Mitigating the greenhouse gas footprint of Australia's grain sector: national scale modelling of current and alternative management practices

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Abstract

While single year green-house gas (GHG) accounting is often used to set emissions baselines nationally or at industry level, we know that large variations in climate can induce large year-on-year variation in grain production and GHG emissions. Using APSIM we simulated for a 30-year period (1990-2019) using current and alternative crop rotations, and current and alternative N management practices at 50 locations spanning the cropping area across the country. We calculated overall emissions and emissions intensity nationally and these modelled estimates matched closely national level single-year, static accounting approaches. Modelling 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 better match crop demand, total fertiliser use is modelled to increase 3-fold, but net on-farm emissions would slightly decrease because extra emissions are balanced by increased carbon sequestration in soils. Overall, a reduction of GHG intensity (i.e. GHG emissions per tonne of grain) of around 15% may be feasible with improved agronomic management. Unless dramatically higher carbon prices were offered it was optimal in almost all situations to select rotations that generated highest income rather than reducing GHG emissions. Optimising N management is likely to be a critical pathway to further improve the GHG footprint of Australia's grain industry.

Keywords

Green-house gas, simulation, modelling, crop, intensity, nitrogen, economics, systems.

Introduction

Reducing greenhouse gas (GHG) emissions is crucial for the environmental standing and global market access of Australia's agricultural sector. Identifying and implementing practices that reduce emissions or optimise GHG efficiency (maximise productivity per unit of GHG emitted) is a key priority of the Australian grain industry. Increasingly evidence of the GHG emissions credentials is required, which entails GHG accounting, also called carbon accounting, to estimate the GHG's emitted directly or indirectly during production, including any emissions in a chain of processes resulting in a particular product. Greenhouse-gas baselines at a sector level are required as a reference (here a *Historic Baseline* was set at 2005 to align with the Paris agreement and a *Current Baseline* at 2015), but because of Australia's highly variable climate and grain production we also need to understand the annual variability and representativeness of this reference point. Usually, national GHG accounting approaches have applied international or national emissions factors to national statistical information. However, more sophisticated modelling approaches offer higher levels of specificity and can capture important agronomic processes and their interactions with carbon and nitrogen cycles, which are the major drivers of GHG emissions in grain production. Once the key emission sources were established, we estimated the national potential for GHG emissions mitigation via improved agronomic management strategies that could move the grain industry towards better GHG emission efficiency. Here we applied national scale simulation modelling in combination with life-cycle assessment (LCA) methods to estimate the current GHG footprint and mitigation potential across Australia's grain production systems.

Methods

Activity data from 2005 and 2015 for 24 statistical local area spanning the grain production regions of Australia was used to compute area-weighted average estimates of sub-regional, regional and national GHG emissions and production. This sub-regional data was used to characterise APSIM (version 7.10) simulations for the 30-year period from 1990-2019 to derive long-term averages accounting for seasonal variability (details below). APSIM has been previously demonstrated to adequately simulate direct nitrous oxide emissions, nitrate leaching, and carbon dioxide from changes in soil organic carbon (Liu et al. 2016; Mielenz et al. 2016). These outputs were then used as inputs into the LCA instead of using emissions factors available in the national Greenhouse Gas Inventory. All other emission sources, such as fuel use, carbon dioxide emissions of urea and lime application, indirect nitrous oxide emissions from volatilization, and all embedded emissions, utilise the traditional static assumptions. More methodological details can be found in Sevenster et al. (2002).

Baseline APSIM simulations

Fifty climate stations with high-quality data were selected based on their representation of national production districts, with each covering a similar cropping area within a 50 km radius. At each site, the three most common soil types found within the 50 km radius were simulated (Hochman et al. 2016). In each subregion, crop area data from 2005 and 2015 (ABS 7121) together with expert knowledge of commonly used crop rotations were used to develop a list of 3-6 crop rotations that were simulated; the relative area of each was associated with their proportion of sown area reported for each crop. All simulations were phased so that each crop occurred in each year of the climate record. Simulations were run for 15 years prior to the 30-year analysis period (1991-2019) to allow the model to reach an equilibrium and reduce the influence of model initialisation on simulated outputs. Fertiliser inputs for non-legume crops were calculated based on statistical data on N use in 2005 (35 kg N/ha) and 2015 (51 kg N/ha) and these were then matched based on relative yields across regions so that a common fertiliser application per tonne of yield was applied. In southern and western regions, only 10 kg N/ha was applied at sowing and the remainder applied at cereal growth stage 31, while in the northern region all N was applied at sowing.

Mitigation scenarios

Two main agronomic practice changes were simulated in APSIM compared to the practices in the 2005 and 2015 baselines: improved nitrogen fertiliser management, and altered crop rotation. Two improved N management scenarios were simulated: 1) a model reflecting current best-management guidelines (*BestN*) where adequate N was provided at sowing to reach minimum expected seasonal yields, and then additional N fertiliser was applied between floral initiation and flowering when soil water conditions were high enough that a fertiliser response was expected, otherwise no additional N was applied; 2) a model where N supply ‘perfectly’ matched crop N demand to maximise water-limited yield potential in any season by maintaining soil profile (0-90 cm) mineral N around 50 kg N/ha until flowering (*MaxN*). The potential to optimise rotations was examined by simulating a set of 7-10 diverse crop rotations relevant in each sub-region that varied in their balance of cereal, legume and oilseed crops. The rotation/s producing the highest ratio of income per kg CO_2-eq at each simulated location-soil were chosen and scaled accordingly.

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Results

Baseline GHG emissions

There was close alignment between reported production in 2005 (43 M tonnes) and long-term simulated production (45 M tonnes) at regional and national scales. However, long-term simulations generally predicted higher average emissions (806 kg CO_2-equivalents (eq.)/ha) than those calculated using a static accounting approach for 2005 (618 kg CO_2-eq./ha). This was largely due to higher simulated N_2O emissions in the Northern region, while in Southern and Western regions there was close correspondence between long-term predicted GHG and 2005 estimates. Using our simulation approach, around 30% of the total emissions were Scope 3, or embedded emissions associated with fertiliser or crop protection inputs, but 70% of emissions occurred on-farm (Scope 1). Most on-farm emissions were associated with N_2O emissions from the soil, but fuel use for operations and CO_2 emissions from the urea hydrolysis, lime application and soil C loss were also important contributors.

Nationally the GHG intensity modelled for Australian grain systems was estimated to be 393 kg CO_2-eq. per tonne of grain using 2005 practices. There were significant regional differences with 388, 321 and 462 kg CO_2-eq. per tonne of grain estimated for South, West and Northern regions, respectively. Practice changes (higher N application and changed crop frequencies) between 2005 and 2015 increased GHG intensity by about 7%.

Improved N management improves GHG intensity

Compared to both baselines, improving the N management approach to better match crop demand increased overall N application rates significantly. The 2005 activity data estimated an average national N application rate of 35 kg N/ha, which was increased to 87 and 100 kg N/ha under the *BestN* and *MaxN* scenarios, respectively. Using the 2015 activity data the average N application rate was increased from 51 kg N/ha to 88 and 101 kg N/ha under the *Best N* and *Max N* scenarios. These higher N inputs induced up to a 40%

increase in the estimated total GHG emissions (Fig. 1), but the improved N management also induced a significant and larger relative increase in predicted overall grain production potential, which was larger than the relative increase in total emissions. As a result, these improved N management scenarios reduced emissions intensity by 13-20% compared to the baselines, with reasonably consistent results across the regions (Fig. 1).

While overall emissions increased under improved N management, this was largely due to higher embedded (Scope 3) emissions associated with higher fertiliser inputs. However, somewhat unexpectedly and counter to traditional GHG accounting, the system simulations did not predict an increase in Scope 1 emissions (Fig. 2). Direct and indirect N_2O emissions did increase, but this was largely offset by a more positive soil C balance. Compared to lower N inputs, the model predicted that more biomass was grown and returned to the soil under more optimal N inputs and hence a higher level of soil C was maintained. Overall, this meant that on-farm (Scope 1) GHG emissions per unit of production, was significantly lower under improved N management practices.

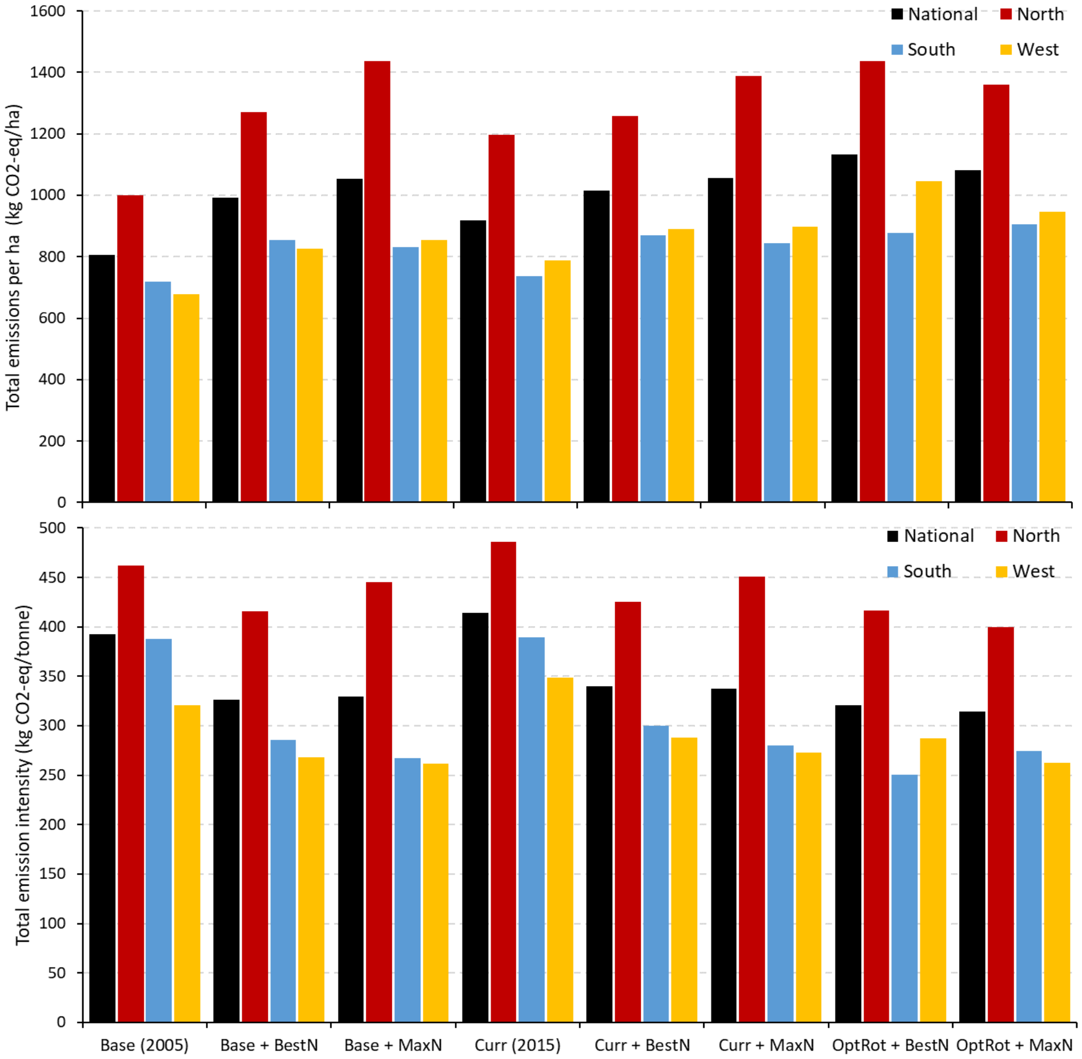


Figure 1. Total emissions (kg CO_2-equivalents per ha; top) and emissions intensity (kg CO2-equivalents per tonne of grain; bottom) across regions and nationally for long-term simulations of 2005 (Base) and 2015 (Curr) baseline practices and with simulated scenarios of best current N management (BestN) or perfect N management (MaxN) and optimised crop rotations (OptRot).

The two scenarios where optimised crop rotations were employed nationally resulted in increases in total GHG emissions compared to the current crop mix, however, optimised rotations reduced emissions intensity by about 18%. Though this reduction was not consistent across the regions (Figure 1), with reductions predicted in the Northern and Southern regions, but benefits were less in the west. The crop rotations that optimised emissions intensity, defined as GHG emissions per $ of revenue, were those that generated the highest predicted returns and often these had a high proportion of cereal crops along with high crop frequency (Figure 3). Under the higher N supply scenarios, this appeared to be driven by a more positive soil C balance and lower N losses than systems with more frequent legumes or oilseed crops.

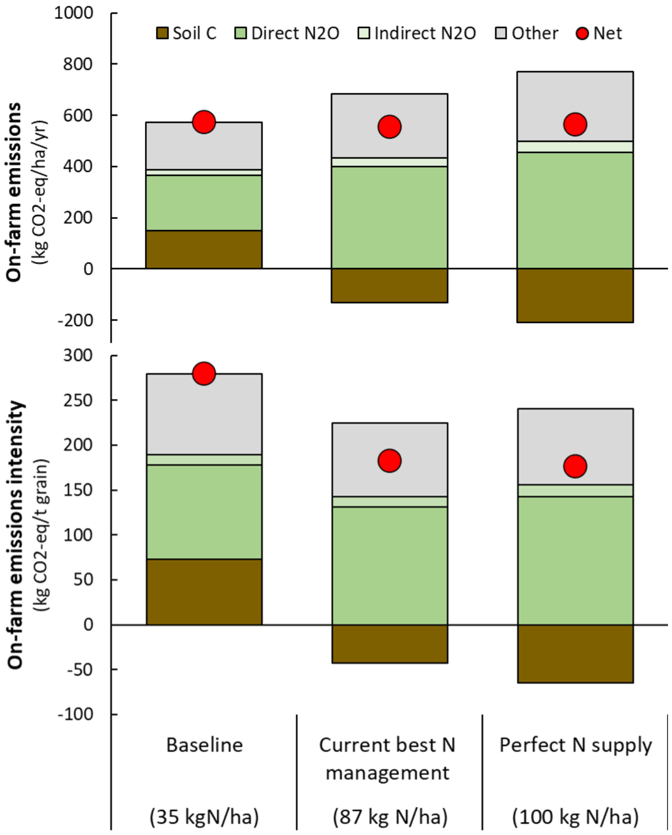
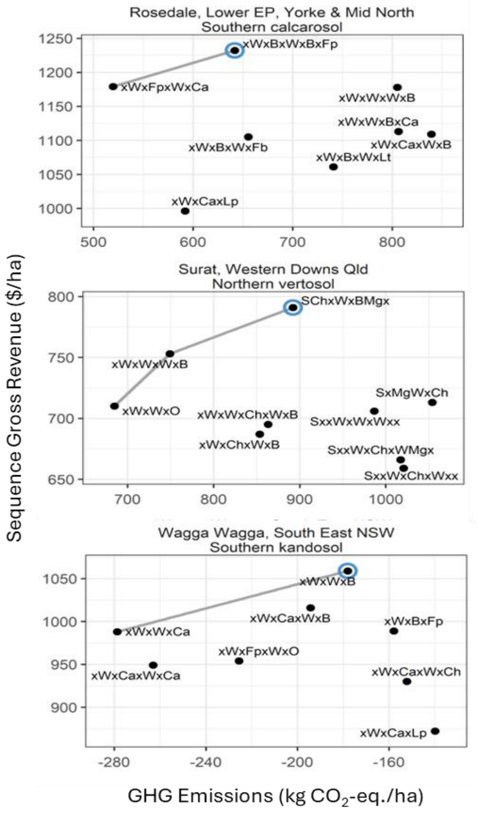


Figure 2. Improved N management practices are not predicted to alter net on-farm net emissions (top) and reduced emissions intensity (bottom) as the additional N_2O emissions (green) are offset by improved soil C balance.



W -Wheat, B – Barley, O – oats, Ca – Canola, Fp – field pea, Lp – lupin, Ch – chickpea, S – Sorghum, Mg - Mungbean

Figure 3. Examples of simulated optimal crop sequences at a selection of sites and soils. The crop rotation achieving the highest ratio of income/GHG emission are highlighted in blue.

Conclusion

This national GHG assessment integrates spatial data with simulation modelling to provide a detailed GHG inventory across Australia's grains industry. Estimates of GHG intensity were low by international standards and much lower than previously calculated for Australia. On-farm emissions contribute 70% of the GHG footprint, while about 30% came from embedded emissions in agricultural inputs. Clearly there is potential for reducing GHG emissions via both on-farm practices and production of inputs. Fertilisers were a critical source of GHG emissions but also an important driver of productivity. Improving fertiliser application practices were critical to lowering overall GHG intensity. Achieving carbon neutrality or making large absolute reductions in GHG emissions across Australia's grain sector is likely to be difficult due to an intrinsic trade-off between total emissions and system productivity.

References

ABS 7121: Agricultural Commodities, by financial year. https://www.abs.gov.au/statistics/industry/agriculture/agricultural-commodities-australia

Hochman Z., Gobbett D., Horan H., Navarro Garcia J. (2016) Data rich yield gap analysis of wheat in Australia. Field Crops Research 197, 97-106.

Liu DL, et al. (2016) Modelling soil organic carbon 2. Changes under a range of cropping and grazing farming systems in eastern Australia. Geoderma 264, 227-237.

Mielenz H, et al. (2016) Nitrous oxide emissions from grain production systems across a wide range of environmental conditions in eastern Australia. Soil Research 54, 659-674.

Seventster M., Bell L., Anderson B., Jamali H., Horan H., Simmons A., Cowie A., Hochman Z. (2022) Australian Grains Baseline and Mitigation Assessment. Main Report. CSIRO, Australia. (https://doi.org/10.25919/j7tc-kz48).