soil, and ESW>=50mm then add 100 kg N/ha.

Legumes

- Sowing: Add 2005/2015 N amounts

Perfect N management – Max N (Scenario 3)

In these scenarios the N fertiliser management rules applied in APSIM were altered to maintain soil mineral N status at a level that was sufficient to maximise plant growth over the season. This was checked daily in the simulations and sufficient N applied to again re-establish the mineral N in the soil within the boundaries for each crop as predicated below. Hence, the application of N to the crops varied each year based on crop demand, so that in conditions where N demand was high more N was supplied and vice versa. This N application management was applied to both the Baseline crop rotations (Scenario 03) as well as the Current crop rotations (Scenario 13).

Winter cereals & oilseeds

- Sowing: Top-up soil to ensure 50 kg N/ha in top 60 cm
- Emergence – Anthesis: Top-up mineral N to 50 kg N/ha in top 60 cm if N < 45 kg/ha

Sorghum

- Sowing: Top-up to ensure 120 kg N/ha in top 90 cm of soil.
- Emergence – Anthesis: Top-up mineral N to 120 kg N/ha in top 90 cm if N < 115 kg/ha

Maize

- Sowing: Top-up to ensure 50 kg N/ha in top 90 cm of soil.
- Emergence – Anthesis: Top-up mineral N to 50 kg N/ha in top 60 cm if N < 45 kg/ha

Legumes

- Sowing: Add N amounts as shown in Table A4 and A6 for the Baseline and Current crop system simulations.
- No further N applied

A.2 Values used for production metrics

The intensity of GHG emissions (i.e. the ratio of GHG emitted to production) was calculated in different ways across the full set of baseline and mitigation scenarios. The calculated GHG emissions was assessed against total production, as well as total protein, energy and economic value produced in each scenario to calculate GHG intensity. These metrics were calculated using the values for each crop in the table below. The baseline price reflects 2005 prices. The prices used in mitigation scenarios reflects the prices over 2007-2017. Not all intensity results are shown in the report because the relative reduction of GHG intensity did not vary between the different metrics.

Table A7. Values used to calculate total protein, energy and revenue produced from each crop.

	Crude Protein (kg/kg)	Energy (gross)(MJ/kg)	Price baseline (AUD2005/ton)	Price mitigation scenarios (AUD2017/ton)
Wheat	0.11	15.8	214	269
Barley	0.10	16.0	180	218
Oats	0.10	17.1	192	241
Sorghum	0.09	16.4	179	221
Maize	0.08	16.1	256	281
Triticale	0.10	15.8	195	236
Millets/panicums	0.11	17.1	398	500
Cereal rye	0.09	15.6	214	269
Canary seed	0.11	15.8	398	500
Lupins	0.33	18.4	192	292
Field peas	0.21	15.8	230	350
Chickpeas	0.20	17.4	310	504
Faba beans	0.25	16.2	235	382
Vetch	0.04	3.6	166	270
Peanuts	0.28	28.0	995	1800
Mungbeans	0.23	16.2	554	900
Navy beans	0.22	16.6	461	750
Pigeon peas	0.20	16.7	310	504
Soybeans	0.35	21.0	405	530
Cowpeas	0.23	16.8	230	350
Lentils	0.24	16.3	310	504
Canola	0.19	26.6	384	503
Sunflower	0.15	26.6	534	700
Safflower	0.04	18.9	384	410
Linseed	0.22	24.8	384	500

A.3 Details for reforestation modelling

Current profitability of agriculture is compared with the estimates of the profitability of two types of tree plantings, environmental and mallee, for carbon sequestration across six methods. The block method assumes all eligible land in an approximately 250m x 250m area is planted and the belt method assumes 5% of the eligible land is planted. Carbon sequestration is calculated based on the method used by FullCAM (Richards, 2001; Richards and Brack, 2004; Richards and Evans, 2004; Brack et al., 2006; Waterworth et al. 2007). Profitability of the carbon sequestration is calculated as the net present value over 25 years given each carbon price and with estimates of establishment costs (Summers et al. 2015), transaction costs and annual management costs. Belt plantings also assume extra costs for additional fencing. Agricultural profitability is calculated as the net present value over 100 years based on Marinoni et al. (2012) and compared with the 25-year net present value of carbon sequestration as a permanence requirement of 100 years for plantings is used. Decisions to change are based on the profitability over an assumed 25-year contract period when most tree growth occurs. Under the Emissions Reduction Fund methodology only land cleared for more than 5 years and land that has the potential to attain forest cover is considered eligible. Additionally, for the Mallee plantings methods only areas in the less than 600mm long term average rainfall zone are eligible.

Analysis across a range of combinations of factors are presented below were undertaken with results for the most profitable method presented These factors are type of ERF method, carbon price, current land use and hurdle rate. The hurdle rate is the extent to which the new land use is more profitable than the current land use. For example a hurdle rate of 1x means that the new land use has to be equal to or greater than the estimate of current profitability of agriculture. A hurdle rate of 1.2x sees change at 20% greater, 1.5x sees change at 50% greater and 2x sees change at 100% greater. As the actual level of reluctance to change is unknown the results provide for a range of likely outcomes given a range of levels of risk aversion or reluctance to change.

The variables considered are:

- Emissions Reduction Fund method
  - Environmental plantings Block Environmental Services
  - Mallee Block Environmental Services
  - Environmental plantings Belt - Low stocking
  - Environmental plantings Belt- High stocking
  - Mallee Belt - High stocking
  - Mallee Belt - Low stocking
- Carbon price [10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100, 125, 150, 200, 250]
- Current land use
  - Crop land in the broadacre zone (cereals (excluding rice), legumes and oilseeds)
- Hurdle rate [1x,1.2x,1.5x,2x]

A.4 Estimation of current N rates

Nitrogen application rates (N rates, in kg N/ha) are a key factor driving greenhouse gas emissions as well as yield and soil carbon changes. Unfortunately, N rates are not widely monitored or surveyed in detail to allow for annual evaluation of changes in this parameter. For the static baseline calculations, N rates were derived using the rates that were established for the National Grains Life Cycle Inventory (NGLCI; Simmons 2017; Simmons et al. 2019) as representative for the year 2012. In the current study, N rates for 2005 across each region were calculated using the 2012 partial productivity factor of N fertiliser (PPFN, tonne crop/tonne N) by crop and the 2005 yields (see Methodology Report). In this way, N fertiliser rates were matched to yield potential across regions. The resulting N rate, averaged over the 13 leviable cereal and oilseed crops and 3 Regions, is 38 kg N applied per ha. For wheat, the average N rate is 42 kg N/ha. The equivalent PPFN averaged over the 13 crops is 53 tonne/tonne N applied.

Based on available national statistics as well as anecdotal evidence and self-reporting, it is clear that the same approach cannot be used to project the 2012 N rates forward to more recent times. N rates have increased and PPFN has decreased since the first years after the Millennium drought. Time series for total nitrogen sold in Australia collected by Fertiliser Australia (AGEIS 2021) show a 74% increase between 2005/06 and 2015/16. The breakdown of these values by crop categories shows a 125% increase in total N used in non-irrigated crops over that same period (see Figure A1).

However, the top-down statistics show a large discrepancy with the bottom-up calculation using the N rates established in much more detail for the NGLCI and hence used for the 2005 baseline in this study. The total N calculated for the baseline year, combining all 25 crops and 3 Regions, is 786 kt N. The total N sold in the previous year is 1009 kt N (AGEIS 2021) of which only 394 kt N is attributed to non-irrigated crops. With such a discrepancy, the national statistics can’t be used to estimate the changes in N application rates in grains between the baseline year and the current era (2015/16 is targeted in this analysis as the most recent year with detailed survey data by ABS). N application rates from grey literature and areas of production for commodities from ABS (7121 and 4627) are used to estimate the N applied in non-grain industries (i.e. dairy pastures, cotton, sugar cane and rice) for the year 2015/2016. The values are listed in Table A8 and compared to those used in NGGI.

Table A8. The amount of N applied (kg N/ha) from grey literature and the NGGI for main commodities/land uses.

Commodity/land use	Grey literature	NGGI
Irrigated crops	N/A	80
Irrigated pastures	N/A*	80
Cotton	275/32+	246
Horticultural crops	80	125
Sugar cane	240^	160/180
Rice	173	N/A
Dairy	120#	N/A

* Irrigated pastures for dairy production were included under the dairy category. It was assumed that other irrigated pastures were lucerne based that do not have N applied. + values for irrigated/dryland cotton production. ^ values for sugar ranged from 170 to 590 kg N/ha for sugar cane. # calculated on a per L of milk basis and converted to per ha basis.

Taking a top-down approach using national statistics suggests that approximately 350 kt of N was applied to non-grain commodities. Subtracting this value from the N sold in that previous year (AEGIS 2021) leaves ~1000 kt of N applied to grain crops across Australia. This equates to 74% of all N applied being applied to grain crops. This estimate includes irrigated grains, but this is only 1% to 1.5% of the total area of grains cultivation (see Methodology Report). Even with a considerably higher N rate for irrigated grains the difference in total N with or without irrigated areas would only be ~5%. This approach is supported by the analysis in Angus and Grace (2017) who attribute about 68% of total national N use to dryland grains, although it should be noted that the total domestic N use they derive is higher than reported for the relevant years (AGEIS 2021).

An alternative bottom-up approach is based on reported values for N rates in cereal and oilseed cropping. Angus (2001) reports a rate of 30 kg N/ha for dryland cereal around the year 2000. The average estimated application for dryland cereals and oilseeds for 2010-2014 is 45 kg N/ha (Angus and Grace, 2017). The latter value is close to one obtained in surveys in South West Australia over 2010-2015, with 39 kg N/ha for non-legume grains (Harries et al. 2021).

In Figure A1 those values are plotted as reference points along with the value for cereals and oilseeds of the baseline and the National Grains LCA as mentioned above. The value of 45 kg N/ha is on the high side and therefore taken to be representative for the financial year 2014 instead of the whole period 2010-2014 referenced by Angus and Grace (2017). These reference points match the trends reported for total N sold well, in a relative sense (Figure A1).

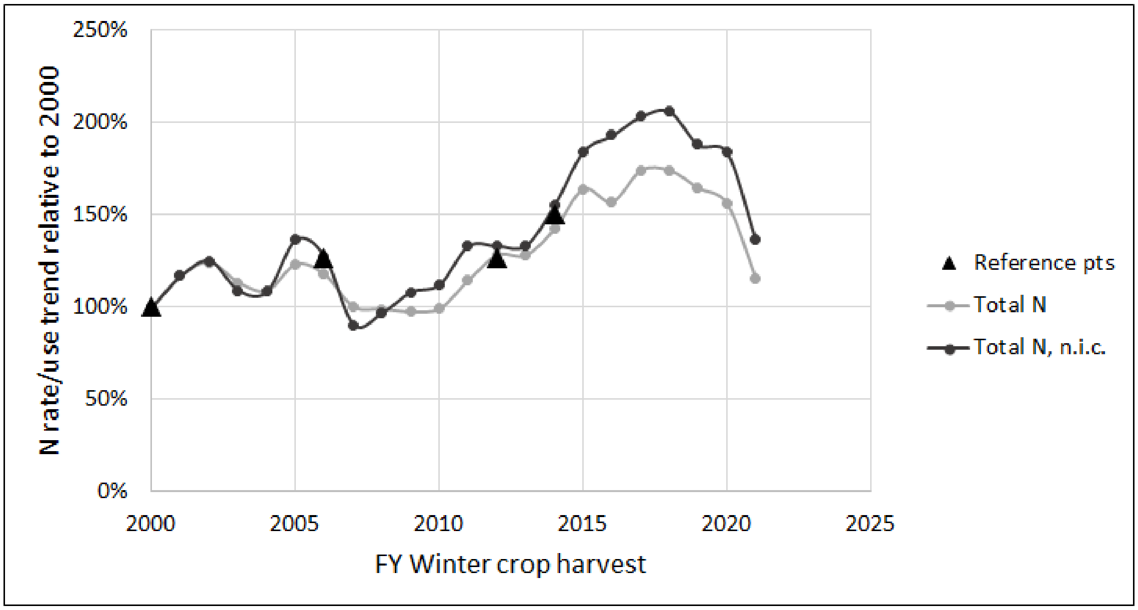

Figure A1. N rates (kg N/ha) for cereals/oilseeds relative to the year 2000 (reference points) and total N sold in Australia (total N) and attributed to non-irrigated crops (n.i.c.) respectively. Reference points are Angus (2001), baseline this study, National Grains LCA and Angus and Grace (2017), from left to right. The values for total N (AGEIS 2021) have been shifted by one year with respect to the other data points to reflect that N is usually sold in the financial year before the crop is harvested (winter crops dominate).

When multiplying the N rates suggested by Angus (2001), Angus and Grace (2017), the N rates derived from the baseline in this study and the NGLCI by the areas cultivated for cereals and oilseeds in the respective years (ABS 7121), the total N use for cereals and oilseeds is around 75% of the total N sold in Australia (Figure A2). This is in line with the outcome derived above via a top-down approach above. It suggests that the total N attributed to non-irrigated crops (excluding sugar, cotton and horticulture) in the NGGI may be too low.

The crucial difference appears to be that a considerable amount of N (~35% of the total) is attributed to "non-irrigated pasture" in the NGGI, whereas our analysis shows that results in unlikely low N rates for non-irrigated crops. The N attributed to non-irrigated pasture in the NGGI is around 80% of the N attributed to non-irrigated crops. ABS 4627 data for 2015/16 give a ratio of 33% only. While the absolute values in ABS 4627 are not internally consistent and the land use categories don't align fully with those used in the NGGI, this supports the hypothesis that more N is used in non-irrigated crops than indicated in AGEIS (2021). The derived 75% attribution of total N to non-irrigated crops is very high but does align with the bottom-up reference points for N rates as show in Figure A2.

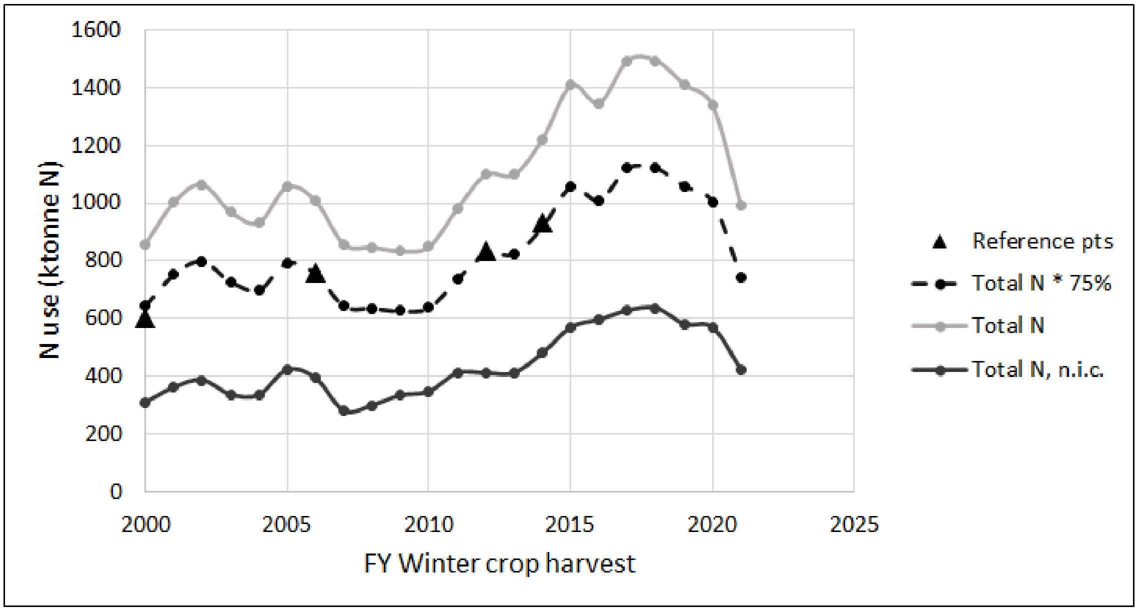

Figure A2. Absolute N use for the same data series as in Figure A9. For the reference points, an area of 20-22 Mha under cereals/oilseeds (ABS 7121) was multiplied by the N rates shown in Figure A9. The assumption that 75% of the total N sold in the previous financial year is used in dryland grains gives a good match for the reference points (see text for further discussion).

Using the dashed line in Figure A2 to determine total N use in cereals and oilseeds, a correction for the constant PPFN approach can be made. Between the baseline and 2015/16, the PPFN has changed by 30%, to 38 tonne/tonne N. Applying this correction gives 55 kg N/ha for cereals and oilseeds, and 59 kg N/ha for only wheat, averaged across all GRDC regions. The N rates established this way have been applied in the Current scenario (see 5.1.1).

The PPFN approach applied here was further checked with the Planfarm Bankwest Benchmark reports N rates for cereals in WA. Reporting does not align directly with the GRDC subregions as used in this study, but for areas in Kwinana West (high rainfall 4, medium rainfall 2) values of around 60 kg N/ha are reported for the 2015 harvest. The value obtained for wheat for Kwinana West using the corrected PPFN approach is 62 kg N/ha. PPFN values for wheat, estimated based on the data in the Planfarm Bankwest Benchmark, range from around 32 tonne/tonne N to over 80 tonne/tonne N. It is not possible to compare the Planfarm values in detail with estimates in this study because they are reported for farm groups defined by operating surplus rather than by crop, region or area. Nevertheless, the values of approximately 60 kg N/ha provide a validation of the adjusted PPFN and resulting N rates used here for 2015/16.

Other relevant data sources (ABS 4627, ABS 4618 and ABARES 2021a) were explored for data on N rates as well as land use areas for the top-down approach. Due to inconsistencies in land use definitions, it was not possible to fully align those sources and use them for additional triangulation of the derived PPFN correction.

Appendix B Variability of APSIM results

The long-term simulations over the period 1991-2019 using historical weather data enable us to gain insights into the variability of the GHG emissions of crop production amongst the various mitigation scenarios.

This variability is shown in Figure A3 for the direct N_2O emissions as well as the emissions (removals) due to soil carbon change. The figure shows that the differences in direct N_2O emissions are considerable and scenarios that involved higher N application do increase these across all regions and most years. The variability in the scenarios involving best-practice and maximum nitrogen application (BestN and MaxN) is higher because of the higher seasonal variability of nitrogen inputs associated with climate variation driving crop demand and hence N applications rates. For emissions due to changes in soil carbon, the opposite trend is seen and variability in terms of absolute emissions is much greater (note the difference in range along the vertical axes).

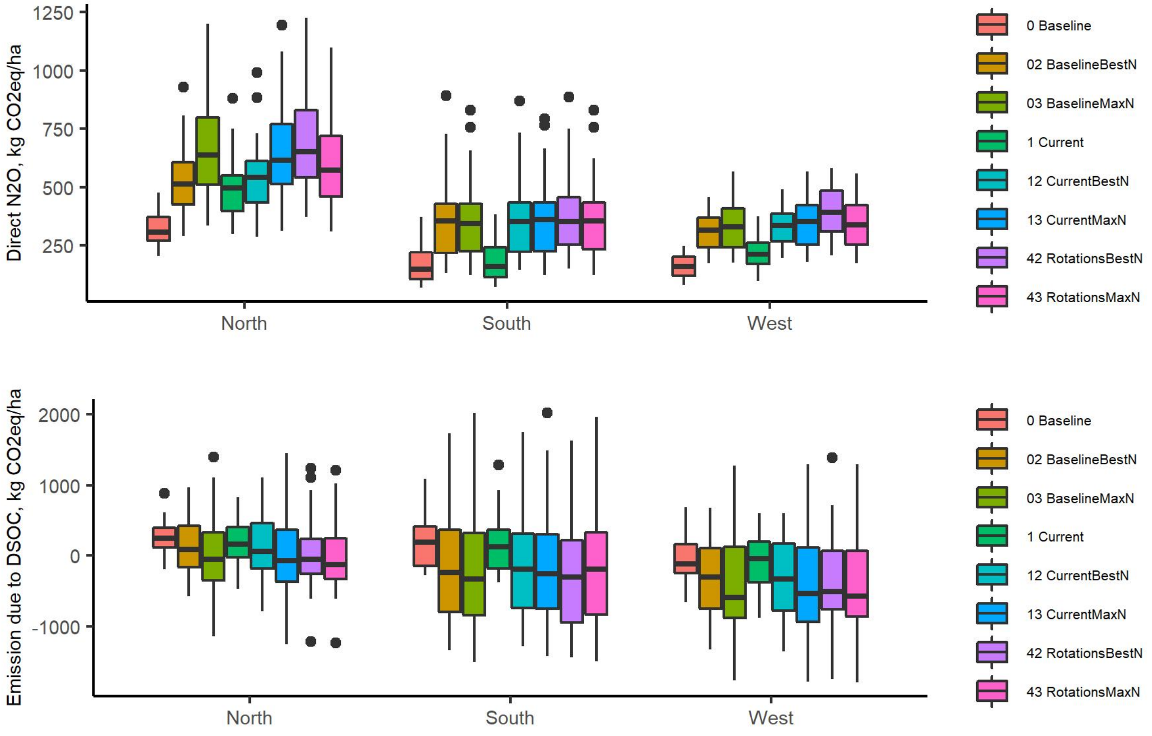

Figure A3. Variability in simulated direct N_2O emissions and the emissions (removals) due to soil carbon changes over 29 simulated years for each of the dynamic scenarios. The box hinges indicate the 25 and 75 percentiles. DSOC indicates soil organic carbon change.

When looking at the variability in the total GHG emissions intensity, there are large annual fluctuations, around median values that are lower for the high-N scenarios (Figure A4). This is as expected, because the N_2O emissions and soil carbon sequestration cancel each other out to a degree, as shown in Figure A3. In some years, a net-negative GHG intensity occurs, particularly in the southern and western regions, when a large increase in soil carbon is modelled.

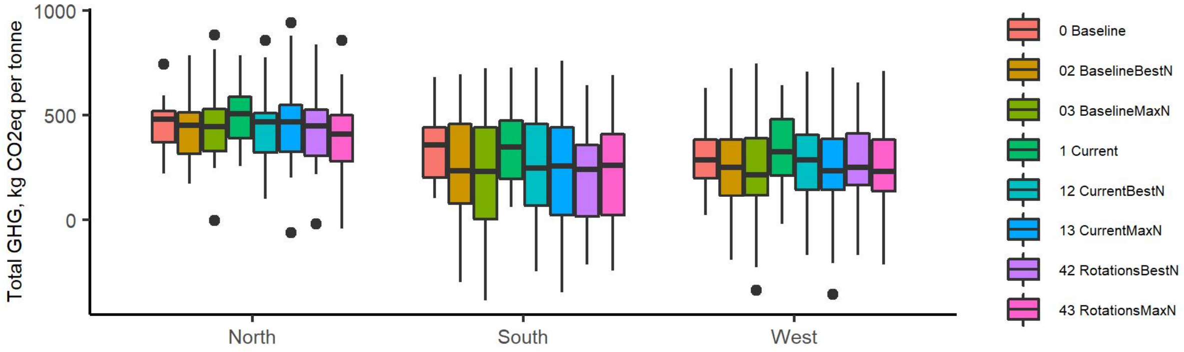

Figure A4. Variability in the total GHG emissions per tonne (including all Scope 1,2 and 3 emission sources) over 29 simulated years between different mitigation scenarios.

The variability in annual values should not be interpreted as indicative of uncertainty in the mean values. This variability is in fact highly correlated between scenarios because all are subject to the same annual weather conditions. Hence, it is important to explore how each mitigation scenario compares to the baseline result in the same year. Figure A5 shows this for five scenarios, for total production, total emissions and emission intensity. Scenarios 12 and 13 show similar distributions to scenarios 02 and 03, respectively, except for a shift toward higher emissions and emission intensities given that the Current scenario 1 has slightly higher emissions and emission intensity that the Baseline (scenario 0).

Figure A5 shows that production is higher than for the baseline in every single year for the high-N mitigation scenarios. This is also true for the Current scenario, except for the South, where the result production is lower than the Baseline for about 30% of the years. Total emissions are higher in 50% to 90% of the years across all scenarios. For the high-N scenarios, GHG intensity is lower than the baseline value in 55% to 80% of years, with the South showing lower intensity in most years as well as a higher percentage of strongly negative values.

This does show that in 25% to 40% of years the intensity result may be higher than the Baseline, even when on average it is lower. This reflects the inherent variability of agriculture and the influence of weather patterns on production as well as emissions. This variability is reduced in static accounting, compared to modelling, because of the use of constant emission factors. Nevertheless, annual results will be variable - if good annual activity data are available - and effects of mitigation efforts will only be visible as longer-term trends.

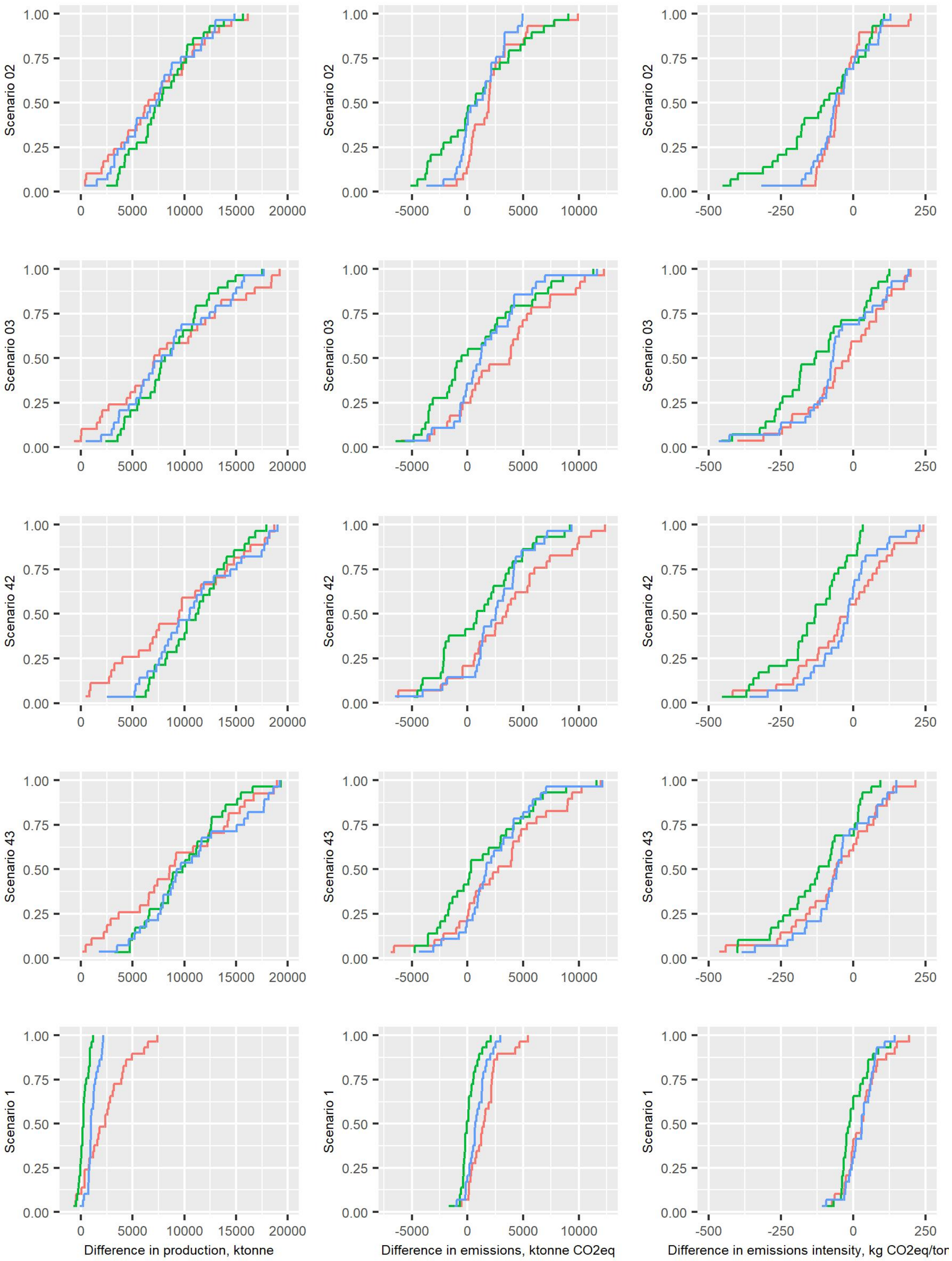

Figure A5. Annual differences between scenario and baseline, plotted as cumulative distributions, for modelled production (ktonne grain produced, panels on the left), total emissions (ktonne CO2-equivalent, panels in the middle) and emission intensity (kg CO2-eq/tonne, panels on the right). Values for South are plotted in green, North in red and West in blue.

Appendix C APSIM's capacity to simulate GHG emissions in farming systems

The APSIM model includes modules that have been specified and widely tested to simulate soil nitrogen dynamics (Probert et al. 1998, Probert et al. 2005; Thorburn et al. 2010), soil water processes (Probert et al. 1998), soil temperature, and residue break-down processes (Probert et al. 1998, Thorburn et al. 2001; Dimes and Revanuru, 2004), along with a range of widely tested crop modules to simulate crop growth processes, water and N extraction (Holzworth et al. 2014). A range of soil and climatic conditions will drive these processes which in turn influence the N_2O and C fluxes from the soil.

Critical here is the demonstrated capacity of the model to simulate soil C processes (Luo et al. 2011; Godde et al. 2016; Liu et al. 2016; O'Leary et al. 2016) and N_2O emissions from soils (Mielenz et al. 2016) especially in relation to practices that influence inputs of organic matter (Meier et al. 2017) or fertilizer inputs. These capabilities have also been widely tested and applied to predicting the soil C and N dynamics from grain and other agricultural production systems (Dumbrell et al. 2017, Meilenz et al. 2016, Meier et al. 2020).

APSIM has been shown to predict with a high level of accuracy the long-term changes in soil C across a diversity of cropping systems under a wide range of management practices (Luo et al. 2011; Huth et al. 2010). As shown in Figure A6 this showed how the model predicts the decline in soil carbon under cropping systems ranging from Central Queensland to Southern NSW.

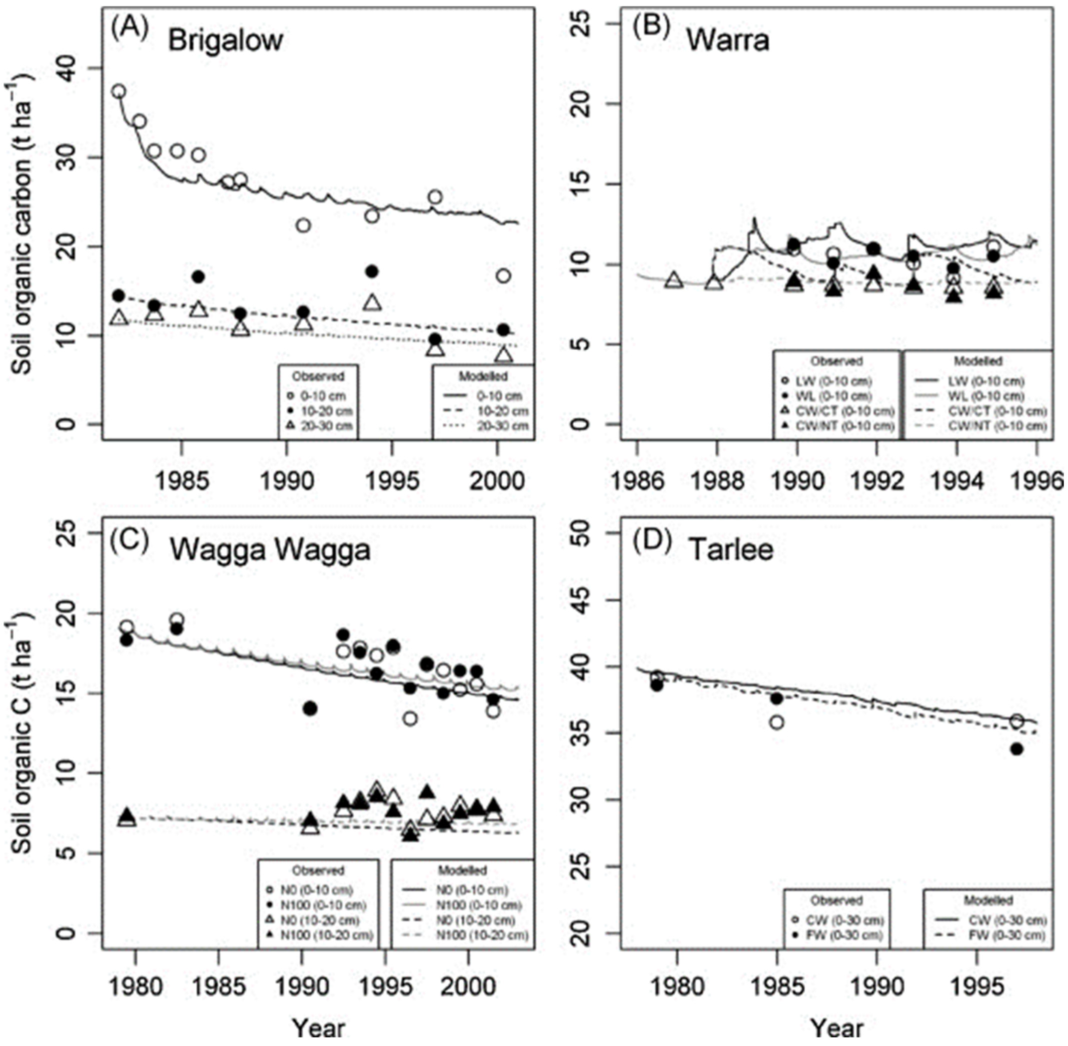

Figure A6. Modelled and observed soil organic carbon in different soil layers in four locations under different agricultural practices in Australia. (A) Bristow, wheat–sorghum rotation system with residue retention. (B) Warra, lucerne–wheat (LW) and wheat–lucerne (WL) rotation and continuous wheat (CW) with conventional tillage (CT) and without tillage (NT). (C) Wagga Wagga, continuous wheat with residue burning and N applications of 0 (N0) and 100 kg ha−1 yr−1 (N100). (D) Tarlee, continuous wheat (CW) and fallow-wheat (FW) with residue retention. Source: Luo et al. (2014).

While there are several uncertainties with modelling N_2O emissions, Meilenz et al. (2016) demonstrate APSIM was able to robustly predict seasonal N_2O emission measured from six multi-year field experiments distributed across the major grain growing environments of eastern Australia (i.e. at Kingaroy and Kingsthorpe in southern Qld, Tamworth and Wagga Wagga in NSW and Horsham and Hamilton in Victoria). This work demonstrated high accuracy of predicting seasonal N_2O emissions with a correlation coefficient of 0.91, and root mean square error of 0.4 and a model efficiency (Nash-Sutcliffe) of 1.0 (Figure A7). To obtain such high accuracy of model prediction of observed data requires some site-specific calibrations particularly to the relationship between water-filled pore space above which denitrification starts or, in other cases, the potential denitrification rate coefficient (Thorburn et al., 2010; Huth et al., 2010). However, this ratio was shown to vary only a small amount (0.99-1.11) across all sites, with the mean of 1.05 acceptable for use as a default value suggested. This well tested and robust approach to simulating denitrification was used throughout out simulations.

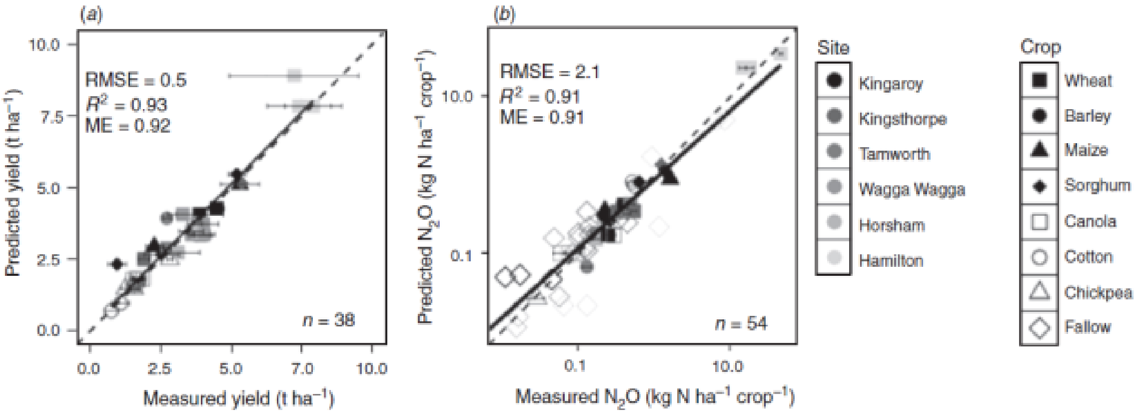

Figure A7. Measured vs APSIM predictions of crop grain yields (a) and seasonal N2O emissions (b) from 6 experimental sites covering Australia's eastern grain growing regions. 1:1 line (dashed) and regression line (solid), along with root mean square error (RMSE), correlation coefficient (R) and modelling efficiency (Nash-Sutcliffe, ME) for each are provided. Source: Meilenz et al. 2016.

Other authors have also shown APSIM to accurately simulate CO_2 fluxes and urea hydrolysis processes (Smith et al. 2020). However, they claimed that the long-term nitrification processes were not well captured and were overpredicted in the model. This finding was in direct contrast to the findings of Meilenz et al. (2016). It seems that some differences were due to an unconventional specification of initial C pools in the study of Smith et al. (2019) that may have been suitable to calibrate some processes in the model to that experimental site. In this work, we used the more conventional and widely tested specification approach, as outlined above.

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