Greenhouse Gas Emissions and Soil Carbon Stocks in Dairy Farming Systems

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Statement of Originality

This is to certify that the content of this thesis is my own work. This thesis has not been submitted for any other degree or purpose.

I certify that the intellectual content of this thesis is the product of my own work, and that all assistance received in preparing this thesis and all sources have been acknowledged.

Mulisa Faji Dida

10 April 2026

Author Attribution Statement

This thesis is presented in publication style. Chapters 3 to 7 are stand-alone manuscripts, each containing its own abstract, introduction, materials and methods, results, discussion, conclusion, acknowledgements, and references. Chapters 3, 4, 5 and 6 have been published in peer-reviewed journals (*Journal of Dairy Science* [Chapters 3 and 4], *Smart Agricultural Technology* [Chapter 5], and *Environmental Impact Assessment Review* [Chapter 6]) and the published versions are included in this thesis. Chapters 7 has been submitted to *Environmental Technology & Innovation journal* and is currently under review. These chapters are formatted according to the submission guidelines of the respective journals. Mulisa Dida is the first author on all chapters and associated publications. The research concepts, study design, data analysis, and writing of all chapters/publications in this thesis were the responsibility of the candidate, Mulisa Dida, working under the supervision of Professor Luciano Gonzalez and Professor Sergio Garcia at The University of Sydney. The inclusion of co-authors in Chapters 3–7 reflects collaborative contributions and acknowledges input into team-based research.

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As the lead supervisor for the candidature, I can confirm that the authorship attribution statement above is correct.

Luciano Gonzalez

10 April 2026

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Publications

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Chapter 8: General Discussion

Abbreviations

The following abbreviated terms have been used throughout the thesis and are defined at first use within each chapter.

ADCC	Australian Dairy Carbon Calculator
ADF	Acid detergent fibre
AUD	Australian Dollar
BW	Body weight
C	Carbon
CCC	Concordance correlation coefficient
CH_4	Methane
CO_{2eq}	Carbon dioxide equivalent
CP	Crude protein
DA	Dairy Australia
DCCEE	Department of Climate Change and Energy Efficiency
DFMP	Australian Dairy Farm Monitoring Project
DM	Dry matter
DMD	Dry matter digestibility
DMI	Dry matter intake
DOMD	Digestible organic matter in dry matter
DSM	Digital soil map
EBIT	Earnings before interest and tax
EE	Ether extract
EI	Emission intensity
FAO	Food and Agricultural Organization
FCE	Feed conversion efficiency
FPCM	Fat protein corrected milk
g	Gram
GF	Greenfeed system
GHG	Greenhouse gases
GWP100	Global warming potential for 100 yr horizon
H_2	Hydrogen
ha	Hectare
IPCC	Intergovernmental Panel on Climate Change
Kg	Kilogram

LCA	Life cycle assessment
MAE	Mean absolute error
MBE	Mean bias error
ME	Metabolisable energy
MES	Model Evaluation System
MF	Milk fat
MFY	Milk fat yield
MP	Milk protein
MPY	Milk protein yield
MS	Milk solids
MY	Milk yield
n	Number of observations
N	Nitrogen
N_2O	Nitrous oxide
NDF	Neutral detergent fibre
NE	Net energy
NSW	New South Wales
L	Litres
REP	Repeatability
RFID	Radio-Frequency Identification
RMSE	Root means square error
RMSEP	Root means square error of prediction
SD	Standard deviation
SE	Standard error
SLGA	Soil and Landscape Grid Australia
SOC	Soil organic carbon
t	Tone
TN	Total nitrogen
TP	Total phosphorus
UNFCCC	United Nations Framework Convention on Climate Change
VS	Volatile solids
WSC	Water soluble carbohydrate
yr	Year

Abstract

Dairy farming is integral to global food security but remains a contributor to greenhouse gas (GHG) emissions and nutrient losses that contribute to climate change. Consequently, the sector faces dual challenges: meeting the growing demand for animal products while mitigating its environmental footprint and adapting to climate-driven risks such as feed shortages, heat stress, and disease outbreaks that threaten productivity and animal welfare. In Australia, dairy farms range from pasture-based to confinement systems, each presenting distinct environmental impacts and management complexities. The present thesis evaluated the environmental performance of these systems and associated monitoring technologies through five interconnected studies.

Chapter 3 compared GHG emissions from five confinement and five pasture-based farms using a life cycle assessment approach that incorporates tree carbon (C) sequestration. Emission intensities were similar ($P > 0.05$), at 1.02 ± 0.038 and 1.07 ± 0.069 kg carbon dioxide equivalents (CO_2-eq)/kg fat and protein corrected milk (FPCM) for confinement and pasture-based systems, respectively. Enteric methane (CH_4) accounted for 54% of total emissions in confinement systems and 58% in pasture-based systems. Manure contributed 31% of emissions in confinement systems and 13% in pasture-based systems, pre-farm embedded emissions from external inputs accounted for 8% and 14%, and on-farm soil amelioration inputs (nitrogen fertiliser and lime emit nitrous oxide [N_2O] and CO_2) added 2% versus 7%, respectively. Tree sequestration offset up to 6% of emissions in pasture-based systems but only 1% in confinement systems. These findings underscore where priorities may lie to mitigate climate change in each production system such as improved manure management in confinement systems, fertiliser optimisation in pasture systems, and enteric CH_4 reduction across both systems.

Chapter 4 analysed the effects of concentrate supplementation on enteric CH_4, manure CH_4 and N_2O emissions across 120 dairy farms. Feeding 2–3 t dry matter (DM)/cow/year was associated with higher milk yield ($P < 0.001$) and a 14% reduction in emission intensity compared with ≤1 t DM/cow/year ($P < 0.05$). Although farms feeding different concentrate levels showed large numerical differences in gross margin, earnings before interest and tax, and net income, these economic outcomes were not statistically significant ($P > 0.05$). Overall, these findings suggest that while moderate concentrate supplementation can reduce emission intensity, economic outcomes vary widely among farms, highlighting the need for further research to better understand the drivers of economic performance across different dairy production systems.

Chapter 5 evaluated low-cost gas sensors (MQ-4 for CH_4, MQ-8 for H for hydrogen [H_2]) against the head chamber GreenFeed (GF) system. Over 45 days, 3.88×10^6 paired measurements were collected from 28 heifers. Spearman correlations for CH_4 (MQ-4 vs GF) averaged 0.62 (weekly), 0.56 (daily), 0.49 (hourly), and 0.47 (minute). Repeated-measures correlation between both methodologies was 0.30 whereas the repeatability was 0.31 for GF and only 0.13 for MQ-4 sensor. The GF detected more peaks with faster processing due to eructation events, while the sensor showed wider peaks. The performance of the low-cost sensor was moderate for CH_4 and H_2, however accuracy remains insufficient for interchangeable use without methodological refinement.

Chapter 6 investigated the effects of dairy farming system and land use (improved pasture [IP], mixed pasture–cropping [MPC], cropping, tree areas [TA], and natural pasture [NP]) on soil organic carbon (SOC) and nutrient stocks using 810 soil samples from nine commercial dairy farms with laboratory analysis. Pasture-based farms had 75% ($P < 0.01$) more SOC and 65% ($P < 0.05$) more total nitrogen (TN) per hectare than confinement farms, partly attributed to differences in land use, rainfall and soil parent material. Total phosphorus (TP) stocks were 3.7 ($P < 0.01$) times higher in confinement systems. The farming system × land use interaction showed that SOC and TN stocks were highest ($P < 0.001$) in IP and TA for pasture-based systems, whereas land use had no effect in confinement systems ($P > 0.05$). Natural pastures had higher SOC and TN than MPC and cropping within pasture-based systems only ($P < 0.05$).

Chapter 7 evaluated the Soil and Landscape Grid of Australia (SLGA) for predicting SOC, TN, and TP against over 800 laboratory samples from Chapter 6. SLGA performed moderately for SOC ($R^2 = 0.79$, CCC = 0.88 at farm scale) and TN ($R^2 \leq 0.87$, CCC ≤ 0.79). However, TP predictions were very poor ($R^2 \leq 0.02$, CCC ≤ 0.02). Error metrics (mean absolute error and mean bias error as % of observed means) showed moderate errors for TN, lower for SOC, and consistently high errors for TP. SLGA captured differences in SOC and TN across land uses and farming systems but failed to detect differences in TP reliably, indicating its utility for farm-scale SOC and TN baseline estimation, but not for TP or sub-farm application.

In summary, confinement and pasture-based dairy systems exhibited comparable GHG emission intensities despite contrasting production characteristics and emissions profile. SOC and nutrient stocks were greatest under permanent pasture and tree cover, but only within pasture-based systems in higher-rainfall environments. These findings indicate that sustainable progress will depend on whole-farm strategies that coherently link animal nutrition, manure management, fertiliser use, and soil stewardship. Targeted mitigation strategies combining enteric CH_4 abatement for both production systems including concentrate supplementation in pasture-based dairy, improved manure management in confinement systems, fertiliser optimisation in pasture-based systems, and stewardship of carbon in soils and trees can reduce emission intensity and improve productivity and profitability in Australian dairy systems and beyond.

Chapter 1. Introduction

Global food demand continues to rise as population growth and higher consumer incomes increase the need for nutrient-dense livestock products such as milk (FAO, 2023; Rivera-Ferre et al., 2016). Dairy farming plays a vital role in human nutrition, providing approximately 5% of global calories and 11% of human-edible protein (FAO, 2022; Li et al., 2024). However, the dairy sector emits 4.0% of global anthropogenic greenhouse gas (GHG) emissions, primarily through enteric methane (CH_4), manure-derived CH_4 and nitrous oxide (N_2O), and carbon dioxide (CO_2) from energy and feed production (Singaravadivelan et al., 2023). Across all livestock species, enteric CH_4 represents the single largest source of agricultural CH_4, accounting for approximately 30% of global anthropogenic CH_4 emissions, highlighting CH_4 mitigation as a key priority for reducing the climate impact of ruminant production systems (Crippa et al., 2021; Jackson et al., 2020). In Australia, the dairy sector accounts for approximately 12% of agricultural GHG emissions, with enteric CH_4 responsible for more than half of the total emissions (Australian Government DCCEEW, 2023). Absolute GHG emissions have increased throughout the last 3 decades, however emission intensities have declined globally, largely due to improvements in milk productivity (FAO, 2020; IPCC, 2018). Between 2005 and 2015, the global dairy sector's GHG emissions increased by 18% following a 30% rise in global milk production and an 11% increase in the number of dairy cows (FAO and GDP, 2018). Australian dairy farms have an average emission intensity of 1.07 (±0.02) kg CO_2-e/kg FPCM much lower than the global FAO average of 2.4 kg CO_2-e/kg FPCM with a national goal to reduce this further to 0.70 kg CO_2-e/kg FPCM by 2030 (Christie et al., 2018, 2012; Garnett and Eckard, 2024). Improving environmental performance while maintaining or improving milk production is therefore central to achieving national and global climate objectives.

A major structural transformation is occurring across the Australian dairy industry as many farms shift from predominantly pasture-based systems to more intensive, confinement-style feeding systems to buffer increasing climatic variability and maintain more stable milk production throughout the year and over the years (Joubran et al., 2021). However, no Australian studies have quantified or compared the full GHG profile of pasture-based versus confinement systems despite this rapid transition. International comparisons provide inconsistent and sometimes contradictory results because methodological approaches differ, emission factors vary across regions, feedbase characteristics are strongly influenced by local climate and soils, off- and on-farm inputs differ, and many studies overlook carbon (C) sequestration by trees (Belflower et al., 2012; O'Brien et al., 2014). This lack of region-specific evidence creates uncertainty for industry planning, policy design, and whole-farm mitigation strategies. Robust comparisons of these systems under

Australian conditions are therefore needed, particularly as farms respond to increasingly volatile weather patterns and feed availability.

Feeding practices, particularly concentrate supplementation, play a central role in both productivity and GHG emissions (Hristov et al., 2013; Muñoz et al., 2018). Most dairy farmers feed concentrates such as cereal grains, protein meals, and dairy pellets because pasture alone may not provide the nutrition required for high milk production (Douglas, 2020). Previous studies indicated that more than 60–65% of Australian dairy farms feed over 1 t DM/cow/year of concentrates, and supplementation is increasing as farmers attempt to stabilise milk yield under climatic stress (Dairy Australia, 2017). Moderate concentrate feeding can increase dry matter intake (DMI) and reduce GHG emissions intensity and sometimes absolute enteric CH_4 emissions by shifting rumen fermentation toward propionate production (Bannink et al., 2006; Niu et al., 2018). However, excessive supplementation can reduce profitability, increase manure nitrogen loads, and shift emissions from enteric CH_4 toward manure- and soil-derived N_2O (Hristov et al., 2013; Nampoothiri et al., 2018). Despite this information and the extensive work conducted under controlled experimental conditions, the combined effects of concentrate feeding level on whole-farm CH_4 and N_2O emissions under commercial Australian pasture-based conditions remain unquantified. Given the economic importance and widespread use of concentrates, evaluating these trade-offs is essential for developing feeding strategies that balance productivity, cost, and environmental outcomes.

Efforts to evaluate feeding strategies and mitigation options are further constrained by limitations in GHG measurement tools (Andreini et al., 2017). Respiration chambers and GreenFeed units provide highly accurate enteric CH_4 measurements but are expensive, labour-intensive, and unsuitable for routine farm use (Pinares-Patiño and Clark, 2008; Zimmerman, 2011). This has increased interest in low-cost CH_4 sensors and sniffer techniques (Garnsworthy et al., 2019), which are inexpensive and easy to deploy but currently lack rigorous validation for ruminant enteric CH_4 measurement. The absence of validated, affordable measurement technologies limits the capacity of the industry to monitor emissions and evaluate mitigation strategies.

Beyond animal emissions, soils represent another critical component of the dairy C balance (Rotz, 2018). Global interest in increasing soil organic carbon (SOC) in agricultural landscapes is growing due to its potential to mitigate GHG emissions, but agricultural intensification may reduce C stocks depending on management practices (Abbas et al., 2020; Bai and Cotrufo, 2022). However, there is limited evidence on the differences between dairy farming systems and land use on SOC and nutrient stocks, particularly at the whole-farm scale and under commercial conditions. Pasture-based systems generally store more SOC and N than confinement dairy systems, primarily because they rely on perennial pastures with extensive root systems that enhance below-ground biomass inputs, minimise soil disturbance, and allow direct manure deposition to promote organic matter recycling, although these benefits depend strongly on climatic conditions particularly rainfall and on management practices such as grazing intensity and nutrient application (Becker et al., 2022; Dietz et al., 2024). This could contribute to long-term mitigation of climate change and soil health, whereas confinement systems often store manure around housing and effluent areas, increasing phosphorus accumulation and associated environmental risks (Batalla et al., 2015; Dondini et al., 2023). Despite their importance for C accounting and nutrient management, SOC and nutrient stocks remain unquantified in many Australian dairy regions. Sustainable monitoring of SOC and nutrients also requires affordable, low-cost, reliable tools for the industry such as digital soil prediction systems (e.g., the Soil and Landscape Grid of Australia, [SLGA]), because traditional laboratory analyses are time-consuming and expensive (McBratney et al., 2003; Zhang et al., 2017). However, their accuracy may depend on landscape and nutrient type, underscoring the need for empirical evaluation before they can be reliably used for C accounting and reporting, and farm planning. Taken together, these knowledge gaps highlight the need for integrated, region-specific evidence on system-level GHG emissions, feeding strategies, CH_4 measurement technologies, and soil C and nutrient dynamics across Australian dairy systems. The present thesis aims to fill these knowledge gaps by examining the environmental performance of contrasting production systems and exploring practical tools that support climate-resilient and sustainable dairy development in Australia.

1.1. Thesis Objectives

The overarching aim of the present thesis is to generate region-specific evidence that can be used to improve the environmental sustainability of Australian dairy farming systems while maintaining productivity and profitability. Specifically, the objectives of the present thesis are to:

1. Quantify and compare GHG emissions from pasture-based and confinement dairy systems under Australian conditions and identify the main emission sources within each system.
2. Evaluate the effects of concentrate supplementation level on milk production, GHG emission intensity (enteric CH_4, manure-derived CH_4 and N_2O), and farm profitability in pasture-based commercial dairy farms.
3. Assess the performance of low-cost CH_4 sensors (MQ-4) against the GreenFeed system for practical on-farm monitoring of enteric CH_4 emissions.
4. Quantify soil organic carbon and nutrient stocks (total nitrogen and phosphorus) of confinement and pasture-based dairy systems and of different land-use types (improved pasture, mixed pasture-cropping, cropping, tree areas, and natural pasture).

5. Evaluate the predictive accuracy of Soil and Landscape Grid of Australia, a digital remote sensing product for estimating soil organic carbon, total nitrogen, and phosphorus at farm and sub-farm scales.

These objectives collectively aim to inform climate-smart strategies that integrate animal nutrition, manure management, land use and management, and soil stewardship within whole-farm decision frameworks.

1.2. Structure of the Thesis

This thesis is presented in a publication-style format and is organised into eight chapters:

- **Chapter 1: Introduction**
  Provides the background, research problem, and rationale for the thesis.

- **Chapter 2: Literature Review**
  Synthesises current knowledge on livestock greenhouse gas emissions, mitigation strategies, enteric CH_4 measurement techniques, soil organic carbon dynamics, and digital soil mapping, and identifies key knowledge gaps that frame the empirical research.

- **Chapters 3–7: Research Papers (Standalone Studies)**
  Each chapter is written as an independent manuscript with its own abstract, introduction, materials and methods, results, discussion, and references:

    - **Chapter 3**: Greenhouse gas emissions of confinement and pasture-based dairy farms: Implications for mitigation.
    - **Chapter 4**: Dietary concentrate supplementation increases milk production and reduces predicted greenhouse gas emission intensity in pasture-based commercial dairy farms.
    - **Chapter 5**: Potential applications of a low-cost gas sensor to monitor enteric methane emissions from ruminant animals
    - **Chapter 6**: Environmental impacts of dairy farming intensification and land use on soil organic carbon stocks and physicochemical properties.
    - **Chapter 7**: How reliable are national digital soil maps for farm-scale baseline assessment? A multi scale assessment using dairy farm data.

- **Chapter 8: General Discussion and Conclusions**
  Integrates findings across all studies, discusses implications for sustainable dairy management, highlights limitations, and proposes future research directions.

1.3. References

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Chapter 2. Literature Review

Overview

This literature review summarises recent and foundational research on greenhouse gas (GHG) emissions from livestock with a focus on the Australian dairy sector. It synthesises evidence on emissions sources and sinks, measurement techniques, mitigation strategies, the role of soil organic carbon (SOC) and digital soil mapping. The review highlights current gaps and frames the rationale for the empirical chapters that follow in this thesis.

2.1. Global Livestock Greenhouse Gas Emissions

The livestock sector faces the dual challenge of reducing its environmental footprint while adapting to the adverse impacts of climate change and meeting the rising global demand for animal products (Gerber et al., 2013). Driven by population growth, urbanization, and dietary shifts, demand for animal protein has risen, with livestock now supplying ~37% of global protein and 17% of calories, figures expected to rise with increasing incomes (FAO, 2023; Poore and Nemecek, 2018). Despite gains in production efficiency, livestock GHG emissions have grown ~1% annually since 2000 and could rise 20% by 2050, corresponding with an anticipated 20% increase in animal protein demand (FAO, 2023). For instance, a 30% rise in milk production between 2005 and 2015 led to an 18% increase in GHG emissions from the dairy sector (FAO and GDP, 2018), which suggests a significant improvement in efficiency and reduction of the environmental footprint of each unit of milk produced. Livestock contribute 14.5-16.5% of total anthropogenic GHGs (Gerber et al., 2013; Twine, 2021). The primary GHGs associated with livestock production are methane (CH_4) and nitrous oxide (N_2O), with global warming potentials 27× and 265× that of carbon dioxide (CO_2), respectively, over a 100-year period (IPCC, 2021). Methane arises mainly from enteric fermentation and manure whereas N_2O originates from manure and fertiliser use (Munidasa et al., 2025). In terms of contribution by source, global livestock emissions consist of enteric CH_4 (46%), manure CH_4 (7.8%), feed CH_4 (0.32%), manure N_2O (5%), feed N_2O (9.8%), direct on-farm CO_2 (2.5%), embedded on-farm CO_2 (0.52%), feed CO_2 (12%), land-use change CO_2 (10.9%), and post-farm CO_2 (5.4%) (FAO, 2023). The extent of emissions varies by region, production system, and species, with ruminant livestock, particularly cattle and sheep, dominating due to enteric CH_4 production, and cattle alone responsible for ~62% of livestock emissions (FAO, 2023; Opio et al., 2013). Pigs, poultry, buffaloes, and small ruminants contribute 14%, 9%, 8%, and 7%, respectively. By commodity, meat from all livestock species accounts for 67% of emissions, followed by milk (30%) and eggs (3%) (FAO, 2023). According to the FAO's GLEAM V3 model (FAO, 2023), global emission intensities expressed as kilograms of CO_2-equivalent per kilogram of product vary by species. Beef, buffalo meat, chevon, mutton, pork, and chicken generate 35.8, 32.5, 26.9, 19.1, 5.98, and 3.59 kg CO_2-eq per kilogram of carcass-equivalent meat, respectively, while milk from sheep, goats, buffalo, and cattle emits 6.00, 4.53, 3.63, and 2.01 kg CO_2-eq per kilogram of raw milk. (FAO, 2023). Although pigs and poultry emit less per unit of product, their growing populations offset gains in emission intensity (FAO, 2023). Beyond their contribution to global emissions, livestock systems are themselves highly vulnerable to the effects of climate change. Rising temperatures and altered rainfall patterns affect grain and forage production and quality, and increase the water requirements of both animals, crops, and pastures (Prasad et al., 2022). Climate-induced heat stress is expected to reduce animal productivity and welfare, and shifts in pest, disease, and weed distributions will further challenge livestock systems globally (Prasad et al., 2022).

2.2. Australian Dairy Industry and Emissions Profile

This section provides an overview of the Australian dairy industry, describing its structure, dominant production systems, and associated GHG emissions profile.

2.2.1. Structure and production systems

In 2023/2024, the Australian dairy industry ranked as the third-largest rural sector, contributing AU$6.23 billion in farmgate value and supporting approximately 31,300 jobs (Dairy Australia, 2025). Across 3,889 farms nationwide, each averaging 342 milking cows, milk utilisation comprised 30% for drinking, 39% for domestic manufacturing, and 31% for export and per capita consumption reached 88 litres per year (Dairy Australia, 2025). Australian dairy systems are broadly categorized into grazing-based and contained housing systems (Dairy Australia, 2024). Grazing-based systems rely on year-round grazing access with supplementary feeding, whereas contained housing systems involve full confinement in facilities such as free-stalls, barns, or feed-pads, with total mixed ration (TMR) provided under controlled conditions (Dairy Australia, 2024). To reflect the diversity of feeding practices, confinement systems are further categorized into: (i) low-bail systems, which involve year-round grazing with minimal grain supplementation (typically up to one tonne per cow annually); (ii) moderate- to high-bail systems, which include more than one tonne of grain per cow annually to increase milk yield while maintaining full grazing access; (iii) partial mixed ration (PMR) systems, which combine controlled feeding of mixed rations on pads with continuous pasture grazing; (iv) hybrid systems, which integrate PMR feeding with limited pasture access (less than nine months per year); and (v) total mixed ration (TMR) systems, which entail complete confinement with cows fed exclusively on nutritionally balanced rations (Christie, 2019). In recent years, Australian dairy farming has seen a growing shift toward contained house feeding systems to mitigate challenges like climate variability, seasonal feed and water shortages, and heat stress, while enhancing production efficiency, productivity, and animal welfare alongside environmental sustainability viability (Dairy Australia, 2024; Williams et al., 2019). At the most intensive end of the spectrum, the TMR system entails complete confinement of cows and exclusive feeding of nutritionally balanced mixed rations. Though less common due to high costs, TMR systems offer precise dietary control and stable milk output in regions where pasture growth is unreliable and grazing opportunities are limited (Dairy Australia, 2024).

2.2.2. GHG emissions in Australian dairy systems

The Australian dairy industry emits approximately 9-10 Mt CO_2eq annually, accounting for around 2-3% of national emissions and 12-14% of agricultural emissions (Australian Government, 2023). In 2023, emissions from dairy farms were primarily from enteric CH_4 (58%), followed by manure CH_4 (10%), direct N_2O from manure on pastures (4%) and manure spreading (3%), N_2O from fertiliser (4%), electricity (6%), diesel consumption (2%), purchased concentrates (high-energy or high-protein supplementary feeds such as grains and oilseed meals) (8%), fodder (conserved forage like hay and silage that are produced off-farm) (2%), and fertiliser use (3%) (Dairy Australia, 2023). Average emissions on grazing-based farms were 1.07 ± 0.02 kg CO_2eq/kg Fat-protein corrected milk (FPCM) with over 100% variation between the lowest and highest emitters (Christie et al., 2018, 2012). Compared internationally, Australian farms generally show higher emission intensities than those in New Zealand, Uruguay, and the UK, where footprints range from 0.7 to 6 kg CO_2eq/kg FPCM (Mazzetto et al., 2022), although it is important to note that the accounting systems can be very different across different countries.

2.3. Sources of Greenhouse Gas Emissions in Dairy Farming

The major GHG sources in dairy farming are enteric CH_4 from ruminant digestion, CH_4 and N_2O from manure management, and N_2O from fertiliser use (DoEE, 2018). Additional emissions include indirect ("Scope 2") from purchased electricity and embodied ("Scope 3") from the production and transport of inputs like feed and fertiliser (Christie, 2019). This subsection explains each of these sources and the factors that influence their magnitude and variability

2.3.1. Enteric methane emissions

Enteric CH_4 is produced via methanogenesis during ruminal fermentation, where methanogenic Archaea convert H_2 and CO_2 into CH_4 under anaerobic conditions (Attwood et al., 2020). This process allows ruminants to digest fibrous, human-inedible feed, but results in a 6-10% loss of gross energy intake as CH_4 (Hristov et al., 2013). Methane production begins around four weeks of age when solid feed enters the rumen (Anderson et al., 1987). Rumen gases typically contain 67% CO_2 and 26-31% CH_4, depending on diet and physiology (Kleiber et al., 1943; Moate et al., 1997). Methane emissions vary across production systems, averaging 369 g CH_4/cow/day (range: 79-729), 20.1 g/kg DMI, 13.5 g/kg ECM, and 6.0% of gross energy intake (range: 2.7-9.8%), although it is influenced by diet, breed, and management (Niu et al., 2018). In Australia, a standard emission factor of 20.7 g CH_4/kg DMI is used for cattle (Charmley et al., 2016). Enteric CH_4 accounts for approximately 61% of total dairy farm emissions (range: 34-86%), with lower contributions observed in intensive dairy systems (Mazzetto et al., 2022).

2.3.2. Manure management emissions

Manure management contributes approximately 10-15% of total livestock GHG emissions, with its magnitude influenced by climate, management systems, and production intensity (IPCC, 2006; Rotz, 2018). In Australia, manure management contributes around 11% of total dairy farm emissions as CO_2eq from CH_4 and 12% as CO_2eq from N_2O, representing approximately 23% combined of the farm's GHG footprint (DoEE, 2018). Methane from manure is primarily produced under anaerobic conditions during the storage, treatment, or decomposition of dung and urine (Saggar et al., 2004), and is estimated using volatile solids production, constants, and a CH_4 conversion factor that reflects the proportion of waste treated in different systems (Christie et al., 2012; DoEE, 2018). Nitrous oxide emissions result from microbial transformations of N compounds via nitrification (aerobic oxidation of NH_4^+ to NO_3^-) and denitrification (anaerobic reduction of NO_3^- to N_2), with N_2O as an intermediate by-product (De Klein and Eckard, 2008). The magnitude and type of GHG emissions depend strongly on manure handling and storage systems. Farms using daily hauling systems, where manure is removed from animal housing and transported to storage or fields each day, typically have low GHG emissions from manure but may experience high ammonia volatilisation, contributing to indirect N_2O (Rotz, 2018). In contrast, long-term storage (4–12 months) in liquid (5% DM) or slurry systems (5-12% DM) promotes CH_4 formation under anaerobic conditions. Manure handled as semisolid (12-15% DM) or solid (>15% DM) emits less CH_4 but more CO_2 and N_2O due to increased aeration (Rotz, 2018). Empirical studies report CH_4 emissions of 74 kg/m² from slurry tanks, 6.5 kg/m³ for slurry, and 2.3 kg/m³ for solid manure, with N_2O emissions ranging from 0.01 to 0.13 kg/m³ depending on crust formation (Chianese et al., 2009; Kaharabata et al., 1998; Rotz, 2018). The IPCC (2006) Tier 2 model estimates CH_4 emissions based on volatile solids, CH_4-producing capacity, and system-specific CH_4 conversion factor, which ranges from 10–50% for slurry with crust, 17–80% for uncovered slurry, 2-5% for solid storage, and 0.5-1.5% for composted systems. Grazing dairy cattle emit around 27 kg CH_4 per cow annually, whereas N_2O emissions range from 0-25 g/kg body weight per annum depending on management (IPCC, 2006). Manure is rich in nutrients and organic matter, with dairy cattle excreting over 70% of dietary N and 65% of P averaging 141 kg N and 17.9 kg P per cow annually (Van der Meer, 2008). The amount and form of nutrient excretion are strongly influenced by diet composition, particularly crude protein (CP) content, as higher CP intake increases urinary nitrogen losses. Additional factors such as feed digestibility, animal breed, lactation stage, and overall feed efficiency also play important roles in determining nutrient concentrations in manure.

Despite its nutrient value, the availability of cheap synthetic fertilisers and increasing livestock specialisation have reduced manure recycling to croplands (Van der Meer, 2008). Consequently, manure is often treated as waste, contributing to soil, water, and air pollution (Saggar et al., 2004).

2.3.3. Fertiliser-derived emissions

Nitrogen fertilisers, lime, and other fertiliser products contribute to greenhouse gas emissions in dairy production through CO_2 release during manufacture, transport, and field application (FAO, 2023). Synthetic N fertiliser use has increased sharply due to rising demand for feed and forage, substantially adding to agricultural emissions (FAO, 2020). The main GHG emitted from fertilisers is N_2O through microbial nitrification and denitrification following N application (De Klein and Eckard, 2008; Eckard et al., 2010; Saggar et al., 2004). IPCC (2006) guidelines distinguish between direct N_2O emissions from field application and indirect emissions from volatilised NH_3, NO_x, or leached NO_3^- that are redeposited and transformed elsewhere (De Klein and Eckard, 2008). The default emission factor estimates that 1% of applied N is emitted as N_2O–N, with a range of 0.3–3% depending on environmental conditions (IPCC, 2006). Fertiliser manufacturing via the Haber–Bosch process typically releases 1.8–2.4 tonnes of CO_2 per tonne of N in modern plants, contributing to Scope 3 emissions (IEA, 2021). Australian dairy pastures receive an average of 214 kg N/ha/year from external inputs, with intensively stocked farms receiving up to 426–506 kg N/ha/year from all sources (Garnett and Eckard, 2024; Rawnsley et al., 2019). Fertiliser-derived N_2O accounts for approximately 2.8% of total GHG emissions from an average Australian dairy farm, with emission magnitude influenced by application rate, soil moisture, and rainfall, especially under irrigation (Christie et al., 2018). In addition to N_2O emissions from nitrogen fertilisers, lime application emits CO_2 as it reacts in soil, and similar processes occur with urea and other carbonate-based fertilisers, adding to the farm's carbon footprint.

2.3.4. Energy use and carbon dioxide emissions

Energy use in dairy farming contributes directly and indirectly to CO_2 emissions through fuel combustion and electricity consumption. Though smaller than biological sources, energy-related CO_2 forms a significant portion of the sector's C footprint, especially in intensive or irrigated systems due to higher energy consumption (DCCEE, 2009). In Australia, these emissions account for 5–15% of total dairy farm GHG output, depending on system type and energy source, with higher shares in confined systems reliant on electricity for milk cooling, water pumping, and feeding (Christie et al., 2018; DCCEE, 2009). Combustion of diesel, petrol, natural gas, and liquefied petroleum gas releases 2.7, 2.3, 2.2, and 1.6 kg CO_2 per litre respectively (IPCC, 2019; DCCEE, 2009). Electricity powers operations such as milking, milk cooling, water heating, irrigation, and feed production (Upton et al., 2014). Emissions from electricity vary by generation source, averaging 0.49 kg CO_2/kWh globally (IPCC, 2019), but reaching 1.4 t CO_2e per 1,000 kWh in Australia due to heavy reliance on coal, particularly brown coal in Victoria (DCCEE, 2009).

2.4. Carbon Sinks and Sequestration Opportunities in Dairy Farms

This section reviews opportunities for C sequestration in dairy farming systems, focusing on two major approaches: soil organic carbon (SOC) accumulation and tree-based strategies. It summarises current knowledge on their potential to offset GHG emissions, associated limitations, and relevance to Australian dairy systems.

2.4.1. Soil organic carbon

Soil organic carbon is widely recognised as a valuable component of agricultural GHG mitigation, with several international and national initiatives formalising its accounting (Verra, 2011; "4 per 1000" Initiative, 2015). Australia is notable for having compliance-level SOC methodologies under the Carbon Farming Initiative/Emissions Reduction Fund, including approved approaches for grazing systems (Australian Government Department of the Environment 2015). When SOC changes are included in GHG assessments they can materially alter the net balance, so best practice recommends accounting for all relevant GHGs when evaluating management options (Dendooven et al., 2014). In grazing systems, SOC accrues through root, litter, and manure inputs under sustainable pasture management. Modelling suggests modest accumulation rates (~0.2–0.5 t C ha^{-1} yr^{-1}) in south-eastern Australian pastures, potentially offsetting 3.7–4.5% of regional livestock emissions (Meyer et al., 2018; Robertson and Nash, 2013). Practices such as improved manure handling, nutrient recycling, reduced tillage, and adaptive grazing enhance organic inputs and reduce synthetic fertiliser reliance (Eckard and Cullen, 2011; Van der Meer, 2008). Integrated approaches combining C sequestration in soil and trees have shown co-benefits, with some beef and sheep operations achieving net-zero emissions, 11% from soils and 89% from trees despite ongoing challenges with enteric CH_4 production (Macdonald et al., 2025; Van der Meer, 2008).

Conversion of cropland to pasture consistently increases SOC, but associated CH_4 and N_2O emissions from livestock and nutrient management must be considered to assess net GHG impacts (Conant et al., 2001; Meyer et al., 2016). However, SOC sequestration is finite, variable, and reversible (Meyer et al., 2016). Soils approach an equilibrium C level based on climate, texture, and land-use history, limiting further gains as this threshold is reached (Marland et al., 2003). Fundamentally, SOC is best viewed as a medium-term buffer (25–50 years) complementing direct emission reductions (Munidasa et al., 2025). Empirical and modelling work in Australia indicates the potential for SOC sequestration within dairy systems is generally considered limited. This is primarily because most dairy farms are located in regions with high rainfall and inherently fertile soils, where long-established perennial pastures have already contributed to elevated and relatively stable SOC levels (Eckard and Clark, 2020). Under these conditions, SOC concentrations are relatively high but often near their saturation point, leaving little room for additional sequestration (Wang et al., 2023). In some soil types, SOC may even decline under well-fertilised, intensively grazed pastures (Schipper et al., 2017). Furthermore, management strategies capable of enhancing SOC under intensive grazing remain poorly defined, and some interventions may inadvertently reduce C stocks elsewhere on the farm or compromise milk production (Eckard and Clark, 2020; Schipper et al., 2017; Wang et al., 2023). Climate variability, drought, increased stocking rates, and land-use change further threaten stored C (Macdonald et al., 2025; Meyer et al., 2018). Therefore, SOC should be treated as a complementary mitigation strategy. Protecting existing stocks, applying adaptive pasture management, and integrating SOC with other approaches such as tree planting, manure biogas, and improved feed efficiency can maximise climate and productivity benefits while reducing reversal risks (Macdonald et al., 2025; Meyer et al., 2018).

Despite these limitations, certain pasture species and management practices may still offer opportunities for maintaining or slightly enhancing SOC in specific regions. Pastures dominated by C_4 grasses such as Kikuyu have been found to store more soil C than C_3 temperate grasses like ryegrass, due to their higher productivity and minimal soil disturbance (Garnett et al., 2017). Studies from South Africa and coastal New South Wales have shown that Kikuyu-based systems can achieve SOC levels comparable to native forests, suggesting that these pastures could contribute meaningfully to the C balance of subtropical Australian dairy regions such as NSW and Queensland (Chan et al., 2010; Milne and Haynes, 2004). However, most Australian SOC studies have not been conducted in major dairy regions or under current management conditions (Robertson, 2015). Modelling by Thomas et al., (2012)indicates that converting arable land from annual crops to Kikuyu pasture could reduce emissions intensity by eightfold (measured as meat GHG intensity in t CO_2-e per tonne of liveweight and annual SOC gains of 0.80 t CO_2e ha^{-1} yr^{-1} when converting arable land from annual crops to Kikuyu pasture. Any SOC-based policy or carbon crediting scheme must account for full GHG impacts, site-specific constraints (e.g., soil type, saturation, moisture), and require robust long-term monitoring to ensure permanence and credibility (Conant et al., 2001; Meyer et al., 2018).

2.4.2. Tree planting and agroforestry

Tree planting is a recognised strategy for C sequestration and climate mitigation due to trees' ability to absorb and store atmospheric CO_2 (Doran-Browne et al., 2018). It increases both above- and below-ground C stocks, lowering net GHG emissions from agricultural systems (Douglas et al., 2020). In Australia, integrating trees into sheep and beef farms has shown significant mitigation potential over a 25-year period (Doran-Browne et al., 2018). However, implementation on dairy farms is more complex, which often occupy regions with high rainfall and fertile soils, making them among the most cleared agricultural lands in the country (Adams and Engert, 2023; Eckard and Clark, 2020). The high economic value of these lands limits opportunities for establishing large-scale tree plantations purely as C sinks (Reisinger et al., 2017). Afforestation is generally not economically viable on high-value dairy land in Australia and New Zealand (Reisinger et al., 2017). Despite these constraints, strategic tree integration offers both environmental and production benefits. Planting along watercourses, windbreaks, riparian zones, and in less productive areas can deliver mitigation and adaptation outcomes without disrupting farm operations (Eckard and Clark, 2020). These plantings improve animal welfare by providing shade and shelter, reducing heat and cold stress, and potentially enhancing milk yield (England et al., 2020; Fisher et al., 2008; Kendall et al., 2006). Access to lower-value land is essential for large-scale tree establishment (Garnett and Eckard, 2024). Beyond mitigation, trees offer adaptation benefits by creating microclimates, protecting livestock during heat events, and reducing topsoil loss through windbreaks (Monckton and Mendham, 2022). When well-placed and appropriately selected, tree plantings can also yield high-value timber, diversify farm income, and reduce risk (Monckton and Mendham, 2022). In Tasmania’s northern midlands, shelterbelts increased paddock productivity by ~8%, primarily through improved livestock performance and pasture growth (Monckton and Mendham, 2022). However, after ~25 years, tree growth slows, providing little additional C sequestration and eventually becoming net emitters. Although these incremental offsets are valuable, substantial emission reductions in dairy systems will depend more on cost-effective technologies targeting CH_4 and N_2O emissions from enteric fermentation and waste management (Eckard and Clark, 2020; Garnett and Eckard, 2024). Further research is needed to optimise tree species, spatial configurations, harvest times, and management practices to maximise carbon sequestration and agricultural co-benefits.

2.5. System-Level Impacts on Emissions

Dairy farming systems broadly categorized as pasture-based, mixed, or confinement vary in herd structure, land-use patterns, and management intensity, all of which significantly influence their greenhouse gas emission profiles (Cooner et al., 2009). Confinement systems rely on feed produced on arable land, whether grown on-site or purchased, whereas pasture-based systems often use land unsuitable for cropping, supporting biodiversity and C storage, though their sustainability and land-use efficiency depend on local environmental and socio-economic conditions (Cooner et al., 2009; Salari et al., 2025). Pasture-based systems rely primarily on grazing with minimal external inputs, mixed systems combine grazing with significant supplementary feeding and partial housing, whereas confinement systems involve full confinement, zero grazing, and TMR feeding, often with high mechanization and input use (Pandey and Upadhyay, 2022; Robinson et al., 2011). Each system influences emissions differently. In pasture-based systems, CO_2 emissions are largely associated with land-use changes such as deforestation and desertification, and CH_4 and N_2O emissions arise mainly from enteric fermentation and manure decomposition (Saggar et al., 2004; Steinfeld and Wassenaar, 2007). In contrast, confinement systems contribute CO_2 through synthetic fertiliser use, machinery operation, feed production, and soil C loss, with CH_4 and N_2O emissions stemming from intensive manure management and fertiliser application (Schils et al., 2008). However, some of this global trend literature is not consistent with the Australian context. For instance, Australian pasture-based farms frequently rely on substantial off-farm inputs such as concentrate supplementation, particularly in high-producing herds (Dida et al., 2025). Conversely, confinement systems in Australia contribute CO_2 primarily through manure management rather than fertiliser application (Dida et al., 2025). Similarly, while international studies attribute CO_2 emissions in pasture-based systems to land-use changes such as deforestation, these processes are negligible in Australia. These differences highlight a critical gap: much of the global literature does not reflect Australian conditions, emphasizing the need for country-specific research. These differences highlight a critical gap: much of the global literature does not accurately reflect Australian conditions, underscoring the need for country-specific research. This thesis addresses this gap by quantifying GHG emissions across Australian pasture-based, and confinement systems, providing context-specific evidence to challenge global generalizations and inform locally relevant mitigation strategies.

The global shift toward confined or partially housed systems is driven by the need to support higher-yielding cows, manage larger herds, address variability in pasture availability and quality, and integrate technologies like automatic milking systems (Arnott et al., 2015; Jackson et al., 2022). In Australia, increasing climate variability and inconsistent pasture growth and quality have similarly led to a gradual shift toward confinement systems, particularly in northern New South Wales and northern Victoria, where TMR feeding are increasingly adopted to ensure feed quality, maintain productivity, and enhance profitability (Joubran et al., 2021). Confinement systems typically yield higher milk volume per cow and better body condition scores, especially when pasture-based cows receive limited concentrates (Arnott et al., 2015). Studies report milk yield increases of 3–7 kg/day in confined cows on high-concentrate diets, though differences narrow when concentrate intake is equalized (Arnott et al., 2015). Conversely, pasture-based systems are associated with better animal health and welfare, including reduced incidences of lameness and mastitis, and a behavioural preference for grazing, particularly at night (Legrand et al., 2009) whereas typically lower in productivity. Environmentally, pasture-based systems support manure distribution, C sequestration, and reduced fossil fuel use, though nutrient hotspots and water contamination near feeding areas remain concerns (Arnott et al., 2015).

Importantly, GHG emissions vary not only by production system but also by management intensity. Confinement systems may emit more GHG per hectare, but can achieve lower emissions per unit of milk through improved feed conversion and productivity (Capper et al., 2009). Conversely, pasture-based systems may have lower emissions per hectare but higher emissions per unit of milk due to lower productivity (O'Brien et al., 2012). Globally, intensification tends to reduce emissions per kilogram of milk but may increase total emissions due to larger herd sizes and embedded emissions from feed production (Garnett et al., 2017). Within-system, intensification such as increasing concentrate use can reduce CH_4 intensity and enhance milk output, and transitions between systems involve structural changes with distinct environmental trade-offs (Herrero et al., 2013). National C footprints reflect these dynamics; for instance, pasture-based countries like New Zealand and Uruguay exhibit high CH_4 emissions from enteric fermentation, whereas intensive systems in Europe and North America show greater emissions from manure management, feed production, and fertiliser use (Mazzetto et al., 2022). Generally, greater milk yield per cow reduces GHG emissions per unit of milk, though trade-offs with eutrophication and soil degradation must be acknowledged (FAO, 2010). However, these studies were conducted outside of Australian dairy systems, and our research indicates that in Australia, there is no significant difference in GHG emission intensity per unit of milk between confinement and pasture-based systems (Dida et al., 2025). This highlights the importance of considering local conditions, including herd structure, diet quality, input use, and management strategies, when evaluating emissions**.** Therefore, findings from research completed elsewhere should not be directly extrapolated to other regions because differences in production system must be accounted for.

2.6. Effect of Land Use on Soil Organic Carbon

Land-use changes profoundly influence SOC stocks and nutrient cycling by altering organic matter inputs, decomposition rates, and erosion dynamics (Guo and Gifford, 2002). Agricultural intensification often depletes SOC and macro and micronutrients, whereas perennial systems and tree-based land use generally promote SOC accumulation and nutrient retention (Guo and Gifford, 2002; Kaur et al., 2021). Forested or tree-dominated systems typically maintain the highest SOC and nutrient concentrations due to continuous litter inputs, stable microclimates, and minimal disturbance. These systems can store up to 80 t C ha^{-1} in the top 30 cm of soil, compared with 50 t C ha^{-1} in croplands and 35 t C ha^{-1} in vineyards (Kaur et al., 2021; Martin et al., 2011). Tree-based systems such as *Faidherbia albida* agroforestry have been shown to increase SOC by 46%, total N by 50%, available P by 21%, and exchangeable K by 32% compared to adjacent open fields, particularly on nutrient-poor sites, through mechanisms like litterfall and nutrient uplift (Sileshi, 2016). Conversion from native forest to cropland can reduce SOC by about 42%, whereas pasture-to-cropland transitions may cause losses exceeding 50%, mainly through increased mineralization and leaching. Conversely, reversion to pasture or secondary forest from cropping enhances SOC by 19-53% and improves nutrient retention through greater microbial activity and root turnover (Conant et al., 2001; Guo and Gifford, 2002). Pasture systems especially improved or managed pastures are generally more effective at maintaining or restoring SOC compared with croplands. Improved pastures increase residue input, root exudation, and microbial stabilization, enhancing SOC and subsoil nutrients relative to natural savannas or degraded grasslands (Kim et al., 2023; Sileshi, 2016). Similarly, mixed crop–pasture and agroforestry systems combine perennial cover with annual crops, improving organic matter inputs and enhancing nutrient recycling especially for P and K while minimizing nutrient losses (Kaur et al., 2021; Veloso et al., 2018). Evidence from a 60-year field experiment showed that SOC stocks in the 0–20 cm layer under crop–pasture rotation were about 34% higher than in continuous annual grain cropping, underscoring the long-term benefits of diversified systems for soil C sequestration (González-Sosa et al., 2024).

Cropping systems, especially those with intensive tillage and residue removal, typically experience significant SOC and micronutrient depletion. However, conservation practices such as no-till, legume rotations, and cover crops can narrow the SOC gap with pastures over time by increasing organic matter inputs and improving aggregate stability (Veloso et al., 2018). These management effects underscore that land-use type interacts strongly with management intensity in determining soil C and nutrient outcomes. In dairy farm systems, these land-use effects are particularly pronounced. Pasture-based dairy farms generally sustain higher SOC and nutrient stocks per hectare than confinement systems due to continuous manure deposition, root biomass, and ground cover (O’Brien et al., 2014). For example, holistic grazing management, which involves rotational grazing with frequent moves to avoid overgrazing and allow forage recovery, in improved pastures can increase SOC by 1-2 t C ha^{-1} yr^{-1} after conversion from degraded cropland, with the greatest gains often occurring in the initial years after establishment as the system builds soil organic matter, while also enhancing potassium and micronutrient availability through species-diverse swards (Rowntree et al., 2020; Stanley et al., 2018). In contrast, confinement feeding often relies on cropping forage, imported feed, creating nutrient surpluses and elevating N and P losses via runoff (Rowntree et al., 2020; Stanley et al., 2018). Despite confinement’s lower GHG intensity per unit milk, pasture-based systems contribute more to long-term SOC sequestration and soil fertility (Kim et al., 2023). However, our Australian case study reveals a different pattern: confinement farms predominantly rely on on-farm feed production and show GHG intensities comparable to those of pasture-based systems (Dida et al., 2025). Overall, land-use transitions from tree-based systems and natural pastures to cropping tend to reduce SOC and nutrient stocks. In contrast, integrated systems such as improved pastures, mixed crop–pasture configurations, and agroforestry offer effective pathways to restore soil fertility and enhance C sequestration. Therefore, both land-use type and management practices must be jointly considered to sustain SOC and nutrient balances, particularly under dairy farm intensification (Kaur et al., 2021; Kim et al., 2023; Veloso et al., 2018).

2.7. Adaptation and Mitigation Strategies to Reduce Greenhouse Gas Emissions in Dairy Farms

Multiple strategies are known and available to mitigate GHG gas emissions, and others are continuously being investigating. This section explored different approaches that integrate multiple strategies, and other single strategies.

2.7.1. Integrated approaches

The livestock sector is a significant emitter of CH_4, N_2O, and CO_2, and without targeted action, may hinder progress toward climate goals including the Paris Agreement (Global Research Alliance on Agricultural GHG, 2024). Australia has committed to a 43% emissions reduction by 2030 and net-zero by 2050 (DCCEEW, 2022). In response, the dairy industry aims to cut GHG emission intensity by 30% by 2030 (Dairy Australia and Agriculture Victoria, 2021). Emissions reductions can be achieved through absolute reductions or by lowering emission intensity per unit of milk produced, requiring coordinated efforts to maintain productivity and profitability (Cadez et al., 2019; Garnett and Eckard, 2024). Historically, mitigation has been prioritized over adaptation, but increasing heat stress, erratic rainfall, and feed shortages highlight the need for integrated strategies (Munidasa et al., 2025). Mitigation reduces GHGs, while adaptation minimises climate impacts and leverages new opportunities (Howarth and Robinson, 2024). However, adaptation may also lead to increased productivity and efficient, which may ultimately reduce GHG emissions or its intensity. These strategies can support or hinder mitigation and vice versa making integration essential. Integrated approaches offer co-benefits; for example, deep-rooted, summer-active pasture species containing plant secondary compounds can reduce CH_4 emissions and enhance drought resilience by accessing deeper soil moisture during dry periods, and heat-tolerant, low-emission cattle breeds enhance both adaptation and mitigation (Munidasa et al., 2025). However, integration must also protect food security, livelihoods, and equity (Howarth and Robinson, 2024). Adaptation strategies are categorized as incremental, systemic, or transformative (Rickards and Howden, 2012). Incremental changes include feed adjustments, forage conservation, and climate-resilient fodder (Park et al., 2012). Systemic adaptations involve infrastructure upgrades like shading, irrigation, and pest control. Transformative strategies require fundamental shifts, such as transitioning from pasture-based to confinement systems, adopting new livestock species, relocating farms, or diversifying enterprises (Loboguerrero et al., 2019). Though riskier, transformative approaches offer long-term resilience (Wilson et al., 2020). Mitigation relies on technological, biological, and management innovations, including improved feed efficiency, breeding animals for low emissions, and advanced manure management (Garnett and Eckard, 2024). Adoption is often limited by financial, infrastructural, and knowledge barriers, especially in resource-constrained settings. No single solution can eliminate all emissions; combining complementary strategies yields the greatest impact (Munidasa et al., 2025). Effectiveness depends on local compatibility, resources, and farmer capacity.

2.7.2. Enteric methane emissions mitigation strategies

This section reviewed the most promising approaches to reduce enteric CH_4 emissions including animal and feed management, diet formulation and rumen manipulation.

2.7.2.1. Animal management

This section reviews the major animal-related interventions currently used or under investigation for enteric CH_4 mitigation in dairy systems, including genetic selection, extended lactation, improved animal health, heat abatement, and emerging technologies such as CH_4-oxidizing devices.

Breeding

Animal breeding offers a promising avenue to mitigate enteric CH_4 emissions, primarily by targeting traits such as feed conversion efficiency, residual feed intake (RFI), and genetically lower CH_4 production (Beauchemin et al., 2020). Although breeding for lower CH_4 yield (g CH4/kg DMI) is theoretically possible, it faces challenges due to low heritability (0.19), measurement difficulties, and potential trade-offs with milk yield. As a result, breeding programs often focus on improving feed efficiency, particularly through RFI, where animals with lower (negative) RFI consume less feed for the same level of milk production, which generally leads to lower total CH_4 emissions because CH_4 production is often proportional to feed intake (Beauchemin et al., 2020). In Australia, farmers can select for feed efficiency, primarily through RFI, using estimated breeding values in the Australian Dairy Herd Improvement Scheme (2015), which provides semen selection tools (Garnett and Eckard, 2024). Methane mitigation through genetic selection can be direct (e.g., g CH_4/hd/d by respiration chambers) or indirect via correlated traits like RFI (Fouts et al., 2022). Modelling studies suggest that selecting for low RFI could reduce CH_4 production by 11-26% over ten years, assuming feed intake remains stable; otherwise, increased intake may offset gains (De Haas et al., 2011; Pickering et al., 2015). Although CH_4 traits are not yet part of Australia's national breeding goals, integrating them with fertility, health, and productivity traits holds strong potential (Garnett and Eckard, 2024). Documented variation in CH_4 production (g CH_4/hd/d), yield (g CH_4/kg DMI), intensity (g CH_4/kg FPCM), and residual CH_4 production (g CH_4/hd/d, calculated as the difference between observed and DMI-predicted CH_4) supports their inclusion as a breeding trait, with residual CH_4 particularly suitable for breeding indices without compromising key traits such as LW and milk production (Manzanilla-Pech et al., 2021). Adjusting emphasis on existing traits can also reduce emissions though gains are modest (Nguyen et al., 2023; Richardson et al., 2022). The Australian sustainability index (2022) allows selection of bulls to lower herd GHG emissions intensity, with projected reductions of 5.5-7.6% by 2050 (Nguyen et al., 2023). Incorporating a dedicated CH_4 trait into multi-trait indices could cut emissions intensity by 21.3% and per-cow emissions by 8.2% over 30 years, and assuming C is valued at AU$250/t could make economically feasible (Garnett and Eckard, 2024; Richardson et al., 2022). Despite its potential, genetic selection for CH_4 abatement faces several challenges. Developing a CH_4 trait requires large-scale measurements or proxies across many animals in commercial farms, and no validated trait is yet available for widespread use (Richardson et al., 2021). Unintended consequences must also be considered because selecting for emission intensity may increase total herd emissions, whereas focusing on absolute emissions could reduce cow size and milk yield (de Haas et al., 2021; González-Recio et al., 2020; Manzanilla-Pech et al., 2021). High-yielding exotic breeds may also bring trade-offs like reduced milk protein/fat or increased disease susceptibility (de Haas et al., 2021; Khasapane et al., 2023). Breeding improvements may be less feasible in systems with low-quality or limited feed, especially in low- and middle-income countries and interactions between CH_4 traits, diet, and health require further study (Beauchemin et al., 2020; Manzanilla-Pech et al., 2021). In summary, genetic selection is a low-cost, permanent, and cumulative approach to CH_4 mitigation. Although progress is constrained by measurement and trade-offs, refining CH_4 traits and integrating them into breeding programs could make this a cornerstone of sustainable dairy production in Australia and globally (Richardson et al., 2021).

Extended lactation.

Research indicates that extending lactation can maintain milk production efficiency while potentially reducing herd-level GHG emissions. Auldist et al. (2007) found that cows lactating for 16 months produced 99% of the annualised milk solids of those on a standard 10-month cycle, with similar proportions reaching the target duration. However, lactations beyond 16 months saw fewer cows achieving this target. Modelling by Browne et al. (2011) suggested that extending lactation from 10 to 16 months lowered both absolute emissions and emissions intensity, mainly due to a 9% drop in heifer-replacement rates. However, it is unclear whether extended lactation would effectively reduce the number of heifers or not on commercial farms. Conversely, Christie (2019) showed that when heifer replacement rates remained constant, extended lactation increased total emissions but reduced emissions intensity due to higher milk yield per cow. The mitigation potential of extended lactation depends largely on its ability to reduce replacement rates (Browne et al., 2011), though this may hinder genetic progress, reduce culling of older, high-emission cows, and shift emissions off-farm when surplus young stock are sold (Christie, 2019; Knapp et al., 2014).

Improving animal health.

Healthy animals are generally more productive and efficient, leading to lower emissions per unit of product (Özkan et al., 2022). Addressing specific diseases and health conditions can reduce mortality and morbidity, enhance growth, and improve feed conversion, thereby lowering emissions intensity (Fox et al., 2018; Özkan et al., 2022). Parasitic infections may reduce feed efficiency and increase CH_4 yield by up to 33% (Fox et al., 2018). Combining disease control with vaccination and heat stress mitigation has reduced emissions by 10% in mixed dairy systems (Mottet et al., 2017). In the UK, improved health could cut GHG emissions by 10% (Ruminant Health & Welfare, 2022), contributing to a global reduction of 0.2 Gt CO_2-eq annually (Herrero et al., 2016). Although healthier animals may consume more feed and live longer, potentially increasing emissions at the individual animal level, overall supply-chain emissions can decline because improved health reduces the need for replacement animals and product losses due to disease (Özkan et al., 2022). The potential benefits are particularly substantial in low- and middle-income countries, where the prevalence of disease is high and institutional capacity for prevention or treatment is limited (Özkan et al., 2022).

Optimising temperature

In pasture-based dairy systems, summer heat stress reduces feed intake, milk yield, and reproduction (Oliveira et al., 2025). Heat abatement strategies such as fans, sprinklers, misters, foggers, and cooled waterbeds help maintain feeding behaviour and metabolic efficiency, improving feed utilisation and lowering enteric CH_4 emissions per unit of milk (Macavoray et al., 2023). To prevent offsetting these gains through energy-related GHG emissions, such systems should be powered by renewable energy.

Methane-Oxidizing Devices

Devices like ZELP, which attach to livestock and capture emitted CH_4, have shown reductions of 26–53% in steers (Budan et al., 2022). While the concept is promising, independent validation and assessment of practicality, durability, and cost-effectiveness particularly in extensive systems are needed (Beauchemin et al., 2022).

2.7.2.2. Feed management

This section reviews the major feed-related interventions currently used or under investigation for enteric CH_4 mitigation in dairy systems, including feed processing, increasing feeding level and improving pasture management and forage quality.

Feed processing.

Mechanical treatments like grinding and pelleting reduce forage particle size, accelerating ruminal passage and shifting fermentation toward propionate, which lowers CH_4 yield per unit of feed especially at high intake levels, where reductions of 20–40% are observed (Blaxter, 1989; Johnson and Johnson, 1995). However, when feed intake is restricted, these benefits are less apparent because longer ruminal retention time may increase feed digestibility and thus CH_4 yield (Johnson and Johnson, 1995). Thermal and mechanical treatments such as steam-flaking corn enhance starch availability and reduce CH_4 by 17% compared to dry-rolled corn (Beauchemin et al., 2022). Grinding, crushing, or rolling oilseeds improves lipid availability, with oils more effective than crushed seeds in suppressing CH_4 (Beauchemin et al., 2022, 2008). However, forage processing may increase total CH_4 emissions in animals fed ad libitum, especially on low-quality diets, due to higher DMI (Arndt et al., 2022). Faster passage also reduces carbohydrate digestibility in the lower tract, increasing undigested fibre in manure and potentially offsetting ruminal CH_4 reductions (Beauchemin et al., 2022).

Increasing feeding level

Higher feed intake in ruminants accelerates digesta passage through the rumen, reducing retention time and microbial access to OM. This decreases rumen fermentation and yield, as well as the CH_4 conversion factor (Ym), which represents the proportion of gross energy intake lost as CH_4. However, total CH_4 emissions may still rise due to increased feed consumption (Arndt et al., 2022). Meta-analyses show that a 58% increase in feeding level reduced milk CH_4 intensity by ~17%, with a similar rise in milk yield (Arndt et al., 2022). Assuming diet composition remains constant, enhanced intake lowers milk emission intensity and the C footprint of animal-derived foods by redirecting energy lost as CH_4 toward production and reducing maintenance energy needs (Goopy et al., 2020; Hristov et al., 2013). Potential impacts on manure-derived CH_4 emissions, linked to reduced fibre digestibility, warrant further study (Arndt et al., 2022). This strategy applies across feedlot, mixed, and grazing systems, and is especially relevant in underfed grazing systems with limited or poor-quality forage (Demanet et al., 2015).

Improving pasture management and forage quality

Forage management practices like harvesting at vegetative stages, reducing sward maturity, and managing pre-grazing biomass can enhance digestibility, DMI, and reduce CH_4 intensity (Macome et al., 2018; Vargas et al., 2022). Higher forage digestibility increases DMI and shifts rumen fermentation toward propionate, reducing CH_4 yield and intensity (Pacheco et al., 2014; Van Lingen et al., 2016). Meta-analyses show that a ~25% increase in digestibility raises DMI by ~14% and CH_4 production by ~8%, while CH_4 yield and intensity dropped by 10% and 19%, respectively (van

Gastelen et al., 2019). However, responses vary by forage type, species, and feeding level, with a linear increase in CH_4 production at maintenance feeding (Blaxter and Clapperton, 1965). Legume inclusion improves DMI and productivity, as legumes are more digestible and higher in protein than grasses, which reduces CH_4 intensity; however, effects on CH_4 yield vary with species, maturity, and secondary compounds (Arndt et al., 2022). Certain legumes, such as red clover, may slightly increase CH_4 yield, while tannin-rich legumes can reduce both enteric CH_4 and manure N_2O emissions (Eugène et al., 2021; Gidlund et al., 2017). Perennial legumes also fix N, enhance soil C, and improve pasture resilience, though high CP intake may increase NH_3 and N_2O emissions, warranting region-specific assessments (Schultze-Kraft et al., 2018). High-starch forages such as corn silage can decrease fibre content and shift rumen fermentation toward propionate, reducing CH_4 yield and intensity while improving milk production (Garcia-Chávez et al., 2020). High-sugar ryegrass cultivars increase water-soluble carbohydrates, enhancing microbial protein synthesis and reducing urinary N losses, potentially lowering CH_4 and N_2O emissions (Rivero et al., 2020). However, their effect may diminish when conserved, and lower CP must be considered for high-yielding cows (Soteriades et al., 2018). Grazing strategies such as optimizing stocking rate, sward height, rotational grazing, and silvopastoral systems can improve pasture quality, productivity per hectare, and reduce CH_4 intensity, though absolute emissions may rise with higher DMI (Vargas et al., 2022). Forages with secondary metabolites like tannins and saponins offer further mitigation potential (Kozłowska et al., 2020). Emerging forage species adapted to Australian conditions, including deep-rooted summer-active species like chicory and lucerne, in C4 grasses such as paspalum and Kikuyu, may help extend the grazing season under climate change while potentially mitigating CH_4 (Badgery et al., 2023; Havrilla et al., 2023). Selecting forage varieties with high digestibility, starch, sugar, or beneficial compounds, alongside sound agronomic practices, presents a promising strategy to reduce enteric CH_4 while sustaining or improving milk production (Badgery et al., 2023; Beauchemin et al., 2022).

2.7.2.3. Diet formulation

Diet formulation such as forage to concentrate ratio, mineral and salts, dietary lipids, essential oils and other secondary plant compounds, as well as feed additives such as direct-fed microbials can also reduce daily emissions and emissions intensity.

Decreasing forage to concentrate ratio.

Supplementing dairy diets with concentrates enhances performance and reduces CH_4 yield and intensity (Arndt et al., 2022; Hristov et al., 2022). For instance, a diet with concentrate at 386 g/kg DM lowered CH_4 yield and FPCM intensity by 14% and 27%, respectively (van Gastelen et al., 2019). These effects are attributed to the higher digestibility, increased energy density, reduced structural carbohydrates, faster rumen outflow, and lower ruminal pH all of which suppress methanogenesis (Capper et al., 2009). Fermentable starch promotes propionate production, an alternative H_2 sink that diverts hydrogen away from methanogenesis, whereas low pH inhibits protozoa, reducing methanogen protection from O_2 toxicity and H_2 availability (Newbold et al., 2015). The extent of CH_4 mitigation varies with grain type and processing, and effects in grazing systems depend on pasture quality, substitution rates, and intake estimation methods (Arndt et al., 2022; Vargas et al., 2022). Combining concentrates with oil supplements or inhibitors like 3-NOP can yield additive reductions (Bayat et al., 2017; Schilde et al., 2021). However, trade-offs include increased CO_2 and N_2O emissions from feed production, reduced soil C from pasture conversion, and altered manure composition (Beauchemin et al., 2009). Excessive concentrate use may raise costs, risk acidosis, and reduce milk fat and protein especially with wheat or oat-based diets (Hristov et al., 2022). Moreover, although CH_4 intensity may decrease, absolute emissions can increase if higher concentrate use results in greater stocking rates (Garnett and Eckard, 2024). Higher concentrate proportions may also increase manure N_2O emissions due to elevated N intake (Nampoothiri et al., 2018). Therefore, mitigation strategies must account for potential emission leakage across the supply chain, but such research is lacking in the Australian context with the inclusion of emissions from manure and production and purchase of concentrates. Overall, increasing dietary concentrate can effectively reduce CH_4 yield and intensity when diets are well balanced particularly in terms of protein and energy (Arndt et al., 2022). However, implementation should also consider factors such as feed availability, animal health, product quality, land-use change, and the full life cycle of GHG emissions. Further research is needed to refine grain type, processing, and ration formulation to achieve optimal mitigation and profitability (Garnett and Eckard, 2024).

Minerals and salts

Strategic supplementation with minerals and salts, including kaolin clays, can reduce enteric CH_4 emissions by 10–23% by altering rumen microbial populations and fermentation pathways (Islam et al., 2025; Li et al., 2017). Mineral salts reduced CH_4 emissions by 10.5% in lactating Holstein cows by lowering the acetate-to-propionate ratio and reducing methanogen abundance, as the higher propionate proportion redirects H_2 away from methanogenesis toward propionate synthesis, limiting substrate availability for methanogens (Li et al., 2017). Iron-rich kaolin clay (KaoFe) showed even greater in vitro reductions up to 37% likely due to enhanced H_2 sink capacity and inhibitory ions (Fe^{2+}, Al^{3+}, Si^{4+}) without impairing rumen function (Islam et al., 2025). However, in vivo research is lacking in this and many other feed additives which limits a comprehensive assessment on GHG emissions.

Essential oils and plant-derived compounds

Essential oils are natural feed additives composed of volatile lipophilic compounds such as terpenoids, alcohols, aldehydes, phenylpropanoids, and sulphur-containing molecules. These compounds pose antimicrobial properties that disrupt microbial membranes and enzymes, often suppressing gram-positive bacteria linked to H_2 production (Benchaar and Greathead, 2011). In vitro studies have frequently shown substantial CH_4 inhibition from essential oils such as oregano, thyme, and garlic oil (Cobellis et al., 2016), but in vivo results are inconsistent, likely due to differences in composition, dosage, diet, and microbial adaptation (Benchaar and Greathead, 2011; Hristov et al., 2022). Some commercial blends show modest success in reducing CH4 production such as oregano oil and green tea extract reduced CH_4 yield by 16-22% (Kolling et al., 2018); Mootral by 23% (Roque et al., 2019); and Agolin ruminant lowered CH_4 production by 9% (Belanche et al., 2020). However, overall mitigation potential is rated low (≤5%) with limited confidence (Hegarty et al., 2021). Although most oils do not impair performance or product quality (Benchaar et al., 2009), some may depress digestion or alter sensory traits (Cobellis et al., 2016), and compounds like estragole and methyl eugenol may pose health risks at high doses (Burt, 2004). Due to their volatility and compositional variability, developing stable, targeted formulations of essential oils remains challenging (Cobellis et al., 2016). Further in vivo research is required to identify selective and cost-effective strategies that demonstrate consistent long-term efficacy without compromising feed efficiency or product quality.

Dietary lipids

Fat supplementation reduces CH_4 production by inhibiting rumen methanogens and protozoa, promoting biohydrogenation of unsaturated fatty acids, and shifting fermentation toward propionate (Newbold et al., 2015). Replacing fermentable carbohydrates with unfermentable lipids also limits substrates for methanogenesis (Beauchemin et al., 2022). Meta-analyses show oilseeds can reduce CH_4 production by approximately 20%, yield by 14%, and milk CH_4 intensity by 12%, with minor reductions in DMI (6%) and fibre digestibility (4%), but no significant impact on milk yield or daily gain (Arndt et al., 2022). Methane yield decreases linearly by 3.8-4.3% per 10 g/kg DM of supplemental fat, with medium-chain and polyunsaturated fats such as those in linseed, sunflower, and canola oils being particularly effective (Patra, 2014, 2013). However, inclusion above 6–7% DM may impair intake, digestibility, and milk fat synthesis (Beauchemin et al., 2008; Palmquist and Jenkins, 2017). In Australia, lipid supplementation is effective in pasture-based systems reliant on low-fat temperate forages, especially in summer (Moate et al., 2011). However, its adoption is limited in systems to farms with mixed rations, and higher supplementation may alter overall emissions profiles. Lipid-rich by-products like cottonseed, brewers' grain, canola oil, grape marc, and hominy meal are feasible options, with upstream GHG emissions attributed to primary industries, improving lifecycle balances (Moate et al., 2016; Williams et al., 2014). Adoption depends on cost, logistics, and milk yield impacts, while transport distance may offset on-farm CH_4 reductions (Williams et al., 2014).

Plant secondary metabolites

Tannins can be classified as condensed or hydrolysable polyphenols, and both can reduce methanogenesis by inhibiting methanogens and rumen protozoa (Aboagye and Beauchemin, 2019). Their effects on feed intake and digestibility vary by source, molecular weight, and concentration (Aboagye and Beauchemin, 2019; Jayanegara et al., 2012). A meta-analysis reported a 3.53% CH_4 yield reduction per 10 g/kg DM tannin, with a 2.6% decline in OMD (Jayanegara et al., 2012). Hydrolysable tannins are more effective compared to condensed tannins and less disruptive to digestibility, though excessive intake (>30 g/kg DM) can be toxic (Bargo et al., 2002). Temperate legumes like sainfoin (*Onobrychis viciifolia*), birdsfoot trefoil (*Lotus corniculatus*), and cicer milkvetch (*Astragalus cicer*) contain low tannin concentration (<20–50 g/kg DM), resulting in modest CH_4 reductions compared with tropical shrubs and legumes that are richer in tannins (Aboagye and Beauchemin, 2019). To enhance efficacy, concentrated tannin extracts from plants such as *Acacia mearnsii*, chestnut (*Castanea* spp.), and quebracho (*Schinopsis balansae*) have been used as dietary supplements (Aboagye and Beauchemin, 2019). Tannin-rich forages can reduce CH_4 by up to 32% (e.g., Sericea lespedeza), though fibre digestibility may drop ~7%, potentially increasing manure CH_4 emissions (Arndt et al., 2022). Condensed tannins reduced CH_4 yield by 12%, but also lowered fibre digestibility by 12% (Arndt et al., 2022). Beyond CH_4 mitigation, tannins can improve N utilisation by binding dietary proteins, reducing urinary N losses and NH_3/N_2O emissions, though reduced protein digestibility may be problematic in N-deficient pastures (Hristov et al., 2022; Jayanegara et al., 2012).

Saponins are triterpene or steroid glycosides found in plants like *Yucca schidigera, Quillaja saponaria, Camellia sinensis*, and *Medicago sativa* which can suppress protozoa and methanogens, promoting propionate formation (Aboagye and Beauchemin, 2019; Jayanegara et al., 2014). In vitro studies show a curvilinear CH_4 yield reduction (approximately 1.32% per 10 g/kg DM), but in vivo results are inconsistent, and high doses (>5% DM) may be toxic (Jayanegara et al., 2014). More trials are needed to determine optimal inclusion rates and long-term effects of saponins (Yurtseven et al., 2018) although most recent research suggest tannins, essential oils, and saponin have limited potential to significantly reduce emissions in dairy cows.

Direct-fed microbials (DFM)

DFM are live microorganisms that, when administered to ruminants, can modify rumen fermentation to improve fibre digestion, stabilize pH, and potentially reduce CH_4 emissions by redirecting H_2 toward alternative pathways like lactate, succinate, propionate, reductive acetogenesis, or anaerobic respiration (Jeyanathan et al., 2014). DFM supplementation can improve milk yield, potentially lowering CH_4 intensity (Hristov et al., 2013). Although upstream GHG emissions from DFM production are minimal, their effects on digestibility, manure composition, and subsequent CH_4 and N_2O emissions remain uncertain (Beauchemin et al., 2022). However, short rumen persistence may limit their effectiveness in extensive pasture-based systems. Practicality, stability, and dosing optimisation are key to future adoption (Beauchemin et al., 2022).

2.7.2.4. Rumen manipulation

In ruminants, CH_4 is primarily produced by methanogenic archaea using H_2 and CO_2 in the rumen (Attwood et al., 2020). As archaea share a distinct methanogenesis pathway, they can be selectively inhibited without major disruption to other microbes (Beauchemin et al., 2022; Moate et al., 2016). Inhibiting methanogenesis could theoretically retain up to 6–10% of gross energy intake which may improve feed efficiency, provided H_2 is redirected to safe alternative sinks; otherwise, H_2 accumulation can impair fermentation, reducing DMI and milk yield (Attwood et al., 2020; Hristov et al., 2013). Promising inhibitors include synthetic 3-nitrooxypropanol (3-NOP), bromoform and its natural option *Asparagopsis taxiformis*, both showing strong CH_4 reduction potential and progressing toward commercial use (Kebreab et al., 2023).

3-nitrooxypropanol (3-NOP)

The synthetic CH_4 inhibitor 3-NOP blocks methyl-coenzyme M reductase, the final enzyme in methanogenesis (Duin et al., 2016). Average reductions of 32.7%, 30.9%, and 32.6% have been reported at 70.5 mg/kg DM (Kebreab et al., 2023). In dairy systems, 3-NOP has minimal effects on DMI, milk yield, or body weight, but tends to increase milk fat (0.19%) and milk fat yield (90 g/d) and digestibility of OM, CP, and NDF (Kebreab et al., 2023; Moschini et al., 2025). Increases in milk urea N and rumen butyrate concentration have also been reported, suggesting enhanced NH_3 absorption due to elevated ruminal blood flow (Melgar et al., 2021). The efficacy of 3-NOP is dose-dependent but plateaus beyond ~100–150 mg/kg DMI (Hristov et al., 2022). Long-term inhibition is achievable, though low doses may show reduced effectiveness over time (Kebreab et al., 2023). The 3-NOP has no consistent negative effects on digestibility or animal health, and its C footprint from production and transport is <5% of the CH_4 reduction achieved (Feng et al., 2020; Kebreab et al., 2023). The 3-NOP carbon is largely metabolized to CO_2, carbohydrates, fatty acids, and amino acids, with less than 5% of the original compound excreted in urine (Thiel et al., 2019). Manure GHG emissions remain unaffected, though soil-dependent effects have been noted (Beauchemin et al., 2022). In grazing systems, effectiveness is limited due to dosing constraints typically only during morning and evening milkings (Costigan et al., 2024). Inclusion in TMR prevents post-feeding CH_4 peaks, with peak reductions occurring approximately 4 hours after feeding (Melgar et al., 2020). This indicates that 3-NOP must be present consistently in the rumen for substantial abatement to occur and slow-release rumen boluses may offer a solution. An Australian grazing study showed a 28.5% reduction during the 3 hours post-feeding, but daily abatement averaged only ~5%, with no impact on DMI or milk yield and a 36% increase in H_2 production (Costigan et al., 2024). Estimated cost is ~AU$0.5 per cow/day (Borrello, 2023), and without consistent productivity or feed efficiency gains, adoption will rely on C incentives, prices or policy support (Costigan et al., 2024). Slow-release delivery methods or boluses may improve feasibility in pasture-based systems. Despite these limitations, 3-NOP remains the most advanced and scalable chemical inhibitor for CH_4 mitigation due to its specificity, safety, and low toxicity (Thiel et al., 2019).

Macroalgae (*Asparagopsis spp.*)

Red macroalgae, particularly *Asparagopsis taxiformis* and *A. armata*, contain halogenated compounds like bromoform that inhibit the final step of methanogenesis (Machado et al., 2016). Meta-analyses of in vivo studies indicate that an average tribromomethane ($CHBr_3$) dose of about 28.3 mg/kg DM reduced CH_4 production by 47.3%, CH_4 yield by 43.3%, and CH_4 intensity by 39.0%, with higher doses achieving greater mitigation (Kebreab et al., 2025). Variability across studies is linked to bromoform concentration (3-51 mg/kg DMI), delivery method, and diet composition (Roque et al., 2021; Vijn et al., 2020). Although *Asparagopsis* can improve feed efficiency, high inclusion rates may reduce DMI and milk yield (Stefenoni et al., 2021). Confined systems show strong CH_4 abatement but also increased H_2 output and reduced intake at high doses (Cowley et al., 2024; Kinley et al., 2020). In grazing systems, oil-based formulations allow twice-daily supplementation, though some reduction in milk solids has been observed (Alvarez-Hess et al., 2023). Bromoform, bromine, and iodine residues in milk and meat are generally below safety thresholds when oil-based delivery is used, but iodine concentration in milk may exceed limits for children (Glasson et al., 2022; Kinley et al., 2020; Stefenoni et al., 2021). Cost (~AU$0.4/cow/day) and maintaining consistent bromoform levels are key challenges (Peel, 2024). Concerns about bromoform's carcinogenicity, animal health, and ozone impact persist, though low-dose studies show no harmful residues in milk or meat (Kinley et al., 2020; Reisinger et al., 2021). Iodine accumulation can be managed through formulation control (Stefenoni et al., 2021). Widespread adoption depends on scalable, sustainable production and regulatory approval, and slow-release rumen boluses of bromoform could offer a practical and long-lasting alternative to feeding as it is the case for many additives. Further research is needed to confirm long-term efficacy, optimize dosing, and address delivery and cost barriers in pasture-based systems (Hristov et al., 2022).

Ionophores

Ionophores like monensin disrupt gram-positive bacteria and protozoa, reducing H_2 availability and shifting rumen fermentation toward propionate (Beauchemin et al., 2022). A meta-analysis showed that supplementation at 21 mg/kg DMI modestly reduced enteric CH_4 production by 3.6% in dairy cows (Ranga Niroshan Appuhamy et al., 2013). The effects of monensin on N metabolism are inconsistent and manure CH_4 emissions remain unchanged, whereas feed conversion efficiency improves (Arikan et al., 2018; Beauchemin et al., 2022). Ionophores are included at low dietary concentrations (<50 mg/kg DM), resulting in negligible additional emissions from their manufacture (Beauchemin et al., 2022). They are approved in some countries but banned in others including many European countries. Slow-release formulations support use in grazing systems, though concerns over antimicrobial resistance may limit broader adoption (Beauchemin et al., 2022).

Electron sinks

Electron sinks redirect metabolic H_2 away from methanogenesis, offering a promising strategy to reduce enteric CH_4 emissions (Beauchemin et al., 2022). These include inorganic compounds like nitrate and sulphate, and organic intermediates such as fumarate and malate, which are metabolized to VFAs such as propionate and absorbed by the host (Puniya et al., 2015). Malate and fumarate can reduce CH_4 production by 10-23% (Puniya et al., 2015). Fumarate and malate are approved feed additives in the EU and US, but their practical use is limited due to the large inclusion rates required to achieve meaningful CH_4 reductions making them economically unviable (Puniya et al., 2015). Meta-analyses indicate that nitrate supplementation can reduce enteric CH_4 production by an average of 14% at mean nitrate doses of 16.7 g/kg DM in dairy cattle (Feng and Kebreab, 2020). Similarly, a meta-analysis by Arndt et al. (2022) reported that nitrate supplementation decreases enteric CH_4 production, yield, and intensity by 17%, 15%, and 13%, respectively, with only slight reductions in DMI (approximately 3%) and no negative effects on overall animal productivity. However, nitrate's efficacy is offset by increased measured N_2O emissions associated with nitrate-supplemented animals, with losses up to 3.4% of N intake at high doses, reducing net GHG mitigation from -47% to -40% (Petersen et al., 2015). Rapid nitrite accumulation poses toxicity risks like methemoglobinaemia if animals are not properly adapted or overconsume the product, and elevated urinary N can increase NH_3 and N_2O emissions during manure handling (Hristov et al., 2022). Economically, nitrate (e.g., calcium nitrate) is more expensive than urea and considered unviable in European systems (Callaghan et al., 2014). In Australia, nitrate use qualified for C credits in beef systems but it has now expired and it is not available anymore (Australian Government, 2015), but adoption in pasture-based dairy remains limited due to high forage protein and toxicity risks (Moate et al., 2016). It may be more suitable for N-deficient tropical and subtropical diets, where improved intake and daily gain have been observed with nitrate supplementation (Nguyen et al., 2016). Furthermore, grazing trials showed variable results due to inconsistent intake and adaptation challenges (Beauchemin et al., 2022). Exploring high-nitrate forages in temperate Australian systems may offer a safer, more practical mitigation pathway (Garnett and Eckard, 2024).

Phage and lytic enzymes with activity against methanogens

Archaeal phages produce lytic enzymes that degrade pseudomurein in methanogen cell walls (Beauchemin et al., 2022). The enzyme PeiR, displayed on bio-nano particles, reduced CH_4 production by up to 97% in targeted methanogen cultures over five days (Altermann et al., 2018). However, efficacy declined against distant methanogen strains, and no in vivo or mixed-culture studies have been reported. Though still at the proof-of-concept stage, this approach is considered low risk due to the established use of phages in medicine and food safety (Beauchemin et al., 2022).

Biochar

Biochar, produced via pyrolysis of biomass at 350-600°C under limited O_2, may influence methanogenesis by enhancing microbial biofilm formation and electron transfer (Chen et al., 2014). Despite its theoretical potential, most in vivo studies have shown no significant CH_4 mitigation (Sperber et al., 2021; Terry et al., 2019). Efficacy may depend on biomass type, pyrolysis conditions, and post-treatment methods, warranting further investigation (Beauchemin et al., 2022).

Defaunation

Eliminating rumen protozoa removes their methanogenic symbionts, reducing CH_4 production by approximately 10% (Arndt et al., 2022). Methods include chemical treatments, lipid supplementation, freezing rumen contents, or isolating newborn animals (Newbold et al., 2015). However, sustaining protozoa-free animals is challenging due to rapid re-inoculation (Beauchemin et al., 2022).

Immunization against methanogens

Anti-methanogenic vaccines aim to induce antibodies against rumen methanogens and have been studied for over two decades (Zhang et al., 2015). These antibodies, present in serum and saliva, can persist in rumen fluid and agglutinate methanogens in vitro (Subharat et al., 2016). However, in vivo CH_4 reductions have been small or inconsistent, likely due to microbiome variability and limited broad-spectrum efficacy (Baca-González et al., 2020). Currently, both efficacy and cost-effectiveness remain uncertain (Garnett and Eckard, 2024). Despite these challenges, immunization remains a promising long-term option, especially for grazing systems like those dominating Australia (Beauchemin et al., 2022).

Early-life intervention

Modifying the rumen microbiota in pre-ruminants offers a cost-effective strategy for long-term CH_4 mitigation, particularly where continuous supplementation is impractical (Beauchemin et al., 2022). Heifers given 3-NOP until 14 weeks of age showed a reduction of 17.5% in CH_4 production at 57-60 weeks of age (Meale et al., 2021). Immune-mediated methanogen suppression via colostrum transfer is another avenue under investigation. Overall, early-life interventions hold promise for durable, low-cost CH_4 reduction in grazing systems (Beauchemin et al., 2022).

2.7.3. Strategies to reduce manure methane and nitrous oxide emissions

Technologies such as anaerobic digestion with biogas capture and conversion to energy, acidification, composting, and covered storage are widely adopted in Europe and North America (Christie, 2019; Rotz, 2018). Anaerobic digesters, when combined with biogas capture and energy conversion, can reduce CH_4 emissions from manure storage by up to 29% and N_2O emissions by 23% compared to conventional uncovered storage systems (Mohankumar Sajeev et al., 2018; Rotz, 2018). Effluent ponds are major CH_4 sources, whereas N_2O and NH_3 play secondary roles as contributors to GHG emissions and N losses from manure management (Van der Meer, 2008). Covering manure ponds to limit gas diffusion and enable biogas capture, reducing volatile solids to curb anaerobic decomposition, and shortening storage periods to minimise emission windows are effective strategies for mitigating CH_4 and N_2O emissions from liquid manure management (Mohankumar Sajeev et al., 2018; Rotz, 2018). Acidification suppresses methanogenesis and nitrification, cutting CH_4 by 74% and N_2O by 55% (Mohankumar Sajeev et al., 2018). Frequent manure removal from barns (e.g., daily or several times weekly, with transfer to external low-emission storage) can decrease CH_4 and N_2O emissions by 55% and 41%, respectively, across the manure management chain compared to infrequent in-barn accumulation (Mohankumar Sajeev et al., 2018). Dicyandiamide (DCD) application can reduce N_2O emissions from dairy effluents by 46–90%, depending on the effluent type and storage conditions (Li et al., 2014). However, some interventions like surface covers and composting may increase N_2O due to aerobic-anaerobic cycling or N volatilization (Mohankumar Sajeev et al., 2018). Lowering dietary CP and balancing energy-to-protein ratios improves N use efficiency and reduces urinary N losses, achieving up to 50% N_2O reduction (Eckard and Clark, 2020). Recent technologies like EcoPond® and covered anaerobic ponds (CAPs) show promise. EcoPond® trials on dairy farms involved dosing effluent ponds with polyferric sulphate and sulfuric acid to inhibit methanogenesis via sulphate-reducing bacteria, achieving over 90% CH_4 reduction from ponds equivalent to approximately 7% of total farm GHG emissions (EcoPond® technology). Chemical treatments like lime and polyferric sulphate can remove up to 99% of volatile solids, significantly reducing CH_4 production potential, though high costs and limited long-term data hinder adoption (Cameron and Di, 2021). Salt supplementation to animals can reduce N leaching by 10-22% by increasing urination frequency and diluting urinary N, but excessive salt may impact milk yield and soil health (Ledgard et al., 2015). Genetic selection for lower urinary N or improved N-use efficiency has been proposed, though heritability and measurement challenges constrain progress (Garnett and Eckard, 2024). Although global manure management technologies offer substantial mitigation potential, their applicability in Australia is limited by the predominance of grazing-based systems. This constrains the use of infrastructure-dependent solutions, such as digesters and covered lagoons, which are more suitable for confined systems (Dairy Australia. 2023b). Confinement dairies are suitable for mitigation technologies but represent a small proportion of the national industry (approximately 20% of total milk production) albeit increasing in popularity, and adoption remains limited even within these systems (Dairy Australia, 2024). Consequently, in pasture-based systems, mitigation can be achieved by improving feed quality and digestibility, and enhancing herd efficiency through better nutrition, productivity, and overall animal management (Van der Meer, 2008). For instance, lowering CP from 19% to 14% can halve urinary N (Misselbrook et al., 2005), and modelling shows up to 52% N_2O reduction when CP drops from 26% to 15% (Christie et al., 2014). Condensed tannins can shift N excretion from urine to feces, lowering N_2O potential, though excessive use may reduce milk yield when protein is marginal (Griffiths et al., 2013). Although manure management contributes only a minor share of total emissions in most pasture-based Australian dairies, it still presents opportunities for targeted mitigation. Participation in the Emissions Reduction Fund (ERF) allows dairy farms to earn Australian Carbon Credit Units (ACCUs) through improved effluent management (Aguirre-Villegas and Larson, 2017; Dairy Australia, 2021). Estimated abatement potential from upgraded manure treatment systems in confinement dairies is around 225 tonnes of CO_2-equivalent annually per farm, corresponding to roughly $11,000 per year at a carbon price of $50 per ACCU (Christie, 2019). Therefore, biodigesters have potential to reduce emissions from manure under that system where this is of high prevalence, but adoption needs to be accompanied by incentives and policies.

2.7.4. Nitrous oxide emission reduction from fertiliser application

Improving nitrogen use efficiency (NUE) through better fertiliser management is one of the most practical and cost-effective strategies for reducing N losses and enhancing farm profitability (Eckard and Clark, 2020). Key management practices such as optimising fertiliser rate, source, type, and timing significantly influence pasture productivity and N losses (De Klein and Eckard, 2008). Synchronising N application with plant demand improves NUE and reduces emissions. For example, modelling across five Australian sites showed that demand-based fertiliser application improved NUE by 17-41% and reduced N losses by 19-45% (Smith et al., 2018). Strategic manure and effluent application under low soil moisture conditions can reduce N_2O emissions by up to 96%

(Luo et al., 2010). Delaying effluent applications following grazing also reduces the surplus of mineral N in soil and associated emissions (Luo et al., 2010). Restricting grazing during autumn and winter reduced direct N_2O emissions and nitrate losses by 57% and 41%, respectively, likely because limiting animal access decreases urine deposition on wet soils, which in turn lowers soil N availability for nitrification and denitrification processes that generate N_2O and nitrate leaching (de Klein et al., 2006). Additionally, limiting cow access to pasture during wet conditions further reduced whole-farm N_2O emissions (Luo et al., 2010). Urease inhibitor N-(n-butyl) thiophosphoric triamide (NBPT; Agrotain®) reduced NH_3, NO_3^-, and N_2O emissions by 45%, 47%, and 5%, respectively, while increasing pasture yield by 17% (Zaman et al., 2008). Nitrification inhibitors (NIs) reduced N_2O and nitrate leaching by ~57% and 50%, with occasional pasture growth improvements (Di and Cameron, 2016). However, effectiveness varies with soil type, temperature, and moisture. Furthermore, higher pasture yields may also increase enteric CH_4 emissions if stocking rates rise (Di and Cameron, 2016). Importantly, N inputs can be reduced by 10–50% without yield penalties by tailoring application rates to pasture demand and implementing management practices that reduce the intensity of urine patches such as controlling stocking density, using rotational grazing to avoid repeated deposition in the same area, or applying dietary interventions to lower urinary nitrogen excretion (Rawnsley et al., 2019). Enhanced-efficiency fertilisers, combining nitrification and urease inhibitors, slow soil N transformations and reduce losses via leaching, volatilisation, and denitrification (Li et al., 2018). However, their success depends on soil properties, formulation, climate, and baseline emissions. Urease inhibitors can reduce NH_3 volatilisation by 20–88%, but may increase N_2O emissions if retained N enhances nitrification potential (Li et al., 2018). Similarly, NIs may elevate NH_3 losses, offsetting N_2O benefits. Combined use of urease and nitrification inhibitors is more effective, with meta-analyses showing ~50% reduction in total N_2O emissions (Li et al., 2018).

2.7.5. Energy-derived and pre-farm embedded emissions

Reducing energy related such as fuel or electricity, and pre-farm embedded emissions from purchased inputs such as feed and fertiliser are increasingly feasible as technology advances lower costs and improve adoption incentives. Agriculture is actively working to reduce fossil fuel reliance and emissions embedded in inputs like fertilisers (Garnett and Eckard, 2024). Producing nitrogen fertiliser using clean energy, such as green ammonia, could eliminate emissions from conventional production (Ojelade et al., 2023). On-farm, improving energy efficiency remains a major opportunity. Upgrading equipment can cut electricity use by about 20% on dairy farms in Australia and New Zealand (Ilyas et al., 2020). Approximately 50% of Australian dairy farms use solar systems, however mismatches between generation and peak demand, along with high battery costs, limit realising full benefits (Best and Burke, 2023). Future gains may come from low- or zero-emission machinery, including hybrid, battery-electric, and fuel-cell tractors, though power and runtime limitations remain (Stakens et al., 2023). Overall, strategies such as cleaner input production, renewable energy adoption (e.g. solar power), energy-efficient technologies, and bioenergy recovery from waste offer significant potential to reduce the dairy sector's C footprint (Christie et al., 2018).

2.8. Methods for Monitoring Enteric Methane Emissions in Ruminants

Accurate quantification of enteric CH_4 emissions from ruminants is critical for understanding emission drivers, evaluating mitigation strategies, improving national inventories, and supporting breeding and management interventions. However, achieving this remains technically challenging because measurement approaches must balance accuracy, representativeness of commercial farming conditions, scalability, and cost. Over time, numerous techniques have been developed, each with distinct strengths and limitations in terms of precision, practicality, and suitability for grazing systems. These methods range from controlled laboratory-based approaches to on-farm animal-level measurements, group- and ecosystem-scale assessments, proxy-based techniques, and modelling frameworks.

Among these, open-circuit respiration chambers (RC) remain the benchmark for precision (Hammond et al., 2016). These quantify CH_4 from enteric fermentation via nasal and rectal routes by analysing airflow entering and exiting the chamber using gas analysers, infrared photoacoustic detectors, or gas chromatography (Brouček, 2014; Goopy et al., 2016; Patra, 2016). Typically, a small number of animals are monitored continuously over 24-hour periods for 3 to 7 days (Hammond et al., 2016; Huhtanen et al., 2015). To ensure data reliability, chambers require routine calibration and controlled conditions of temperature (<27 °C), humidity (<90%), CO_2 (<0.5%), and airflow (250-260 L min^{-1}) (Goopy et al., 2016; Hristov et al., 2018). Chambers offer high precision, making them ideal for evaluating mitigation strategies and serving as the research benchmark for CH_4 measurement (Goopy et al., 2016; Hristov et al., 2018; Patra, 2016). Despite their accuracy, RCs are technically complex, costly, and can accommodate only a few animals at a time (Huhtanen et al., 2015). Additionally, the confined environment may alter animal behaviour, particularly DMI, which affects CH_4 production and energy loss estimates (Storm et al., 2012). These behavioural shifts raise concerns about the applicability of chamber data to grazing systems, especially those pastures with heterogeneous botanical composition where animal selection and energy expenditure are critical on the outcomes. Its artificial setting and operational demands limit their practicality for large-scale or field-based studies (Patra, 2016). These limitations have driven the development of alternative methods that better reflect grazing conditions.

One such alternative is the GreenFeed (GF) system, which offers a compromise between accuracy and practicality. It uses an automated feeder to dispense small portions of pelleted concentrate at pre-set intervals between 20-40 seconds, attracting animals to a semi-enclosed hood for voluntary visits lasting 3-7 minutes during which multiple eructation events are captured (Arthur et al., 2017; Hammond et al., 2015). During each visit, the system continuously monitors CH_4 and CO_2 concentrations, airflow, and head position using infrared sensors to ensure accurate nostril sampling (Arthur et al., 2017; Hammond et al., 2015). Air is drawn through the hood by an extractor fan (26-40 L/s) and subsampled using non-dispersive infrared sensors. Background concentrations are interpolated from pre- and post-visit readings and adjusted for temperature, humidity, and pressure (Hristov et al., 2015; Huhtanen et al., 2015; Patra, 2016). Daily CH_4 emission rates are calculated using airflow, fractional air capture, and the difference between sample and background CH_4 concentrations. Emissions are aggregated across multiple visits over days or weeks, showing strong agreement with RC (Goopy et al., 2016; Hammond et al., 2015). The GF offers key advantages over RC methods by enabling CH_4 measurement in freely moving animals under natural conditions, without confinement or technical complexity (Hammond et al., 2016; Hristov et al., 2018; Pickering et al., 2015). It is well-suited for large-scale studies, breeding programs, and nutritional trials (Hammond et al., 2015). Reliable estimates of daily CH_4 production require sufficient sample duration (≥3 min) and frequency (≥30 visits) (Arthur et al., 2017; Hristov et al., 2018). However, GF data can be biased by uneven sampling across the day, as CH_4 emission rates fluctuate diurnally with feeding patterns, typically increasing by 50-70% above trough levels within 1-3 hours post-feeding in confined systems (Cottle et al., 2015; Judy et al., 2018). Variable animal participation at pasture may require longer sampling or larger sample sizes for statistical reliability. The GF also shows greater within-day variability than RC or SF_6 methods, necessitating extended monitoring for precise comparisons (Hammond et al., 2015). It is unsuitable for rumen-cannulated animals, underestimating CH_4 by approximately 40% due to gas loss through fistulae (Hammond et al., 2016), and cannot detect hindgut CH_4, which accounts for approximately 3% of total emissions (Hristov et al., 2013).

The sulphur hexafluoride (SF_6) tracer technique was specifically developed for grazing systems to overcome confinement bias (Zimmerman, 1993). It involves releasing a physiologically inert, non-toxic, and stable tracer gas (SF_6) from a calibrated permeation tube placed in the rumen, where it mixes with rumen gases similarly to CH_4 (Storm et al., 2012). Calibration is performed by measuring daily weight loss of the tube in a 39 °C water bath until the release rate stabilizes (Storm et al., 2012). Once inserted, air near the nostrils is continuously sampled using a lightweight yoke fitted with a halter, collection canister, and capillary tubing to regulate sampling rate (Brouček, 2014; Okpara, 2018; Zimmerman, 1993). Methane emissions are calculated from the CH_4:SF_6 ratio in the collected air, corrected for background concentrations and analysed via gas chromatography (Hammond et al., 2016). Sampling typically spans 24-hour periods over at least five consecutive days to ensure representative estimates (Hammond et al., 2016). While widely used in pasture-based research, SF_6 is labour-intensive, costly, and sensitive to calibration and background corrections, with reported discrepancies compared to RC measurements (Storm et al., 2012). These operational challenges limit its scalability for routine farm use.

Low-cost, non-invasive tools such as laser methane detectors (LMD) provide flexibility for ranking animals or comparing treatments (Sorg, 2021). LMDs measure CH_4 concentration in exhaled air using infrared absorption spectroscopy and can be deployed in barns, parlours, or paddocks (Chagunda, 2013). However, outdoor measurements are highly sensitive to wind, humidity, and animal movement, and the method estimates concentration rather than flux, restricting its use for absolute emission quantification (Patra, 2016; Roessler and Schlecht, 2021). Lack of standardised protocols further constrains reliability (Sorg, 2021). Similarly, sniffer systems integrated into feed bins or milking stations offer frequent, low-cost measurements and show moderate heritability, making them useful for genetic selection (Huhtanen et al., 2015). Yet, accuracy is strongly influenced by head position and airflow, resulting in higher variability than chamber-based techniques (Hammond et al., 2016; Huhtanen et al., 2015).

Other animal-level techniques include face-mask systems, ventilated hood systems, and portable accumulation chambers. Face masks and ventilated hoods operate similarly to RCs but are less expensive and portable, though they remain labour-intensive, disrupt normal behaviour, and exclude flatulence emissions (Bhatta and Enishi, 2007; Goopy et al., 2016). Portable accumulation chambers enable rapid screening of large numbers of grazing animals, but short measurement windows require careful consideration of feeding timing and postprandial CH_4 dynamics (Hammond et al., 2016). At broader spatial scales, micrometeorological approaches such as mass balance, tracer dispersion, and eddy covariance allow estimation of CH_4 emissions from groups of animals or entire paddocks under natural conditions (Harper et al., 2011; Rosenstock et al., 2016). These methods avoid animal handling and confinement but cannot resolve individual variation and require complex instrumentation, modelling, and animal tracking, limiting routine application (Patra, 2016).

Complementary approaches include in vitro incubation techniques for screening feeds and additives, which are cost-effective but unable to replicate the complexity of the rumen ecosystem (Bekele et al., 2022; Storm et al., 2012). Blood-based tracer methods and intraruminal telemetry sensors provide mechanistic insights but remain experimental due to labour demands and sensor durability constraints (Goopy et al., 2016; McSweeney, 2015). Molecular techniques targeting methanogenic activity offer promise as predictive proxies, though links to whole-animal emissions remain under development (Gibbs, 2008). CO_2 tracer approaches estimate CH_4 from CH_4:CO_2 ratios and calculated heat production, offering scalability but lower accuracy than direct flux measurements (Goopy et al., 2016).

Finally, mathematical modelling integrates empirical and mechanistic understanding to estimate CH_4 emissions at animal, herd, and farm scales. Models underpin international frameworks such as IPCC Tiers 1–3 and tools including GLEAM, ADCC, and D-GAF, which are critical for national inventories and policy evaluation (Christie and Dairy Australia, 2024; FAO, 2023b; IPCC, 2006). However, uncertainty remains high due to inter-model variability, reliance on chamber-derived parameters, and poor representation of intake variability under grazing conditions, where CH_4 estimates for the same diet can vary by up to 35% (Goopy et al., 2016; Tomkins et al., 2011). In summary, no single method meets all criteria for accuracy, scalability, and pasture applicability. Key research gaps include limited validation of techniques under extensive grazing, insufficient integration of animal-level and paddock-scale measurements, lack of standardised protocols for low-cost sensors, and over-reliance on confinement-derived data for modelling. There is also a critical need to quantify how diurnal intake variability, pasture heterogeneity, and animal behaviour influence CH_4 estimates. Addressing these gaps will require hybrid frameworks that combine micrometeorological approaches for herd-level fluxes, GF or SF_6 for detailed animal-level data, and locally parameterized models, complemented by low-cost sensors for genetic selection.

2.9. Digital Soil Mapping in Monitoring Soil Organic Carbon

Soils are central to global challenges such as food and water security, climate change mitigation, and biodiversity conservation, making systematic monitoring critical for management, sustainable policy and decision-making (Chen et al., 2022). Consequently, efficient monitoring of SOC is crucial for assessing soil health and guiding land management across spatial scales (Keesstra et al., 2016). Traditional soil surveys, though foundational, cover less than one-third of the globe at scales finer than 1:1 million, rely on outdated data, and lack spatially continuous, updatable information due to declining investment (Rossiter, 2016). This underscores the urgency of robust soil monitoring, especially for quantifying SOC stocks, which store two-thirds of terrestrial C and regulate key ecosystem functions (Wadoux et al., 2023). Digital Soil Mapping (DSM) offers a transformative solution to these limitations (McBratney et al., 2003) integrating legacy data, GIS, geo-statistics, terrain analysis, and remote sensing to generate spatially continuous, high-resolution (e.g., 90 m) predictions of soil properties with quantified uncertainties (Arrouays et al., 2017). Unlike conventional lab analyses restricted to discrete samples, DSM enables scalable, cost-effective mapping from local to national levels (McBratney et al., 2003; Minasny and McBratney, 2016). DSM employs the scorpan- soil spatial prediction function with spatially autocorrelated errors framework, which predicts soil properties as a function of environmental covariates including climate, topography, parent material, age, time, and spatial position (Chen et al., 2022; Grundy et al., 2015). DSM is increasingly used to track SOC dynamics in agriculture, with interest on carbon sequestration offsetting GHG emissions (Feeney et al., 2022). It identifies SOC hotspots and potential loss areas at farm scales, supports nutrient management, and informs policy (Chen et al., 2022; Minasny et al., 2019). However, prediction variability can arise from differences in input data, covariates, and modelling approaches (Lemercier et al., 2022; Rossiter et al., 2021). From 2003 to 2021, DSM research expanded globally, with 244 studies (78%) focused on organic carbon and topsoil (<30 cm), whereas deeper layers (100–200 cm) remain underrepresented (21.7%) (Chen et al., 2022). Despite its advancements, DSM faces significant drawbacks, such as reaching a model skill ceiling without new strategic field data acquisition, leading to limitations in prediction accuracy for national-scale products, and poor performance for properties like coarse fragments and soil depth ($R^2 < 0.28$), with decreasing reliability at deeper soil intervals (Chen et al., 2022; Malone and Searle, 2021). Australia's Soil and Landscape Grid (SLGA) exemplify DSM's national-scale impact. Released in 2015, SLGA delivered Global Soil Map-compliant products at 90 m resolution for 11 soil attributes to 2 m depth, with quantified uncertainties (Grundy et al., 2015). Version 2 (2018–2023) expanded to 24 products including clay, silt, sand, volumetric soil moisture at –33 kPa, volumetric soil moisture at –1.5 MPa, available water capacity, bulk density (whole soil), coarse fragments, total volumetric soil moisture content, proportion of 'rootzone' full, soil organic carbon, soil organic carbon fractions, soil organic fraction densities and stock, soil microbial biodiversity, soil pH (1:5 water), soil pH (1:5 $CaCl_2$), total nitrogen, total phosphorus, available phosphorus, cation exchange capacity, Australian soil classes, soil colour, soil thickness, and regolith depth adding microbial and moisture data to support SOC baseline mapping and climate monitoring (Malone et al., 2025; Wadoux et al., 2023). Enhanced data integration reduced RMSE by 2–3%, enabling volumetric stock estimates and vadose zone analysis (Malone and Searle, 2021). As a free web-based platform under the Australian Soil Resource Information System, SLGA supports ecosystem modelling, policy development, and farm-scale carbon auditing, demonstrating DSM's role in linking global sustainability goals to local action (Grundy et al., 2015; Malone et al., 2017). These products offer an incredible potential for dairy farms to monitor and track SOC trends and the effects of environmental and management factors. However, research is needed to evaluate its potential and accuracy for Australian dairy systems.

2.10. Conclusions

This review demonstrates that ruminant livestock are major contributors to GHG emissions in global livestock systems, with dairy cattle accounting for a notable share and with enteric CH_4 and manure-related CH_4 and N_2O dominating the overall footprint. Productivity and efficiency gains to date have not been sufficient to offset the projected increase in demand for animal protein, indicating continued upward pressure on emissions unless targeted mitigation strategies are implemented. At the same time, the literature shows that much of the available evidence cannot be meaningfully synthesised at global or continental scales, as such aggregation obscures the substantial heterogeneity that exists among countries, production systems, and diets. This limitation is particularly relevant in the Australian context, where applying global generalisations without validation under local conditions risks misinforming policy and practice. Within Australia, the dairy sector contributes a notable share of national emissions, with enteric CH_4 remains the dominant source at farm level, followed by manure CH_4/N_2O, fertiliser-derived N_2O, and energy-related CO_2. Emission intensity varies widely among farms, driven by feed quality, management intensity, herd structure, and input sourcing. A key conclusion from the synthesis is that system labels alone (e.g., "pasture-based" versus "confinement") are insufficient predictors of milk-based emission intensity under Australian conditions; rather, the balance of diet composition, and manure handling practices shapes the emission profile. Consequently, mitigation must be designed and evaluated within Australian systems rather than extrapolated from overseas literature. On sinks, SOC and tree-based sequestration offer complementary buffers but cannot, on their own, deliver large or permanent offsets in intensively grazed, high-rainfall dairy landscapes where soils are often near C saturation and land values constrain large-scale afforestation. Protecting existing stocks, maintaining ground cover, and strategically integrating trees in lower-value areas (e.g., riparian zones, shelter belts) can contribute to resilience and incremental offsets, but durable emission reductions will depend more on practical measures targeting CH_4 and N_2O. Across mitigation options, single interventions rarely suffice. Effective action in dairy systems requires portfolios that combine animal genetics and health, feed and forage management, diet formulation, rumen manipulation, manure treatment, fertiliser strategies, and energy efficiency/renewables. Importantly, mitigation choices must consider whole-farm leakage: for example, lowering enteric CH_4 through concentrate supplementation may increase upstream CO_2 in feed production or shift N losses through manure. Technologies such as 3-NOP and "*Asparagopsis*" seaweed show strong CH_4 abatement in controlled or confined settings, yet dosing, costs, and performance under grazing conditions remain critical constraints that require Australian validation. Measurement is foundational to credible mitigation. Gold-standard respiration chambers provide precision for controlled trials but lack scalability and external validity for pasture-based systems. Field-deployable tools (e.g., GreenFeed hoods, LMD, "sniffers") vary in accuracy, cost, and practicality; none alone fully meets the need for affordable, scalable, and accurate measurement under extensive grazing. A hybrid measurement modelling framework combining paddock- or herd-level flux measurements, low-cost sensor, and locally parameterized mechanistic/empirical models can offer a pragmatic pathway to robust farm inventories and evaluation of interventions at scale. Finally, DSM products provide high-resolution SOC baselines and related attributes with quantified uncertainty, enabling monitoring of soil status alongside emission mitigation. However, accuracy declines at depth and validation in intensively grazed dairy systems is limited. Integrating DSM with targeted field sampling can support credible C accounting, while ensuring that SOC strategies complement, rather than substitute for, direct CH_4/N_2O abatement. Taken together, the evidence supports a thesis focus on Australian-validated, system-specific mitigation portfolios; hybrid measurement strategies aligned to pasture realities; and whole-farm analyses that quantify trade-offs and leakage across emission sources and embedded supply chains.

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Chapter 3. Greenhouse Gas Emissions of Confinement and Pasture-Based Dairy Farms: Implications for Mitigation

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Overview

This chapter compares GHG emissions from confinement and pasture-based dairy farms in Australia using a life cycle assessment approach. Emissions were estimated with the Australian Dairy Carbon Calculator, accounting for both direct sources and carbon sequestration by trees. Results indicated similar environmental footprint of each unit of fat and protein corrected milk (1.02 ± 0.038 and 1.07 ± 0.069 kg CO_2-eq/kg FPCM for confinement and pasture-based systems, respectively). Enteric CH_4 was the dominant source, contributing 54% of total emissions in confinement systems and 58% in pasture-based systems. Secondary sources differed between systems: manure accounted for 31% and 13%, whereas pre-farm embedded emissions comprised 8 and 14%, and direct on-farm fertiliser use contributed 2 and 7% in in confinement and pasture-based systems, respectively. Notably, pasture systems benefited from up to 6% carbon offsets through tree sequestration, compared with only 1% in confinement systems. These results emphasize system-specific mitigation priorities: improving manure management in confinement farms, optimizing fertiliser use and supply chains in pasture systems, and targeting enteric CH_4 reductions across both systems to advance toward net-zero goals.

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Greenhouse gas emissions of confinement and pasture-based dairy farms: Implications for mitigation

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ABSTRACT

Despite extensive research on the environmental effects of dairy farming, comparative GHG emissions from confinement and pasture-based systems remain unclear due to inconsistent findings from prior studies, which were often specific to the local conditions of each system and overlooked carbon sequestration by trees. The present study aimed to compare the GHG emissions of 2 Australian milk production systems (confinement and pasture-based) using a life cycle assessment approach that incorporates C sequestration by trees. The confinement system used a TMR, whereas the grass-based system primarily relied on grazed forage with concentrate supplementation. The Australian Dairy Carbon Calculator, a Tier 3 tool, predicted emission intensity using the National Greenhouse Gas Inventory and Intergovernmental Panel on Climate Change methods, as reported to the United Nations Framework Convention on Climate Change. Emission intensity was calculated as net GHG exchange in CO_2 equivalents (CO_{2eq}), allocated to milk and meat. Animal emissions dominated: 85% of total emissions in confinement systems (54% enteric CH_4, 31% manure) and 71% in pasture-based systems (58% enteric CH_4, 13% manure). The confinement system showed 13% lower enteric CH_4 intensity and 88% lower prefarm embedded intensity (kg CO_{2eq}/kg fat- and protein-corrected milk [FPCM]) but 129% higher manure-related GHG intensity than the pasture-based system. Emission intensities for milk (1.02 ± 0.038 vs. 1.07 ± 0.069 kg CO_{2eq}/kg FPCM) and meat (5.51 ± 0.779 vs. 6.76 ± 0.868 kg CO_{2eq}/kg liveweight) were similar between systems. The emission offset by tree C sequestration (kg CO_{2eq}/kg FPCM) was relatively low in both systems, contributing about 1% of total CO_{2eq} emissions in confinement systems and up to 6% in pasture-based systems. Targeted mitigation should address manure emissions in confinement systems, prefarm embedded, and fertilizer emissions in pasture-based systems, and enteric CH_4 in both.

Key words: dairy, manure, methane, milk yield

INTRODUCTION

The livestock sector faces the dual challenge of increasing productivity while reducing GHG emissions and adapting to a changing climate (Gerber et al., 2013). Livestock currently contributes 34% of global protein intake and 17% of calorie consumption, with demand continuing to rise due to population growth, urbanization, and increasing incomes (FAO, 2022). Dairy products alone contribute 11% of global protein and 5% of calorie intake (FAO, 2022). However, livestock is responsible for 14.5% of global anthropogenic GHG emissions, with ruminants accounting for 75% of these (IPCC, 2019). Dairy farming plays a substantial role in these emissions, contributing 4.0% of global GHG emissions (2.7% from milk production and 1.3% from meat from dairy cattle), accounting for 20% of total global livestock emissions (Gerber et al., 2013). In Australia, the dairy sector contributes 2% of total national and 14% of agricultural emissions (Australian Government, 2023). Addressing the effect of livestock production on climate change is urgent because rising temperatures, variable precipitation, and increased CO_2 concentration negatively affect livestock performance and feed supply (FAO, 2019). In addition, the global demand for both animal- and plant-based foods is projected to double by 2050 (FAO and GDP, 2018; Enahoro et al., 2021; van Dijk et al., 2021) and sustainable intensification of food production may be required (Muscat et al., 2021).

In dairy farming, confinement is one form of intensification, but one key debate concerns its environmental effect compared with pasture-based systems. Confinement systems, which include any type of contained housing such as freestall, loose housing, compost barns, and dairy dry lots (Dairy Australia, 2024), are often considered more efficient in terms of emissions per unit of output due to improved feed conversion and animal productivity

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The list of standard abbreviations for JDS is available at adsa.org/jds-abbreviations-25. Nonstandard abbreviations are available in the Notes.

(Gerber et al., 2011). However, concerns arise regarding feed production or off-farm feed purchases and energy consumption, and competition for arable land that could otherwise be used for grain production for human consumption (Van Zanten et al., 2018). In contrast, pasture-based systems are often perceived as more environmentally friendly, as they typically rely on land unsuitable for arable crops, although this view overlooks the potential for such land to support biodiversity or C sequestration (Wuepper et al., 2020).

Extensive research has been conducted globally on the environmental effects of dairy farming. However, due to the inconsistent results, there remains a lack of clear evidence regarding the comparative sources of GHG in pasture-based and confinement systems. For instance, Flysjö et al. (2011), Belflower et al. (2012), and O'Brien et al. (2014), reported that grass-based and confinement dairy systems have similar C footprints per ton of ECM if grassland C sequestration is not considered. However, O'Brien et al. (2014) and Belflower et al. (2012) found that grass-based systems showed 5% and 14% lower C footprints, respectively, when grassland C sequestration was included compared with confinement systems. Conversely, other authors argue that intensive dairy systems have lower GHG emissions per unit of milk produced due to better feed efficiency and higher productivity (Capper et al., 2009; Gerber et al., 2011, 2013). Although extensive research has been conducted internationally, much of it focused on production systems where most of the feed is sourced off-farm, as is common in confinement systems. In contrast, production systems that rely primarily on feed produced on-farm, such as those prevalent in Australia, remain underexplored in terms of the environmental implications, highlighting the need for further investigation to address this knowledge gap. Notably, previous studies (Flysjö et al., 2011; Belflower et al., 2012; O'Brien et al., 2014) have overlooked the potential role of trees on C sequestration to mitigate dairy farm GHG emissions. Therefore, the present study aimed to address this gap comparing GHG emissions from confinement and pasture-based dairy farms and identifying key emission sources within systems using the Australian Dairy Carbon Calculator (Christie-Whitehead and Dairy Australia, 2024). The findings provide valuable insights for producers, industry organizations, policymakers, and businesses seeking to balance productivity with environmental sustainability in the dairy sector.

MATERIALS AND METHODS

Data

Data were collected from 10 commercial dairy farms (5 pasture-based and 5 confinement) in New South Wales (**NSW**), Australia, during the 2022 to 2023 fiscal year. The farms represented the diversity of the industry in terms of milk production, milking herd size, farm input usage, and production system but not ecological region or weather. The selection process involved identifying farms that were representative of typical management practices within each system (pasture-based and confinement) in NSW, ensuring a balanced sample for comparative analysis. Given the limited sample size of 5 farms per system, this study represents a focused exploratory approach, and caution should be exercised when generalizing findings beyond the specific contexts of these farms. Ethical approval was not required for this study as it was based on farm data collection without direct animal experimentation.

Farm Characteristics

The study comprised 2 dairy production systems (confinement and pasture-based) with Holstein-Friesian, Jersey, and Holstein-Jersey crossbreeds. However, 1 confinement farm exclusively raised Jersey. Confinement farms mainly produced wheat (*Triticum aestivum*) and corn (*Zea mays*) as the major crops for silage, grain, and green feeding, with lucerne (*Medicago sativa*) and vetch (*Vicia sativa*) also grown for hay and silage. Confinement farms primarily fed cows a TMR, with some farms allowing grazing for nonlactating animals, while 1 farm practiced zero-grazing, keeping the entire herd fully confined. The dominant pasture species in the grazing system included Kikuyu grass (*Cenchrus clandestinus*), ryegrass (*Lolium multiflorum* L.), and legumes, such as clover species (*Trifolium* spp.). The TMR was formulated from silage, hay, straw, concentrate, and minerals in varying proportions. Concentrates were made from grains, such as barley (*Hordeum vulgare*) and wheat, supplemented with protein-rich ingredients, such as canola (*Brassica napus*) meal, lupin (*Lupinus* spp.) seed, and cotton (*Gossypium* spp.) seed. Silage was primarily derived from corn, lucerne, and vetch. Hay consisted of vetch, lucerne, and oats (*Avena sativa*). Cereal straw came from wheat, barley, and oats. Some farms also incorporated almond (*Prunus amygdalus*) husk into the TMR. To balance the diet and provide essential nutrients, minerals, such as lime, magnesium sulfate, copper, and selenium, and vitamin-mineral premixes were added to the TMR in most farms.

Lactating and dry cows, along with heifers, grazed year-round in the pasture-based system. The pasture was divided into irrigated sections (utilizing center-pivot units, travelers, and solid-set guns) and nonirrigated systems, further subdivided into individual paddocks using high-tensile electric fences. For the pasture-based farming systems, the percentage of area under irrigation ranged from 13% to 92%, with a mean of 61%. In contrast, the confinement farming systems had a higher percentage of irrigated areas, ranging from 67% to 98%, with a mean of 84%. The pastures contained a variety of grass and legume species, including Kikuyu grass, annual ryegrass, oats, Bermuda grass (*Cynodon dactylon*), Setaria (*Setaria* spp.), fescue (*Festuca arundinacea* L.), clover (*Trifolium* spp.), lucerne, Rhodes grass (*Chloris gayana*), prairie grass (*Bromus wildenowii*), chicory (*Cichorium intybus* L.), and Paspalum (*Paspalum* spp.). In this system, cows were also fed silage and hay. The silage was primarily made from forage crops, such as ryegrass, Kikuyu, millet (*Pennisetum glaucum*), sorghum (*Sorghum sudanense*), soybean (*Glycine max*), and corn, whereas hay consisted of a mix of legumes and grasses, including lucerne, vetch, oats, Kikuyu, and ryegrass. Additionally, pellets formulated from blended grains, byproducts, and protein supplements, provided a consistent source of energy and protein. Minerals, including calcium, phosphorus, and magnesium, were incorporated into the pellets or added to the concentrate. Cows received grain during milking, consisting mainly of corn, wheat, barley, and Triticale (*Triticosecale*), supplemented with canola meal, minerals, and pellets, with average daily concentrate intake varying from 4.30 to 7.80 kg/cow day among the farms.

Feed Nutritional Content

The nutritional quality of feed for the milking cow herd is presented in Table 1. Feed nutritional analysis was conducted using wet chemistry (Dumas, AOAC 990.03; AOAC International, 2000). The results were averaged based on the proportion of each ingredient in the diet to represent the nutritional content of various feed categories. For instance, feeds classified as concentrates, such as grains and grain byproducts, were averaged according to their proportion in the diet to determine the nutritional value of concentrates. Feed samples for concentrate, hay, minerals, and silage were collected 1 time per farm during the 2022 to 2023 fiscal year. Pasture samples were collected and analyzed monthly, with results averaged to account for seasonal variations.

Functional Unit and Global Warming Potential

The global warming potential for 100 years horizon (**GWP100**) index was used to assess the contribution of different gases to total GHG emissions. According to the Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC, 2019), the GWP100 characterization factors are 1 for carbon dioxide (CO_2), 28 for methane (CH_4), and 265 for nitrous oxide (N_2O). All areas used for dairy-related activities, including the milking platform and support areas, and runoff areas for raising

Table 1. Nutritional content of feeds (mean ± SD; % DM) used on commercial dairy farms to estimate GHG emissions

	Confinement						Pasture-based				
Nutrient[1]	Concentrate	Silage	Hay	Cereal straw	Almond husk	TMR	Concentrate	Silage	Hay	Pasture	Pellet
NDF	39.7 ± 7.437	42.3 ± 6.834	53.0 ± 5.663	74.4 ± 0.460	31.8 ± 0.884	35.7 ± 4.080	23.7 ± 6.543	56.4 ± 9.160	46.8 ± 8.620	52.5 ± 2.456	23.1 ± 7.354
ADF	26.1 ± 3.958	27.8 ± 4.944	32.9 ± 3.865	45.0 ± 0.134	22.1 ± 0.915	20.6 ± 2.232	10.1 ± 5.911	30.7 ± 5.299	31.5 ± 4.649	24.5 ± 1.108	10.2 ± 6.364
CP	22.6 ± 11.52	16.4 ± 2.862	16.5 ± 4.397	5.80 ± 1.556	5.13 ± 0.351	17.0 ± 0.908	16.4 ± 9.810	13.8 ± 6.836	16.3 ± 6.806	23.0 ± 1.724	17.1 ± 4.009
WSC	6.23 ± 3.285	2.74 ± 1.734	8.57 ± 8.631	2.75 ± 2.192	24.6 ± 0.252	4.46 ± 0.673	5.39 ± 1.999	4.38 ± 2.354	9.40 ± 7.568	7.60 ± 2.150	4.5 ± 0.919
DMD	80.1 ± 11.17	63.6 ± 8.928	66.5 ± 5.089	40.8 ± 2.475	60.0 ± 3.430	74.7 ± 3.969	82.9 ± 8.134	67.0 ± 8.962	60.4 ± 4.771	72.0 ± 2.391	84.0 ± 7.787
DOMD	67.9 ± 9.098	60.6 ± 8.435	61.1 ± 1.041	40.4 ± 3.394	59.8 ± 3.315	70.0 ± 3.795	81.8 ± 7.816	58.9 ± 7.030	58.0 ± 4.060	67.7 ± 2.007	79.5 ± 6.647
Ash	5.73 ± 2.117	11.6 ± 6.019	12.9 ± 8.058	11.9 ± 1.344	10.3 ± 4.139	8.71 ± 0.483	5.40 ± 5.243	12.1 ± 2.641	9.35 ± 1.066	10.8 ± 1.196	7.55 ± 0.354
OM	94.3 ± 2.117	88.4 ± 6.019	87.1 ± 8.058	88.2 ± 1.344	89.7 ± 4.139	91.3 ± 0.483	94.6 ± 5.243	87.9 ± 2.641	90.6 ± 1.066	89.1 ± 1.281	92.4 ± 0.354
ME	13.2 ± 1.300	9.70 ± 1.349	9.40 ± 0.265	5.00 ± 0.990	9.70 ± 0.346	11.9 ± 0.596	12.9 ± 1.023	9.42 ± 1.113	8.78 ± 0.854	10.7 ± 0.410	12.3 ± 0.919
EE	10.3 ± 8.436	2.98 ± 0.901	1.83 ± 0.757	0.90 ± 0.424	2.20 ± 0.557	5.14 ± 0.577	2.60 ± 1.149	2.88 ± 0.742	—	—	1.80 ± 0.000

[1] DMD = DM digestibility; DOMD = digestible OM in DM; EE = ether extract; WSC = water soluble carbohydrate; all units are in %, except for ME, which is in MJ/kg DM.

replacement stock and growing pastures and crops for forage conservation or grain production, were included in the total farm usable area. The milking platform is the portion of the farm's land specifically dedicated to supporting the milking herd. The present study reports GHG emissions in CO_2 equivalents (**CO_{2eq}**) per kilogram of liveweight for meat at the farm gate. The percentage contribution of each animal class to total farm GHG emissions was based on their enteric CH_4, manure CH_4, and N_2O. Fat- and protein-corrected milk (**FPCM**) was calculated according to the formula provided by Seventer and Jong (2008), as follows:

$$\text{FPCM (kg)} = \text{M (kg)} \times (0.337 + 0.116 \times \text{fat content [\%]} + 0.06 \times \text{protein content [\%]}),$$

where M is the raw milk mass (kg), calculated as milk volume (L) × 1.03.

Australian Dairy Carbon Calculator

The Australian Dairy Carbon Calculator (**ADCC**) version 5.2 (https://www.dairyaustralia.com.au/climate-and-environment/greenhouse-gas-emissions/australian-dairy-carbon-calculator) was employed to estimate GHG emissions. The ADCC was constructed in Microsoft Excel and consists of 10 user forms and 19 worksheets. These worksheets include algorithms, emission factors, and methodologies to calculate CO_2 emissions from embedded prefarm inputs, as well as on-farm CH_4, N_2O, and CO_2 emissions. The sources of GHG emissions considered in the present study were CO_2 from electricity (scopes 2 and 3), diesel (scopes 1 and 3), urea and lime (scope 1), prefarm gate embedded sources (scope 3: purchased grain, concentrate, forages, and fertilizers), CH_4 from enteric fermentation and manure (scope 1), and N_2O (scope 1) from direct emissions from dung and urine voided onto pastures, direct emissions from manure (storage and spreading), indirect N waste, and direct and indirect N_2O from fertilizers. Indirect N_2O emissions result from N in urine, dung, effluent, or N-based fertilizers being lost to the environment, redeposited onto soils or watercourses, and subsequently transformed into N_2O through nitrification and denitrification. The ADCC calculated enteric CH_4 and manure N_2O and CH_4 for each farm using required data on livestock (number and weight of animals), average lactation length in days, milk production, milk composition (milk fat and protein content in percentage), and feed DM digestibility and CP. Manure CH_4 and N_2O emissions were calculated based on the proportion of time (d/yr) animals spent grazing versus in confinement yards, accounting for systems with both grazing growing stock and confined milking cows. All input data for the ADCC were collected directly from the farms. Carbon sequestration by trees was accounted for as a sink based on the local environmental conditions, tree species, age, and tree area recorded for each farm using the ADCC method. The annual C sequestered by trees was then subtracted from the total gross GHG emissions to calculate the net farm emissions. Only woody vegetation in permanent or semipermanent tree areas was included in the estimation. The major tree species grown by the farms included honey locust (*Gleditsia triacanthos*), sweet osmanthus (*Osmanthus fragrans*), eucalyptus (*Eucalyptus* spp.), blackwood (*Acacia melanoxylon*), and Australian silky oak (*Grevillea robusta*). Dry matter intake was calculated by the ADCC using a series of algorithms and methodologies from the Australian Agricultural Council (1990). All prediction equations used to estimate DMI, enteric CH_4, and manure N_2O and CH_4 are provided as supplemental files (see Notes) and can also be found in our previous publication (Dida et al., 2024).

System Boundary

On- and off-farm GHG sources associated with dairy production, from production inputs to the point where milk is sold from the farm, were estimated in kilogram of CO_{2eq}. In the ADCC, emissions were allocated between milk and meat production based on their respective energy demand proportions (Christie-Whitehead and Dairy Australia, 2024). Emissions from electricity and prefarm embedded emissions (from concentrates) were solely attributed to milk, whereas emissions from other livestock (<1 yr of age) were fully attributed to meat production. For shared emissions, such as those from the milking herd, replacement heifers, and general farm activities, the allocation was based on the proportion of total energy requirements for milk and meat production. Greenhouse gas emissions from housing construction, cleaning agents, antibiotics, and pharmaceuticals are excluded due to their minimal contribution, typically less than 5% of total farm emissions (Gerber et al., 2011; Rotz and Thoma, 2017).

Statistical Analysis

The ADCC was run for each of the 10 farms mentioned previously, and the output estimates were then exported and consolidated for all farms, along with the input data, for statistical analysis. Feed ingredient proportions and DMI results apply to the milking herd only, whereas emission intensities per unit of milk, land area, and cow were based on total farm emissions. Enteric and manure emissions per cow were calculated by dividing total emissions from all herd compositions by the number of milking cows, reflecting total farm emissions per milking cow. Before analysis, the normality of the data distribution was assessed using the Shapiro–Wilk test. A *t*-test was used to compare GHG emissions, milk production, and feed intake between confinement and pasture-based production systems. Untransformed data were analyzed for normally distributed variables. Results are reported as mean ± SE for each production system, along with the *P*-value from the *t*-test. All statistical analyses were performed using R software, version 4.4.2 (R Core Team, 2020).

RESULTS

Farm Area, Herd Size, and Production Metrics of Farms

The farm area, herd size, and production performance metrics of the farms are presented in Tables 2 and 3. For the total per-farm values, *P*-values were included for descriptive reference only, as they are not based on standardized or directly comparable metrics. The average total usable area was 72% larger ($P = 0.044$), and the milking platform area was 90% smaller ($P = 0.002$) on confinement than pasture-based farms (Table 2). The irrigated farm area ($P = 0.025$), support area ($P = 0.033$), sulfur fertilizer rate (t/ha per year; $P = 0.012$), and diesel use per total usable area (L/ha per year; $P = 0.005$) were larger on confinement farms. However, there were no significant differences ($P > 0.05$) in nonirrigated farm area, tree area, electricity uses per total usable area (kWh/ha per year), diesel consumption per hectare, nitrogen, phosphorus, potassium fertilizer rates (t/ha per year), or feed inputs (Table 2). The number of milking cows ($P = 0.018$), milk solids (kg/cow per year; $P = 0.002$), and 2-yr-old replacement heifers ($P = 0.042$) was also larger in the confinement farms (Table 3). Furthermore, calves from confinement farms were sold heavier at sale ($P = 0.007$), and the proportion of silage in the milking herd's diet was also higher ($P = 0.004$) in confinement compared with the pasture-based farms. In contrast, there were no differences ($P > 0.05$) in the milking herd liveweight, lactation length, number of

Table 2. Key farm input for confinement and pasture-based dairy production systems used to estimate GHG emissions[1]

Key farm input	Pasture-based	Confinement	*P*-value
Total usable area (ha)	233 ± 47.32	609 ± 150.5	0.044
Milking platform area (ha)	98.2 ± 19.28	10.0 ± 1.715	0.002
Farm area – irrigated (ha)	115 ± 21.97	370 ± 90.56	0.025
Farm area – nonirrigated (ha)	118 ± 46.27	239 ± 118.2	0.368
Support area (ha)	133 ± 30.40	602 ± 149.2	0.033
Tree area (ha)	11.9 ± 3.896	18.9 ± 8.536	0.485
Tree area (% usable area)	6.08 ± 0.283	2.77 ± 0.058	0.246
Electricity use (thousands of kWh/yr)	150 ± 30.08	287 ± 115.09	0.308
Electricity use (kWh/ha/yr)	693 ± 224.3	561 ± 116.9	0.117
Diesel use (thousands of L/yr)	31.8 ± 6.650	236 ± 132.0	0.199
Diesel use (L/ha/yr)	165 ± 50.41	447 ± 239.9	0.005
Nitrogen fertilizer (t/yr)	41.1 ± 2.452	45.5 ± 17.16	0.815
Nitrogen fertilizer rate (t/ha/yr)	0.21 ± 0.037	0.09 ± 0.032	0.051
Phosphorus fertilizer (t/yr)	9.14 ± 3.357	6.66 ± 2.916	0.592
Phosphorus fertilizer rate (t/ha/yr)	0.05 ± 0.021	0.02 ± 0.009	0.234
Potassium fertilizer (t/yr)	6.17 ± 3.002	0.44 ± 0.392	0.129
Potassium fertilizer rate (t/ha/yr)	0.03 ± 0.016	0.001 ± 0.0007	0.139
Sulfur fertilizer (t/yr)	2.81 ± 0.508	1.12 ± 0.734	0.099
Sulfur fertilizer rate (t/ha/yr)	0.01 ± 0.003	0.003 ± 0.0018	0.012
Lime fertilizer (t/yr)	11.0 ± 7.404	26.5 ± 10.10	0.282
Lime fertilizer rate (t/ha/yr)	0.05 ± 0.038	0.08 ± 0.037	0.629
Purchased concentrates (t DM/yr)	763 ± 91.34	5,455 ± 2,863	0.177
Home-grown concentrates (t DM/yr)	19.3 ± 15.12	396 ± 396.0	0.396
Home-grown concentrates (t DM/ha/yr)	0.11 ± 0.078	0.65 ± 0.396	0.511
Purchased silage (t DM/yr)	21.2 ± 8.692	70.0 ± 70.00	0.526
Home-grown silage (t DM/yr)	443 ± 150.7	8,039 ± 3,302	0.083
Home-grown silage (t DM/ha/yr)	2.03 ± 0.505	15.2 ± 6.198	0.100
Purchased hay (t DM/yr)	195 ± 75.69	1,254 ± 863.4	0.288
Home-grown hay (t DM/yr)	61.4 ± 49.07	189 ± 156.4	0.473
Home-grown hay (t DM/ha/yr)	0.20 ± 0.124	0.30 ± 0.184	0.679
Purchased other feeds (t DM/yr)	108 ± 50.54	2,948 ± 2021	0.233

[1] All reported land areas (milking platform, irrigated and nonirrigated farm areas, support area, and tree area) are components of the total usable area. The fertilizers (N, P, K, S, and lime) and home-grown feed (concentrate, hay, and silage) values presented per hectare may not reflect the true values because they were calculated by simply dividing the total amounts by the total usable area; therefore, the results should be interpreted with caution. Values are given as mean ± SE.

Table 3. Key herd structure and inputs of confinement and pasture-based dairy production systems used to estimate GHG emissions[1]

Herd size and input[2]	Pasture-based	Confinement	*P*-value
Milking herd size (number of cows)	335 ± 13.56	1,073 ± 247.2	0.018
Milking herd average liveweight (kg)	568 ± 13.56	627 ± 37.27	0.197
Lactation length (d)	304 ± 8.718	322 ± 10.07	0.214
Milk solids (kg/cow/yr)	472 ± 41.73	876 ± 70.62	0.002
Number of cows sold per year	43.0 ± 10.57	155 ± 71.82	0.160
Liveweight of cow at point of sale (kg)	578 ± 21.07	675 ± 165.5	0.330
Herd size of 1-yr-old replacement heifers	107 ± 12.83	708 ± 263.8	0.052
1-yr-old replacement heifers sold	1.00 ± 0.400	17.0 ± 17.00	0.491
Herd size of 2-yr-old replacement heifers	103 ± 16.23	602 ± 205.0	0.042
2-yr-old replacement heifers sold	1.00 ± 0.400	8.00 ± 8.000	0.396
Mature bull's herd size	2.00 ± 0.748	36.0 ± 34.96	0.351
Number of mature bulls sold	2.00 ± 0.400	19.0 ± 18.80	0.412
Other stock <1 yr of age	33.0 ± 24.26	123 ± 60.37	0.201
Other stock, <1 yr of age, sold	0.00	42.0 ± 42.00	—
Other stock >1 yr of age	1.00 ± 0.200	88.0 ± 50.56	0.121
Other stock, >1 yr of age, sold	6.00 ± 6.00	55.0 ± 55.00	0.425
Number of calves sold per year	152 ± 50.02	225 ± 67.40	0.195
Liveweight of calves at point of sale (kg)	45.5 ± 0.289	50.0 ± 0.577	0.007
Stocking rate (cows/ha)	1.67 ± 0.281	2.13 ± 0.505	0.457
Concentrate (% of DMI, milking herd)	32.5 ± 2.704	38.6 ± 3.702	0.219
Silage (% of DMI, milking herd)	19.2 ± 5.574	44.5 ± 2.867	0.004
Hay (% of DMI, milking herd)	8.72 ± 1.352	6.44 ± 2.525	0.448
Pasture (% of DMI, milking herd)	35.1 ± 6.159	0.00	—
DMD of the milking herd diet (g/kg DM)	719 ± 1.684	747 ± 1.120	0.654
CP of the milking herd diet (g/kg DM)	171 ± 1.173	189 ± 0.941	0.281

[1] The stocking rate is calculated based solely on the milking herd size. Values are given as mean ± SE.

[2] DMD = DM digestibility; other stock <1 yr age = young bulls, steers, and nonreplacement heifers that are 0 to 1 yr of age; other stock >1 yr age = replacement bulls, and for steers and nonreplacement heifers that are 1 to 2 yr of age.

cows sold, 1-yr-old replacement heifers, other stock and mature bull herd size, stocking rate, dietary components, and other production-related metrics.

DMI, Milk Yield, and Composition

Estimated DMI, milk yield, and composition of the pasture-based and confinement systems are shown in Table 4. Predicted total DMI ($P = 0.013$), concentrate ($P = 0.024$), and silage ($P = 0.002$) were higher in the confinement than in the pasture-based system, while the intake of hay and other feed types was similar ($P > 0.05$). Greater milk yield ($P = 0.014$) resulted in >70% greater FPCM ($P = 0.007$), and milk fat, protein, and milk solids yield per cow ($P = 0.006$) on confinement compared with pasture-based farms. However, there was no difference in milk fat and protein concentration between production systems ($P > 0.05$). Confinement farms also showed 23% higher ($P = 0.029$) milk yield per unit of DMI (kg FPCM/kg DMI) and a substantial 140% increase in milk yield per hectare of total usable area.

Farm GHG Emissions and Emissions Sources

Net total farm emissions were higher ($P = 0.017$) in the confinement than in the pasture-based system (Table 5). However, C sequestered by trees and the proportion of net emissions allocated to milk and meat were similar ($P > 0.05$) in both systems. Carbon sequestration by trees was consistent with similar tree areas leading to no differences between production systems ($P > 0.05$). The current tree coverage offsets ~4.5% of GHG emissions in the pasture-based system and about 0.8% in the confinement system.

Enteric fermentation was the most important source of CO_{2eq} in both production systems, accounting for more than half of the total GHG emissions. Total CH_4 emissions were higher in the confinement system ($P = 0.003$), driven by higher manure CH_4 emissions ($P = 0.002$), whereas enteric CH_4 emissions were higher in the pasture-based system ($P = 0.013$). The next 2 largest sources differed between systems, with emissions from manure (CH_4 and N_2O) accounting for 31% in confinement, followed by prefarm embedded emissions. Comparatively, pasture-based systems had prefarm embedded emissions as the second largest source, followed by manure emissions. The proportion of total emissions from fertilizer, urea, and lime in the present study was ~5-fold greater in pasture-based compared with confinement systems ($P = 0.001$). Emissions from energy (electricity and fuel) constituted the fourth largest source of GHG emissions in both production systems. Confinement farms had a

Table 4. Effects of dairy production system on milk production and composition and predicted DMI of milking cows

Parameter[1]	Pasture-based	Confinement	*P*-value
Predicted feed intake, kg DM/cow per day			
Total DMI	18.0 ± 0.650	25.4 ± 1.837	0.013
Pasture	6.22 ± 1.049	0.00	—
Concentrate	5.88 ± 0.626	9.85 ± 1.173	0.024
Silage	3.54 ± 1.163	11.4 ± 1.313	0.002
Hay	1.58 ± 0.258	1.54 ± 0.537	0.944
Others	0.78 ± 0.399	2.59 ± 1.135	0.193
Milk yield			
Milk (L/cow per day)	21.6 ± 1.814	36.6 ± 3.840	0.014
FPCM yield (kg/cow per day)	22.1 ± 1.992	38.1 ± 3.553	0.007
Milk fat (kg/cow per day)	0.85 ± 0.082	1.48 ± 0.137	0.006
Milk protein (kg/cow per day)	0.71 ± 0.067	1.25 ± 0.116	0.006
Milk solids (kg/cow per day)	1.56 ± 0.146	2.73 ± 0.249	0.006
Milk constituents, g/kg milk			
Milk fat	3.92 ± 0.136	4.10 ± 0.259	0.560
Milk protein	3.27 ± 0.064	3.45 ± 0.106	0.198
Milk production efficiency			
FPCM/DMI (kg/kg)	1.22 ± 0.080	1.50 ± 0.065	0.029
Milk yield per usable area (t FPCM/ha)	10.6 ± 1.269	25.4 ± 6.766	0.094

[1] Values are given as mean ± SE. FPCM = fat and protein-corrected milk; others feed = minerals, byproducts.

Table 5. Total farm GHG emissions, with a breakdown by source, the contribution of herd composition to total GHG emissions, and the proportion allocated to meat and milk

Parameter[1,2]	Pasture-based	Confinement	*P*-value
Net total farm emissions (t CO_{2eq}/yr)	2,591 ± 200.78	15,218 ± 4,221	0.017
Carbon sequestered by trees (t CO_{2eq}/yr)	117 ± 39.29	128 ± 29.10	0.819
Net emissions allocated to milk (%)	91.2 ± 1.158	92.2 ± 1.020	0.535
Net emissions allocated to meat (%)	8.80 ± 1.158	7.80 ± 1.020	0.535
Breakdown by source, % of total CO_{2eq}			
Total CH_4 (manure plus enteric CH_4)	62.2 ± 0.735	74.2 ± 2.035	0.003
Enteric CH_4	58.2 ± 1.020	53.6 ± 1.030	0.013
Manure CH_4	4.00 ± 1.517	20.6 ± 2.874	0.002
Total N_2O from manure management	9.20 ± 0.730	10.4 ± 0.678	0.002
Direct N_2O from urine and feces voided to pasture	4.00 ± 0.601	0.90 ± 0.270	0.004
Direct N_2O from manure storage	1.40 ± 1.158	6.30 ± 1.068	<0.001
Indirect N_2O animal waste	3.80 ± 0.374	3.20 ± 0.200	0.206
Total manure (N_2O + CH_4) emissions	13.2 ± 1.241	31.0 ± 2.966	0.002
Total N_2O N fertilizer (on-farm)	4.60 ± 0.400	1.20 ± 0.490	<0.001
Direct N_2O N fertilizer	2.40 ± 0.245	0.60 ± 0.245	<0.001
Indirect N_2O N fertilizer	2.20 ± 0.200	0.60 ± 0.245	0.001
CO_2			
Urea and lime from the soil	2.20 ± 0.200	0.60 ± 0.245	0.001
Energy consumption	8.20 ± 1.158	5.20 ± 1.068	0.093
Diesel	3.52 ± 0.678	3.54 ± 0.690	0.987
Electricity	4.69 ± 0.763	1.51 ± 0.550	0.006
Prefarm embedded	13.6 ± 0.510	8.40 ± 1.503	0.023
Concentrate	5.50 ± 0.576	4.09 ± 1.017	0.273
Forage	1.55 ± 0.496	2.89 ± 2.036	0.554
Fertilizers	6.56 ± 0.709	1.42 ± 0.581	<0.001
Breakdown by herd composition, % of total CO_{2eq}			
Milking cows	58.8 ± 1.393	68.0 ± 2.950	0.032
Heifers >1 yr age	7.60 ± 1.503	9.20 ± 1.158	0.425
Heifers <1 yr age	3.40 ± 0.400	4.40 ± 0.600	0.208
Mature bulls	0.15 ± 0.076	0.61 ± 0.597	0.488
Other stock <1 yr age	0.80 ± 0.583	0.80 ± 0.374	1.00
Other stock >1 yr age	0.01 ± 0.010	1.80 ± 0.800	0.889
Total emissions from the animals	71.4 ± 1.030	84.6 ± 2.293	0.002
On-farm emissions (%)	86.4 ± 0.510	91.6 ± 1.503	0.023

[1] The percentage contribution of each animal class to total farm GHG emissions is calculated as the sum of their enteric CH_4, manure CH_4, and N_2O emissions. Values are given as mean ± SE.

[2] CO_2 emissions from energy consumption = CO_2 emissions from diesel and electricity; CO_2 emissions from prefarm embedded sources = CO_2 emissions from concentrate, forage, and fertilizers; CO_{2eq} = CO_2 equivalents; total N_2O from manure management = direct N_2O + indirect N_2O from manure management; total N_2O from N fertilizer (on-farm) = direct N_2O + indirect N_2O from N fertilizer (on-farm).

lower ($P = 0.023$) proportion of the total emissions associated with pre-embedded emissions despite higher concentrate and silage use. On-farm activities accounted for a higher ($P = 0.023$) proportion of total emissions in the confinement compared with the pasture-based system. Milking cows contributed more significantly ($P = 0.032$) to total farm emissions in the confinement than in the pasture-based system (Table 5). Other yearling stock and stock over 1 yr showed similar ($P > 0.05$) contributions to total GHG emissions in both systems. The total contribution from animals through enteric CH_4 and direct manure emissions to total farm emissions was greater ($P = 0.002$) in the confinement compared with the pasture-based system. Animal emissions dominated both systems, representing 85% (enteric CH_4 and manure CH_4 and N_2O) of total emissions in confinement and 71% in pasture-based systems.

GHG Emissions Intensity per Hectare of Total Usable Area

The emission intensity per unit of usable area (t CO_{2eq}/ha) was higher on confinement farms for most GHG sources (Table 6). Total CH_4 emissions (from both manure and enteric fermentation) per unit of area were over 2-fold greater on confinement compared with pasture-based farms ($P = 0.053$). Methane ($P = 0.003$) and direct N_2O ($P = 0.011$) emissions from manure storage per unit of area were also higher on confinement farms. Total manure-related emissions ($CH_4 + N_2O$) per unit of area were over 4-fold greater ($P = 0.006$) in confinement farms. In contrast, C sequestered by trees, CO_2 emissions from urea and lime application and energy-related emissions, including those from diesel and electricity, prefarm emissions, and emissions from purchased concentrate and forage per unit of area were not different ($P > 0.05$) between farming systems. However, fertilizer-related emissions intensity was 51% lower ($P = 0.043$) on confinement compared with pasture-based farms.

GHG Emissions Intensity per Cow

Total farm GHG emissions intensity per cow per year was higher ($P = 0.004$) on confinement compared with pasture-based farms (Table 7). Total CH_4 emissions (including manure and enteric CH_4) per cow per year were more than 2 times as high ($P < 0.001$) in confinement farms. Furthermore, confinement farms exhibited higher ($P = 0.002$) total manure-related emissions ($N_2O + CH_4$), including CH_4 from manure, total N_2O emissions, and

Table 6. Greenhouse gas emissions intensity (t CO_{2eq}/ha; of total usable area) in confinement and pasture-based dairy production systems[1]

GHG source[2]	Pasture-based	Confinement	P-value
Total farm emissions	12.5 ± 1.729	28.3 ± 7.349	0.098
Carbon sequestered by trees	0.64 ± 0.283	0.23 ± 0.058	0.223
CH_4			
Total CH_4 (manure plus enteric CH_4)	7.78 ± 1.040	21.0 ± 4.697	0.053
Enteric fermentation	7.28 ± 1.084	15.20 ± 4.334	0.144
Manure management	0.50 ± 0.198	5.83 ± 0.816	0.003
N_2O			
Total N_2O from manure management	1.15 ± 0.174	2.94 ± 0.688	0.071
Direct N_2O from urine and feces voided to pasture	0.50 ± 0.112	0.26 ± 0.129	0.237
Direct N_2O from manure storage	0.17 ± 0.032	1.78 ± 0.341	0.011
Indirect N_2O from N waste	0.48 ± 0.086	0.91 ± 0.224	0.195
Total manure ($N_2O + CH_4$) emissions	1.65 ± 0.173	8.77 ± 1.239	0.006
Total N_2O from N fertilizer (on-farm)	0.58 ± 0.097	0.34 ± 0.122	0.081
Direct N_2O from N fertilizer	0.30 ± 0.059	0.17 ± 0.061	0.076
Indirect N_2O from N fertilizer	0.28 ± 0.042	0.17 ± 0.061	0.097
CO_2			
Urea and lime from the soil	0.28 ± 0.042	0.17 ± 0.061	0.097
Energy consumption	1.03 ± 0.233	1.47 ± 0.818	0.493
Diesel	0.44 ± 0.144	1.00 ± 0.648	0.305
Electricity	0.59 ± 0.106	0.43 ± 0.211	0.584
Prefarm embedded	1.70 ± 0.285	2.38 ± 1.388	0.483
Concentrate	0.69 ± 0.162	1.16 ± 0.385	0.366
Forage	0.19 ± 0.040	0.82 ± 0.771	0.356
Fertilizers	0.82 ± 0.174	0.40 ± 0.144	0.043

[1] Values are given as mean ± SE.

[2] CO_2 emissions from energy consumption = CO_2 emissions from diesel and electricity; CO_2 emissions from prefarm embedded sources = CO_2 emissions from concentrate, forage (emissions from purchased silage, hay, and other feeds), and fertilizers (CO_2 emissions from nitrogen, phosphorus, sulfur, potassium, and lime); CO_{2eq} = CO_2 equivalents; total N_2O from manure management = direct N_2O + indirect N_2O from manure management; total N_2O from N fertilizer (on-farm) = direct N_2O + indirect N_2O from N fertilizer (on-farm).

Table 7. Greenhouse gas emissions per milking cow (t CO_{2eq}/cow per year) in confinement and pasture-based dairy production systems[1]

GHG source[2,3]	Pasture-based	Confinement	P-value
Total farm emissions	7.70 ± 0.364	13.5 ± 1.065	0.004
Carbon sequestered by trees	0.36 ± 0.127	0.12 ± 0.023	0.125
CH_4			
Total CH_4 (manure plus enteric CH_4)	4.79 ± 0.239	10.0 ± 0.552	<0.001
Enteric fermentation	4.48 ± 0.141	7.24 ± 0.397	0.013
Manure management	0.31 ± 0.136	2.78 ± 0.404	0.003
N_2O			
Total N_2O from manure management	0.71 ± 0.043	1.43 ± 0.136	0.016
Direct N_2O from urine and feces voided to pasture	0.31 ± 0.019	0.12 ± 0.010	<0.001
Direct N_2O from manure storage	0.11 ± 0.018	0.85 ± 0.105	0.003
Indirect N_2O from N waste	0.29 ± 0.017	0.43 ± 0.035	0.205
Total manure (N_2O + CH_4) emissions	1.02 ± 0.119	4.16 ± 0.493	0.002
Total N_2O from N fertilizer (on-farm)	0.35 ± 0.028	0.14 ± 0.060	0.022
Direct from N_2O N fertilizer	0.18 ± 0.015	0.07 ± 0.030	0.017
Indirect from N_2O N fertilizer	0.17 ± 0.016	0.07 ± 0.030	0.029
CO_2			
Urea and lime from the soil	0.17 ± 0.016	0.08 ± 0.030	0.029
Energy consumption	0.63 ± 0.107	0.70 ± 0.174	0.716
Diesel	0.27 ± 0.051	0.48 ± 0.138	0.199
Electricity	0.36 ± 0.074	0.22 ± 0.073	0.102
Prefarm embedded	1.05 ± 0.034	1.13 ± 0.253	0.679
Concentrate	0.42 ± 0.032	0.55 ± 0.141	0.331
Forage	0.12 ± 0.041	0.39 ± 0.312	0.406
Fertilizers	0.51 ± 0.047	0.19 ± 0.068	0.004
Liveweight (kg CO_{2eq}/kg liveweight/yr)	6.76 ± 0.868	5.51 ± 0.779	0.316

[1] Values are given as mean ± SE.

[2] The GHG emission intensity per cow is calculated based on the total farm emissions. This includes all enteric and manure emissions from other herd compositions, which are added to the milking herd's enteric and manure emissions and then divided by the number of milking cows. Therefore, these results represent the total farm emissions distributed per cow.

[3] CO_2 emissions from energy consumption = CO_2 emissions from diesel and electricity; CO_2 emissions from prefarm embedded = CO_2 emissions from concentrate, forage, and fertilizers; CO_{2eq} = CO_2 equivalents; total N_2O from manure management = direct N_2O + indirect N_2O from manure management; total N_2O from N fertilizer (on-farm) = direct N_2O + indirect N_2O from N fertilizer (on-farm).

direct N_2O emissions from manure per cow. In contrast, there was no difference ($P > 0.05$) in indirect N_2O emissions from N waste between the 2 systems. Nitrous oxide emissions per cow from N fertilizer were higher ($P = 0.022$) on pasture-based farms, driven by both direct ($P = 0.017$) and indirect ($P = 0.029$) N_2O emissions per cow. Additionally, emissions intensity from urea and lime applied to soil was higher ($P = 0.029$) on pasture-based farms. In contrast, C sequestered by trees, energy-related (diesel and electricity), and prefarm embedded emissions did not differ ($P > 0.05$) between the systems. Similarly, the total farm GHG emissions intensity per kilogram of liveweight per year showed no difference ($P > 0.05$) between the systems.

GHG Emissions Intensity of FPCM

Results revealed that GHG intensity of FPCM (kg CO_{2eq}/kg FPCM), did not differ ($P = 0.610$) between systems (Table 8). However, FPCM emission intensity from manure CH_4 ($P = 0.003$), total manure (N_2O + CH_4) emissions ($P = 0.004$), direct N_2O from urine and feces voided to pasture ($P = 0.007$), and manure storage ($P < 0.001$) was higher on confinement farms. In contrast, FPCM emission intensity from prefarm embedded sources was lower on confinement ($P = 0.023$) compared with pasture-based farms. Despite the higher electricity usage in confinement farms, the FPCM emission intensity from electricity consumption (kg CO_2/kg FPCM) was lower ($P = 0.002$) in the confinement system. The FPCM emission intensity from N fertilizer, urea, and lime (g CO_{2eq}/kg FPCM) was higher ($P < 0.001$) on pasture-based farms.

DISCUSSION

The comparison of GHG emissions from confinement and pasture-based dairy systems remains debated, with studies offering conflicting evidence on their relative emission intensities. In this study, which included a detailed appraisal of all possible emission sources, we observed no difference in the intensity of C emissions between pasture- and confined-based systems, albeit C sequestration in soil was not accounted for. Confinement systems are often credited with lower GHG emissions

Table 8. Greenhouse gas emissions intensity (kg CO_{2eq}/kg FPCM) in confinement and pasture-based dairy production systems[1]

GHG source[2]	Pasture-based	Confinement	*P*-value
Total farm emissions	1.07 ± 0.069	1.02 ± 0.038	0.610
Carbon sequestered by trees	0.06 ± 0.021	0.01 ± 0.002	0.086
CH_4			
Total CH_4 (manure plus enteric CH_4)	0.66 ± 0.040	0.76 ± 0.036	0.108
Enteric fermentation	0.62 ± 0.043	0.55 ± 0.022	0.188
Manure management	0.04 ± 0.019	0.21 ± 0.036	0.003
N_2O			
Total N_2O from manure management	0.10 ± 0.011	0.11 ± 0.008	0.809
Direct N_2O from urine and feces voided to pasture	0.04 ± 0.008	0.01 ± 0.003	0.007
Direct N_2O from manure storage	0.02 ± 0.004	0.06 ± 0.005	<0.001
Indirect N_2O from N waste	0.04 ± 0.006	0.03 ± 0.003	0.086
Total manure (N_2O + CH_4) emissions	0.14 ± 0.014	0.32 ± 0.037	0.004
Total N_2O from N fertilizer (on-farm)	0.05 ± 0.009	0.01 ± 0.007	<0.001
Direct N_2O from N fertilizer	0.03 ± 0.003	0.01 ± 0.003	<0.001
Indirect N_2O from N fertilizer	0.02 ± 0.003	0.01 ± 0.003	<0.001
CO_2			
Urea and lime from the soil	0.02 ± 0.002	0.01 ± 0.003	<0.001
Energy consumption	0.09 ± 0.013	0.05 ± 0.011	0.104
Diesel	0.04 ± 0.010	0.04 ± 0.009	0.861
Electricity	0.05 ± 0.006	0.01 ± 0.007	0.002
Prefarm embedded	0.15 ± 0.015	0.08 ± 0.015	0.023
Concentrate	0.06 ± 0.009	0.04 ± 0.013	0.279
Forage	0.02 ± 0.006	0.03 ± 0.022	0.571
Fertilizers	0.07 ± 0.009	0.01 ± 0.006	<0.001

[1] Values are given as mean ± SE.

[2] CO_2 emissions from energy consumption = CO_2 emissions from diesel and electricity; CO_2 emissions from prefarm embedded sources = CO_2 emissions from concentrate, forage (emissions from purchased silage, hay, and other feeds), and fertilizers (CO_2 emissions from nitrogen, phosphorus, sulfur, potassium, and lime); CO_{2eq} = CO_2 equivalents; total N_2O from manure management = direct N_2O + indirect N_2O from manure management; total N_2O from N fertilizer (on-farm) = direct N_2O + indirect N_2O from N fertilizer (on-farm).

per unit of milk due to enhanced feed efficiency and productivity (Capper et al., 2009; Gerber et al., 2011, 2013). Conversely, pasture-based systems may achieve lower net emissions when grassland C sequestration is considered (Belflower et al., 2012; O'Brien et al., 2014). Without accounting for grassland C sequestration, the C footprint of both systems was comparable in agreement with previous studies (Flysjö et al., 2011; Belflower et al., 2012; O'Brien et al., 2014). Amidst this debate, the dairy industry's shift from pasture- to confinement-based systems seems to be driven by frequent drought, water scarcity, floods, inconsistent pasture growth, and higher cow productivity and efficiency (Wales et al., 2013; Wilkinson et al., 2020; Moscovici Joubran et al., 2021). The present study found similar stocking rates and tree-covered areas between systems, despite confinement systems having larger usable areas and herd sizes compared with pasture-based systems. However, it is uncertain whether the farms used in the present study are an accurate representation of the broader population of Australian dairy systems or only reflect characteristics specific to the 10 farms accessed, and caution is warranted when interpreting the results beyond this context. Although extensive research has been conducted internationally, much of it focuses on confinement systems that rely on off-farm feed (Belflower et al., 2012; O'Brien et al., 2014), whereas production systems that are primarily dependent on home-grown feed, such as those common in Australia and the present study, remain underexplored. Additionally, C sequestration by trees was not accounted for in prior research (e.g., Belflower et al., 2012; O'Brien et al., 2012, 2014). Therefore, the present study filled that knowledge gap to better understand the environmental implications of such confinement systems with large farm areas and on-farm feed production compared with pasture-based systems using a life cycle approach incorporating tree C sequestration.

The total farm GHG intensity, per unit of area (t CO_{2eq}/ha) and FPCM (kg CO_{2eq}/kg FPCM), were similar between the 2 systems. This lack of difference is largely attributed to total manure (N_2O + CH_4) emissions, which were 5.3-fold higher per unit of area (t CO_{2eq}/ha) and 2.3-fold higher per FPCM (kg CO_{2eq}/kg FPCM) in the confinement compared with the pasture-based system. This result is consistent with Flysjö et al. (2011), Belflower et al. (2012), and O'Brien et al. (2014), who reported that grass-based and confinement dairy systems have similar C footprints per ton of ECM without accounting for grassland C sequestration. The lack of a significant difference in emission intensity for milk between confinement and pasture-based dairy production systems of the present study indicates that enhancing dairy productivity alone may not substantially reduce the emission intensity for milk production. This is because other factors such as manure management systems may play an important role, as reflected by a 72% and 140% increase in FPCM milk production per cow and per hectare of usable land, respectively, in confinement systems. This emphasizes the necessity for supplementary strategies targeting reductions in animal GHG emissions and addressing prefarm embedded emissions. Confinement systems showed higher GHG emission intensity per cow (t CO_{2eq}/cow per year) than pasture-based systems, driven by 109% higher enteric CH_4 and 308% higher total manure (N_2O + CH_4) emissions, whereas milk production was 72% higher. Consequently, manure-related emission intensities (kg CO_{2eq}/kg FPCM, t CO_{2eq}/ha, t CO_{2eq}/cow per year) were greater in confinement, reflecting increased CH_4 and direct N_2O emissions from manure storage compared with pasture-based systems. Total N_2O emissions from animal waste per cow (t CO_{2eq}/cow per year) were higher in confinement, likely due to greater manure storage. Additionally, the higher DMI of confinement cows likely led to increased manure N_2O emissions due to greater N intake and fecal excretion, as reflected in greater direct emissions of manure per cow in the present study. The N_2O emissions are closely linked to the amount of N ingested by ruminants with ~2% of the N excreted by the animals being released as N_2O (Hao et al., 2004). In contrast, despite higher manure-related emissions, confinement systems provide more opportunities to capture, handle, store, and apply advanced manure treatment strategies such as acidification, anaerobic digestion, nitrification–denitrification, or chemical inhibitors (Chadwick et al., 2011; Montes et al., 2013), which can help mitigate the environmental effect compared with pasture-based systems, where most manure is excreted directly on the paddocks.

Enteric CH_4 emissions from milking cows were consistent with total DMI and milk production. This relationship is expected, given experimental studies demonstrating a positive correlation between enteric CH_4 production, DMI, and milk yield per cow (Ulyatt et al., 2002a,b; Lovett et al., 2005; O'Neill et al., 2011; Hardan et al., 2022). Emission intensity (t CO_{2eq}/kg FPCM and t CO_{2eq}/cow per year) from N fertilizer (N_2O) was higher in pasture-based systems, which could be attributable to larger usable areas in confinement farms and use of stored liquid and slurry effluent as fertilizer, reducing reliance on inorganic fertilizers (Garnett and Eckard, 2024). However, the present study did not record data on the amount of manure storage and utilization as fertilizers, and further research in this field is recommended. The result for total N_2O from N fertilizer falls within the range of 0.4 to 2.0 t CO_{2eq}/ha per year, as reported in previous studies based on field measurements (Eckard et al., 2003; Phillips et al., 2007). Despite higher energy use (electricity and diesel) in confinement, emission intensities from energy (kg CO_{2eq}/kg FPCM, t CO_{2eq}/ha, t CO_{2eq}/cow per year) did not differ between systems, partly because 2 confinement farms sourced 50% of their electricity (53,507 kWh/yr total) from solar power (data not shown).

Carbon sequestration, particularly through tree vegetation, emerged as an important factor in mitigating net GHG emissions from dairy production and warrants careful consideration in system comparisons (Ghale et al., 2022; Christie-Whitehead and Dairy Australia, 2024). In the present study, C sequestration by trees (kg CO_{2eq}/kg FPCM) was relatively low in both systems. Tree sequestration offset (kg CO_{2eq}/kg FPCM) ~6% of total emissions in pasture-based systems and less than 1% in confinement systems because the proportion of tree area over the total usable area was 1.6-fold lower and C sequestration per hectare was 1.4-fold lower in the latter. Pasture-based farms of the present study sequestered 9.41 t CO_{2eq}/ha and confinement farms 7.05 t CO_{2eq}/ha according to the ADCC model (data not shown), which may be partly explained by regional and weather differences.

The larger total usable area and irrigated farm area in the confinement system align with its higher reliance on home-grown feed production. These findings support the notion that confinement systems are designed for high production efficiency, often at the expense of higher input use (Rotz et al., 2010). The higher yield of milk solids per cow, DMI, and milk production efficiency in confinement compared with the pasture-based system support the concept that confinement systems often achieve higher productivity per animal due to optimized nutrition (Capper et al., 2009). In contrast, the lower yield of milk solids per cow in the pasture-based system may indicate a trade-off between lower input use and reduced productivity (Hristov et al., 2022).

Notably, the stocking rate in our study, calculated per total usable area, was similar between systems, albeit with a large variability. This contrasts with the definitions by FAO (2020) and O'Brien et al. (2014), which express stocking rate per grazed area. Under this definition, confinement systems typically have higher stocking rates than pasture-based systems because animals are concentrated in smaller, intensively managed areas. However, confinement dairy farms of the present study had a significant portion of the area used for forage cropping to support grain and silage production, which may contribute to this deviation from the global norm. These results highlight the importance of considering the structure of domestic dairy industries to develop mitigation strategies that are suitable and effective to reduce GHG emissions.

Despite confinement farms showing numerically higher total amounts of home-grown silage, hay, and concentrates, average N fertilizer used per farm (t N/yr) was similar between systems, yet N fertilizer usage per hectare of total usable land tended to be significantly higher in pasture-based farms. The present study was not designed to unravel the reasons for this finding, including potential differences in N fertilizer use efficiency, and, thus, it is difficult to draw firm conclusions. However, it is plausible that the lower N use in confinement systems could be partly explained by frequent utilization and recycling of manure. This includes liquid manure and sediments from lagoons, as well as fresh or composted manure, which are applied to cropping areas to supplement or partially replace synthetic N fertilizers. Such practices could improve N use efficiency (Garnett, 2024). In contrast, pasture-based systems rely on excretion of manure on the grazing paddocks and often require consistent N applications to sustain pasture productivity under frequent grazing throughout the year (Gourley et al., 2012a,b), particularly in regions with seasonal fluctuations in pasture growth. However, these results should be interpreted with caution, as we lack quantitative data on grazed pasture, which may also affect total N use.

The predicted total DMI of cows in the confinement system was higher than that of cows in the pasture-based system, and these results are partly explained by the greater observed milk production and cow BW, which are the key predictors of DMI in the ADCC model (Dida et al., 2024). The TMR provides balanced and consistent nutrients, energy, and fiber, throughout the year enhancing DMI compared with pasture, which constantly varies in nutrient quality (NRC, 2001). The greater milk yield in confinement systems is consistent with O'Brien et al. (2014), who reported a 74% increase in milk production in confinement systems versus pasture-based systems in Europe. This may be attributed to genetic selection for milk production (heavier BW with greater production potential), as well as the use of TMR diets in confinement systems (O'Brien et al., 2014), with associated higher DMI per cow (Bargo et al., 2002, 2003). Consistent with our findings, O'Brien et al. (2014) also reported 20% greater milk yield efficiency (kg ECM/kg DMI) for confinement than pasture-based systems. Milk yield per usable area tended to be higher in the confinement compared with pasture-based systems. Although not statistically significant, this tendency suggests the confinement system may enhance milk production efficiency (milk yield per hectare), potentially due to controlled feeding strategies. The higher number of animals per hectare in confinement systems can contribute to higher milk output per hectare, provided that nutrition and management are optimized (Macdonald et al., 2008).

Total yearly net farm emissions were 6-fold greater in confinement compared with pasture-based systems, mainly due to the larger scale of the business, including more land area and larger herds. In both production systems, enteric fermentation emerged as the dominant source of GHG emissions, contributing more than half of the total emissions. This finding is consistent with Flysjö et al. (2011) and Kristensen et al. (2011), who reported that enteric methane contributed a greater share of total farm GHG emissions in pasture-based systems (62% and 54%, respectively) compared with confinement systems (54% and 52%, respectively). The second largest emission sources differed between production systems, with manure emissions being the second largest in confinement systems and prefarm embedded emissions in pasture-based systems. The higher GHG emissions from manure in confinement systems can be attributed to the reliance on lagoon storage, which has higher CH_4 production than manure deposited on grazing paddocks (Montes et al., 2013). Pasture systems allow more manure recycling back into the soil and the feces dry faster to reduce microbial activity, reducing the overall GHG emissions associated with manure storage. These findings partly agree with O'Brien et al. (2012), who reported that emissions from manure accounted for 31% of total farm emissions in confinement systems and 8.3% in grass-based systems, with similar trends observed in this study.

Milking cows were the largest source of emissions in both systems, as previously reported (Christie et al., 2012), representing a higher percentage in confinement compared with those in pasture-based systems. Consistent with these findings, previous studies (Christie et al., 2012; Christie-Whitehead and Dairy Australia, 2024) have reported that animals account for ~75% (71% to 83%) of total farm GHG emissions across various Australian dairy farms. The present study expands on these results by demonstrating that the contribution of animals is even greater in confinement systems, due to higher enteric CH_4, manure CH_4, and N_2O emissions per animal, as well as a higher proportion of replacement heifers in confinement compared with pasture-based systems.

These findings highlight the need for targeted mitigation strategies tailored to the specific GHG emission profiles of each dairy production system. For confinement dairy production systems, manure management strategies, such as covered storage, anaerobic digesters (which can also generate renewable energy and reduce emissions from energy usage), acidification, aeration, antimicrobial agents, and solid-liquid separation, may help reduce emissions (Smith et al., 2008; Guzmán-Luna et al., 2022; Ambrose et al., 2023). For instance, acidifying cattle slurry to a pH of 5.5 can reduce its CH_4 emissions by up to 99% (Ambrose et al., 2023), whereas covering effluent storage, along with burning or harvesting the methane, can lower whole-farm emissions by 5% to 10% (Garnett and Eckard, 2024). Additionally, feed management options, such as CH_4-reducing additives, can help lower enteric CH_4 emissions in both production systems and improve feed efficiency (Eckard and Clark, 2018; Hristov et al., 2022). Furthermore, reducing prefarm embedded emissions through sustainable feed sourcing and improving the efficiency of fertilizer use could be more relevant to pasture- compared with confinement systems. Most of the grain, concentrate, and hay used in pasture-based systems of the present study were purchased. Therefore, reducing wastage and growing more forage on-farm could help substitute supplements and decrease prefarm embedded emissions. Both systems should also explore the potential to reduce energy-related emissions by adopting renewable energy sources, such as solar and wind power, and biodigesters which are feasible for confinement systems (Garnett and Eckard, 2024).

One limitation of this study is that concentrate, hay, and silage feed samples were collected only once and at different times from each farm. Therefore, this approach provides a snapshot of feed quality at specific points, rather than reflecting whole-year averages. This limitation is particularly relevant for silage and hay, as their composition can vary by season. Future research should assess the effects of more accurate and frequent diet information on the estimation of yearly GHG emissions. Additionally, the present study did not account for C sequestered by pastures and soils, which could have provided a more comprehensive understanding of the environmental benefits associated with different farming practices. Future research should address synchronized feed sampling throughout the year and consider C sequestration in soil to provide a more complete analysis of farm-level effects.

CONCLUSIONS

The results of the present study revealed that enteric CH_4 emissions were the largest source of GHG emissions in both confinement and pasture-based systems, while manure (N_2O and CH_4) and prefarm embedded emissions were the second largest sources in confinement and pasture-based systems, respectively. Despite a 72% increase in daily milk production per cow in the confinement compared with the pasture-based system, milk emission intensity was similar in both systems. This underscores the need for additional strategies to reduce GHG emissions from animals and address prefarm embedded emissions and fertilizer emissions. The emission offset by tree C sequestration (kg CO_{2eq}/kg FPCM) was relatively low in both systems; however, a greater potential to offset livestock emissions was observed in pasture-based systems (6% vs. 1%). In conclusion, targeted mitigation strategies tailored to specific dairy production systems should be implemented because the sources of GHG emissions differ between the systems, with feed being the primary source of emissions in both systems and manure management a significant contributor in the confinement system.

NOTES

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Nonstandard abbreviations used: ADCC = Australian Dairy Carbon Calculator; CO_2 emissions from energy consumption = CO_2 emissions from diesel and electricity; CO_2 emissions from prefarm embedded sources = CO_2 emissions from concentrate, forage, and fertilizers; CO_{2eq} = CO_2 equivalents; DMD = DM digestibility; DOMD = digestible OM in DM; EE = ether extract; FPCM = fat and protein-corrected milk; GWP100 = global warming potential for 100 yr horizon; NSW = New South Wales; total N_2O from N fertilizer (on-farm) = direct N_2O + indirect N_2O from N fertilizer (on-farm); WSC = water soluble carbohydrate.

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Chapter 4. Dietary Concentrate Supplementation Increases Milk Production and Reduces Predicted Greenhouse Gas Emission Intensity in Pasture-Based Commercial Dairy Farms

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Overview

This chapter investigated the effect of dietary concentrate supplementation level on milk production and GHG emission intensity in pasture-based dairy farms. Data from 120 commercial farms and the Australian Dairy Carbon Calculator were used. Results showed that higher concentrate level increased milk yield and above 1 t DM/cow/yr reduced emission intensity per unit of milk. However, manure-derived CH_4 and N_2O emissions also increased. Economic analysis showed improved profitability with moderate to high supplementation. The findings underscore the importance of balancing nutritional strategies with environmental and economic outcomes.

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Dietary concentrate supplementation increases milk production and reduces predicted greenhouse gas emission intensity in pasture-based commercial dairy farms

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ABSTRACT

Controlled studies have extensively documented that concentrate supplements typically increase enteric CH_4 emissions and milk yield and reduce emissions per unit of milk produced and dry matter intake. However, no studies have been conducted to determine the effect of concentrate on predicted greenhouse gas emissions from dairy farms representing the Australian pasture-based farming system. Thus, this study sought to determine how dietary concentrate supplementation affects enteric and manure CH_4, and N_2O of Australian pasture-based dairy farms. The Australian Dairy Carbon Calculator was used, which incorporates emission factors and methodologies used in the National Greenhouse Gas Inventory as reported to the Intergovernmental Panel on Climate Change. Primary data were collected and analyzed from 120 commercial farms in Australia's major dairy regions. Then the farms were divided into 4 groups based on their dietary concentrate supplementation: ≤1 (low; 15 farms), 1 to 2 (moderate; 35 farms), 2 to 3 (high; 35 farms), and ≥3 (very high; 35 farms) t of concentrate dry matter (tDM) per cow per year. Sources of greenhouse gas emissions were CO_2 from concentrate production, enteric CH_4, and manure CH_4 and N_2O. Total dry matter intake, milk yield, and daily enteric CH_4 production (g/d) quadratically increased with concentrate level, whereas greenhouse gas emission intensity of milk production (kg of CO_2 equivalent per kg of fat- and protein-corrected milk) decreased by 14% for farms supplementing with ≥3 tDM/cow per year compared with those supplementing with ≤1 tDM/cow per year of dietary concentrate. The N_2O and CH_4 emissions from manure increased quadratically and linearly, respectively, with the increasing supplementation of concentrate. Farms supplementing 2 to 3 tDM/cow per year showed substantial increases in gross income, gross margin, earnings before interest and tax, and net income ($/cow per year) compared with those supplementing of ≤1, 1 to 2, and ≥3 tDM/cow per year. Overall, increasing dietary concentrate supplementation for dairy cows resulted in increased milk production per cow, reduced greenhouse gas emissions per unit of milk produced, and increased income and profit. However, a comprehensive life cycle assessment study is needed to account for carbon sequestration by other farm components, such as pastures and trees, which were not considered in the present study. In addition, the present study was based on modeling and did not gather ground truth information for DMI, digestibility, crude protein, and urinary and fecal N excretion. Therefore, data should be interpreted with caution, and studies gathering such information are encouraged.

Key words: milk yield, methane, nitrous oxide

INTRODUCTION

Methane and N_2O are the most important greenhouse gases (**GHG**) from dairy farms, with 28 and 265 times the global warming potential of CO_2, respectively, (IPCC, 2018). Methane is a short-lived climate pollutant, with an atmospheric perturbation lifetime of around 12.5 years (IPCC, 2014). In 2021, CH_4 concentrations were at 1,908 ppb, and N_2O concentrations were at 334.5 ppb in the atmosphere, representing 262% and 124% of preindustrial levels, respectively (Citaristi, 2022). Methane and N_2O account for 16% and 6% of total global GHG emissions, respectively (Hockstad and Hanel, 2018). Methane from livestock contributes 5% of global GHG and 30% of anthropogenic CH_4 emissions (Jackson et al., 2020; Crippa et al., 2021). Enteric fermentation accounts for 88% of global livestock CH_4 emissions (FAO, 2019). The most significant source of GHG emissions from dairy production systems is enteric CH_4 (>70%), followed by N_2O (13%) and CH_4 (12%) from the animal waste of total on-farm non-CO_2 emissions (Eckard and Clark, 2018). The Australian dairy industry emits 10.0 Mt of CO_2 equivalent (**CO_{2eq}**), which accounts for 2% of total national emissions and 14% of agricultural emis-

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The list of standard abbreviations for JDS is available at adsa.org/jds-abbreviations-24. Nonstandard abbreviations are available in the Notes.

sions (Dairy Australia, 2021). Enteric CH_4 emissions account for about 57% of dairy GHG emissions in Australia, whereas manure N_2O and CH_4 emissions account for 11% and 10% of dairy GHG emissions, respectively (Christie, 2019).

In addition to its impact on climate change, enteric CH_4 results in energy losses in lactating dairy cows ranging from 2.7% to 9.8% of gross energy intake (Niu et al., 2018). Consequently, there is a growing interest in the development of nutritional strategies to reduce CH_4 emissions from food-producing ruminant animals. Dietary concentrate supplementation is widely used to enhance milk and meat production (Purwin et al., 2016; Ruiz-Albarran et al., 2016) and is considered an effective CH_4 mitigation strategy (Martin et al., 2010; Moate et al., 2014; Hristov et al., 2022). Many studies have demonstrated that increasing the amount of concentrate supplementation significantly reduces the CH_4 emission intensity of milk production. The CH_4 intensity of milk production (g CH_4/kg of fat- and protein-corrected milk [**FPCM**]) decreased by 27%, with an average increase of 386 g of concentrate/kg DM (van Gastelen et al., 2019). Arndt et al. (2022) also reported that reducing the dietary forage-to-concentrate ratio (47%:53% after reduction) reduced CH_4 intensity by an average of 9% (9%–17%), and increased milk yield by 17% (10%–24%) compared with control treatments within studies. One of the reasons for such effects is that concentrates contain more digestible nutrients than roughages, leading to increased animal productivity and consequently reduced CH_4 emission intensity (Capper et al., 2009). This is because concentrates contain nonstructural carbohydrates like starch and sugar, which ferment rapidly, resulting in lower ruminal pH and a detrimental impact on methanogenic microbial populations (Bannink et al. 2006; Bannink et al. 2008).

On the other hand, increasing the proportion of concentrate in the diet (from 20% to 60% of total DMI) increases manure N_2O (mg of N_2O/kg of manure on a DM basis) due to higher intake and fecal excretion of N, and manure CH_4 production remains unaffected (Nampoothiri et al., 2018). The emission of N_2O is closely related to the amount of N ingested by ruminants, where approximately 2% of the N excreted by the animals is released as N_2O (Hao et al., 2004). Overfeeding protein to animals beyond their requirements results in an increased N burden on the environment and wastes protein (Hristov et al., 2011). Consequently, Külling et al. (2002) observed higher N_2O emissions from dairy cow manure when the cows were fed a high-protein diet.

Dietary concentrate supplementation of grazing dairy cows typically increases milk production per cow, enabling higher stocking rates and greater milk production per unit of land. In recent times, Australia has experienced significant changes in feeding systems, with more concentrate feeding to dairy cows on pasture. Currently, more than 64% of Australian dairy farmers feed moderate to high amounts of concentrate, over 1 t of concentrate DM (**tDM**) concentrate per cow per year (Dairy Australia 2019). This trend is driven by dairy farmers' motivation to enhance milk production per cow and hectare (Moscovici Joubran et al., 2021). The benefits of dietary concentrate supplementation for increasing milk production and decreasing GHG emissions intensity are clear, but limited quantitative information is available regarding its effect on enteric- and manure-derived CH_4 and N_2O emissions in grazing dairy cow systems. Furthermore, as highlighted by Moate et al., (2020), no research has been published on the CH_4 mitigation potential of concentrate supplementation in commercial pasture-based dairy systems. Therefore, accurate estimation of CH_4 and N_2O emissions from commercial dairy farms based on concentrate level supplementation is required to enable governments to improve their GHG inventories, serving as a foundation for policymakers to develop effective mitigation strategies. Consequently, the objective of this study was to estimate enteric CH_4 and manure CH_4 and N_2O emissions from commercial dairy farms based on the quantity of concentrate provided per cow. These predictions were made using the Australian Dairy Carbon Calculator, which incorporates emission factors and methodologies reported in the National Greenhouse Gas Inventory to the Intergovernmental Panel on Climate Change. We hypothesized that higher concentrate supplementation would reduce GHG yield (g CO_{2eq}/kg DMI) and intensity (g $CO_{2\ eq}$/kg FPCM) of commercial dairy farms. This study also includes information about the costs of feeding concentrate.

MATERIALS AND METHODS

Farm Selection and Dataset

The sample data (n = 120) were selected from a dataset of the Australian Dairy Farm Monitoring Project (**DFMP**) collected for a comprehensive production and financial analysis of Australian dairy farms (Dairy Australia 2021). The selected farms were representative of the Australian dairy industry, with differences in geographical location, farm size, herd size, supplement levels, milk production per cow, and stocking rates. Of the 120 farms, 25 were from South Australia, 26 from New South Wales, 28 from Tasmania, and 41 from Victoria. The farms were selected from the dataset using a stratified random method by taking geographical location and concentrate supplementation into account. The farms in the dataset were first grouped by state, and

Table 1. Farm and herd input data used to estimate enteric CH_4 and manure CH_4 and N_2O of 120 commercial Australian dairy farms (mean values with range shown in parentheses)

	Concentrate supplementation (tDM/cow per year)[1]			
Parameter	≤1 (n = 15)	1–2 (n = 35)	2–3 (n = 35)	≥3 (n = 35)
Cow number	472 (180–994)	441 (96.0–1,238)	363 (103–1,321)	380 (136–1,117)
Milk solids (kg/cow per year)	362 (313–455)	475 (343–626)	507 (379–636)	557 (466–698)
Milking area (ha)	189 (64.5–365)	162 (56.0–442)	141 (50.0–305)	164 (52.0–450)
Total usable area (ha)	253 (65.0–498)	279 (92.0–1,030)	255 (888–848)	297 (64.0–1,000)
Stocking rate (cows/ha)	2.03 (0.70–3.32)	1.70 (0.54–3.46)	1.54 (0.63–3.30)	1.57 (0.55–3.53)
Pasture utilization (tDM/ha)	10.3 (6.09–16.4)	9.30 (3.90–14.2)	7.88 (1.84–15.5)	6.84 (2.80–12.2)
Concentrate (kg DM/cow per day)	2.19 (0.55–2.87)	4.39 (2.89–5.60)	7.03 (5.66–8.22)	10.0 (8.37–13.40)
Concentrate in the milking herd diet (% of total DMI)	14.5 (3.64–15.5)	25.8 (18.2–33.6)	39.9 (30.6–52.0)	54.2 (42.6–73.2)

[1] n = number of farms.

then they were categorized into 4 groups based on their concentrate supplementation levels (≤1, 1–2, >2–3, and ≥3 tDM/cow per year). Finally, farms from each of the 4 concentrate level groups were randomly selected for this study. Information on the number of dry and milking dairy cows, milk production, the amount of concentrate supplement, and milk fat and protein contents was collected by DFMP for 2021 dairy farm production and financial analysis (Table 1). The one-year farm data were then used as input in a model spreadsheet developed to estimate GHG emissions. The Australian Dairy Carbon Calculator (**ADCC**; https://www.dairyaustralia.com.au/resource-repository/2023/01/30/australian-dairy-carbon-calculator) was employed to calculate enteric CH_4, manure CH_4, and N_2O (Christie et al. 2011, 2016; Christie 2019). No approval was obtained from an Institutional Animal Care and Use Committee, as the study did not involve any animal subjects.

Australian Dairy Carbon Calculator

The ADCC version 5, currently used in the Australian National Inventory (AGDISER, 2022), was employed to calculate enteric CH_4 and manure N_2O and CH_4. The ADCC is constructed in Microsoft Excel and consists of 10 user forms and 18 worksheets. The 18 worksheets include algorithms, emission factors, and methodologies for calculating CO_2 emissions from embedded pre-farm inputs, as well as on-farm CH_4, N_2O, and CO_2 emissions. The sources of GHG emissions considered in this study were CO_2 from concentrate production, CH_4 from enteric and manure, and as N_2O from manure. The ADCC calculated enteric CH_4 and manure N_2O and CH_4 for each farm using required data on livestock (number of animals on farm), average lactation length in days, milk production (kg of milk solids per herd per annum), milk composition (milk fat and protein content in percentage), concentrate intake (kg DM/d), and pasture dry matter digestibility (**DMD**) and CP. All input data for ADDC were from the DFMP data, except BW, DMD, and CP content of the feed, which had not been collected by DFMP for individual farms. Thus, for the latter variables, we assumed the values used by the National Inventory Report: 550 kg of BW, and annual CP and DMD for concentrate and pasture of 20 and 18 (g/100 g DM) and 85 and 75 (g/100 g DM) DMD, respectively (Christie et al., 2012; DISER, 2020). Carbon sequestration by pasture and tree was not included in this study because it was beyond the scope. The concentrate comprised mixed grains, sorghum, wheat, and barley, cottonseed and soybean meals, whole cottonseed, and molasses (Chataway et al., 2010; Wales and Kolver, 2017). Dry matter intake is calculated by the ADCC using a series of algorithms and methodologies from the Australian Standing Committee on Agriculture (SCA, 1990). Daily DMI (DMI_{ijk}, kg DM/head per day) is calculated as

$$DMI_{ijk} = (1.185 + 0.00454 \times BW_{ijk} - 0.0000026 \times BW^2_{ijk} + 0.315 \times BWG_{ijk})^2 \times MR + MI_{ijk}, \quad [1]$$

where BW_{ijk} = body weight (kg), LWG_{ijk} = body weight gain (kg/d), MR = metabolic rate when producing milk (1.1 for mature cows and 1.0 for all other classes) and MI_{ijk} = additional intake required for milk production (kg DM/head per day; as calculated in Equation 2 below); i = individual animal within a group or population, j = specific period or condition, k = particular treatment or group within the population.

The additional intake required for milk production (MI_{ijk}; kg DM/head per day) is calculated as

$$MI_{ijk} = MP_{ijk} \times NE/(k \times q \times 1.84), \quad [2]$$

where MP_{ijk} = milk production (kg/head per day), NE = 3.054 MJ (net energy/kg milk; SCA, 1990), k = 0.60 (efficiency of use of ME for milk production), q = metabolizable energy of the diet, and 18.4 = gross energy content of feed (MJ/kg DM; SCA, 1990), where this value is assumed for all feeds (DCCEE, 2009):

$$q = 0.00795 \times DMD_{ijk} - 0.0014, \qquad [3]$$

where DMD_{ijk} = dry matter digestibility (g/100 g DM) of the diet.

Intake relative to that required for maintenance (L_{ijk}) is calculated as

$$L_{ijk} = DMI_{ijk}/(1.185 + 0.00454 \times BW_{ijk} - 0{:}0000026 \times BW^{2}_{ijk} + 0.315 \times LWG_{ijk})^{2}, \qquad [4]$$

where BW_{ijk} = body weight (kg), and LWG_{ijk} is set to zero.

The ADCC calculates the daily enteric CH_4 production (g CH_4/head per day) using the formula given by Charmley et al. (2016). The total daily production of enteric CH_4 is calculated as

$$M_{ijk} = 20.7 \times DMI_{ijk}, \qquad [5]$$

where M_{ijk} = daily enteric CH_4 production (kg enteric CH_4/head per day), DMI_{ijk} = daily DM intake (kg DM/head per day), and 20.7 g of CH_4 per kg of DMI is assumed (Charmley et al., 2016).

The ADCC calculated CH_4 emissions from manure management using a series of emission factors, algorithms, and methodologies based on Williams (1993) and IPCC (2018) guidelines. In ADCC's default setting, it is assumed that 79.3% of annual feces and urine is deposited onto pastures during grazing, 12% is stored in a lagoon system, 2.4% is dispersed via a sump system, 1.2% drains into the paddock, and 5.1% is stored as a slurry for later application (Reyenga et al., 2015). To calculate CH_4 production (kg CH_4/head per day) from manure, the calculation necessitates determining the volatile solids (**VS**) excreted per head per day, based on DMI and DMD as follows:

$$VS_{ijk} = DMI_{ijk} \times [1 - (DMD_{ijk}/100)] \times (1 - A), \qquad [6]$$

where I_{ijk} is the DM intake (kg/head per day; as calculated in Equation 1), DMD_{ijk} is the dry matter digestibility (g/100 g DM) of the diet, and A is the ash content, expressed as a fraction (assumed to be 8% of fecal DM).

From this, daily animal waste CH_4 production is calculated as

$$M_{ijk} = VS_{ijk} \times B_o \times MCF \times \rho, \qquad [7]$$

where M_{ijk} = waste CH_4 (kg CH_4/head per day), VS_{ijk} = volatile solids (kg/head per day; Equation 6), B_o = emissions potential (0.24 m^3/kg VS), MCF = integrated CH_4 conversion factor (2.73% defaults state-based factors and fractions; DCCEE, 2009), and ρ = density of CH_4 (0.662 kg/m^3).

The ADCC calculates N_2O emissions associated with manure excretion using Australian-specific emission factors, algorithms, and methodologies (DCCEE, 2009), based on research by the Standing Committee on Agriculture Ruminants Subcommittee (1990) and Freer et al. (1997). The emission factors and equations used to estimate direct and indirect N_2O emissions from feces, urine, and stored as well as spread waste are detailed in Table 2. The CP intake (CPI_{ijk}; kg/head per day) is calculated as

$$CPI_{ijk} = DMI_{ijk} \times (CP_{ijk}/100), \qquad [8]$$

where DMI_{ijk} = DM intake (kg DM/head per day; Equation 1) and CP_{ijk} = CP (g/100 g DM) of the diet.

The amount of N excreted in feces (F_{ijk}; kg/head per day) is calculated as

$$F_{ijk} = \{[0.3 \times (CPI_{ijk} \times \{1 - [(DMD_{ijk} + 10)/100]\})] + [0.105 \times ME_{ijk} \times DMI_{ijk} \times 0.008]$$

Table 2. Emission factors and equations were used to estimate direct and indirect nitrous oxide (N_2O) emissions from feces, urine, and stored as well as spread waste[1]

Emissions factor	Equation
Direct	
Feces excreted onto pastures	0.005 × feces N × % feces deposited onto pastures during grazing × 1.57
Urine excreted onto pastures	0.004 × urinary N × % urine deposited onto pastures during grazing × 1.57
Stored waste	0.001 × sum of feces and urinary N × % feces and urinary N stored in lagoons and as liquid/slurry × 1.57
Spread stored waste	0.01 × (feces and urinary N × % of feces and urinary N stored − N_2O lost during the storage phase − N_2O lost through volatilization) × 1.57
Indirect	
Volatilization (feces and urine)	{0.01 × [(% feces and urinary N deposited onto pastures x 0.2) + (% feces and urinary N stored in lagoon × 0.35) + (% feces and urinary N stored as liquid/slurry × 0.4) + (% feces and urinary N spread daily × 0.07)]} × 1.57
Leaching/runoff (feces and urine)	0.3 × 0.0125 × (feces N + urinary N + spread and stored waste N) × 1.57

[1] Sources: Standing Committee on Agriculture Ruminants Subcommittee, 1990; Freer et al., 1997; DCCEE, 2009.

$$+ [0.0152 \times \mathrm{DMI}_{ijk}]\}/6.25, \qquad [9]$$

where CPI_{ijk} = CP intake (kg/head per day; Equation 8), DMD_{ijk} = dry matter digestibility (g/100 g DM) of the diet, ME_{ijk} = metabolizable energy (MJ/kg DM; calculated as 0.1604 × DMD_{ijk} − 1.037; Minson and McDonald, 1987), DMI_{ijk} = DM intake (kg DM/head per day; Equation 1) and 1/6.25 = factor for converting CP into N.

The amount of N that is retained by the animal in milk and body tissue is calculated as

$$\begin{aligned}\mathrm{NR}_{ijk} &= ([0.032 \times \mathrm{MP}_{ijk}] + [0.212 - 0.008 \\ &\times (\mathrm{L}_{ijk} - 2)] - [0.140 - 0.008 \times (\mathrm{L}_{ijk} - 2)]/ \\ &(\{1 + \exp[-6 \times (\mathrm{Z}_{ijk} - 0.4)]\} \\ &\times [\mathrm{BWG}_{ijk} \times 0.92])/6.25, \qquad [10]\end{aligned}$$

where NR_{ijk} = N retained by the animal in milk and body tissue (kg/head per day), MP_{ijk} = milk production (kg/head per day), L_{ijk} = intake relative to maintenance (as calculated in the equation above), Z_{ijk} = relative size (body weight/standard reference weight for each stock class; available in DCCEE 2009), LWG_{ijk} = body weight gain (kg/d), and 1/6.25 = factor for converting CP into N.

The amount of N excreted in urine (U_{ijk}; kg/head per day) is calculated as

$$\begin{aligned}\mathrm{U}_{ijk} &= (\mathrm{CPI}_{ijk}/6.25) - \mathrm{F}_{ijk} - \mathrm{NR}_{ijk} \\ &- (1.1 \times 10^{-4} \times \mathrm{BW}_{ijk}{}^{0.75})/6.25, \qquad [11]\end{aligned}$$

where CPI_{ijk} = CP intake (kg/head per day; Equation 8), F_{ijk} = N excreted in feces (kg N/head per day; Equation 9), NR_{ijk} = N retained by the animal (kg N/head per day; Equation 10), BW_{ijk} = body weight (kg/head), and 1/6.25 = factor for converting CP into N.

The CO_2 emissions from concentrate production were considered pre-farm embedded emissions, with CO_2 emissions associated with the production of concentrate assumed at an emission factor of 0.3 kg CO_2/kg of concentrate (Christie et al., 2011). The CO_2 emissions from concentrate encompass the CO_2 emissions resulting from the consumption of energy (electricity and fuel) and the pre-farm gate embedded CO_{2eq} emissions associated with the production and manufacturing of concentrates, which were also considered in the estimations.

Unit

The total usable area was calculated as the total hectares managed minus land with no value for livestock production, such as shed and house areas. The milking area was determined by subtracting the runoff areas from the total usable area. The stocking rate was calculated using the total farm area and the number of cows. The ADCC calculates pasture utilization based on total DMI and concentrates level. Milk production was quantified as FPCM. It was determined by the following formula: FPCM (kg) = raw milk (kg; calculated by multiplying liters by 1.03; Sevenster and Jong, 2008) × [0.337 + (0.116 × fat content) + (0.06 × protein content)], with fat content and protein content measured as g/100 g milk (FAO, 2010). The CO_{2eq} emissions were determined by applying the 100-year global warming potential values specified in the IPCC assessment report 5 (IPCC, 2018). These 100-year global warming potential values are 1 for CO_2, 28 for CH_4, and 265 for N_2O (IPCC, 2018).

Net Profit of Concentrate Feeding. The profitability and productivity of concentrate feeding were calculated using the Malcolm et al. (2005) method. Gross farm income encompasses various sources, including milk cash income (net), livestock trading profit, feed inventory changes, and other sources, such as milk share dividends. The primary income source was derived from milk, calculated by multiplying the price received per unit by the total number of units. Variable costs, specific to each enterprise, included expenses related to the herd, shed, and feed. The gross margin was determined by subtracting the variable costs of the dairy enterprise from the gross farm income. Overhead costs encompassed expenses incurred in the general operation of the business, which were grouped into cash and noncash categories. Cash overheads included expenses such as rates, insurance, repairs, and maintenance. Noncash overheads covered costs that did not involve actual cash receipts or expenditures, such as equipment depreciation, along with imputed operators' allowances for labor and management. Earnings before interest and tax (**EBIT**) were calculated by subtracting variable and overhead costs from gross farm income. Net farm income, derived by subtracting interest and lease costs from EBIT, represented the reward attributed to the business' capital. Interest and lease costs were considered as financing expenses, relating to borrowed money or leased land used within the business.

Statistical Analysis

The ADCC was run for each of the 120 farms stated above, and the output estimations were then exported and consolidated for all farms together with the input data for statistical analyses. Linear, quadratic, and cubic regression relationships between concentrate level and observed variables were analyzed using a linear model, where concentrate amount was treated as a linear variable. Pearson correlation coefficients were used to obtain a correlation matrix. All statistical analyses were conducted using the

Table 3. Effects of concentrate feeding on milk production and composition and DMI of dairy cattle at pasture, mean ± SE

	Concentrate level (tDM/cow per year)[1]				*P*-value[2]		
Parameter	≤1 (n = 15)	1–2 (n = 35)	2–3 (n = 35)	≥3 (n = 35)	L	Q	C
Total DMI (kg/cow per day)	15.1 ± 0.173	17.0 ± 0.245	17.7 ± 0.222	18.6 ± 0.178	<0.001	0.003	0.246
Pasture DMI (kg/cow per day)	12.9 ± 0.754	12.6 ± 1.247	10.7 ± 1.345	8.52 ± 1.544	<0.001	0.003	0.246
Milk yield (L/cow per day)	14.7 ± 0.436	20.1 ± 0.634	22.4 ± 0.578	25.5 ± 0.475	<0.001	0.005	0.262
Milk fat (g/kg)	4.63 ± 0.075	4.43 ± 0.068	4.15 ± 0.068	3.97 ± 0.037	<0.001	0.320	0.546
Milk protein (g/kg)	3.59 ± 0.048	3.51 ± 0.039	3.44 ± 0.036	3.34 ± 0.019	<0.001	0.398	0.909
Milk fat yield (kg/ cow per day)	0.70 ± 0.025	0.91 ± 0.022	0.95 ± 0.018	1.04 ± 0.017	<0.001	<0.001	0.068
Milk protein yield (kg/cow per day)	0.54 ± 0.018	0.72 ± 0.020	0.79 ± 0.018	0.88 ± 0.016	<0.001	0.004	0.177
FPCM yield (kg/cow per day)	16.5 ± 0.532	21.8 ± 0.577	23.5 ± 0.495	26.1 ± 0.439	<0.001	<0.002	0.123
Milk solids (kg/cow per day)	0.99 ± 0.130	1.30 ± 0.188	1.39 ± 0.166	1.52 ± 0.151	<0.001	0.001	0.080
Milk yield/DMI (kg/kg)	0.97 ± 0.018	1.17 ± 0.020	1.26 ± 0.017	1.37 ± 0.013	<0.001	<0.001	0.182
Milk yield per milking area (t FPCM/ha)	15.5 ± 1.100	21.5 ± 0.997	22.7 ± 1.530	24.6 ± 1.560	<0.001	0.595	0.243

[1] n = number of farms.

[2] L = linear; Q = quadratic; C = cubic.

R software, version 4.3.1 (https://cran.r-project.org/bin/windows/base/old/4.3.1/NEWS.R-4.3.1.html).

RESULTS

DMI, Milk Yield and Composition

Total DMI increased quadratically with an increase in concentrate feeding ($P < 0.01$) (Table 3). The highest total DMI was observed on farms that fed ≥3 tDM/cow per year concentrate, whereas those feeding ≤1 tDM concentrate had the lowest total DMI ($P < 0.01$). Farms that fed ≥3 tDM/cow per year of concentrate had a 23% greater predicted total DMI compared with those that fed 1 tDM/cow per year of concentrate.

Milk yield increased quadratically ($P < 0.01$) with increasing concentrate (Table 3). The increase in milk yield between ≤1 and ≥3 tDM of concentrate was 58%, and the corresponding increase in total DMI was only 23%. This discrepancy is reflected in the increased efficiency (L/kg DMI). The concentration of milk protein and fat linearly decreased ($P < 0.001$) with increasing concentrate level. In contrast, milk fat yield and protein yield exhibited a quadratic increase ($P < 0.01$) due to the increase in concentrate levels, driven by the increase in milk yield. Milk production per kilogram of DMI increased quadratically ($P < 0.001$), and milk production per hectare of milking area linearly increased ($P < 0.001$) in response to concentrate feeding.

Enteric and Manure Methane Emission

Enteric and manure CH_4 production (g/d) increased quadratically ($P < 0.01$) and linearly ($P < 0.001$) with increasing concentrate feeding levels, respectively (Table 4). Total CH_4 (enteric plus manure) production increased quadratically ($P < 0.05$) with increasing concentrate feeding level. The intensity of enteric CH_4 (g CH_4/kg milk fat and g CH_4/kg FPCM) showed a negative association ($P < 0.05$) with concentrate feeding. Likewise, enteric CH_4 per milk protein yield decreased quadratically ($P < 0.05$)

Table 4. Effects of concentrate feeding amount on enteric and manure methane emissions from dairy cattle at pasture, mean ± SE[1]

	Concentrate level (tDM/cow per year)[2]				*P*-value		
Emission intensity	≤1 (n = 15)	1–2 (n = 35)	2–3 (n = 35)	≥3 (n = 35)	L	Q	C
Enteric CH_4 (g CH_4/d per cow)	315 ± 3.632	357 ± 5.207	371 ± 4.734	390 ± 3.794	<0.001	0.003	0.238
Manure CH_4 (g CH_4/d per cow)	48.6 ± 0.560	48.9 ± 0.652	50.4 ± 0.740	52.1 ± 0.764	<0.001	0.078	0.884
Total CH_4 (g CH_4/d per cow)	364 ± 4.141	406 ± 5.272	422 ± 5.451	442 ± 4.113	0.009	0.012	0.291
FPCM EI (g enteric CH_4/kg FPCM)	19.3 ± 1.508	16.6 ± 1.460	15.9 ± 0.957	15.0 ± 0.671	<0.001	<0.001	0.012
Milk fat yield EI (kg enteric CH_4/kg fat)	0.45 ± 0.011	0.40 ± 0.007	0.39 ± 0.004	0.38 ± 0.003	<0.001	<0.001	0.019
Milk protein yield EI (kg enteric CH_4/kg protein)	0.59 ± 0.012	0.50 ± 0.009	0.47 ± 0.006	0.45 ± 0.004	<0.001	<0.001	0.076
Milking area EI (t enteric CH_4 per ha)	0.30 ± 0.019	0.35 ± 0.016	0.36 ± 0.023	0.37 ± 0.023	0.505	0.921	0.372
Total farm area EI (t enteric CH_4 per ha)	0.23 ± 0.023	0.22 ± 0.018	0.21 ± 0.015	0.22 ± 0.016	0.574	0.927	0.436

[1] EI = emission intensity; total CH_4 = manure CH_4(g CH_4/d per cow) + enteric methane (g CH_4/d per cow); L = linear; Q = quadratic; C = cubic.

[2] n = number of farms.

Table 5. Effects of concentrate feeding amount on direct and indirect nitrous oxide emissions from manure from dairy cattle at pasture, mean ± SE[1]

	Concentrate level (tDM/cow per year)[2]				*P*-value		
Emission intensity	≤1 (n = 15)	1–2 (n = 35)	2–3 (n = 35)	≥3 (n = 35)	L	Q	C
Direct N_2O from urine and feces avoided to pasture (g/d per cow)	1.94 ± 0.025	2.06 ± 0.025	2.11 ± 0.019	2.18 ± 0.025	<0.001	0.001	0.224
Direct N_2O from manure storage (g/d per cow)	0.67 ± 0.009	0.72 ± 0.009	0.74 ± 0.008	0.76 ± 0.009	<0.001	0.004	0.230
Indirect N_2O from N waste (g/d per cow)	1.99 ± 0.026	2.12 ± 0.027	2.17 ± 0.020	2.24 ± 0.026	<0.001	0.003	0.189
Total N_2O (g N_2O/d)	4.60 ± 0.058	4.90 ± 0.060	5.02 ± 0.047	5.18 ± 0.059	<0.001	0.002	0.209
DMI EI (g N_2O/kg DMI)	0.32 ± 0.002	0.30 ± 0.002	0.28 ± 0.001	0.26 ± 0.002	<0.001	<0.001	0.152
FPCM yield EI (g N_2O/kg)	0.28 ± 0.029	0.23 ± 0.027	0.21 ± 0.017	0.19 ± 0.013	<0.001	<0.001	0.003
Milking area EI (kg N_2O/ha)	4.19 ± 0.299	4.87 ± 0.236	4.72 ± 0.293	4.38 ± 0.270	0.109	0.849	0.424
Total farm area (kg N_2O /ha)	3.13 ± 0.358	2.83 ± 0.253	2.61 ± 0.203	2.42 ± 0.196	0.002	0.783	0.398

[1] EI = emission intensity; total N_2O = direct N_2O from urine and feces avoided to pasture (g/d) + direct N_2O from manure storage (g/d) + indirect N_2O from N waste (g N_2O/d); L = linear; Q = quadratic; C = cubic.

[2] n = number of farms.

with concentrate feeding. Farms that fed ≥3 tDM/cow per year had 21% higher total CH_4 emissions and 23% lower emission intensity (total CH_4 g/kg of FPCM) than those that fed ≤1 t/DM cow per year.

Nitrous Oxide Emission

Direct N_2O from urine and feces that avoided pasture and manure storage, indirect N_2O from N waste, and total N_2O emissions from the manure exhibited a quadratic increase ($P < 0.01$) as the level of concentrate feeding increased (Table 5). As the levels of concentrate feeding increased, the N_2O intensity of the total farm area (kg/ha) exhibited a linear decrease ($P < 0.01$). The N_2O intensity of the total farm area (kg/ha) decreased linearly ($P < 0.01$) with increasing levels of concentrate feeding.

Milk and Farm Emissions Intensity

Emissions intensity expressed as kg CO_{2eq}/kg of FPCM, milk solids, and milk fat yield decreased cubically ($P < 0.05$) with increasing levels of concentrate feeding (Table 6). A negative quadratic response ($P < 0.01$) to increasing concentrate levels was observed for CO_{2eq} emissions per kilogram of milk protein yield.

The CO_2 emissions from concentrate production (kg CO_2/kg of concentrate) increased linearly ($P < 0.001$) with increasing concentrate feeding (Table 7). A quadratic relationship ($P < 0.05$) was observed between the concentrate level and the emission intensity of fat protein-corrected milk, considering emissions from concentrate production. This intensity exhibited a cubic decrease ($P < 0.05$) as concentrate feeding increased. Emission intensity decreased by only 14% between 1 and ≥3 tDM/cow

Table 6. Effects of concentrate feeding amount on direct and indirect nitrous oxide emissions from manure from dairy cattle at pasture, mean ± SE[1]

	Concentrate level (tDM/cow per year)[2]				*P*-value		
Emission intensity	≤1 (n = 15)	1–2 (n = 35)	2–3 (n = 35)	≥3 (n = 35)	L	Q	C
FPCM emission intensity (kg CO_{2eq}/kg FPCM)	0.85 ± 0.019	0.72 ± 0.010	0.68 ± 0.007	0.63 ± 0.005	<0.001	<0.001	0.005
Milk solids emission intensity (kg $CO_{2\ eq}$/kg MS)	11.7 ± 0.276	9.95 ± 0.141	9.51 ± 0.106	8.90 ± 0.072	<0.001	<0.001	0.007
Milk fat emission intensity (kg CO_{2eq}/kg milk fat)	16.6 ± 0.412	14.3 ± 0.236	13.9 ± 0.167	13.1 ± 0.115	<0.001	<0.001	0.013
Milk protein emission intensity (kg $CO_{2\ eq}$/kg milk protein)	21.4 ± 0.473	18.0 ± 0.323	16.7 ± 0.224	15.5 ± 0.146	<0.001	<0.001	0.056
DMI emission intensity (kg CO_{2eq}/kg DMI)	0.76 ± 0.002	0.75 ± 0.001	0.74 ± 0.001	0.73 ± 0.001	<0.001	0.130	0.515
Milking area emission intensity (t CO_{2eq}/ha of milking area)	10.8 ± 0.688	12.6 ± 0.572	12.7 ± 0.796	12.7 ± 0.802	0.186	0.902	0.390
Farm area emission intensity (t CO_{2eq}/ha of total farm area)	8.54 ± 0.823	7.86 ± 0.631	7.32 ± 0.543	7.61 ± 0.561	0.304	0.983	0.444
Cow emission intensity (t CO_{2eq}/cow per year)	4.44 ± 0.209	5.16 ± 0.445	5.55 ± 0.392	6.03 ± 0.332	0.007	0.003	0.235

[1] MS = milk solids; L = linear; Q = quadratic; C = cubic.

[2] n = number of farms.

Table 7. Effects of concentrate feeding on emission intensity of FPCM before and after emission from concentrate production included, mean ± SE

	Concentrate level (tDM/cow per year)[1]				P-value[2]		
Emission intensity	≤1 (n = 15)	1–2 (n = 35)	2–3 (n = 35)	≥3 (n = 35)	L	Q	C
Emission from concentrate production (t CO_2/cow per year)	0.24 ± 0.072	0.48 ± 0.099	0.77 ± 0.092	1.10 ± 0.147	<0.001	0.996	0.412
Emission from concentrate production per milking area (t CO_2/ha)	0.61 ± 0.242	1.30 ± 0.425	2.03 ± 0.789	2.86 ± 1.214	<0.001	0.488	0.355
FPCM emission intensity for concentrate production (kg CO_2/kg FPCM)	0.05 ± 0.014	0.07 ± 0.013	0.11 ± 0.015	0.14 ± 0.020	<0.001	0.112	0.902
FPCM emission intensity including concentrate production emission (kg $CO_{2\ eq}$/ kg FPCM)	0.90 ± 0.071	0.79 ± 0.065	0.79 ± 0.049	0.77 ± 0.039	<0.001	<0.001	0.022
FPCM emission intensity excluding concentrate production emission (kg CO_{2eq}/ kg FPCM)	0.85 ± 0.019	0.72 ± 0.010	0.68 ± 0.007	0.63 ± 0.005	<0.001	<0.001	0.005

[1] n = number of farms.

[2] L = linear; Q = quadratic; C = cubic.

per year when emission from concentrate production is included, compared with a decrease of 26% between 1 and ≥3 tDM/cow per year for emission intensity without considering emission production.

Correlations Between Concentrate Level, Emission Intensity, Milk Yield and Composition

We found a negative correlation ($P < 0.001$) between concentrate feeding and emission intensity (kg CO_{2eq}/kg of FPCM and milk solids), as well as with milk fat and protein (Table 8). Milk yield per cow, total CH_4 production (manure plus enteric CH_4), DMI, feed conversion efficiency, milk protein, and fat yield were positively correlated ($P < 0.001$) with concentrate level. A negative correlation was observed between DMI and emission intensity (kg CO_{2eq} per kg of FPCM and MS). Feed conversion efficiency showed a positive ($P < 0.001$) correlation with total DMI, total CH_4, total N_2O, milk yield, and milk protein and fat yield, and it exhibited a negative ($P < 0.001$) correlation with milk fat and protein. Higher levels of concentrate feeding were associated with lower CO_{2eq} per kg of DMI ($P < 0.01$) and higher CO_{2eq} per cow per year.

Net Return of Concentrate Feeding

The gross income, total variable cost, gross margin, total overhead cost, EBIT, and net return per kilogram of milk solids are provided in Table 9. Both feed and total variable costs increased linearly ($P < 0.001$) with increasing concentrate feeding however overhead cost was not affected ($P > 0.05$) by supplement feeding amount.

Table 8. Pearson correlation matric between concentrate level (kg DM/cow per day) and various measures of greenhouse gas emissions from dairy cattle at pasture[1]

Measure	Concentrate level	EIFPCM	EIMS	Milk fat	Milk protein	MFY	MPY	DMI	FCE	Milk yield
EIFPCM	−0.79***									
EIMS	−0.75***	0.99***								
Milk fat	−0.57***	0.38***	0.28**							
Milk protein	−0.42***	0.21*	0.10	0.79***						
MFY	0.68***	−0.95***	−0.93***	−0.40***	−0.28**					
MPY	0.72***	−0.91***	−0.88***	−0.59***	−0.31***	0.95***				
DMI	0.67***	−0.84***	−0.79***	−0.71***	−0.52***	0.92***	0.96***			
FCE	0.75***	−0.99***	−0.97***	−0.40***	−0.23*	0.98***	0.95***	0.89***		
Milk yield	0.75***	−0.87***	−0.81***	−0.72***	−0.53***	0.92***	0.97***	0.99***	0.90***	
Total CH_4	0.60***	−0.81***	−0.76***	−0.70***	−0.51***	0.91***	0.95***	1.00***	0.87***	0.98***

[1] Total CH_4 is the sum of enteric and manure (g CH_4/cow per day). EIFPCM = FPCM emission intensity (kg CO_{2eq}/kg FPCM); EIMS = milk solid emission intensity (kg CO_{2eq}/kg MS), MFY = milk fat yield (kg), MPY = milk protein yield (kg); DMI = kg DM/d, FCE = feed conversion efficiency (kg), FPCM/kg DMI.

*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.

Table 9. Effects of concentrate feeding on gross income, gross margin, earnings before tax and lease, and net income ($/kg of milk solids), mean ± SE

	Concentrate level (tDM/cow per year)[1]				*P*-value[2]		
Cost and income	≤1 (n = 15)	1–2 (n = 35)	2–3 (n = 35)	≥3 (n = 35)	L	Q	C
Milk income ($/kg milk solids)	5.58 ± 0.129	5.95 ± 0.146	6.36 ± 0.157	6.15 ± 0.140	0.014	0.365	0.057
Other income ($/kg milk solids)	0.40 ± 0.166	0.60 ± 0.082	0.77 ± 0.067	0.75 ± 0.077	0.048	0.982	0.185
Gross income ($/kg milk solids)	5.98 ± 0.243	6.54 ± 0.168	7.13 ± 0.194	6.91 ± 0.187	0.005	0.487	0.039
Feed cost ($/kg milk solids)	2.27 ± 0.121	2.66 ± 0.098	3.07 ± 0.098	3.53 ± 0.090	<0.001	0.198	0.956
Total variable cost	2.76 ± 0.129	3.21 ± 0.105	3.64 ± 0.116	4.09 ± 0.095	<0.001	0.186	0.792
Gross margin ($/kg milk solids)	3.22 ± 0.282	3.33 ± 0.141	3.49 ± 0.142	2.82 ± 0.171	0.393	0.884	0.030
Cash overheads ($/kg milk solids)	1.52 ± 0.112	1.32 ± 0.093	1.35 ± 0.090	1.43 ± 0.104	0.756	0.761	0.222
Noncash overheads ($/kg milk solids)	0.83 ± 0.179	1.27 ± 0.119	1.10 ± 0.098	0.91 ± 0.083	0.325	0.698	0.029
Total overheads ($/kg milk solids)	2.35 ± 0.168	2.59 ± 0.146	2.45 ± 0.125	2.34 ± 0.113	0.300	0.924	0.364
Total operating cost ($/kg milk solids)	5.11 ± 0.223	5.80 ± 0.197	6.09 ± 0.211	6.43 ± 0.171	0.009	0.406	0.455
EBIT ($/kg milk solids)	1.07 ± 0.295	0.77 ± 0.142	1.05 ± 0.128	0.54 ± 0.136	0.816	0.605	0.146
Interest and lease cost ($/kg milk solids)	0.84 ± 0.157	0.51 ± 0.082	0.61 ± 0.064	0.59 ± 0.063	0.185	0.033	0.341
Net income ($/kg milk solids)	0.03 ± 0.438	0.23 ± 0.198	0.43 ± 0.136	−0.12 ± 0.143	0.606	0.495	0.097

[1] n = number of farms.

[2] L = linear; Q = quadratic; C = cubic.

Gross income, total variable cost, gross margin, total overhead cost, EBIT, and net return per cow per year of concentrate feeding are indicated in Table 10. Concentrate supplementation led to cubic, quadratic, and linear increases in gross income ($P < 0.01$), variable costs ($P < 0.05$), and overhead costs ($P < 0.01$) per cow per year, respectively.

DISCUSSION

Previous studies conducted under controlled conditions have extensively documented that diets with a higher proportion of concentrate tend to increase DMI, milk yield, and daily enteric CH_4 production (g/d), and reduce emissions per unit of DMI and per unit of milk produced (Agle et al. 2010; Aguerre et al. 2012; Arndt et al. 2022). However, limited studies have used data collected from commercial dairy farms to quantify the effect of concentrate supplementation on milk yield, CH_4 and N_2O emissions, and emission intensity. Previous studies (Christie et al. 2016; Gollnow et al. 2014; Christie 2019) have been conducted to account for GHG emissions from Australian dairy farms using commercial dairy farm data; however, none have predicted the effects of concentrate on GHG inventories. Thus, this study sought to determine how concentrate feeding influences the environmental footprint of milk production from dairy farms by increasing milk production and lowering enteric CH_4 and manure N_2O and CH_4.

Total DMI increased quadratically with increasing concentrate feeding, likely due to the concentrate supplying abundant energy and a protein substrate to the

Table 10. Effects of concentrate feeding on gross income, gross margin, earnings before tax and lease, and net income ($/cow per year), mean ± SE

	Concentrate level (tDM/cow per year)[1]				*P*-value[2]		
Cost and income	≤1 (n = 15)	1–2 (n = 35)	2–3 (n = 35)	≥3 (n = 35)	L	Q	C
Milk income ($/cow per year)	2,035 ± 112.30	2,823 ± 95.787	3,208 ± 87.467	3,428 ± 95.972	<0.001	0.018	0.008
Other income ($/cow per year)	155 ± 60.66	278 ± 43.81	392 ± 35.02	420 ± 45.70	<0.001	0.840	0.094
Gross income ($/cow per year)	2,191 ± 152.36	3,102 ± 104.78	3,600 ± 108.71	3,848 ± 124.00	<0.001	0.003	0.006
Feed cost ($/cow per year)	829 ± 55.84	1,255 ± 46.070	1,556 ± 58.983	1959 ± 49.881	<0.001	0.040	0.051
Total variable cost ($/cow per year)	1,003 ± 62.996	1,515 ± 50.615	1,844 ± 70.726	2,270 ± 54.695	<0.001	0.031	0.320
Gross margin ($/cow per year)	1,188 ± 127.31	1,586 ± 83.929	1,755 ± 66.539	1,578 ± 103.66	0.001	0.476	0.005
Cash overheads ($/cow per year)	557 ± 47.36	626 ± 45.18	684 ± 46.43	796 ± 57.90	0.003	0.479	0.704
Noncash overheads ($/cow per year)	285 ± 57.54	589 ± 50.54	540 ± 42.39	501 ± 45.29	0.221	0.294	0.008
Total overheads ($/cow per year)	1,996 ± 54.676	2,598 ± 65.012	2,874 ± 53.137	3,540 ± 62.276	0.001	0.159	0.071
Total operating cost ($/cow per year)	1,844 ± 92.893	2,731 ± 90.872	3,068 ± 107.21	3,566 ± 96.145	<0.001	0.028	0.090
EBIT ($/cow per year)	347 ± 143.03	371 ± 71.05	532 ± 63.13	282 ± 81.47	0.310	0.762	0.084
Interest and lease cost ($/cow per year)	289 ± 49.04	236 ± 35.62	310 ± 32.92	326 ± 31.85	0.305	0.265	0.949
Net income ($/cow per year)	58.5 ± 160.9	135 ± 88.24	222 ± 65.52	−44.5 ± 79.66	0.610	0.860	0.120

[1] n = number of farms.

[2] L = linear; Q = quadratic; C = cubic.

ruminal microorganisms and the animal improving the efficiency of ruminal fermentation, and thus enhancing DMI (Hristov et al. 2013, 2022). A higher proportion of concentrate led to a linear increase in DMI, which could potentially enhance rumen microbial protein outflow (Agle et al., 2010) and reduce fiber content in the diet (McDonald et al., 2001). In addition, diets high in forage tend to be bulkier and reduce DMI because of the fill of the gastrointestinal tract. Huhtanen and Hetta (2012) and Min et al. (2022) reported positive correlations between concentrate level and total DMI, milk yield, energy-corrected milk yield, and milk protein in a meta-analysis of concentrate supplementation studies using lactating dairy cows. The total DMI in the present study was comparable to that reported by Christie (2019) for Australian dairy farms, which ranged from 12 to 26 kg/cow per day and closely resembled the findings of previous grazing studies evaluating the effect of concentrate on CH_4 emissions, which were reported at 14.9 (Jiao et al., 2014), 18.8 (Muñoz et al., 2015), 14.0 (Muñoz et al., 2018), 15.9 (van Wyngaard et al., 2018), and 15.5 kg/cow per day (Ferris et al., 2020). However, it is important to point out that the predicted DMI of the present study is predicted by the model through the back-calculation from diet DMD, milk production, BW, and ADG. Furthermore, pasture DMI exhibited a quadratic decrease as the concentrate amount increased, potentially attributed to pasture substitution by concentrate. Therefore, results should be interpreted with caution. Further research measuring diet quality may be required to ascertain the validity of predicted DMI in the present study.

In the present study, greater concentrate supplementation increased milk yield, and such a response at pasture has been widely reported (Muñoz et al., 2018; van Wyngaard et al., 2018; Brito et al., 2022). This increase in milk yield was directly related to the higher DMI reported here, as DMI has been identified as a key factor limiting milk production in dairy cows (Bargo et al., 2003). In addition, several studies reported higher propionate production in the rumen of cows fed higher concentrate (Agle et al. 2010; van Wyngaard et al. 2018), which may stimulate milk production (Danfær, 1994).

Milk fat concentration decreased with increasing concentrate supplementation, which could be attributed to lower rumen acetate production as a precursor of milk fat (Cozma et al. 2013). Similar to the present study's findings, others have reported a decrease in milk fat with increased dietary concentrate (Agle et al., 2010; van Wyngaard et al., 2018; Ferris et al., 2020). Milk protein linearly decreased as the concentrate level increased, which could be attributed to greater DMI microbial protein synthesis, propionate, and glucose.

Daily CH_4 emissions increased linearly with increasing concentrate supplementation in the present study, and this could be a consequence of greater DMI as a key driver of CH_4 emissions (Ellis et al. 2007; Charmley et al. 2016; de Souza Congio et al. 2021). Greater DMI leads to increased CH_4 production by increasing the intake of fermentable substrates, including both structural and nonstructural carbohydrates (Moe and Tyrrell, 1979). The feeding of concentrate led to a decrease in the intensity of enteric CH_4 emissions (g/kg FPCM), likely due to the higher milk yield associated with increased concentrate feeding, as supported by the strong correlation between these factors. Consistent with the results of the present study, Johnson and Johnson (1995) and Boadi et al. (2004) reported that increasing the proportion of concentrate (>90%) in the diet led to lower enteric CH_4 emissions per unit of product as production increased, achieving a reduction in CH_4 losses of 2% to 3% of gross energy intake. Because this loss rate is roughly half of the commonly predicted 6% loss of diet GE as methane. Comparable to the present study, van Wyngaard et al. (2018) reported an increase in CH_4 emissions (258 vs. 302 g/d) and a decrease in CH_4 emissions intensity per kilogram of FCM (17.7 vs. 14.9 g/kg) and per kilogram of milk yield (20.4 to 15.9 g/kg).

The N_2O emissions from urine and feces, which are avoided in pasture and manure storage, consistently increased with increasing concentrate supplementation. This could be attributed to the higher DMI intake and fecal excretion of N. The N_2O intensity of the total farm area (kg/ha) decreased linearly with increasing levels of concentrate feeding. This decrease might be attributed to the reduction in stocking rate with increasing concentrate inclusion in the diet, in addition to the effect of the concentrate level. Feeding more concentrate significantly reduced emissions intensity in kg CO_{2eq}/kg FPCM in the current study, most likely due to increased animal productivity (Gerber et al., 2013; van Gastelen et al., 2019) and the dilution of feed required for maintenance over a larger amount of animal product (Min et al., 2022).

Farms that fed ≥3 tDM/cow per year had 75.6% higher gross income and 32.8% higher gross margin, which resulted in 23.3% lower EBIT and 222% lower net income per cow per year compared with those that fed ≤1 tDM/cow per year. Moreover, farms that fed 2 to 3 tDM/cow per year had higher gross income, gross margin, EBIT, and net income per cow per year by 64.3%, 47.7%, 53.2%, and 279% respectively, in comparison to those that fed ≤1 tDM/cow per year. As the concentrate level increased, there was a linear and quadratic rise in the cost of feed per kilogram of milk solids and per cow per year. This difference arose because animals with low concentrate consumed less feed and received a lower amount of concentrate supplementation. This reduction in supplementation lowered feed costs and contributed to lower overall feed expenses because grass harvested from the paddock by the cows has only the cost of pasture maintenance. The observed trend in gross income exhibited a cubic increase corresponding to variations in concentrate supplementation levels. Farms with higher concentrate supplementation demonstrated greater gross income compared with those with lower concentrate supplementation, primarily due to higher milk yield resulting from the high supplementary feeding. However, the gross margin, EBIT, and net income of farms did not exhibit any linear, quadratic, or cubic increment or decrement between the concentrate supplementation levels. This lack of significant difference could be attributed to the increased cost of the supplement, the requirement for additional labor, and expenses associated with feed, farm equipment, material input, and energy consumption with high supplementation. Furthermore, net income per kg of milk solids and per cow was negative for farms with ≥3 tDM/cow per year. This might because the addition of more variable input no longer adds to the total output, resulting in negative net income. This implies that the total output, primarily milk production, increases at an accelerating rate with additional inputs (exhibiting increasing returns), and the average product increases. However, as more input is added, the average output per unit of input declines. Eventually, the addition of more variable input no longer contributes to the total output for farms that supplement more than ≥3 tDM/cow per year and causes the total output to decline. It is important to acknowledge that this is one year's worth of farm data. Profit measured through gross margin, EIBT, and net income reached its peak at the range of 2 to 3 tDM/cow per year (equivalent to 5.7–8.2 kg DM/cow per day) in the present study. These results agree with Ho et al., (2017), who reported that the optimal supplement amount for maximizing profit ranged between 4.5 and 8 kg DM/cow per day for Victoria's dairy farms in Australia.

A notable limitation of this study is the absence of data regarding the proportion of concentrate that was purchased versus homegrown on the farms. Nevertheless, we calculated CO_2 emissions from concentrate production assuming that all concentrate was purchased off-farm, resulting in total predicted CO_2 emissions of 0.24 and 1.10 t/cow per year for low and high concentrate supplementation, respectively. The present study did not considered carbon sequestered by pastures and soils and a full life cycle assessment study may be needed. Another limitation is not having the actual digestibility of pasture or CP of concentrate and the BW of the animals, which would influence these estimates and have an impact on these results. Currently, our modeling hasn't considered individual variations based on lactation stages for estimating DMI due to the absence of specific data on this aspect. Furthermore, the model (DMI prediction model) we used did not enable the inclusion of the lactation stage as a component of DMI prediction. Hence, our analysis does not report these specific individual variations.

CONCLUSIONS

The results indicate that farms supplementing with ≥3 tDM/cow per year had 73% higher milk production and reduced emission intensity (kg CO_{2eq}/kg FPCM) by 14% compared with farms supplementing with ≤1 tDM/cow per year of dietary concentrate. Comparative analysis revealed that farms feeding 2 to 3 tDM/cow per year demonstrated significantly elevated gross income (+64%), gross margin (+48%), EBIT (+53%), and net income per cow per year (+279%) compared with those feeding ≤1 tDM/cow per year. Therefore, increasing concentrate supplementation from ≤1 to 2 to 3 tDM/cow per year not only increases milk production per cow but also reduces the intensity of GHG emissions from milk production, benefiting both the environment and dairy farmers. More detailed information on carbon sequestration, actual DMI, pasture digestibility, concentrate protein content, and urinary and fecal N excretion measurement could enhance decision-making for concentrate feeding on dairy farms, addressing data gaps identified in this study.

NOTES

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Nonstandard abbreviations used: ADCC = Australian Dairy Carbon Calculator; CO_{2eq} = CO2 equivalent; DFMP = Australian Dairy Farm Monitoring Project; DMD = dry matter digestibility; EBIT = earnings before interest and tax; EI = emission intensity; EIFPCM = FPCM emission intensity; EIMS = milk sold emission intensity; FCE = feed conversion efficiency; FPCM = fat- and protein-corrected milk; GHG = greenhouse gas;

MFY = milk fat yield; MPY = milk protein yield; MS = milk solids; tDM = tonnes of concentrate DM; VS = volatile solids.

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Chapter 5. Potential Applications of a Low-Cost Gas Sensor to Monitor Enteric Methane Emissions from Ruminant Animals

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Overview

This chapter evaluated the performance of low-cost gas sensors (MQ-4, MQ-7, MQ-8) for measuring enteric methane (CH_4) emissions in cattle, comparing them with the GreenFeed system. Sensors were tested in both laboratory and field conditions, with optimal placement identified at the pump outlet of the GreenFeed unit. The sensors showed moderate correlation with GreenFeed data but had lower repeatability and peak detection accuracy. The study demonstrated the potential of affordable CH_4 monitoring tools for scalable field applications, though further refinement is needed for reliable use in commercial settings.

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Potential applications of a low-cost gas sensor to monitor enteric methane emission from ruminant animals

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ABSTRACT

Enteric methane (CH_4) emissions are a significant concern in ruminant production due to its high global warming potential of 28 times that of CO_2. Research is focused on mitigating these emissions through animal and feed management. However, accurately and economically measuring CH_4 emissions from individual animals remains challenging due to current methods' high cost, slow speed, and labor intensity. Therefore, the primary objective of the present study was to evaluate low-cost gas sensors, named MQ-4, MQ-8, MQ-7, by comparing their data with a well-established GreenFeed system (GF). The MQ-4, MQ-8, and MQ-7are sensitive to CH_4, H_2, and CO, respectively. Sensors were assembled on a single board and placed at various points on the GF system (airflow outlet, pump outlet, and feed tray) to determine optimal placement. The pump outlet showed the highest correlation ($r = 0.51$ for CH_4 and $r = 0.65$ for H_2) with GF data. Following this, the gas sensors were placed in a pump outlet for 45 days, and enteric CH_4 and H_2 were measured simultaneously using both devices on 28 heifers, resulting in a total of 3.88×10^6 paired measurements. Correlation between CH_4 and H_2 data from the GF and gas sensors was assessed using Spearman correlation coefficients (SCC), repeatability, and peak measurement algorithms. The SCC values for the CH_4 concentration from the MQ-4 gas sensor and GF averaged weekly, daily, hourly, and minute were 0.62, 0.56, 0.49, and 0.47, respectively. The repeated measures correlation between (from the per second record) the devices was relatively low (0.30). The repeatability of CH_4 concentration was greater for the GF (0.31) than for the MQ-4 gas sensor (0.13). Additionally, there were significant differences in the detected number of peaks, peak duration, and width between the two devices. The peak detection algorithm indicated that the GF detected more peaks and processed data four times faster than the MQ-4 gas sensor. Although results indicate moderate and significant correlations between H_2 and CH_4 voltages measured by the GF and gas sensors, lower repeatability and discrepancies in peak characteristics observed for the gas sensor suggest caution in interchangeable use without further methodological refinement.

1. Introduction

Enteric methane (CH_4) production by ruminants poses a threat to climate change because it is a powerful greenhouse gas (GHG) with 28-fold greater global warming potential than carbon dioxide (CO_2) [1]. Enteric CH_4 accounts for 39 % of livestock sector emissions, making it a major concern worldwide [2]. Reducing such emissions from livestock can be addressed by combining feeding, genetic improvement, vaccines against methanogens, and management strategies [3–5]. However, accurate and large-scale measurements of GHG emissions from individual animals in their production environment are vital to develop and evaluate mitigation strategies and provide realistic GHG emission figures.

Numerous methods for quantifying enteric CH_4 emissions have been developed, each with its advantages and disadvantages [6–9]. One of the most accurate methods is the (closed-circuit) respiration chamber (RC), but it comes with limitations such as animal confinement, cost, and labor intensity, raising questions about its applicability to commercial or grazing systems [9]. In contrast, the (open-circuit) Greenfeed system (GF) offers higher throughput and shorter measurement periods [10]. However, GF's limitation lies in measuring gas exchange while animals

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eat feed (used as an attractant), the frequency at which these measurements can be done, and the cost and labour to maintain the equipment, making CH_4 production estimation challenging. Lower-cost methods have also been investigated such as the laser methane detector, designed for detecting gas leaks, which faces challenges related to environmental conditions like wind speed, humidity, distance to the source, and air pressure [7,11,12]. Breath analyzers (sniffers) have been used with CH_4 and CO_2 sampling points in automated milking systems and can estimate CH_4 production based on ratios and predicted CO_2 production (L/d) but face uncertainties because the cow eats during the recording, and the influence of this activity on the estimation of CH_4 production is not known [13–15].

Prediction equations of CH_4 production based on feed and animal characteristics can be useful but come with limitations to account for the multiple factors in production conditions [16]. All these challenges hinder CH_4 mitigation through animal breeding due to the high cost and infeasibility of measuring from many animals. Consequently, there is a pressing need for more convenient, cost-effective, practical, scalable, and non-invasive methods for quantifying enteric CH_4 produced by animals, which also consider animal welfare and production performance. Low-cost gas sensors that could be placed near or within feed troughs are available. However, their accuracy and how this is affected by their position in the trough is unknown. Therefore, the objective of the present study was to evaluate a sensor to measure the concentration of CH_4 that is inexpensive, and low power and assess the output data against the GF system.

2. Materials and methods

2.1. Low-cost sensor module

The module (Fig. 1) was developed containing a sensor box connected to a Raspberry Pi microcontroller (Raspberry Pi 4 Model B, Raspberry Pi Foundation, UK). The sensor box contained the gas sensors (MQ-4, MQ-8, MQ-7), a temperature and humidity sensor (SHT21), an ESP32 development board, an SD-card module, and a 5V fan. The MQ-4 gas sensor (Hanwei Electronics Group Corporation, Zhengzhou, China) is an inexpensive sensor which is a semiconductor-type CH_4 sensor that consumes less than 150 mA at 5 VDC. This sensor can detect CH_4 in the range of 200 to 10,000 ppm. MQ-8 and MQ-7 sensors are inexpensive sensors with sensitivity to hydrogen (H_2) and carbon monoxide (CO), respectively (Table 1). The sensors were assembled on a board with other electronic components. The board contained three potentiometers (one for each gas sensor) to adjust the voltage input to each gas sensor. The board and all the components were assembled in an enclosure equipped with a fan and gas inlet (Fig. 1).

A sketch was written on Arduino IDE to program ESP32 to turn the fan on and heat MQ sensors. During the operation, the fan was able to suck the air from the gas inlet and pass the gas through the sensors. In addition, ESP32 was programmed to read the output voltage from each sensor every 100 milliseconds. The data was stored on a char buffer and recorded the average of the last 10 readings per second for each sensor on an SD card. The data recorded contained date, time, and voltage from each sensor with higher values at higher concentrations of the gas. The sensor box was powered through a 5 VDC power supply. To visualise and stream the data in real-time, the sensor box was connected to a Raspberry Pi 4 through UART female headers installed on the board. A USB to TTL serial UART RS232 adaptor (PL2303TA, Core Electronics, AU) was employed to connect the sensor box to the Raspberry Pi. An additional line of command was added to the sketch to send the data through the serial port to the Raspberry Pi. A Python script was written and ran on Raspberry Pi to receive the data. A computer could be connected to the Raspberry Pi to monitor, control, and record the data in real-time. In the filed setup, a 12 VDC battery was used to power the system. The battery was connected to a solar panel through a solar charge controller. The 12 VDC voltage was reduced to 5 VDC via a step-down voltage regulator. In the lab setup, a DC adaptor was used to power the module.

2.2. The GreenFeed unit

The GF system is typically set up to dispense small pellets to encourage animals to visit the GF multiple times per day (C-Lock Inc.,

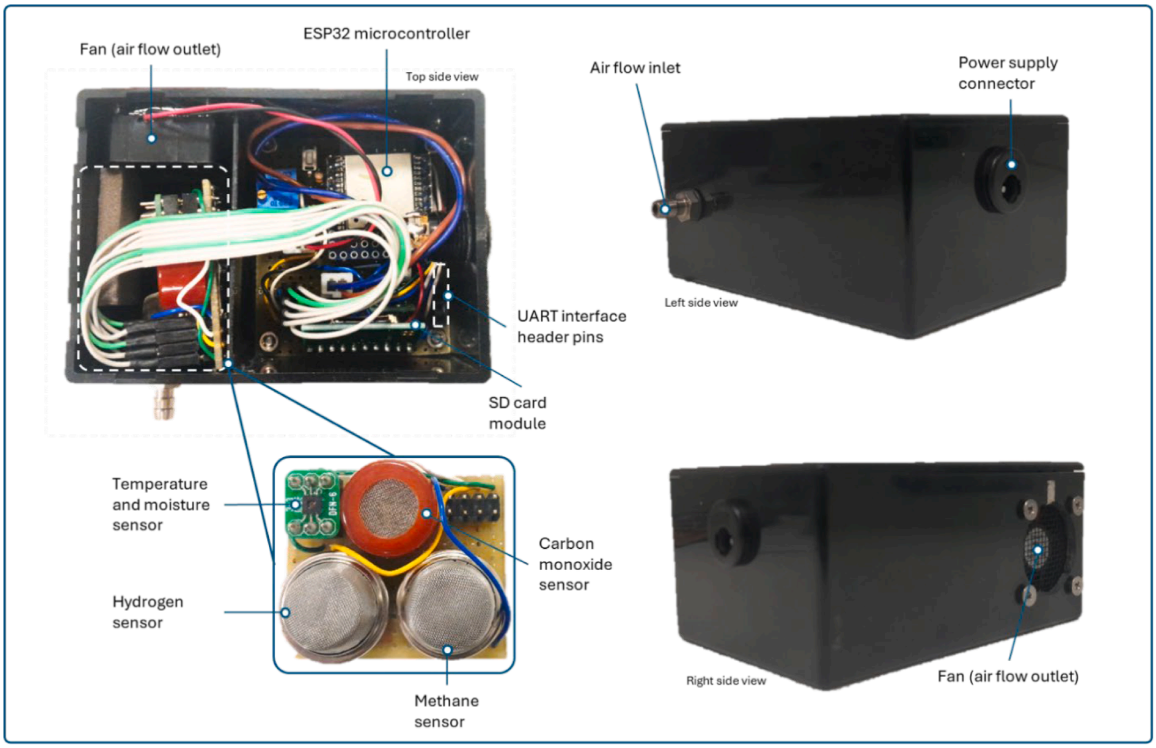

Fig. 1. MQ-4 gas sensor was developed to measure enteric methane emissions from cattle.

Table 1
The list of components and their price in the market

Component	Quantity	Unit price (AUD)	Total price (AUD)
A. Sensor box			
Plastic box (60 × 40 × 85 mm)	1	5.01	5.01
Fan 25 mm 5VDC	1	11.95	11.95
Fitting for tubing	1	5.15	5.15
Bulkhead Male DC Power Connector 2.1 mm	1	3.50	3.50
DC Power Line Connector 9.5mm Shaft 2.1 mm	1	2.85	2.85
MQ-8 Sensor	1	9.50	9.50
MQ-7 Sensor	1	10.42	10.42
MQ-4 Sensor	1	9.40	9.40
ESP32 WiFi-BT-BLE MCU Module / ESP-WROOM-32	1	13.95	13.95
Temperature and humidity sensor	1	14.83	14.83
Pin Headers - Straight	1	0.47	0.47
MicroSD Card Module	1	8.40	8.40
USB to TTL Serial UART RS232 Adaptor	1	4.10	4.10
Trimmer Potentiometer	3	4.03	12.09
Mini SD-Card 32GB	1	8.95	8.95
Capacitors and resistors	6	2.00	12.00
Screws and nuts	12	0.50	6.00
Wires (meter)	1	1.00	1.00
Total			**139.57**
B. Real-time monitoring module[1]			
Raspberry Pi 4 Model B 1GB	1	62.00	62.00
Cellular 4G modem	1	39.00	39.00
Total			**101.00**
C. Power supply			
Sensor Box only[2]			
Power bank 20,000 mAh	1	59.95	59.95
Total			**59.95**
Sensor box + Real-time monitoring module[3]			
20W Adjustable DC-DC Buck Converter	1	7.90	7.90
12V Battery	1	118.00	118.00
Solar panel and solar charge controller 12V 20W	1	64.95	64.95
Total			**190.85**

[1] The real-time monitoring module can be used to monitor the data remotely. Otherwise, the sensor box can work without a real-time monitoring module, and record the data on the SD-Card.

[2] The power supply requirement for the sensor box if the sensor box is used independently.

[3] The power supply requirements if the sensor box is used with the real-time monitoring module.

2023). Individual CH_4 emissions measured by the GF system are reported as daily CH_4 production (g CH_4/day). The duration of visits and the number of records per animal are crucial for accurate CH_4 measurement, as CH_4 emissions typically occur at intervals of 40 to 120 s [17]. The GF operation begins when the animal inserts its head into the shroud [18] (Fig. 2). Subsequently, the proximity sensor in the shroud monitors the head position of the animal during each visit, enabling the exclusion of measurements where animals exit the GF. Air is continually drawn through the shroud and past the animal's neck at a precisely measured flow rate, with the CH_4 concentration quantified in the exhaust air stream [19]. Given that the GF system provides multiple short-term breath measurements, a minimum of 30 measurements lasting at least 3 minutes per visit are required to achieve a minimal variance in CH_4 production rate per animal [20]. Data are logged and transmitted to the C-Lock Inc. data management system, and accessible for download through the website interface (https://greenfeed.c-lockinc.com). The GF system undergoes calibration according to the manufacturer's protocol, and gas recovery is regularly performed.

2.3. Laboratory calibration of the CH_4 gas sensor

The gas sensors detect the concentration of CH_4 gas in the air and generate an analog voltage reading but not the concentration. To obtain the CH_4 concentration output from the gas sensors, the sensor was calibrated in a laboratory setting. The calibration of the sensors took place in a controlled laboratory environment, in preparation for the field testing of the CH_4 sensing system prototype within the concentration range of 200-10,000 ppm CH_4. The sensor was placed inside a 1-liter airtight jar (Fig. 3). A syringe was used to introduce a 20 % CH_4 gas into the jar (nitrogen makes up the remaining 80 % of the gas mixture). The jar was sealed with putty to maintain the total quantity of the introduced gas mixture. The CH_4 gas mixture was injected into the jar in 5 mL increments to produce an increase in the CH_4 concentration of 1000 ppm. After each injection, a 10-min rest period followed to allow the sensor to reach equilibrium with the gas concentration. The CH_4 concentration readings from the MQ-4 gas sensor were calculated using the following formula:

CH_4 concentration $= 2600 + (Raw_t - Raw_{bk}) * C_c$
Where Raw_t = measured voltage by the sensor
Raw_{bk} = calculated background voltage of the sensor
C_c = calibration coefficient for concentration (79)

2.4. Placement of gas sensors within the GF unit

The study involved three similar gas sensors (Sensor 1, Sensor 2, Sensor 3) simultaneously connected via plastic tubing (1/4 inch internal diameter) to the GF's feed tray, airflow outlet, and pump outlet across three periods (Fig. 4). In period 1, sensor 1 was placed at the airflow outlet, sensor 2 at the pump outlet, and sensor 3 at the feed tray. In period 2, sensor 3 was at the airflow outlet, sensor 1 at the pump outlet, and sensor 2 at the feed tray. Finally, in period 3, sensor 2 was at the airflow outlet, sensor 3 at the pump outlet, and sensor 1 at the feed tray. Data for CH_4 and H_2 analog voltage were simultaneously recorded by each sensor for each placement scenario. The research aimed to evaluate how sensor placement affects the correlation between sensor data and concurrent measurements from the GF (Fig. 4). The primary objective was to identify the most suitable gas sensor placement by correlating sensor data with concurrent GF measurements.

2.5. Instrumentation for CH_4 gas sampling in field conditions

This trial obtained animal ethics approval from The University of Sydney Animal Ethics Committee (Approval number 1729). The measurements were conducted over 45 days and involved 28 heifers, including Charolais, Angus, and crossbred Charolais-Angus breeds, with an average weight of 350 ± 50 kg. Heifers were grazing in a rotation of paddocks containing a mixture of Bermuda (*Cynodon dactylon*), Kikuyu (*Cenchrus clandestinus*), Trifolium (*Trifolium repens*), Cenchrus (*Cenchrus ciliaris*), and Rhodes grass (*Chloris gayana*). Both the GF and the gas sensors were used simultaneously for data collection. A large animal GF unit mounted on a cart was positioned near the water trough located centrally to the paddocks to allow free access for all heifers. The GF was calibrated, and measurements followed the protocol outlined by Hristov et al. [21]. A dispenser within the GF delivered concentrate pellets as bait feed to attract the heifers, with an allowance of 1 kg/hd/d which were distributed in a maximum of 5 visits/day, and 5 cups/visit of pellets dropped at 40-s intervals between cups, and a cup weight of 40 g. All heifers were previously trained to use the GF. The gas sensors were connected to the pump outlet of the GF via a PVC tube (1/4-inch internal diameter) to record CH_4 and H_2 analog voltage (Fig. 5). The gas sample obtained from the pump outlet of the GF is passed through the PVC tube to the gas sensors. The setup of the GF and gas sensors in the field is depicted in Fig. 5. This trial was conducted with the gas sensors connected to the pump outlet only because data showed that this location

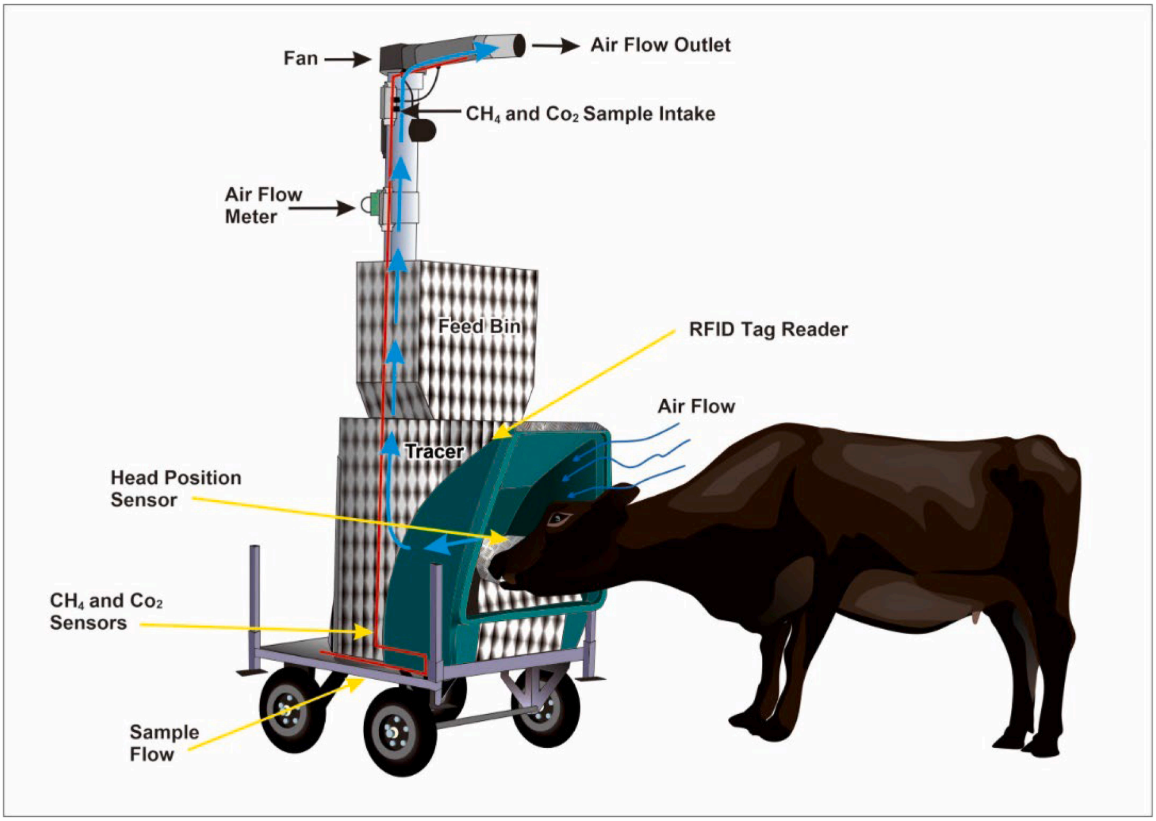

Fig. 2. Open-circuit calorimetry (GreenFeed unit) to measure gas exchange from cattle.

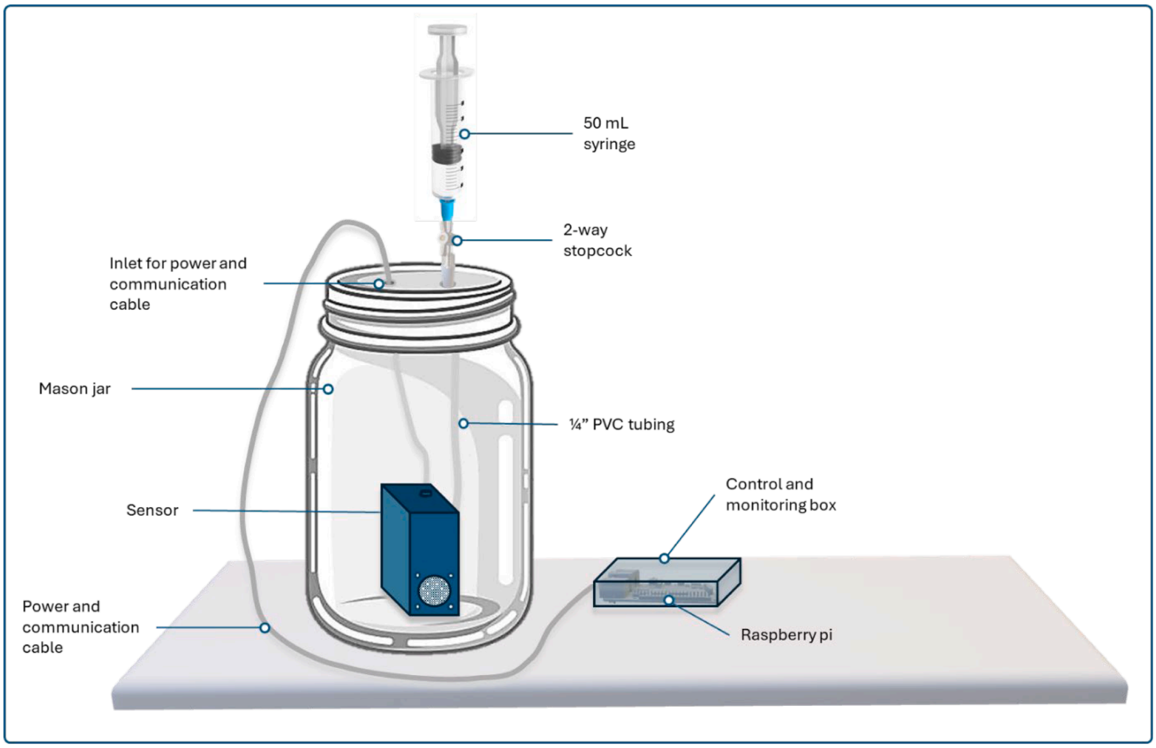

Fig. 3. Low-cost CH_4 gas sensor calibration in the lab.

exhibited the highest correlation between CH_4 and H_2 analog voltage and the GF concentrations ($r = 0.51$ for CH_4 and $r = 0.65$ for H_2). Key weather conditions during the field measurements are shown in Table 2.

2.6. *Statistical analysis*

The GF system provided 2 types of datasets: 1) the visit data con-

Fig. 4. Locations where the low-cost experimental gas sensors were positioned on the GreenFeed unit.

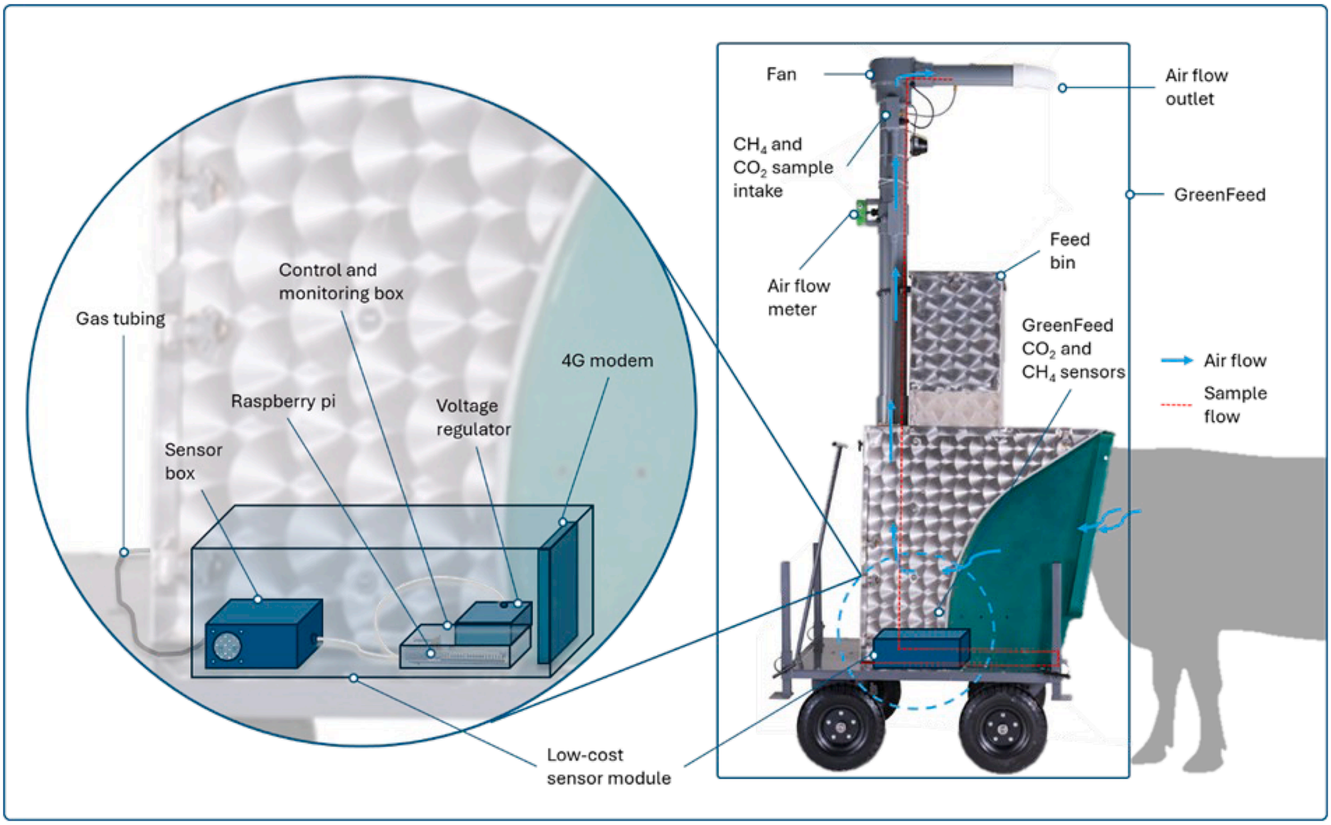

Fig. 5. Gas sensor and Greenfeed setup in field conditions.

Table 2
Summary statistics of the weather conditions observed during the field trial to measure gas production from cattle.

Weather	From the Greenfeed machine		
	Minimum	Maximum	Mean
Temperature (°C)	10.0	38.5	24.2
Wind direction (deg)	167	169	168
Average airflow (L/s)	20.1	46.1	34.2
Wind speed (m/s)	0.00	0.02	0.0002

taining the radiofrequency identification number of each animal in the unit (RFID), the start and end time of the visit to the nearest second, and the estimated gas production rate (g/d) for each gas CH_4, CO_2, and H_2 which was converted to the average concentration of the gas during the visit; 2) the raw data of each gas at approximately 1 Hz in voltage analog units. The gas sensor collected data at approximately 1 Hz and contained the date and time, the voltage analog unit for each gas associated with the concentration of the gas. Notably, both the gas sensor and GF were recording data simultaneously. Each of these 3 datasets were merged by date and time for further analysis. A Spearman's correlation coefficient, repeatability, and a peak detection algorithm test were employed to analyze the data. The arithmetic means of CH_4 concentration values measured with the gas sensor and GF was calculated every 60 s, 60 min, 24 h, and 7 days creating 4 subsets of data. These 4 datasets were then used to estimate Spearman's correlation between the CH_4 concentrations recorded by the GF and the gas sensor. The 1 Hz merged dataset had rows when no animal was present in the GF unit deleted and this was then used to estimate the repeatability of each method by dividing the variance between heifers (σ^2_B) by the variance both between heifers and within heifers (σ^2_W) [22].

$$REP = \frac{\sigma^2 B}{\sigma^2 B + \sigma^2 W}$$

Where: REP represents the repeatability of each method or intraclass correlation coefficient

σ^2_Brepresents the variance in CH_4 between different heifers.

σ^2_W represents the variance in CH_4 within the same heifer across different measurement dates.

The repeated measures correlation (rp) was determined using the formula [23]:

$$\text{rp} = \frac{\sigma^2 \text{B1}}{\sqrt{\sigma^2 B1 x \sigma^2 B2}}$$

Where: rp represents the repeated measures correlation of the two methods

σ^2_{B1} represents the variance in CH_4 between heifers recorded by the MQ-4 sensor.

σ^2_{B2} represents the variance in CH_4 between heifers recorded by the GF.

Peak number, width, and height were detected on the merged 1 Hz dataset using a Gaussian derivative-based peak measurement algorithm, which comprises quick command-line functions for detecting and counting positive peaks in noisy data sets [24] using MATLAB (version R2023a). The identification of the air sampling point with the optimal placement for gas sensors was determined through correlation analysis. A Spearman's correlation coefficient test was conducted using R (version 4.3.1).

3. Results and discussion

The development and validation of various strategies for mitigating enteric CH_4 emissions require accurate and large-scale measurements of CH_4 from ruminant belches in their production environments [25,26]. Different research groups are working on the development and use of various measurement devices for this purpose [8,26–28]. Each of these devices has its own set of advantages, disadvantages, and application ranges. Many of these measurement techniques are expensive, power-intensive, slow, and labour-intensive for large-scale individual animal measurements, and unsuitable for extensive systems such as pastoralism and grazing [14]. Therefore, there is a growing need for more convenient, compact, lightweight, energy-efficient, cost-effective, less labour-intensive, and time-efficient methods to quantify the amount of enteric CH_4 produced by ruminants. The objective of the present study was to address these challenges assessing the feasibility of low-cost gas sensors for continuous monitoring of CH_4 concentrations in ruminants compared to the GF system. In this regard, the approximate cost of the GreenFeed system ranges from AU$100k to 200k, depending on configurations. Additionally, the bulkiness and complexity of transport make it very expensive. In contrast, the low-cost sensor used in this study costs less than 500 AUD, making it a significantly more affordable alternative, with no complex transport issues.

The voltage measured by both the gas sensors and GF devices is shown in Fig. 6. These voltage measurements are positively correlated to the concentration of CH_4 through belching or eructation events reflected in an increase of the voltage which become 'peaks' for both devices (Fig. 6). Visual inspection of the graph reflects the smaller magnitude of the response to increased CH_4 concentration in the MQ-4 compared to the GF sensor.

3.1. Laboratory calibration of CH_4 gas sensor

The results of the laboratory calibration of the MQ-4 gas sensor are depicted in Figs. 7-9. Fig. 7 shows the raw data collected at one-second intervals, whereas Fig. 8 presents the 10-min average of CH_4 voltage. When the CH_4 gas mixture was injected into the jar containing the gas sensors in 5 mL increments to produce an increase in the CH_4 concentration of 1000 ppm, at 10-min intervals, the CH_4 voltage readings increased (Figs. 7 and 8). Fig. 9 shows a linear regression of the 10-minute average CH_4 voltage readings against the estimated concentration of CH_4 after each injection. The data indicate a curvilinear increase in CH_4 voltage with CH_4 concentration and high precision ($P < 0.001$, $r^2 = 0.99$, $RMSE = 145$ for the 10-min averages in Fig. 9). Therefore, these equations can be used to convert voltage to ppm. This result proves that the data provided by the sensor is more accurate and precise when considered over longer periods rather than second-by-second records, highlighting the importance of averaging over time for improved precision. In addition, these results also suggest that the gas sensor performs more consistently and predictably over extended periods, making it more suitable for applications where reliable and stable readings are crucial. The high R^2-value observed also suggests that the calibration equation accurately translates the CH_4 voltage recorded in the field by the gas sensor into accurate concentration values. Additionally, this result underscores the capability of the MQ-4 gas sensor to detect CH_4 concentrations under controlled environments with high accuracy and reliability.

3.2. Gas sensor positioning

The correlation between raw data (voltage base) collected by the GF and gas sensors placed in different locations is shown in Table 3. The results indicated that placing the sensors at the pump outlet resulted in higher correlation coefficients for CH_4 compared to placing them at the airflow outlet and the feed tray. Similarly, for H_2, better correlations were observed when the sensor was positioned at the pump outlet

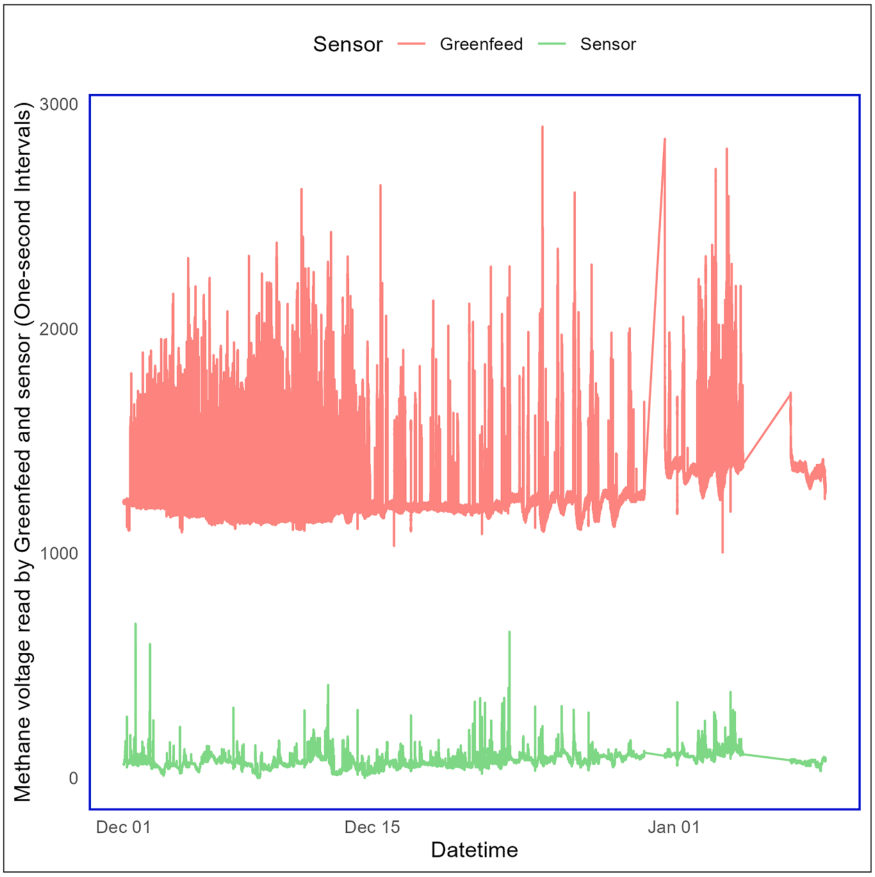

Fig. 6. Voltage from the GreenFeed (top) and the MQ-4 (bottom panel) gas sensors used to measure CH_4 concentration from the exhaled breath of heifers.

compared to the other locations across all three sensors. However, the strength of the correlation was moderate to low for both CH_4 and H_2 albeit significant and promising. Although the strength of the correlation is moderate to low for both CH_4 and H_2, the results are significant and promising. Other sensor placements also show significant correlations, albeit with low R^2 values. However, the pump outlet is selected as the optimal position due to its higher R^2 values, indicating a stronger and more consistent correlation between the sensors and GF. The higher correlation, combined with statistically significant P-values (<0.001), suggests that the pump outlet provides more reliable and accurate measurements of CH_4 and H_2 compared to other positions. This may be attributed to the pump outlet providing a more stable and reliable environment for accurate CH_4 and H_2 measurement, as it allows direct access to the gas outflow after passing through the GF sensor where measurements are recorded. This ensures that the gas sensors receive samples from the source (the same air sample the GF sensors used to detect H_2 and CH_4 concentrations) without any interference or dilution from other airflow sources. According to Fick's laws of diffusion, gas diffusion is influenced by factors such as molecular mass, temperature, and the concentration gradient across a medium [29]. Consistent with this theory, positioning the sensors at the pump outlet minimized interference and dilution effects from other airflow sources, thereby enhancing measurement accuracy. This approach ensured a more direct and undisturbed path for gas samples to reach the sensors immediately after passing through the GF sensor, thus maintaining a stable concentration gradient essential for precise H_2 and CH_4 measurements. Importantly, there were no big differences between sensors placed at the same location. Therefore, the subsequent results comparing the GF and gas sensors data are presented using only data from the pump outlet.

3.3. *Correlation between gas sensors and GF for CH_4 and H_2 measurements*

The repeated measures and Spearman correlations between the gas sensors and GF for voltage measurements averaged for increasing length periods are presented in Table 4. Spearman's correlation coefficients were moderate and increased as the data was averaged for longer periods from 0.43 for the raw data to 0.62 for weekly means. The weaker correlation coefficients with higher temporal resolutions may indicate increased noise or variability in the data at shorter time scales. This could be due to fluctuations in CH_4 emissions within shorter time intervals, leading to less consistent relationships between the measurements of the gas sensor and the GF. Therefore, the correlation between the two devices does not seem strong enough to use their data interchangeably, which may be attributed to the gas sensor's limitations in factors such as sensitivity, measurement range, and frequency of data recording, amongst others. Similar to the findings of the present study, [30] and [31] evaluated the MQ-4 gas sensor at known gas concentrations to measure CH_4 concentration and reported that the MQ-4 sensor was unable to provide acceptable values due to detection limits and demonstrated limited raw response to varying CH_4 concentrations. In summary, although the correlation between CH_4 obtained from the MQ-4 gas sensor and the GF may vary at different temporal resolutions, the consistently significant p-values suggest that the relationship is robust and warrants further exploration, particularly at shorter time scales where the correlation coefficients decrease. In addition, the stronger correlations with data at longer time intervals suggest that the MQ-4 sensor may be suitable for applications in enteric methane production where animals can be held for a long period while measurements are recorded such as while feeding.

The correlation between the H_2 analog voltage obtained from the

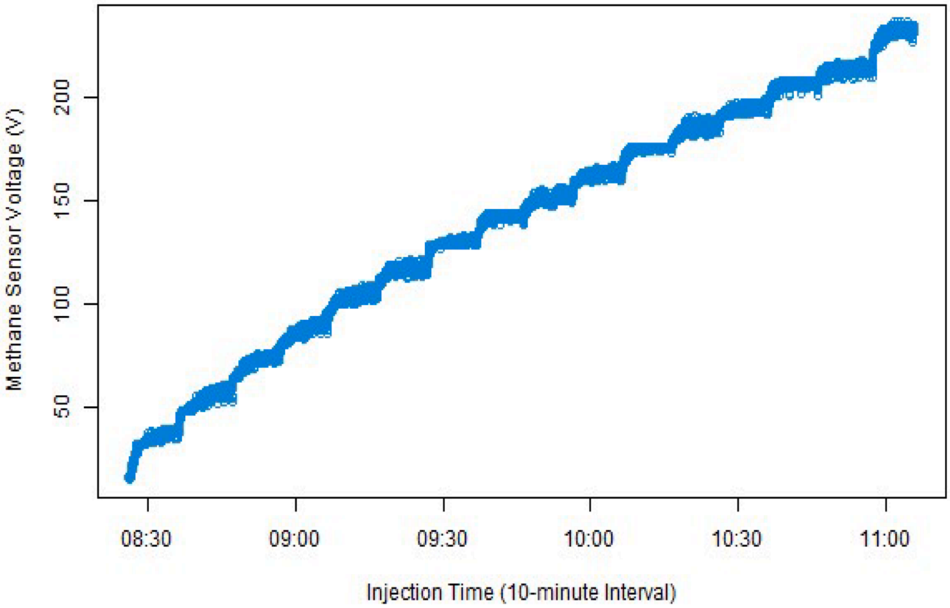

Fig. 7. MQ-4 sensor voltage at 1 Hz over time in response to the injection of 5 mL of 20% CH_4 gas.

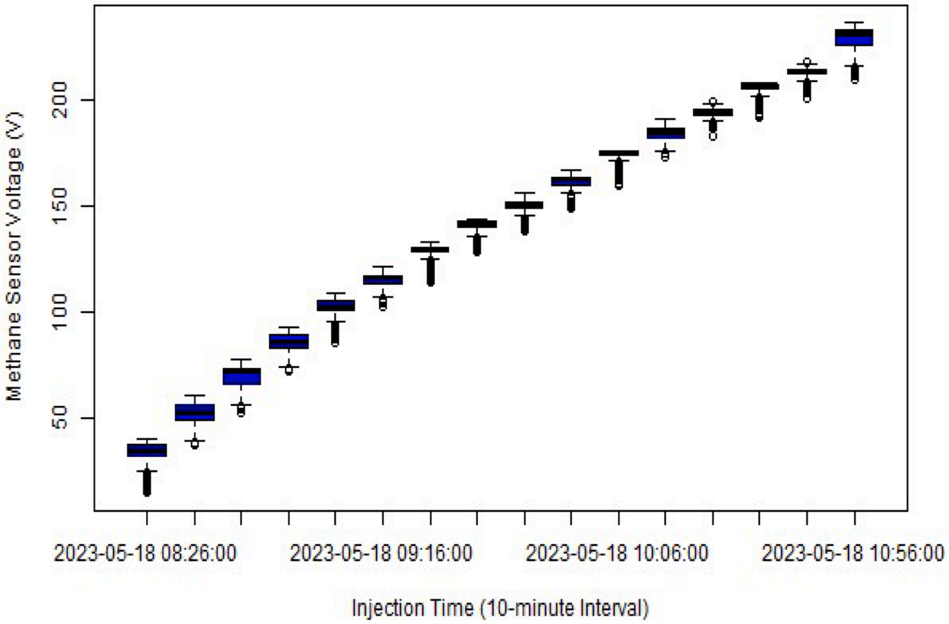

Fig. 8. CH_4 sensor voltage over time, shown as a whisker plot, measured every 10 minutes after the injection of 5 mL of a 20% CH_4 gas mixture.

MQ-8 gas sensor and the GF was also stronger after averaging data for longer time periods (weekly means) yet lacked statistical significance ($P = 0.151$) likely due to the lower number of observations reducing the statistical power. Conversely, correlations weakened with increased temporal resolution yet maintained highly significant p-values ($P < 0.001$), implying robust but weaker associations. These results imply a nuanced relationship between H_2 measurements from the MQ-8 gas sensor and the Greenfeed machine, with temporal resolution playing a significant role in understanding their correlation, underscoring the necessity for further investigation into factors influencing these observed relationships. The repeated measures correlation analysis revealed a moderate consistency in the measurements between the gas sensor and the GF for CH_4 and H_2 (Table 4). These results indicate that although both devices show a statistically significant correlation, the agreement is stronger for H_2 measurements than for CH_4, and for data aggregated for longer time periods. The duration of animal visits and the number of records per visit are crucial factors for obtaining accurate CH_4 measurements. In our study, however, we did not standardize visit durations or the number of records per animal, as our primary objective was to investigate the degree of agreement between the two devices over a continuous monitoring period. This study was conducted over 45 days, during which we collected 876,299 data points (recorded only when the animal was present in the GF unit), with each data point captured at one-second intervals, reflecting the variation in visit duration. Moreover, with a larger number of data points, the reliability of the measurements improves, leading to a more robust understanding of the gas dynamics involved. While longer averaging intervals can indeed enhance measurement accuracy, it is essential to balance this with the need for timely data collection in practical field applications. Further research is needed to determine the optimal averaging interval that balances accuracy and

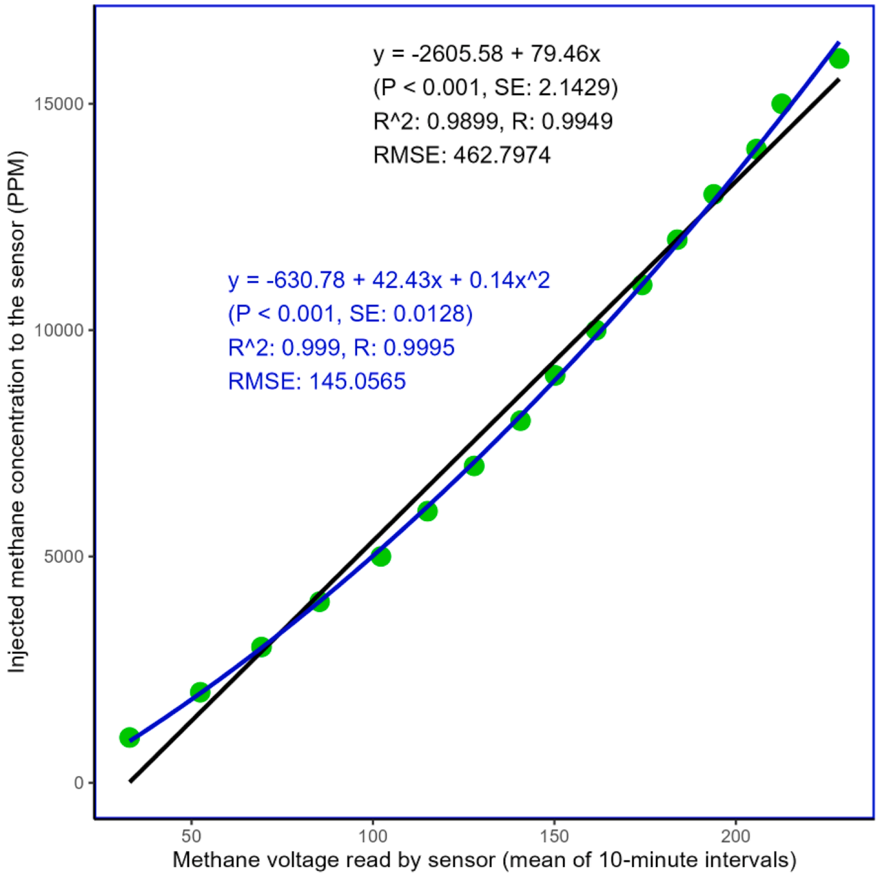

Fig. 9. Relationship between CH_4 sensor voltage and injected CH_4 concentration (mean CH_4 sensor voltage values aggregated over 10-minute intervals).

Table 3
Spearman's correlation between the voltage from CH_4 and H_2 detection using the gas sensor and Greenfeed system placed with grazing cattle.

Placement		CH_4		H_2	
	Sensor	R-value	P-value	R-value	P-value
Pump outlet	1	0.48	<0.001	0.82	<0.001
	2	0.63	<0.001	0.53	<0.001
	3	0.41	<0.001	0.61	<0.001
Airflow outlet	1	0.30	<0.001	0.31	<0.001
	2	0.41	<0.001	0.25	<0.001
	3	0.41	<0.001	0.43	<0.001
Feed tray	1	0.48	<0.001	0.51	<0.001
	2	0.48	<0.001	0.51	<0.001
	3	0.41	<0.001	0.20	<0.001

Table 4
Repeat measures and Spearman's correlation values between the voltage from H_2 and CH_4 of the GF and gas sensors with data averaged weekly, daily, hourly, and minute in a field trial with grazing cattle.

Period		CH_4		H_2	
	No of observation	R-value	P-value	R-value	P-value
Weekly means	6	0.62	0.115	0.57	0.151
Daily means	45	0.56	<0.001	0.32	0.049
Hourly means	1,080	0.49	<0.001	0.32	<0.001
Minute means	64,800	0.47	<0.001	0.35	<0.001
Second basis (raw data)	3.88×10^6	0.43	<0.001	0.33	<0.001
Repeat measures correlation	1.42×10^5	0.30	<0.001	0.41	<0.001

practicality in field conditions.

3.4. Peak characteristics and repeatability

Results from clustering analysis to determine 'peak' characteristics are shown in Table 5. The total number of peaks detected by the Gaussian derivative-based peak measurement algorithm for the GF was 2-fold greater compared to the MQ-4 gas sensor located after the GF sensor outflow tube. This difference may be attributed to the GF sensor's higher sensitivity in detecting small changes in CH_4 concentration and the shorter recording time, resulting in more frequent data collection. In addition, the peak detection algorithm may also play a role in such differences depending on the sensitivity of the parameters to detect the start and end of the peaks [28]. It is therefore unknown whether different or more appropriate algorithms should be used for the MQ-4 gas sensor compared to the GF because the present study used the same parameters for both datasets. Adjusting the peak detection parameters for the MQ-4 sensor could influence its sensitivity and comparability with the Greenfeed (GF) sensor. The MQ-4 sensor's detection accuracy is sensitive to threshold settings, sampling frequency, and averaging intervals [24]. By fine-tuning these settings, it may be possible to capture better rapid fluctuations in CH_4 concentrations, which could improve alignment with the GF sensor's measurements. In particular, lowering the threshold for peak detection might enable the MQ-4 sensor to register smaller CH_4 concentration peaks, enhancing its sensitivity. Additionally, adjusting the sampling frequency and data averaging intervals could allow the MQ-4 sensor to capture more transient gas concentration changes, leading to improved comparability with the GF sensor's output [24]. However, studying all these possible alternatives was beyond the scope of the present study, and further with these are encouraged. Nevertheless, these results suggest that belching events reflect in the data as a brief spike in the voltage related to the increased concentration of CH_4, and these peaks are ultimately used to estimate daily emissions in the GF system [32,33]. There was no missing data from either measurement method (the GF and the gas sensor recorded data at second intervals), and the total data recorded over the 6 weeks was approximately 3.89×10^6 measurements (Table 5).

The gas sensor exhibited a wider peak at half height than the GF sensor, which was directly related to the longer peak duration. The elapsed time between peaks was also shorter for the GF compared to the gas sensor, which may be attributed to the GF sensor's higher sensitivity and frequency of data collection. These results suggest that the GF sensor was more sensitive in detecting CH_4 than the MQ-4 gas sensor, implying that both sensors collect different data likely affected by their sensitivity and response to CH_4 molecules. Nagahage et al. [31], who experimented with evaluating the MQ-4 and TGS 2611 gas sensors for detecting CH_4 from an anaerobic digester, reported that the MQ-4 sensor requires a longer response time to detect CH_4 gas compared to the TGS 2611 CH_4 gas sensor, supporting the present study's findings. Similarly, [30] also observed a higher settling time for the MQ-4 sensor than the TGS 2611 sensor.

In addition, the MQ-4 gas sensor had lower repeatability than the GF sensor which is important because repeatability is within the sensor and not comparing both sensors as in the previous correlation analysis. The correlation between sensors is likely to be low when the repeatability of the measurements is also low [34]. However, it is important to note that the repeatability values obtained in the current study for both sensors were low, potentially influenced by the movement of the animal's head, resulting in muzzle movement, which significantly affects the repeatability of CH_4 concentration measured by the GF [35]. To improve repeatability, adjusting the MQ-4 sensor's mounting position or using shielding mechanisms could reduce the impact of animal movement and airflow disruptions, leading to more stable readings. Another consideration is to increase the sensor's sampling rate or apply a filtering algorithm to smooth transient fluctuations caused by sudden animal movements, thereby improving measurement consistency. Additionally, repeated calibration and increasing the sampling rate can significantly improve the repeatability of gas sensors by ensuring that measurements are consistently accurate over time. Regular calibration accounts for sensor drift and environmental changes, helping to maintain the accuracy of the sensor's readings and reduce variability. Increasing the sampling rate allows for more data points to be collected in a given time frame, which can smooth out transient fluctuations caused by movement or environmental factors, leading to more stable readings. However, frequent recalibrations and higher sampling rates may increase computational demands, which need to be managed to ensure efficient deployment in practical field applications. Finally, repeatability may also be improved by adding a sensor to measure animal distance and head position as it is implemented in the GreenFeed system, which could help delete data that may be less accurate. These repeatability values align with the value of 0.34 reported by [36] for the GF in dairy cows but were higher than the value of 0.23 reported by [34], who used a laser CH_4 detector to measure CH_4 concentration in exhaled gas from dairy cows. The higher mean peak height was recorded for the GF sensor than for the MQ-4 gas sensor, indicating that the GF sensor detected more outliers than the MQ-4 sensor. This finding agrees with the results of [31], who reported that the MQ-4 sensor recorded fewer outliers (indicating lower sensitivity to outlier CH_4) compared to the TGS 2611 sensor.

Table 5
Mean of peak duration, height, and repeatability of CH_4 measured with GreenFeed and MQ-4 gas sensor.

Parameters	Gas sensor	Greenfeed
Expected number of data points	3.89×10^6	3.89 × 106
Recorded number of data points	3.89×10^6	3.89×10^6
Data points (heifers in Greenfeed)	1.42×10^6	1.42×10^6
Peak duration (seconds)	16.5±1.831	7.75±0.883
Width of peaks at half distance	4.44±0.08	2.24±0.02
Peak height (CH_4 concentration)	86.05±0.04	1263±0.11
Number of peaks	271,983	579,795
Repeatability (CI)	0.13 (0.07, 0.20)	0.31 (0.19, 0.42)

CI= Confidence interval

4. Conclusions

Results showed that the Spearman's correlation of the voltage from H_2 and CH_4 molecules measured by GF units and the gas sensor was moderate whereas the repeatability of the measurements was lower for the gas sensor albeit low for both sensors. Therefore, using the gas sensor and GF interchangeably for the estimation of enteric CH_4 concentration and H_2 voltage is not recommended without investigating the sources of disagreement and developing data processing methods specific to each sensor. However, the fact that the correlations were significant is promising. The present study did not assess the full extent of the implications of these differences on methane CH_4 (g/d) or the ranking of animals according to their emissions. Therefore, more research is needed to determine if animals with higher concentration or peak characteristics from the gas sensor also have higher estimated CH_4 production using a 'gold standard' such as respiration chambers.

Ethical declaration

This study was conducted following the ethical standards outlined by the relevant institutional and national guidelines. The research involving animals was reviewed and approved by The University of Sydney's Animal Ethics Committee (Approval Number: 1729). All procedures performed in this study adhered to ethical principles ensuring the welfare of the animals used in the research. The study was conducted in compliance with the Australian Code for the Care and Use of Animals for Scientific Purposes, 8th Edition (2013).

CRediT authorship contribution statement

Mulisa F. Dida: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Milad Bagheri Shirvan:** Writing – review & editing, Visualization, Methodology, Investigation, Data curation. **Toshikazu Kawaguchi:** Writing – review & editing, Validation, Methodology. **Sergio C. Garcia:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Data curation. **Luciano A. Gonzalez:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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Chapter 6. Environmental Impacts of Dairy Farming Intensification and Land Use on Soil Organic Carbon Stocks and Physicochemical Properties

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Overview

This chapter examined differences between dairy farming systems (confinement vs. pasture-based) and land use types (natural pasture, improved pasture, mixed pasture-cropping, cropping, and tree areas) on soil organic carbon (SOC), total nitrogen (TN), and phosphorus (TP) stocks. A total of 810 soil samples from nine farms showed that pasture-based systems had significantly higher SOC and TN concentration and stocks, especially in natural and improved pastures. Confinement systems had higher TP stocks but lower SOC and TN. The findings highlight the role of land use and management in enhancing soil health and carbon sequestration potential.

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Environmental impacts of dairy farming intensification and land use on soil organic carbon stocks and physicochemical properties

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ABSTRACT

The intensification of livestock farming systems can pose significant environmental challenges, including impacts on soil physicochemical properties, carbon sequestration, and biodiversity. This study is the first to quantify the combined effects of dairy system intensification and land-use allocation on soil organic carbon (SOC) stocks and physicochemical properties at the commercial farm scale. We compared confinement and pasture-based systems across five land-use types: improved pasture (IP), mixed pasture-cropping (MPC), cropping, tree areas (TA), and natural pasture (NP, exclusive to pasture-based systems). A total of 810 soil samples were collected from the top 30 cm across nine farms in New South Wales, Australia. Pasture-based farms stored 75% more SOC and 65% more total nitrogen (TN) per hectare than confinement farms, although differences were partly influenced by regional climate and parent material. Interactions between farming system and land use showed that SOC and TN stocks were highest in IP and TA within pasture-based systems. Conversely, total phosphorus (TP) stocks were 3.7 times higher in confinement systems, independent of SOC patterns. Within pasture-based farms, NP consistently had the highest SOC and TN stocks. These results highlight that dairy system intensification interacts with land-use and environmental conditions to shape soil organic carbon and nutrient stocks. The findings provide policy-relevant benchmarks for soil-carbon accounting and emphasize the need for regionally adapted land-management strategies and future work quantifying annual SOC sequestration rates under commercial dairy conditions.

1. Introduction

Grasslands occupy 67% of global agricultural land and 24% of the total land surface, storing about 20% of the world's soil organic carbon (SOC) stocks to 1 m depth (FAO, 2021; Puche et al., 2019). These systems are vital for regulating the global carbon (C) and water cycles, as soils hold far more C (4000 Pg) than the atmosphere (740 Pg CO_2) (Camacho et al., 2023). Agricultural practices shape SOC dynamics through shifts in management, nutrient cycling, and land use intensity (Camacho et al., 2023; Dondini et al., 2023; FAO, I, 2015). Enhancing SOC in grasslands via targeted grazing and legume integration could offset 2.3–7.3 Pg CO_2eq annually (Bai and Cotrufo, 2022). However, land conversion and intensive farming can significantly affect SOC stocks. Strategic grazing in pastures systems can builds SOC by favouring deep-rooted perennials, root exudates, legume N inputs, and surface litter (Chen et al., 2015).

Enhancing agricultural land intensification for animal products can disrupt ecosystems, altering C stocks, biodiversity, and water/air quality based on practices (Erisman et al., 2013; Hertel, 2015; Silveira et al., 2026). Confinement dairy systems where cows are housed year-round on total mixed rations rely on cultivated forages, leading to SOC declines from tillage, mineralization, and erosion (Lal, 1997; Ritchie, 2020). Additionally, such systems amplify N fertilizer use, increasing reactive N losses and environmental risks (de Klein and Monaghan, 2011; Galloway et al., 2008). Confinement systems maintain livestock at high density in small areas with required manure management practices and use high inputs to produce and harvest feed, which can significantly affect soil organic matter and nutrient cycling (Dondini et al., 2023). On the other hand, pasture-based systems maintain livestock grazing in larger areas with animals depositing manure on pastures, requiring lesser manure management and lower soil disturbance, which may provide more opportunities for SOC sequestration (Adewale et al., 2018;

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Morais et al., 2025; Paustian, 2014). However, limited data exist on the effect of dairy farming system on SOC, particularly using confinement systems that rely on forage cropping for feed production as those prevalent in Australia.

Land use type is a critical factor affecting soil physicochemical properties (Kaur et al., 2021; Rodelo-Torrente et al., 2022; Wang et al., 2023). Converting natural ecosystems to agricultural land can deplete SOC pools by up to 60% in temperate regions and by 75% or more in cultivated tropical soils (Lal, 2004a; Padarian et al., 2022). This decline in SOC is caused not only by the loss of plant biomass but also by the accelerated decomposition of soil organic matter, resulting from continuous cultivation and frequent soil disturbance (Kim et al., 2025; Schlesinger and Andrews, 2000). A meta-analysis by Guo and Gifford (2002) quantified SOC shifts: declines of 10% (pasture to plantation), 13% (forest to plantation), 42% (forest to cropland), and 59% (pasture to cropland); gains of 8% (forest to pasture), 18% (cropland to plantation), 19% (cropland to pasture), and 53% (cropland to forest). Additionally, Lal (2003) reported that no-till adoption can cut seasonal C emissions by 30–35 kg C ha^{-1}. In addition, studies also highlight that changes in SOC are significantly influenced by soil type, climate, and management practices (Mazzetto et al., 2023; van Noordwijk et al., 2023), underscoring the importance of research on commercial dairies. A comprehensive understanding of how different dairy systems influence soil quality and nutrient dynamics is essential for advancing are key for sustainable practices and climate goals. Thus, the objective of the present study was to quantify SOC, total nitrogen (TN), and total phosphorus (TP) stocks and other physicochemical properties across contrasting dairy farming systems and land use types. Specifically, the study investigated the interaction between dairy system intensification and land use, considering the underlying climatic and edaphic factors on SOC and other soil quality attributes. We hypothesized that (i) pasture-based dairy systems would exhibit higher SOC stocks and improved soil physicochemical properties compared to confinement systems after accounting for land use type, (ii) perennial pastures and tree areas show higher SOC irrespective of farming system due to enhanced organic inputs, and (iii) interactions between dairy system and land use would explain a substantial proportion of observed soil variability.

2. Materials and methods

2.1. Study area and farm selection

This study encompassed nine dairy farms in New South Wales, Australia: five pasture-based and four confinement farms. Farms were arbitrarily selected to provide a typical spectrum of the different dairy production systems in the state of NSW. Mean annual rainfall (mm $year^{-1}$), calculated from 30-year climatological data averaged 920 mm for pasture-based (range from 670 to 1158 mm) and 594 mm for confinement farms (range from 420 to 768 mm). Mean annual temperature (°C), derived from the same long-term datasets, averaged 24.0 °C for pasture-based farms (ranged from 21.9 to 26.3 °C) and 23.8 °C for confinement farms (range from 23.7 to 24.0 °C). All climate data were sourced from the Australian Bureau of Meteorology using records from the nearest weather stations to each farm (http://www.bom.gov.au/climate/data/). Soil types for each farm were identified using the FAO–UNESCO Soil Map of the World (FAO–UNESCO, 1974) and the Australian Soil Classification map for New South Wales (Department of Planning, Industry, and Environment, 2021), providing both international and national classification contexts. Under the FAO system, pasture-based farms were predominantly classified as Chromic Luvisols, Luvic Phaeozems, and Gleyic Acrisols, whereas confinement farms were mainly characterized by Chromic Luvisols and Calcic Luvisols. According to the Australian Soil Classification, pasture-based farms consisted primarily of Kurosols and Dermosols, whereas confinement farms were dominated by Chromosols and Dermosols. These classifications highlight inherent regional differences in soil properties, reflecting differences in parent material and pedogenic processes.

2.2. Soil sampling design

Maps of the paddocks and farm boundaries were collected from the farmers and imported into Google Earth Pro, along with detailed information on pasture species, crop types, and irrigation management systems for each paddock. These data were used to categorize paddocks into different land use types (natural pasture [NP], improved pasture [IP], mixed pasture-crop [MPC], and cropping). The methodology involved identifying areas of interest, referred to as Carbon Emission Areas (CEAs), following the guidelines outlined in the Australian Carbon Farming Initiative (CFI) Soil Sampling Design Method and Guidelines (Department of the Environment, 2014). For pasturelands, CEAs were designated according to shared pasture management practices (NP, IP, and MPC) and irrigation management (irrigated and unirrigated) to ensure that each CEA represented a homogeneous combination of pasture and irrigation management. For cropland paddocks, CEAs were assigned based on their irrigation status only. Digital maps of the farms were used to delineate these areas, with land use and management system data provided by each farm. An adapted CFI method was used for areas smaller than 10 ha but still of interest; these areas were designated as Extra Estimation Areas (EEAs). Tree cover areas were considered potential sources of additional C emissions or sequestration and designated as EEA. After the identification of CEAs, stratified sampling was then employed within each CEA to ensure representative soil sampling. Each CEA was systematically divided into six equal-sized areas, referred to as 'strata' (S1, S2, S3, S4, S5, S6), which were not based on specific variations but were created to ensure even spatial distribution of sampling points and improve replication (Fig. 1). This approach helped minimize potential sampling bias and enhanced the reliability of the collected data.

2.3. Categorization and management practices of land-use types

In this study, we classified the land management systems across different land-use types: NP, IP, MPC, cropping, and tree area in dairy farms, considering their irrigation, and disturbance practices. Classification considered irrigation (applied when rainfall was insufficient to support plant growth), and disturbance, which included both oversowing improved forage and fertilization practices as follows. Natural pastures included Bermuda grass (*Cynodon dactylon*), Tall fescue (*Schedonorus arundinaceus*), meadow fescue (*Lolium arundinaceum*), carpet grass (*Axonopus affinis*), paspalum (*Paspalum dilatatum*), *Sporobolus* spp., as well as *Cenchrus* spp. and clover (*Trifolium* spp.), which were neither irrigated, fertilized, nor disturbed (disc and plough for oversowing improved forage or fertilization. Improved pastures featured annual ryegrass (*Lolium multiflorum*), oats (*Avena sativa*), kikuyu (*Pennisetum clandestinum*), fescue grass (*Festuca* spp.), prairie grass (*Bromus* spp.) and legumes (clovers - *Trifolium* spp. and lucerne (*Medicago sativa*)). This land use involved both irrigated and non-irrigated areas, all of which were semi-disturbed for oversowing and fertilization. Mixed pasture-cropping systems, such as those combining annual ryegrass or oats in winter with summer soybean cropping (*Glycine* max), involved both irrigated and non-irrigated areas and were disturbed for cropping and fertilization. These systems also included winter ryegrass and wheat (*Triticum aestivum*) or maize (*Zea mays*) cropping, and winter ryegrass-legume with summer wheat, with both irrigated and non-irrigated practices. Cropping areas, including winter wheat and summer maize, winter barley (*Hordeum vulgare*), summer sorghum (*Sorghum bicolor*), and winter vetch (*Vicia* spp.) with summer maize, were fully disturbed (cultivated) for sowing and were primarily practiced by confinement dairy farms on a year-to-year basis. Tree areas, featuring species such as honey locust sweet osmanthus (*Osmanthus fragrans*), (*Gleditsia triacanthos*), blackwood (*Acacia melanoxylon*), Australian silky oak (*Grevillea robusta*), and eucalyptus (*Eucalyptus* spp.), were not irrigated,

Fig. 1. Snapshoot for the distribution of Carbon Emission Areas (CEA), and Strata (S) with corresponding Sampling Points.
Note: Each color represents a different CEA and EEA.

fertilized, or cultivated.

2.4. Farms characteristics

The study examined two farming systems: pasture-based, which relied primarily on grazed forage supplemented with concentrates, silage, and hay; and confinement systems, which were dairy farms utilizing total mixed rations (TMR) where the milking cows do not graze. The average farm area for the pasture-based system was 233 ± 47.32 ha, whereas for the confinement systems it was 611 ± 305.4 ha (mean ± SE). In line with farm size, herd size was from 335 ± 13.56 and 1073 ± 247.2 milking cows for pasture and confinement, respectively. Fertilizer application rates and land-use areas for pasture-based and confinement systems are summarised in Table 1. In the pasture-based farming system, most of the land was allocated to IP, which covered 58% of the farm area and included key species such as ryegrass-oats, kikuyu, fescue-prairie grass, and legumes like vetch, lucerne, and clover. Mixed pasture-cropping, which includes crops such as soybean, wheat, and maize, constituted 34% of the land for pasture-based systems. Natural pasture, characterized by year-round natural species, covered 3.0% of the farm area, while cropping accounted for 1.63%. In contrast, the confinement farming system predominantly focused on cropping, which occupied 85% of the land, including crops such as wheat, maize, lucerne, and vetch. Improved pastures, with species like kikuyu, ryegrass, and Rhodes grass, covered 11% of the area, whereas mixed pasture-cropping was less prominent at 2.0%. The remaining areas in both systems were allocated to tree-covered zones, feed storage, waste storage, water points, milking sheds, animal exercise areas, and built-up zones, which include infrastructure such as housing, machinery storage, and other operational facilities.

Table 1
Minimum, maximum, and mean land use areas for different pasture types and fertilizer application rates in confinement and pasture-based farming systems. Values shown as Mean (Min–Max).

Fertilizers type	Pasture-based	Confinement
Land use area (ha)		
Improved Pasture	134 (108–163)	66.3 (0.00–199)
Mixed Pasture-Cropping	78.9 (0.00–181)	11.4 (9.52–36.2)
Natural Pasture	6.75 (0.00–24.8)	0.00 (0.00–0.00)
Cropping	3.80 (0.00–19.0)	517 (101–851)
Fertilizer application rate (kg/ha/yr)		
Nitrogen (N),	109 (41.9–168)	128 (80.0–188)
Phosphorus (P)	33.1 (7.57–58.2)	17.6 (1.96–44.9)
Potassium (K)	30.9 (0.00–90.7)	0.78 (0.00–25.0)
Sulfur (S)	13.6 (5.91–22.5)	2.56 (0.00–9.14)
Lime	52.4 (0.00–195)	79.1 (0.00–198)

Note: Fertilizer values (N, P, K, S, and lime) per hectare were calculated by dividing total amounts by total usable area; actual application rates may differ among land use types, so interpret with caution.

2.5. Soil sampling and compositing

From each stratum, three soil cores were collected to a depth of 30 cm, maintaining at least 9 m between cores, in accordance with Australia's Carbon Credit Farming guidelines and IPCC recommendations for SOC monitoring (IPCC 2006). In total, 810 soil cores were collected across all strata. Core points were randomly selected using longitude and latitude coordinates on a digital farm map, with randomization performed in R using the runif() function from the base R package to ensure unbiased sampling. Each core was randomly assigned to one of three composites per CEA, ensuring each composite contained one core from each stratum (Fig. 2). Plants, litter, and rocks were removed from the surface of the sampling points to prevent contamination. Soil cores, 5 cm in diameter, were collected using soil corers with a direct push method to avoid turning compaction, which could affect bulk density. The cores were weighed immediately in the field, placed in labeled bags for each CEA and EEA, and kept chilled on ice. Composite samples were prepared by breaking down the soil cores, manually crushing aggregates within the soil, and homogeneously mixing them.

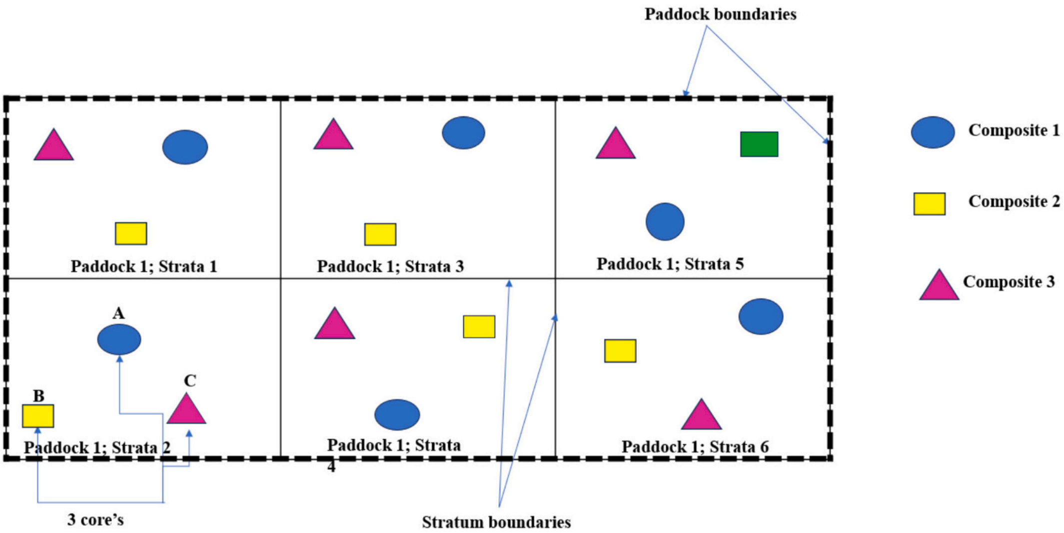

Fig. 2. Composite sampling design for one Carbon Emission Area (CEA), consisting of 6 strata and 18 soil cores (3 per stratum), which are combined into 3 composite samples per CEA.
Note: The colors and shapes indicate the three composite sample groups created within each stratum:
Blue circles → Composite 1
Yellow squares → Composite 2
Pink triangles → Composite 3
Each color/shape represents one of the three composite groups. Within every stratum, three individual core samples (A, B, and C) are taken and assigned to the same composite group to produce one composite sample per group. This ensures consistent distribution of sampling effort across all strata.

2.6. Sample storage, processing, and laboratory analysis

Soil samples were initially stored at low temperatures in a refrigerator and later transported to the laboratory for air-drying. During transport, samples were kept in a Styrofoam box with ice to maintain their condition. After air-drying, visible organic debris was removed, and samples were weighed, crushed, and sieved to isolate the <2 mm fraction from gravel (≥2 mm). Gravel was weighed separately, and the <2 mm fraction was homogenized for subsampling for laboratory testing. Total SOC and N concentrations were determined using dry combustion analysis with an Elementar Vario MAX Cube (Elementar, Langenselbold, Germany) on samples dried at 40 °C for 48 h and ground to <2 mm (Rayment and Lyons, 2011). Exchangeable cations (Ca, K, Mg, Na) were extracted with 1 M ammonium acetate (pH 7.0) and analyzed by inductively coupled plasma optical emission spectroscopy (ICP-OES) (Rayment and Lyons, 2011) and Ca:Mg ratios were calculated. Aluminum was extracted with 1 M KCl and measured by ICP-OES. Mehlich-3 extraction was employed for macro- and micronutrients (Al, B, Ca, Cu, Fe, K, Mg, Mn, Na, P, S, Zn), with concentrations determined by ICP-OES (APHA, 1995).

2.7. Bulk density and soil carbon stock calculation

Soil bulk density (BD) was determined following Blake and Hartge (1986) using the formula:

$$BD = \frac{Ms}{\sum_{i=1}^{n} Vi} \tag{1}$$

where: BD = bulk density of oven-dry soil (g cm^{-3})
M_s = oven-dry mass of the soil sample (g)
Vi = volume of each core (cm^3)
n = number of cores in the sample ($n = 1$ for a single core; for a composite sample, n = number of cores in the composite)
i = index of each specific soil core.

Soil samples were collected using a cylindrical corer with a 5 cm diameter (radius = 2.5 cm) and a total height of 30 cm. The volume of each core was calculated as:

$$V = \pi r^2 t \tag{2}$$

where: V = volume of the soil core (cm^3)
r = radius of the core (cm)
t = actual thickness of the core (cm).

To avoid systematic bias arising from differences in bulk density among farming systems and land use types, all SOC, TN, and TP stocks were calculated using the Equivalent Soil Mass (ESM) method rather than a fixed-depth approach (Ellert and Bettany, 1995; Wendt and Hauser, 2013). Under the ESM framework:

A reference soil mass per unit area (M_{ref}, Mg soil ha^{-1}) is defined based on a common comparison baseline.

For each sample, the soil mass contained within the sampled depth (M_{sample}) is first calculated as:

$$M_{sample} = BD \times \text{Depth} \times 10 \tag{3}$$

where BD is bulk density (g cm^{-3}) and Depth is sampling depth (cm).

If the cumulative soil mass of a sampled layer exceeds or falls below M_{ref}, the SOC concentration of the adjacent soil increment is proportionally adjusted so that all stocks are expressed on an ESM basis. SOC stock standardized to the reference soil mass is then calculated as:

$$SOC_{ESM} = C_{conc} \times M_{ref} \tag{4}$$

where:
SOC_{ESM}= equivalent soil mass standardized SOC stock (Mg C ha^{-1})
C_{conc}= SOC concentration (g C kg^{-1} soil).

This approach ensures that differences in SOC stock reflect true differences in carbon quantity rather than differences in soil mass caused by bulk density variation. The same ESM procedure was applied to TN and TP stocks.

To express SOC per hectare in CO₂ equivalents, the following conversion was applied:

$$\text{SOC}\left(\text{tonnes CO}_2\text{eq ha}^{-1}\right) = \text{SOC}\left(\text{tonnes C/ha}\right) \times 3.671 \tag{5}$$

One tonne of C equals 3.67 t of carbon dioxide (CO₂) (IPCC, 2006).

2.8. Statistical analysis

Generalized linear mixed models (GLMM) were employed to assess the interaction effects of farming systems (pasture-based and confinement) and land use types (cropping, IP, MPC, and tree on soil physicochemical characteristics. Due to the unbalanced dataset, with NP occurring only in the pasture-based system, two GLMM analyses were conducted and presented in the same tables (Tables 5, 6, and 7). The first GLMM evaluated the interaction between farming systems and land use on soil physicochemical characteristics, with differences at $P < 0.05$ indicated by superscripts a, b, c, and d. In this model, farming system and land-use type were specified as fixed effects, whereas farm and CEA were treated as random factor to account for variability between farms and CEA. Mean annual rainfall (30-year average) for each farm was incorporated as a continuous covariate to account for long-term climatic influences on SOC and other soil properties. Rainfall was retained in the final model only when significant ($P < 0.50$) or removed otherwise. Variables significantly influenced by rainfall as a covariate are denoted with an asterisk in the results tables. Farm-level rainfall values were used to capture within-system climatic variability and avoid confounding rainfall effects with farming system. Although irrigation was initially considered as a fixed factor, it was excluded from the model due to its non-significant effect ($P > 0.05$). The second GLMM assessed land use effects within the pasture-based system, comparing cropping, IP, MPC, and tree to natural pasture, with differences from NP ($P < 0.05$) denoted by superscripts x, y, and z. If no x, y, and z superscripts are shown for a given parameter, this indicates no detectable difference between NP and the other land use types. In this analysis, land use type in the pasture-based farming system was treated as a fixed factor, whereas farm and CEA were included as a random factor.

A separate analysis was conducted for the farming system comparison to reflect the actual soil physicochemical concentrations and stocks, calculated based on the area proportion of each land use type within farms, whereas the interaction analysis relied on raw data. For the farming system comparison, the percentage of each land use type was multiplied by its corresponding lab analysis results for soil physicochemical properties and then averaged to determine each farm's overall mean values. This method accounts for differing land use coverage across farming systems, avoiding bias from a simple average, as soil properties vary significantly by land use type. Mixed-effects linear regression was used, specifying farming system as a fixed effect and farm as a random effect to capture between-farm variability. Mean annual rainfall was again included as a covariate and retained only when significant ($P < 0.50$). Variables significantly affected by rainfall are indicated with an asterisk in the results tables. Residuals were checked for normality, and log transformation applied where necessary. Residuals were assessed for normality, and log transformation was applied when required (as noted in the results tables). Significance was determined at $P < 0.05$, with pairwise comparisons adjusted using Tukey's method implemented through the *emmeans* package.

3. Results

The generalized linear mixed model (*P-values*) of land use, farming system, and their interaction is presented in Tables 2, 3, and 4. Methodologically, our statistical framework retained mean annual rainfall as a continuous covariate in all initial models where significant, which provides a more conservative estimate of the effect of management and land-use. The farming system × land use ($P < 0.05$) affected most soil physicochemical properties. However, this interaction did not affect ($P > 0.05$) bulk density, TP concentration (%) and stock (Mg P ha^{-1}; Table 1); cation exchange capacity (CEC), electrical conductivity (EC), magnesium, and sodium cation (Table 2); and micronutrient (aluminum, iron, boron, zinc, magnesium, sodium) and macronutrients (magnesium and sodium) concentrations (mg kg^{-1}) (Table 3).

Table 2
Effect of farming system (FS), land use type (LU), and their interaction on the soil physiochemical properties in dairy farms.

Soil properties	Land use	Farming system	LU × FS
Bulk density, g/cm^3	0.085	<0.001	0.075
C: N ratio	0.002	0.283	0.048
Concentration, %			
SOC *	0.064	0.929	0.001
Total nitrogen *	0.026	0.312	<0.001
Total phosphorus	0.646	0.199	0.452
Log (total phosphorus)	0.948	0.023	0.241
Stock Mg ha^{-1}			
SOC *	0.064	0.929	0.001
CO_{2eq} *	0.064	0.929	0.001
Total nitrogen *	0.026	0.312	<0.001
Total phosphorus	0.646	0.199	0.452
Log (Total phosphorus)	0.948	0.023	0.241

SOC = soil organic carbon; CO_{2eq} = carbon dioxide equivalent; EC = Electrical conductivity; CEC = Cation exchange capacity; pH = pH_(1:5_water); Ca: Mg = calcium to magnesium ratio; NO_3-N = Nitrate-Nitrogen; NH_4_N = Ammonium-Nitrogen; Ca^+ = calcium cation; K^+ = potassium cation; Mg^+ = Magnesium cation; Na^+ = sodium cation. Note: Log-transformed data: Variables marked with "Log" were log-transformed to meet assumptions of normality in the generalized linear mixed models. Variables marked with an asterisk (*) are significantly affected by rainfall; significance levels are indicated as follows: *p < 0.05.

Table 3
Effect of farming system (FS), land use type (LU) and their interaction on soil physiochemical properties in dairy farms.

Soil properties	Land use	Farming system	LU × FS
pH	0.586	0.020	0.008
Log(pH)	0.702	0.020	0.008
EC	0.034	0.298	0.224
Log (EC)	0.047	0.178	0.410
NO_3-N	0.021	0.134	0.012
Log (NO_3-N)	0.023	0.229	<0.001
NH_4_N	0.007	0.067	<0.001
Log (NH_4_N)	0.020	0.024	<0.001
CEC	0.474	0.937	0.435
Ca^+	0.942	0.794	0.041
K^+	0.021	0.001	0.102
Log (K^+)	<0.001	0.005	0.009
Mg^+	0.356	0.766	0.490
Na^+	0.040	0.150	0.078
Log (Na^+)	0.227	0.165	0.079

EC = Electrical conductivity; CEC = Cation exchange capacity; pH = pH_(1:5_water); Ca: Mg = calcium to magnesium ratio; NO_3-N = Nitrate-Nitrogen; NH_4_N = Ammonium-Nitrogen; Ca^+ = calcium cation; K^+ = potassium cation; Mg^+ = Magnesium cation; Na^+ = sodium cation * = result of log-transformed. *Note*: the unit for EC is (dS m^{-1}); for CEC, Ca^+, K^+, Mg^+, and Na^+ is cmole kg^{-1}; for NO_3-N, and NH_4-N is mg kg^{-1}.

3.1. Soil organic carbon, total nitrogen, and phosphorus concentrations and stock

3.1.1. Effect of farming system

Soil characteristics adjusted by the proportion of land dedicated to each land use showed that farming system did not affect ($P = 0.33$) BD and C: N ratio (Table 5). In contrast, pasture-based farms exhibited higher ($P = 0.002$) SOC concentration as well as SOC and CO_2-equivalent stocks compared to confinement dairy farms. Pasture-based systems had 75% greater SOC and CO_2-equivalent stocks compared to confinement systems ($P = 0.002$), whereas TP stock was 3.7 times higher in confinement farms than in pasture-based farms ($P = 0.017$). The TN concentration did not differ between farming systems ($P > 0.05$),

Table 4
Effect of farming system (FS), land use type (LU) and their interaction on soil macro and micronutrients (mg kg^{-1}) in dairy farms.

Soil properties	Land use	Farming system	LU × FS
Aluminum	0.002	0.254	<0.001
Log (Aluminum)	0.018	<0.001	0.150
Boron	0.027	<0.001	0.268
Calcium	0.675	0.859	0.074
Copper	0.563	0.078	0.028
Log (Copper)	0.991	0.077	0.039
Iron	0.217	0.196	0.192
Log (Iron)	0.084	0.125	0.198
Potassium	0.041	<0.001	0.106
Log (Potassium)	0.001	0.001	0.004
Magnesium	0.359	0.851	0.762
Log (Magnesium)	0.484	0.439	0.533
Manganese	0.323	0.018	0.004
Sodium	0.022	0.085	0.040
Log (Sodium)	0.144	0.103	0.891
Phosphorus	0.646	0.199	0.452
Log (Phosphorus)	0.948	0.023	0.241
Sulfur	0.002	0.724	0.021
Log (Sulfur)	0.001	0.894	0.049
Zinc	0.679	0.543	0.564

Note: Log-transformed data: Variables marked with “Log” were log-transformed to meet assumptions of normality in the generalized linear mixed models.

Table 5
Effect of farming system on soil physicochemical properties in dairy farms weighed by the proportional area of each land use.

Soil properties	Farming system		P-value
	Pasture-base	Confinement	
Bulk density, g cm^{-3}	1.07 ± 0.122	1.17 ± 0.137	0.339
C: N ratio	14.2 ± 2.040	11.5 ± 2.280	0.336
Soil organic carbon, %	2.50 ± 0.149	1.43 ± 0.167	0.002
Total nitrogen, % **	0.18 ± 0.012	0.17 ± 0.014	0.654
Total phosphorus, %	0.004 ± 0.002	0.01 ± 0.003	0.017
Soil organic carbon, Mg ha^{-1}	105 ± 6.260	60.0 ± 7.000	0.002
$CO_{2eq,}$ Mg ha^{-1}	385 ± 23.00	220 ± 25.70	0.002
Total nitrogen, Mg ha^{-1}	8.73 ± 0.654	5.30 ± 0.731	0.010
Total phosphorus, Mg ha^{-1}	0.15 ± 0.105	0.56 ± 0.118	0.017
pH	6.71 ± 0.462	7.23 ± 0.516	0.477
EC, dS m^{-1}	0.12 ± 0.019	0.18 ± 0.021	0.062
NO_3-N, mg kg^{-1}	16.7 ± 2.17	21.7 ± 2.420	0.166
NH_4_N, mg kg^{-1}	4.74 ± 0.523	2.71 ± 0.584	0.036
CEC, cmole kg^{-1}	14.4 ± 3.340	15.7 ± 3.730	0.812
Ca^+, cmole kg^{-1}	9.05 ± 2.070	8.53 ± 2.310	0.872
K^+, cmole kg^{-1}	0.48 ± 0.108	0.97 ± 0.121	0.020
Mg^+, cmole kg^{-1}	4.20 ± 1.210	5.33 ± 1.350	0.253
Na^+, cmole kg^{-1}	0.40 ± 0.079	0.79 ± 0.088	0.003
Ca: Mg	3.01 ± 0.395	1.64 ± 0.441	0.054

CO_{2eq} = carbon dioxide equivalent; EC = Electrical conductivity; CEC=Cation exchange capacity; Av. K (mg kg^{-1}) = Available potassium (Ammonium Acetate); pH = pH_(1:5_water). Variables marked with an asterisk (**) are significantly affected by rainfall; significance levels are indicated as follows: **p < 0.01.

although it increased with mean annual rainfall ($P < 0.01$) and TN stocks remained higher in pasture-based systems ($P = 0.010$).

3.1.2. Land use effects within the pasture-based system

Natural pasture had higher ($P < 0.001$) SOC concentration (%), SOC and CO_{2eq} stock (Mg ha^{-1}) than cropping (Table 6). Total N concentrations (%) in NP were higher than in cropping, MPC, and tree areas ($P < 0.001$). Similarly, NP had greater ($P < 0.001$) TN stock (Mg ha^{-1}) compared to cropping and MPC. In contrast, the C: N ratio in NP did not differ ($P > 0.05$) from other land use types.

3.1.3. Interaction effects of farming system and land use type

The farming system × land use effect on SOC, C: N ratio, and TN stock in dairy farms are presented in Table 6. The interaction affected ($P = 0.001$) SOC concentration (%), with the highest values observed in tree areas and IP within the pasture-based system. Soil organic C and CO_{2eq} stocks (Mg ha^{-1}) followed a similar trend as SOC concentration (Table 6). Total N concentration and stocks were also greatest ($P < 0.001$) in IP and tree areas of the pasture-based system. Moreover, SOC and TN concentration, SOC, TN, and CO_{2eq} stocks (Mg ha^{-1}) were affected by mean annual rainfall ($P < 0.05$). Cropping and trees under the pasture-based system, and trees under the confinement system, exhibited higher C: N ratio ($P = 0.048$) compared to MPC under the confinement system.

3.2. Soil physicochemical properties across land use types and farming systems

3.2.1. Effect of farming system

No significant differences ($P > 0.05$) in pH, CEC, Ca, Mg, EC, NO_3-N, or Ca: Mg ratio were observed between the two dairy farming systems (Table 5). However, ammonium nitrogen was higher ($P = 0.036$), while Na^+ ($P = 0.003$) and K^+ ($P = 0.020$) were lower in pasture-based systems compared to confinement systems.

3.2.2. Land use effects within the pasture-based system

The NO_3-N, NH_4-N, and Ca^+ concentrations in NP did not differ ($P > 0.05$) from those in other land uses within the pasture-based system (Table 7). However, pH in natural pasture was higher ($P < 0.05$) than in tree areas. Potassium (K^+) varied by land use ($P < 0.05$), with NP exhibiting higher values than cropping, MPC, and IP, but lower values than tree land use.

3.2.3. Interaction effects of farming system and land use type

The farming system × land use effect on soil pH, NH_4_N, NO_3-N, Ca^+, and K^+ cation are presented in Table 7. Soil pH ($P = 0.008$) was highest in IP and cropping in the confinement system. Soil NO_3-N was highest in cropping and MPC under the confinement system ($P < 0.001$) and lower in IP and tree under the same system. Ammonium-nitrogen ($P < 0.001$) was highest in tree areas of the pasture-based system but lowest in IP under confinement. Calcium (Ca^+) ($P = 0.041$) was highest in MPC under the pasture-based system and lowest in IP and MPC under the confinement system. Potassium (K^+) ($P < 0.001$) was highest in trees under the confinement system and lowest in cropping, MPC, and IP under the pasture-based system.

3.3. Soil macro and micronutrients

3.3.1. Effect of farming system

The results of the soil macro and micronutrient concentrations across different farming systems are presented in Table 8. Aluminum concentration was higher on pasture-based compared to confinement farms ($P = 0.041$). In contrast, B, P, K ($P < 0.05$), and Na ($P < 0.001$) were higher on confinement farms. Potassium concentration was also influenced by mean annual rainfall ($P < 0.05$), with soil K decreasing as rainfall increased. Magnesium, Mn, S, and Zn showed no variation between the two farming systems ($P > 0.05$).

3.3.2. Land use effects within the pasture-based system

Soil macro- and micronutrient concentrations for different land uses within the pasture-based system are shown in Table 9. The concentrations of Cu, K, Mn, Na, and S in NP did not differ ($P > 0.05$) from those in other land uses within the pasture-based system.

3.3.3. Interaction effects of farming system and land use type

The effect of the farming system × land use on soil macro and micronutrient concentrations is presented in Table 9 for those variables with a significant interaction ($P < 0.05$). Copper (Cu) was lowest in cropping and tree areas under the pasture-based system, but the highest

Table 6
Interaction effect of farming system and land use type on the soil bulk density, soil organic carbon (SOC), carbon dioxide equivalent (CO_{2eq}), and total nitrogen (TN) concentration and stock of dairy farms.

Soil properties	Pasture-based					Confinement				P-value
	Cropping	IP	MPC	Tree	NP	Cropping	IP	MPC	Tree	
SOC, % *	1.53 ± 0.347^{ay}	2.23 ± 0.138^{bx}	1.66 ± 0.129^{ay}	2.37 ± 0.181^{bx}	2.87 ± 0.228$^{\times}$	1.87 ± 0.166^{ab}	1.88 ± 0.156^{ab}	2.10 ± 0.206^{ab}	1.88 ± 0.192^{ab}	0.001
TN, % *	0.11 ± 0.033^{ay}	0.19 ± 0.016^{by}	0.13 ± 0.015^{ay}	0.18 ± 0.019^{abx}	0.37 ± 0.039$^{\times}$	0.17 ± 0.017^{ab}	0.18 ± 0.018^{ab}	0.21 ± 0.021^{ab}	0.16 ± 0.020^{ab}	<0.001
Log (TN, %)	−1.90 ± 0.192^{abcy}	−1.53 ± 0.108^{dx}	−1.93 ± 0.113^{aby}	−1.61 ± 0.126^{cdy}	0.27 ± 0.047$^{\times}$	−2.04 ± 0.118^{a}	−1.98 ± 0.127^{a}	−1.76 ± 0.145^{bcd}	−2.12 ± 0.134^{a}	<0.001
C: N ratio	13.2 ± 1.620^{bc}	11.4 ± 0.960^{ab}	12.7 ± 1.000^{ab}	14.0 ± 1.120^{c}	12.6 ± 1.220	11.4 ± 1.050^{ab}	11.1 ± 1.130^{ab}	9.50 ± 1.260^{a}	13.2 ± 1.170^{bc}	0.048
SOC, Mg ha^{-1} *	64.2 ± 14.57^{ay}	93.8 ± 5.788^{bx}	69.9 ± 5.417^{ax}	99.5 ± 7.598^{bx}	120 ± 9.585$^{\times}$	78.4 ± 6.174^{ab}	78.8 ± 6.558^{ab}	88.1 ± 8.660^{ab}	78.8 ± 8.044^{ab}	0.001
CO_{2eq}, Mg ha^{-1}*	236 ± 53.48^{ay}	344 ± 21.24^{bcx}	257 ± 19.88^{abx}	365 ± 27.89^{bx}	441 ± 35.18$^{\times}$	288 ± 22.66^{a}	289 ± 24.07^{a}	323 ± 31.78^{a}	289 ± 29.52^{a}	0.001
TN, Mg ha^{-1} *	4.52 ± 1.370^{ay}	8.17 ± 0.665^{bx}	5.39 ± 0.643^{ay}	7.54 ± 0.786^{abx}	15.7 ± 1.626$^{\times}$	7.30 ± 0.718^{ab}	7.42 ± 0.746^{ab}	9.00 ± 0.898^{ab}	6.70 ± 0.848^{ab}	<0.001
Log (TN, Mg ha$^{-1)}$	1.83 ± 0.192^{aby}	2.21 ± 0.108^{bx}	1.81 ± 0.113^{ay}	2.13 ± 0.126^{bx}	2.43 ± 0.174$^{\times}$	1.70 ± 0.118^{ab}	1.76 ± 0.128^{ab}	1.98 ± 0.145^{ab}	1.63 ± 0.134^{ab}	<0.001

IP = Improved pasture; MPC = Mixed pasture cropping; C: N ratio = Carbon to nitrogen ratio; ^{a,b,c} Means without a common superscript differ across farming systems and land uses ($P < 0.05$). ^{x,y} = Means differ from natural pasture ($P < 0.05$). Note: Log-transformed data: Variables marked with "Log" were log-transformed to meet assumptions of normality in the generalized linear mixed models.

Table 7
Interaction effect of farming system and land use type on the soil chemical properties of dairy farms.

Soil properties	Pasture-based					Confinement				P-value
	Cropping	IP	MPC	Tree	NP	Cropping	IP	MPC	Tree	
pH	5.75 ± 0.357^{ax}	5.99 ± 0.244^{ax}	6.18 ± 0.250^{ax}	5.93 ± 0.272^{ay}	6.36 ± 0.260$^{\times}$	7.10 ± 0.267^{b}	7.08 ± 0.280^{b}	6.64 ± 0.302^{a}	7.09 ± 0.287^{b}	0.008
Log (pH)	1.76 ± 0.052^{a}	1.79 ± 0.037^{ab}	1.82 ± 0.038^{ab}	1.77 ± 0.041^{ab}	–	1.96 ± 0.041^{d}	1.95 ± 0.042^{d}	1.90 ± 0.045^{bc}	1.95 ± 0.043^{cd}	0.008
NO_3-N	12.5 ± 7.296	16.6 ± 2.796	14.1 ± 3.071	11.6 ± 3.985	14.3 ± 3.029	27.0 ± 2.922	15.5 ± 3.560	26.3 ± 4.615	8.28 ± 4.003	<0.001
Log (NO_3-N)	2.35 ± 0.316^{ab}	2.68 ± 0.124^{ab}	2.58 ± 0.136^{ab}	2.54 ± 0.171^{ab}	2.59 ± 0.192	3.10 ± 0.131^{b}	2.48 ± 0.157^{a}	3.08 ± 0.201^{b}	2.31 ± 0.175^{a}	<0.001
NH_4-N	3.17 ± 1.291^{ab}	4.68 ± 0.589^{b}	3.16 ± 0.632^{a}	7.09 ± 0.769^{c}	1.37 ± 0.162	3.21 ± 0.626^{ab}	2.10 ± 0.720^{a}	3.21 ± 0.874^{ab}	3.25 ± 0.778^{ab}	<0.001
Log (NH_4-N)	1.20 ± 0.279^{abc}	1.43 ± 0.133^{b}	1.10 ± 0.142^{abc}	1.91 ± 0.170^{c}	1.60 ± 0.216	1.04 ± 0.142^{ab}	0.72 ± 0.162^{a}	1.02 ± 0.193^{ab}	0.96 ± 0.173^{ab}	<0.001
Ca^+	7.28 ± 2.631^{ab}	8.01 ± 2.320^{ab}	9.59 ± 2.335^{b}	8.74 ± 2.375^{ab}	9.20 ± 2.970	8.80 ± 2.586^{ab}	7.18 ± 2.614^{a}	6.73 ± 2.667^{a}	8.15 ± 2.632^{ab}	0.041
K^+	0.38 ± 0.347^{y}	0.41 ± 0.141^{y}	0.25 ± 0.153^{y}	0.93 ± 0.199^{y}	1.51 ± 0.241$^{\times}$	1.23 ± 0.147	0.96 ± 0.176	1.36 ± 0.224	1.42 ± 0.196	0.103
Log(K^+)	−1.25 ± 0.371^{ay}	−1.17 ± 0.198^{ay}	−1.28 ± 0.208^{ay}	−0.30 ± 0.241^{bz}	0.56 ± 0.186$^{\times}$	0.03 ± 0.214^{bc}	−0.26 ± 0.236^{b}	0.13 ± 0.271^{bc}	0.18 ± 0.248^{c}	<0.001

IP = Improved pasture; MPC = Mixed pasture cropping; pH = pH_(1:5_water); NO_3-N = Nitrate-Nitrogen; NH_4_N = Ammonium-Nitrogen; Ca^+ = calcium cation; ^{a,b,c} Means without a common superscript differ across farming systems and land uses ($P < 0.05$). ^{x,y,z} = Means differ from natural pasture ($P < 0.05$).
Note: the unit for EC is (dS/m); for Ca^+, K^+, is cmole kg^{-1}; for Cl, NO_3-N, and NH_4-N is mg kg^{-1}. Log-transformed data: Variables marked with "Log" were log-transformed to meet assumptions of normality in the generalized linear mixed models.

in these land uses under the confinement system. Potassium concentration was lowest with IP and mixed pasture-cropping in the pasture-based system but greatest in trees, MPC, and cropping in the confinement system. Manganese concentration was lowest ($P = 0.004$) in cropping and tree areas under the pasture-based system and highest in tree areas and IP under the confinement system. Sodium concentration was lowest in MPC in the pasture-based system and highest in tree areas under the confinement system. Sulfur concentration was highest in cropping under the pasture-based system and in tree areas and cropping under the confinement system.

4. Discussion

4.1. Effect of farming system on soil physiochemical properties

Achieving neutral global warming from milk production requires a comprehensive approach to land and grazing management practices that reduce greenhouse gas emissions and enhance C sequestration in both soil and vegetation (Chen et al., 2022). In Australia, grasslands occupy 91% of agricultural land and 43% of the total land area (FAO, 2023; Chan et al., 2010); with dairy farming utilizing only a small fraction of this land. Despite their vast extent, SOC concentration typically ranges from 1% to 5% by mass (Henry, 2023). Human activities, such as grazing intensity and intensive agriculture influence SOC stocks and fluxes in grasslands (McDonald et al., 2023). Implementing effective land and grazing management practices must not only address emissions but also enhance farm profitability, promote environmental stewardship, and maintain the social license to operate (Harrison et al., 2021; Henry et al., 2023). To provide an accurate whole farm comparison, we weighed soil physicochemical properties according to the proportional area occupied by each land use type within farms. This approach corrects differences between farming systems to better reflect their actual land use composition rather than simple unweighted averages, which can obscure system level trends when land use differs substantially. In contrast, the

Table 8
Effect of the farming system on concentrations of macro and micronutrients (mg kg^{-1}) weighed by the proportional area of each land use in dairy farms.

Soil macro and micronutrient	Farming system		P-value
	Pasture-based	Confinement	
Aluminum	861 ± 78.30	568 ± 78.30	0.041
Boron	0.36 ± 0.154	1.45 ± 0.171	0.002
Calcium	1869 ± 429.0	2056 ± 479.0	0.780
Copper	1.23 ± 0.554	2.85 ± 0.554	0.084
Iron	316 ± 39.40	211 ± 44.00	0.121
Potassium *	106 ± 37.70	487 ± 44.40	0.002
Magnesium	562 ± 160.0	669 ± 178.0	0.668
Manganese	52.4 ± 11.00	65.7 ± 12.20	0.445
Sodium	90.4 ± 18.90	200 ± 21.10	<0.001
Phosphorus	36.1 ± 25.10	133 ± 28.10	0.017
Sulfur	18.7 ± 3.690	27.1 ± 4.120	0.141
Zinc	3.64 ± 1.240	5.97 ± 1.390	0.223

* $p < 0.05$.

farming system × land use interaction analysis relied on unadjusted raw data to allow direct comparison of land use categories within and across systems. Together, these complementary analytical frameworks capture both the differences between farming systems in land uses and the consequence of intensification on the whole farm and the localized responses to land use within a farming system.

When corrected for the area occupied by each land use type, the pasture-based farming system showed a 75% greater SOC concentration compared to confinement dairy farms, along with significantly higher SOC stocks (Mg C ha^{-1}) and CO₂eq (Mg ha^{-1}). These results may be attributed to the contrasting environmental conditions and management practices between the two farming systems. The three confinement farms included in the present study were located within inland areas, where drier conditions and lower organic matter inputs may reduce SOC levels. In contrast, all the pasture-based farms were from the coastal regions that could support higher SOC levels. Thus, differences in climate, soil type, and environmental conditions between these regions may have influenced SOC and other measured soil physicochemical properties.

The inclusion of rainfall as a covariate did not significantly influence SOC and TN stocks, although mean annual rainfall was higher in pasture-based coastal farms compared to confinement inland farms. This suggests that management-related factors, such as reduced tillage, the predominance of perennial pastures, and in situ nutrient cycling through grazing (e.g. manure deposition in paddocks), contributed to the observed patterns. However, adjusting for rainfall does not account for other inherent differences, including parent material, long-term temperature regimes, and soil texture, which remain important limitations of the present study. Importantly, the geographical distribution of dairy systems in Australia is not random but reflects long-established production realities: confinement dairy farms are predominantly located in lower-rainfall inland regions, whereas pasture-based systems occur mainly in higher-rainfall coastal areas where grazing productivity is closely linked to rainfall-driven pasture availability. Similar climate-driven patterns occur in other countries; for example, in the United States, pasture-based dairying is far more common in the higher-rainfall Northeast and Upper Midwest, whereas the drier western states rely predominantly on confinement-based operations due to limited pasture growth (Cloutier et al., 2025). This rainfall gradient is therefore a structural feature of national dairy geography rather than a sampling artifact, yet it introduces environmental variation that must be carefully considered when interpreting soil responses. Beyond climatic and edaphic influences, confinement dairy farms predominantly rely on forage cropping and cultivating annual crops often used as ingredients in TMR (Dida et al., 2025). These practices involve frequent soil disturbance which contribute to SOC loss via soil mineralization and erosion (Lal, 1997; Ritchie, 2020). Research supports that tillage disrupts soil structure, accelerates decomposition, and releases SOC as CO₂ (Boschiero et al., 2023; Jordahl et al., 2023). Similarly, Wilson et al. (2011), Jones et al. (2016) and Badgery et al. (2020) also reported that soils from perennial pasture stored more SOC than cropping soils. Furthermore, forage crops cultivated on confinement farms are annual species, which allocate considerably less biomass belowground than perennial grasses (Ritchie, 2020). Crops were often harvested for animal feed, particularly as straw, silage, or hay, which removes the above ground biomass and reduces the amount of OM returned to the soil, further limiting the potential for SOC accumulation. In contrast, pasture-based systems rely on improved pastures dominated by perennial grasses, which allocate more biomass belowground, contributing to enhanced SOC storage (Badgery et al., 2020; Jones et al., 2016; Wilson et al., 2011). Furthermore, pasture-based dairy farms typically rely on grazing rather than harvesting and feeding forage to the animals. Grazing practices contribute to SOC in several ways such as animals trampling physical fragments and incorporating litter into the soil, making it more accessible for microbial decomposition and facilitating SOC formation. Moreover, animal excreta recycle C and nutrients in the paddock. This result is consistent with previous studies that highlight the positive impact of pasture-based systems on SOC sequestration (Lal, 2004b; Stewart et al., 2008).

Overall, SOC of dairy farming systems are influenced by the

Table 9
Interaction effect of farming system and land use type on the soil macro and micronutrients (mg, kg^{-1}) of dairy farms.

Soil properties	Pasture-based					Confinement				P-value
	Cropping	IP	MPC	Tree	NP	Cropping	IP	MPC	Tree	
Cu	0.77 ± 0.663^{ay}	0.99 ± 0.481^{aby}	1.27 ± 0.497^{bcx}	1.02 ± 0.524^{abx}	0.60 ± 0.113$^{\times}$	2.84 ± 0.528^{d}	2.48 ± 0.547^{cd}	1.78 ± 0.581^{bcd}	2.69 ± 0.558^{cd}	0.028
Log (Cu)	0.73 ± 0.283^{a}	0.80 ± 0.278^{ab}	0.92 ± 0.322^{ab}	0.74 ± 0.265^{a}	0.37 ± 0.102	2.56 ± 0.991^{c}	2.27 ± 0.887^{bc}	1.98 ± 0.788^{bc}	2.56 ± 1.005^{c}	0.039
K	155 ± 128.4	149 ± 51.97	86.7 ± 56.36	322 ± 73.38	199 ± 50.10	500 ± 53.93	390 ± 64.97	539 ± 82.69	553 ± 72.26	0.106
Log (K)	4.73 ± 0.350^{ab}	4.77 ± 0.179^{a}	4.58 ± 0.189^{a}	5.59 ± 0.221^{bc}	5.32 ± 0.293	6.06 ± 0.193^{c}	5.78 ± 0.215^{bc}	6.13 ± 0.250^{c}	6.18 ± 0.228^{c}	0.004
Mn	30.4 ± 24.32^{a}	42.1 ± 10.67^{ab}	62.9 ± 11.54^{bc}	30.4 ± 13.97^{a}	672 ± 219.0^{ab}	59.3 ± 11.40^{ab}	89.9 ± 13.19^{cd}	69.7 ± 16.22^{bc}	109 ± 14.36^{d}	0.004
Na	99.8 ± 69.11^{abc}	85.6 ± 37.41^{abc}	67.1 ± 39.26^{a}	83.1 ± 45.09^{abc}	82.3 ± 43.34	188 ± 40.47^{c}	183 ± 44.38^{bc}	98.2 ± 50.92^{abc}	268 ± 46.69^{d}	0.040
S	32.3 ± 11.37^{bx}	15.3 ± 6.456^{ay}	15.1 ± 6.740^{ay}	16.3 ± 7.602^{ay}	41.8 ± 6.862$^{\times}$	30.1 ± 7.025^{b}	12.2 ± 7.609^{a}	14.7 ± 8.604^{a}	35.3 ± 7.957^{b}	0.021
Log (s)	−0.31 ± 0.386^{b}	−0.23 ± 0.348^{a}	−0.09 ± 0.351^{a}	−0.30 ± 0.356^{a}	3.13 ± 0.317	0.94 ± 0.387^{b}	0.82 ± 0.391^{a}	0.68 ± 0.398^{a}	0.94 ± 0.393^{b}	0.049

IP = Improved pasture; MPC = Mixed pasture cropping; Cu = copper; K = potassium; Mn = Manganese; Na = Sodium; S = Sulfur; ^{a,b,c} Means without a common superscript differ across farming systems and land uses ($P < 0.05$). ^{x,y} = Means differ from natural pasture ($P < 0.05$). Note: Log-transformed data: Variables marked with "Log" were log-transformed to meet assumptions of normality in the generalized linear mixed models.

interaction between land use and the climatic and edaphic contexts in which farms operate. Consequently, the differences in SOC between pasture-based and confinement dairy systems should be interpreted cautiously. It is also important to note that the results from the present study should be interpreted with caution because soil samples were obtained at only one point in time and from farms with different environmental conditions. One key factor to consider is that pasture-based systems are typically located in regions with higher, more evenly distributed rainfall throughout the year, whereas confinement systems typically operate in lower-rainfall inland areas where pasture growth is less dependable and feed must be harvested and stored. These differences in rainfall and climate are critical and may significantly influence the findings of the study. Pasture-based systems are heavily dependent on natural forage growth, which is most feasible in areas with consistent and abundant moisture. Coastal regions and areas with high rainfall provide ideal conditions for year-round pasture growth, which is crucial for the sustainability of these systems. In contrast, confinement systems are often found in regions with lower or more seasonal rainfall, where consistent pasture growth could not reliable due to water scarcity or variability in precipitation. Consequently, confinement systems need to harvest and store forage to feed cows. These factors can lead to lower biomass production, higher oxidation or removal of organic matter from the paddock, or both, resulting in lower SOC levels, despite the use of irrigation on these farms. In summary, higher SOC observed in pasture-based dairy farms compared to confinement systems could be partially influenced to the lesser biomass removal, greater carbon cycling in the paddocks through vegetation, perennial nature of the pastures, lower soil disturbance, grazing practices, and the cultivation of diverse plant species, which together contribute to higher soil C. In contrast, SOC of confinement dairy systems seem to be less affected by management practices because the aforementioned factors play a smaller role.

A notable divergence between systems is the higher TP stock in confinement farms despite their lower P fertilizer rates per hectare. This likely reflects cumulative (legacy) P from historical inputs and/or inherent differences in parent material and mineralogy, rather than contemporary annual applications alone. Phosphorus is relatively immobile in soils due to strong sorption to mineral surfaces and can persist as legacy phosphorus from past fertilization or manure applications (Frossard et al., 2000; Holford, 1997; Sattari et al., 2012; Sharpley et al., 2013). Although these mechanisms are a plausible explanation, the experimental design of the present study was not intended to partition legacy P from geological sources. Therefore, these results on soil P should be interpreted caution and further research with targeted P budgeting and mineralogical analyses is recommended.

The concentration of various micro and macro minerals differed between farming systems and the reasons for these are complex to interpret in the present study. One of the most important factors affecting the concentration of minerals and nutrients could be the composition of the parent soil material, the history of mineral extraction through agriculture, along with fertilization regimes. The N compounds including NH_4-N were significantly lower in confinement compared to the pasture-based system, which could be attributed to rapid denitrification, likely driven by frequent soil disturbance and increased microbial activity in cultivated fields. Confinement farming systems showed higher K^+ and Na^+ which can be attributed to higher use of K-rich lime compared to pasture-based (Kaur et al., 2021). Potassium concentration was also influenced by mean annual rainfall, with soil K decreasing as rainfall increased due to greater leaching losses under wetter conditions. This pattern is consistent with the well-established tendency for K, a relatively mobile base cation, to be leached more extensively under wetter climatic conditions (Jalali and Jalali, 2022; Nigon and Kaiser, 2025). Pasture-based farms had higher Al concentrations than confinement farms, likely due to the less frequent use of lime and other soil amendments in these systems, which are typically applied more regularly in confinement systems to maintain soil pH and fertility (Yan et al., 2016).

4.2. *Interaction effect of farming system and land use on soil physiochemical properties*

The results of the present study revealed that the farming systems × land use influenced SOC stock, with improved pasture in pasture-based dairy farming systems showing greater SOC compared to all land use in confinement system. There could be several reasons for the effect of land use on SOC of pasture-based but not in confinement systems. One of the main reasons could be explain by higher rainfall in pasture-based compared to confinement, which may allow greater C cycling between atmosphere, vegetation, and soil. In pasture-based systems, improved pastures likely benefit from grazing through manure deposition and animal trampling that fragments and incorporates litter into the soil, enhancing microbial decomposition, nutrient cycling, and SOC (Sørensen et al., 2009; Wei et al., 2023). In contrast, confinement systems consist of cows primarily fed indoors (Dida et al., 2025) and predominantly utilize improved pastures for hay and silage production rather than grazing, potentially reducing C and nutrient cycling due to lesser manure deposition onto pastures and litter incorporation into soil, which limiting SOC accumulation.

The farming system × land use revealed that land use affected soil pH differently in each farming system. Specifically, confinement systems consistently exhibited higher pH levels across all land use types. This difference may be explained by the coastal location of the pasture-based farms, where higher rainfall and increased leaching could lower pH. In contrast, confinement farms, located inland, experience less rainfall and leaching, which allows basic ions to accumulate, contributing to higher pH levels. Cropping and MBC in confinement systems exhibited notably higher NO_3-N concentration. The reasons for this finding cannot be confirmed in the present study, but it is hypothesized higher fertilization of these land uses could be responsible.

In the system × land-use interaction model, mean annual rainfall was retained as a significant covariate for SOC concentration, SOC stock, CO_2-equivalent stock, and TN concentration and stock. This suggests that the magnitude of differences between land uses within each farming system is partly explained by long-term rainfall gradients, rather than reflecting management or land-use allocation alone. Higher rainfall in the coastal pasture-based farms likely enhances plant productivity, root turnover, rhizodeposition, and microbial processing, thereby amplifying SOC and TN gains in IP, TA, and NP. In contrast, the lower rainfall typical of inland confinement farms could experience limited biomass input, reducing the expression of land-use contrasts even where management differs. This rainfall dependence is consistent with extensive evidence from New South Wales and Eastern Australia. For instance, Hobley et al. (2015) reported that precipitation was a major positive driver of SOC across 1401 sites in NSW and that parent material became increasingly important with depth, whereas land use also influenced SOC distribution and concentration. Similarly, the modulating effects of climatic gradients on SOC was also highlighted in a large regional assessment by Rabbi et al. (2015), who showed that aridity and soil texture were the dominant factors controlling SOC, whereas differences in land-use explained only a small proportion of the variation. At a catchment scale, Badgery et al. (2013) found that 30-year mean annual rainfall was the strongest predictor of SOC at 0–10 cm depth in central NSW, with soil mineralogy and particle-size properties gaining importance deeper in the profile. State-scale digital soil mapping studies likewise demonstrate that wetter climates and fertile lithologies support higher SOC stocks and more stable C fractions, reinforcing that climate and parent material jointly structure SOC across NSW landscapes. Gray et al. (2019) showed that SOC fractions increased systematically with increasingly moist climates and mafic parent materials across NSW. Evidence from grazing systems also support the findings of the present study. McDonald et al. (2023) concluded that rainfall strongly governs whether grazing management translate into measurable SOC gains. In conclusion, results of the present and previous studies contribute to explaining the reasons for SOC and TN “hotspots” (IP, TA, NP) being most clearly expressed in the higher-rainfall pasture-based farms. Numerous Australian comparisons of perennial pastures and cropping show that SOC gains under perennial vegetation are largest in humid or mesic environments. For instance, Chan et al. (2010) found higher SOC under improved pastures compared to cropping in high-rainfall. Collectively, these findings underscore that management and land use outcomes are highly influenced by climatic and edaphic constraints, and that rainfall-adjusted interaction analyses may provide a more realistic basis to identify practices that increase SOC such as trees, perennial pastures, and minimizing soil disturbance in regions with the greatest climatic potential for SOC accumulation.

4.3. Land use effects within the pasture-based system

Results of the present study showed that NP had the highest SOC concentration, compared to the MPC and cropping. These results might be due to the perennial nature of grasses in NP, which could contribute higher OM through root biomass and litter (Bai and Cotrufo, 2022; Conant et al., 2001; Henry and McKenzie, 2018). Additionally, the permanent grass cover protects SOC from wind and soil erosion (Dass et al., 2018) and soil disturbance is lower in NP compared to other land uses such as cropping leading to lesser OM oxidation (Conant et al., 2001). These findings are consistent with previous research showing that perennial vegetation and low soil disturbance promote higher SOC (Conant et al., 2001; Mengist et al., 2023; Pouyat et al., 2006; Six et al., 2002).

Natural pastures in the pasture-based system showed SOC stocks that were 6%, 14%, 46%, and 56% higher than those in tree, IP, cropping, and MPC, respectively. This is likely due to NP often having deeper, which contribute to higher SOC stocks through increased OM input, and enhanced plant C inputs via rhizodeposition and plant litter (Dignac et al., 2017). Natural pastures are also more resilient to extreme heat waves, drought, and wildfires than forests (Conant et al., 2001; Dass et al., 2018), and may benefit from the excreta of grazing livestock or manure used as fertilizer in dairy farms. This finding is further supported by Brown et al. (2023), who emphasized that pastures are more effective in C sequestration compared to cropping systems, particularly pastures with low disturbance and robust root systems. In agreement with this result, Rui et al. (2022) reported that intensive cropping after grassland has released large amounts of C into the atmosphere. Minimizing soil disturbance, diversifying crop rotations, or re-establishing perennial grasslands and integrating livestock can slow or reverse this trend (McDonald et al., 2023; Ogle et al., 2012; Reed, 2014).

In the present study, TN concentration was higher in NP compared to cropping and this could be due to differences in nutrient extraction, as cropping systems typically have higher yields with all biomasses removed as hay or silage, whereas pasture systems have optimal biomass removal rates and greater nutrient recycling through grazing. Animal excretion, including fecal organic debris and urine or dairy manure from the milking cows, returns N to the soil, improving its availability and accelerating litter decomposition by stimulating soil microbial activity (Li et al., 2021; Liu et al., 2015; Song et al., 2017). Dairy cows typically excrete about 70–90% of the N they ingest (Haynes and Williams, 1993), with up to 80% of this N being found in their urine (Di and Cameron, 2002; Jarvis et al., 1995). Similar results have been reported by Puget and Lal (2005), who found that pasture soils contained the highest SOC and N stocks, over 2-fold greater than cultivated soils.

These findings that IP, NP, and tree areas function as consistent SOC hotspots within pasture-based systems has important implications for both farm-level management and regional policy design. Beyond confirming the biophysical potential of perennial vegetation and tree cover to enhance below-ground C inputs, these results highlight the opportunity to integrate silvopastoral strategies into dairy production landscapes as a deliberate C sequestration tool. Tree areas established as shelterbelts, riparian strips, shade lines, or dispersed individual paddock trees create localized microclimates that reduce heat stress, improve water retention, promote litter and root biomass accumulation, and enhance nutrient cycling, all of which contribute to elevated SOC stocks (Eckard and Clark, 2020; England et al., 2020; Fisher et al., 2008). As such, tree-pasture configurations can represent a scalable, low-disturbance C sequestration mechanism that aligns naturally with SOC of TA and IP observed in the present study. For confinement-dominated regions, where lower rainfall and intensive cropping attenuate land-use contrasts, translating these insights into practice could require adapting silvopastoral principles to water-limited environments. Feasible interventions include incorporating drought-tolerant tree belts along cropping areas, establishing scattered shade trees within exercise or loafing areas, integrating deep-rooted woody species into field margins, and adopting shelterbelts that reduce wind erosion and promote soil surface stability. The inclusion of trees can complement reduced tillage, cropping-pasture sequences, cover cropping, residue retention, and improved nutrient stewardship. Together, these measures could provide confinement farms with a practical pathway to offset part of their C footprint by creating stable, long-lived C sinks, while also generating co-benefits such as shade for livestock, improved microclimates for feed crops, biodiversity enhancement, and reduced erosion risk. At the policy level, results of the present study can support incentivizing farm-scale tree retention and establishment through mechanisms such as C credit eligibility for shelterbelts, riparian plantings, and paddock trees, particularly in regions where perennial pastures cannot be expanded. Recognizing tree areas as legitimate SOC reservoirs within agricultural C accounting frameworks would encourage producers to adopt silvopastoral options that enhance farm resilience and contribute to national soil C and livestock-sector mitigation targets.

4.4. Limitations of the study

A key limitation of the present study is the inherent environmental differences between the two farming systems. Pasture-based farms were located in coastal regions with higher rainfall, milder temperatures, and soils predominantly classified as Kurosols and Dermosols. In contrast, confinement farms were situated inland in lower rainfall zones with soils largely comprising Chromosols and Luvisols. These climatic and edaphic differences are known determinants of SOC and nutrient cycling and may partly explain the observed differences between systems even after rainfall included as a covariate in mixed-effects models. Although our statistical approach accounted for farm level variation by treating “farm” as a random effect, confounding factors from long term climatic regimes, mineralogy, and landscape position cannot be fully eliminated in an observational design. Another limitation is the soil sampling depth limited to 30 cm following IPCC Tier 1 and Australian Carbon Farming Initiative protocols, as this layer captures the majority of changes in SOC due to management in agricultural systems. However, deeper sampling to 1 m is common in studies comparing forests, permanent grasslands, and cropping systems. Deeper layers may reveal additional differences in carbon storage, particularly under perennial vegetation where root systems extend well below 30 cm (Jobbágy and Jackson, 2000; Wiesmeier et al., 2019). Future studies incorporating SOC measurements in the full soil profile would therefore provide a more complete assessment of carbon stocks. Finally, the cross-sectional nature of the present study captured soil conditions at a single point in time and does not account for management history, interannual climate variability, or legacy effects of past fertilization and land-use transitions. Longitudinal monitoring would enhance confidence in attributing SOC differences to farming system and land use practices rather than to historical or transient environmental factors.

5. Conclusion

The results of the present study showed that trees and improved pastures in the pasture-based farming system had higher SOC and nutrients compared to cropping. This quantification of SOC in different land uses provides a foundation for improved estimation and accounting of SOC and management practices, such as potential gains in SOC after transitioning from cropping to pasture. However, land use and management practices seemed to have no effect on SOC for the confinement systems located in drier regions. Confinement systems showed lower SOC and soil total N stock compared to pasture-based system, but these differences may be due to climate, land use type, and soil parent material. These findings highlight the potential of improved pastures, natural pastures, and tree areas in pasture-based systems to improve soil health and contribute to sustainable agriculture through better C sequestration and nutrient retention. However, the effect of land use type and management practices on SOC of drier regions typical of confinement dairy systems seems not feasible but more research with larger datasets is needed. Thus, in regions where grazing systems are feasible, perennial pastures and tree areas can be effective levers for building soil carbon stocks. In inland, drier settings typical of confinement systems, a soil conservation framework that reduces disturbance and improves residue and nutrient stewardship is likely required to protect and rebuild SOC while managing legacy nutrients. Continued whole-farm, area-weighted accounting is advisable to ensure that tactical paddock-scale gains translate into genuine farm-scale improvements.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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Chapter 7. How Reliable Are National Digital Soil Maps for Farm-Scale Baseline Assessment? A Multi-Scale Assessment Using Dairy Farm Data

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Overview

This chapter assessed the accuracy of the Soil and Landscape Grid of Australia (SLGA), a digital soil mapping product, in predicting SOC, TN, and TP at paddock and farm scales. Against over 800 laboratory measurements from nine dairy farms, SLGA showed moderate predictive performance for SOC, especially at the farm level, but poor accuracy for TN and TP. Although SLGA effectively detected SOC differences across farming systems and land uses, it showed limited sensitivity to detect differences in nutrient content, suggesting a need for improved modelling in dairy systems. The study supports SLGA's potential for large-scale soil monitoring, particularly when complemented by ground-truth data.

How Reliable Are National Digital Soil Maps for Farm-Scale Baseline Assessment? A Multi-Scale Assessment Using Dairy Farm Data

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Abstract

Digital soil mapping (DSM) provides a scalable approach for monitoring soil health indicators to support sustainable land management and precision agriculture. However, uncertainties associated with input data and fine-scale management factors including land-use type, fertiliser history, and grazing intensity can limit predictive reliability at operational scales. Evaluating the performance of DSM products under real farm conditions is therefore critical to determine their suitability for baseline assessment. This study assessed the accuracy of the Soil and Landscape Grid of Australia (SLGA), a national-scale DSM product, in predicting topsoil (0–30 cm) soil organic carbon (SOC), total nitrogen (TN), and total phosphorus (TP) using more than 800 independently collected topsoil samples from nine Australian dairy farms. The SLGA prediction performance was evaluated at sub-farm (individual Carbon Estimation Areas, CEAs, i.e., paddocks or groups of paddocks with similar land use and management within a farm) and farm scales (aggregated across all CEAs within a farm) using R^2, Lin's concordance correlation coefficient (CCC), mean absolute error (MAE), and mean bias error (MBE). In addition, linear mixed-effects models tested SLGA's ability to detect differences due to land use and farming systems (pasture-based vs. confinement). The SLGA showed moderate accuracy for SOC and TN at the farm scale (SOC: $R^2 = 0.79$, CCC = 0.88; TN: $R^2 = 0.87$, CCC = 0.79), but substantially weaker agreement at the sub-farm scale, and very poor accuracy for TP across both scales ($R^2 \leq 0.01$; CCC ≤ 0.02). Standardized errors were moderate for SOC and TN, and highest for TP. The SLGA successfully detected differences in SOC and TN between pasture-based and confinement systems, demonstrating value for broad farm-scale baseline assessments, but showed limited sensitivity to within-farm land-use variation. Overall, SLGA provides useful farm-scale baseline assessments of SOC and TN in dairy systems; however, improvements are required to enhance sub-farm precision, TP prediction, and the representation of local management effects.

Keywords: *Carbon; Dairy farm; Digital soil mapping; Nitrogen; Land-use; Pasture*

7.1. Introduction

Climate change is intensifying pressures on global food systems, water resources, and biodiversity, highlighting the urgent need for land-management practices that enhance soil resilience and reduce greenhouse gas (GHG) emissions (IPCC, 2023). Soils play a key role in climate mitigation through carbon (C) storage, nutrient cycling, water regulation, and biodiversity preservation; however, soils can also contribute substantially to GHG emissions when poorly managed (Evangelista et al., 2024; Keesstra et al., 2016; Kopittke et al., 2022; McBratney et al., 2014). Soil organic carbon (SOC), in particular, is a key determinant of soil health and agricultural productivity, and its accurate assessment is essential for designing mitigation strategies, improving nutrient-use efficiency, and implementing C farming initiatives (Evangelista et al., 2024; Keesstra et al., 2016; Kopittke et al., 2022; Luo et al., 2025). Accurate soil information also underpins fertiliser management decisions, where improved soil quality can enable reductions in nitrogen (N) application rates (Wang et al., 2026).

Monitoring soil properties such as SOC and nutrients is therefore essential for informed land management and climate mitigation. Traditionally, this has relied on laboratory analyses and conventional soil mapping methods. Although laboratory measurements are accurate, these are labour-intensive, costly, and limited in spatial coverage (Behrens and Scholten, 2006; McBratney et al., 2003; Zhang et al., 2017). Conventional soil mapping depends on field observations, aerial imagery, and expert judgment, but it is subjective, time-consuming, and expensive. It is also often constrained by morphological descriptors that may not align with modern agricultural needs or support practical land management (Miltenyi et al., 2015; Triantafilis et al., 2013; Zare et al., 2018). In recent decades, digital soil mapping (DSM) has emerged as a powerful alternative for predicting soil properties using statistical and geospatial models (Lagacherie and McBratney, 2006; McBratney et al., 2003). Digital soil mapping offers cost-effective and scalable alternatives to conventional methods by integrating soil survey data with geographic information systems (GIS), terrain analysis, remote sensing, machine learning, and high-performance computing (Arrouays et al., 2017; Ma et al., 2019; McBratney et al., 2003; Minasny and McBratney, 2016). Beyond mapping, DSM is increasingly positioned as part of decision intelligence frameworks that support soil health and water quality management (Fan et al., 2026).

Advances in DSM have led to the development of different national-scale products such as the Soil and Landscape Grid of Australia (SLGA; (Malone et al., 2025)), which provide spatially continuous estimates of SOC, total nitrogen (TN), and total phosphorus (TP), and other attributes across multiple depth layers. Despite these advances, uncertainties in DSM predictions could be a barrier to their adoption in site-specific agricultural management. Prediction accuracy varies with data quality, environmental covariates, modelling algorithms, and spatial resolution (Lemercier et al., 2022; Rossiter et al., 2021). This limitation is particularly important when DSM outputs are used as inputs to process-based models, which are highly sensitive to soil parameterisation and may amplify prediction errors (Zhang et al., 2025). Furthermore, the reliability of DSM products at farm and paddock scales especially in heterogeneous land-use systems has not been thoroughly evaluated and is often limited (Han et al., 2022). These limitations may restrict their application in practical decision-making, including nutrient management, C accounting, and land-use planning. Inaccurate spatial representation of soil nutrients can lead to inappropriate management decisions and reduce the effectiveness of mitigation strategies (Fan et al., 2023). Therefore, rigorous validation of DSM products is essential to ensure their suitability for site-specific agricultural applications (Lagacherie and Mcbratney, 2006).

The Soil and Landscape Grid of Australia (SLGA) is a national DSM initiative launched to support environmental and agricultural decision-making across different scales (Malone et al., 2025). It provides freely accessible spatial datasets of key soil and landscape attributes at a standard resolution of 3 arc seconds (~90 m × 90 m pixels). Some products, such as those for SOC, are also available at a finer 1 arc second (~30 m × 30 m) resolution to support higher-resolution applications, depending on platform capabilities and analysis needs. All datasets are aligned with GlobalSoilMap specifications (Grundy et al., 2015; Malone et al., 2025). The SLGA combines traditional soil observations with sensor technologies and advanced modelling techniques (Malone et al., 2025). Although the SLGA has undergone significant updates to enhance its coverage and data quality, its accuracy at the farm and sub-farm scales, has not yet been adequately evaluated with independent datasets.

Under Australia's Carbon Farming Initiative soil carbon methodology, project proponents must delineate Carbon Estimation Areas (CEAs) and implement stratified random sampling within each CEA. In this study, these CEAs are referred to as sub-farms to assess the accuracy of SLGA. Assessing SLGA accuracy over sub-farms and at the farm scale therefore provides a valuable opportunity to determine the utility of SLGA products as baseline assessment tools for designing soil-carbon sampling schemes. The present study aimed to assess the reliability of SLGA in predicting topsoil SOC, TN, and TP at 0–30 cm depth (where the largest variability is observed) comparing them with laboratory-based measurements. The evaluation was conducted at two spatial scales: 1) point-based, where point-to-point comparisons are made between observed and predicted values, and 2) a polygon-based comparison, in which SLGA raster values within each sub-farm boundary were aggregated to produce a sub-farm-level mean for comparison with the corresponding laboratory composite averages. These dual approaches enabled performance assessment at both sub-farm and whole-farm scales, providing insights into the applicability of SLGA as a tool for farm-scale baseline assessment.

7.2. Materials and methods

7.2.1. Study areas

The observational dataset used in the present study was derived from data collected for a study on the impacts of dairy farming systems and land use on SOC stocks and other physicochemical properties (Dida et al., 2026). The study area included nine dairy farms across three regions in New South Wales, Australia: Mid Coast (three farms: two pasture-based and one confinement), the South Coast (one pasture-based and three confinement), and the North Coast (two pasture-based). The nine farms were selected to represent the diversity of the dairy industry in New South Wales in terms of milk production, herd size, input use, and production systems (pasture-based and confinement). Farms were chosen based on their representativeness of typical management practices within each system, enabling a balanced comparison.

Pasture-based systems refer to farming systems that primarily rely on grazed forage, supplemented with concentrates, silage, and hay. In contrast, confinement systems house milking cows and provide total mixed rations (TMR), with no grazing. These three regions have distinct climates, topography, geology, soils, and agricultural contexts. The farms in the Mid Coast experience an annual mean temperature of 24 °C (ranging from 21 °C to 27 °C) and an annual mean monthly rainfall of 76 mm (ranging from 40 to 120 mm). In the South Coast, farms have a slightly lower annual mean temperature of 23 °C (ranging from 20 °C to 26 °C) and a lower annual mean monthly rainfall of 44 mm (ranging from 34 to 48 mm). The North Coast farms exhibit the highest annual mean temperature at 26 °C (ranging from 24 °C to 29 °C) and the highest annual mean monthly rainfall, averaging 89 mm (ranging from 32 to 156 mm). Climate data were obtained from long-term monthly means downloaded from the Australian Bureau of Meteorology website, using records from the nearest weather stations to each farm (http://www.bom.gov.au/climate/data/).

Soil types and fertility across the study farms reflect regional variation. In the South Coast region, the four farms are predominantly situated on Chromosols, with minor occurrences of Rudosols and Dermosols. In the Mid Coast, the three farms are mainly located on Kurosols, with some Dermosols and small areas of natric Kurosols. The three North Coast farms are primarily Kurosols and Vertosols, with Vertosols being more dominant on one of the farms. Soil types for each farm were identified using the Australian Soil Classification (ASC) soil type map of NSW (Department of Planning, Industry, and Environment, 2021).

7.2.2. Farm characteristics and sampling design

Soil samples were collected from the five pasture-based and four confinement farms ensuring uniform distribution across agricultural plots. The average farm area was 233 ± 47.3 ha for pasture-based farms and 611 ± 305 ha for confinement farms, while milking cow herd sizes averaged 335 ± 13.56 and 1,073 ± 247 for pasture-based and confinement farms, respectively (mean ± SE; Dida et al., 2025). Within each farm, paddocks were categorised into five land-use types: cropping, natural pasture, improved pasture, mixed pasture-cropping, and tree areas. Maps of paddocks and farm boundaries were obtained from farmers and imported into Google Earth Pro, along with detailed information on land use types.

Natural pasture paddocks were those that were neither irrigated, fertilised, nor mechanically disturbed (e.g., through disking or ploughing). Improved pastures included both irrigated and non-irrigated areas that were semi-disturbed for oversowing and fertilisation. Mixed pasture-cropping paddocks consisted of seasonal combinations of pasture and crop, such as winter ryegrass with summer maize or wheat, and ryegrass-legume mixtures with summer crops, and involved land disturbance (disking or ploughing) for sowing and fertilisation. Cropping paddocks, primarily used by confinement farms, were fully ploughed for annual planting and included crops such as winter wheat, summer maize, barley, sorghum, and winter vetch. These crops were cultivated specifically as livestock feed in the form of silage or grain. Tree paddocks were areas covered with shrubs and trees such as honey locust (*Gleditsia triacanthos*), sweet osmanthus (*Osmanthus fragrans*), eucalyptus (*Eucalyptus* spp.), blackwood (*Acacia melanoxylon*), and Australian silky oak (*Grevillea robusta*), and were not irrigated nor fertilized. In pasture-based farming systems, paddock areas averaged 21.6 ± 9.51 ha for improved pasture, 17.0 ± 12.5 ha for mixed pasture-cropping, 11.3 ± 12.9 ha for native pasture, and 11.9 ± 8.62 ha for tree cover, while in confinement systems, areas were 33.1 ± 25.8 ha for improved pasture, 22.8 ± 18.8 ha for mixed pasture-cropping, 148 ± 197 ha for forage cropping, and 16.4 ± 11.7 ha for tree cover, contributing to an overall average paddock area of 34.2 ± 148 ha (mean ± SD) driven by high variability in intensive forage cropping.

7.2.3. Soil sampling procedure

A total of 810 soil samples were collected across all nine dairy farms, with all representative paddocks of each farm included to ensure uniform coverage of all land use types within the farms. The areas of interest, representing different land-use types, were referred to as Carbon Emission Areas (CEAs) as defined by Australian Carbon Credit Farming guidelines (Department of the Environment, 2014). In this study, these CEAs were referred to as *sub-farms* to evaluate the accuracy of SLGA predictions for TP, TN, and SOC. Each representative sub-farm within a farm was stratified into six zones (strata) to ensure even spatial distribution of sampling points and improve replication. From each stratum, three soil cores were collected to a depth of 30 cm, giving a total of 18 cores per sub-farm.

The sampling followed the Australian Carbon Credit Farming guidelines (Department of the Environment, 2014) and the IPCC (2006) recommendations for monitoring SOC. A depth of 0–30 cm was selected because this interval aligns with the IPCC (2006) guidelines for SOC monitoring and the Australian Carbon Farming Initiative (CFI) soil carbon methodology, as this layer captures the majority of management-induced changes in SOC in agricultural systems (IPCC 2006). Core locations were randomly selected using longitude and latitude coordinates generated in R with the runif() function to ensure unbiased sampling. Each core was randomly assigned to one of three composite samples per sub-farm, such that each composite included one core from each stratum (**Figure 1**). At each point, surface litter, vegetation, and rocks were removed to avoid contamination. Soil cores (5 cm diameter) were collected using a direct-push corer to minimize compaction. Cores were weighed in the field, labelled in plastic bag to prevent moisture loss, chilled on ice, and transported to the laboratory.

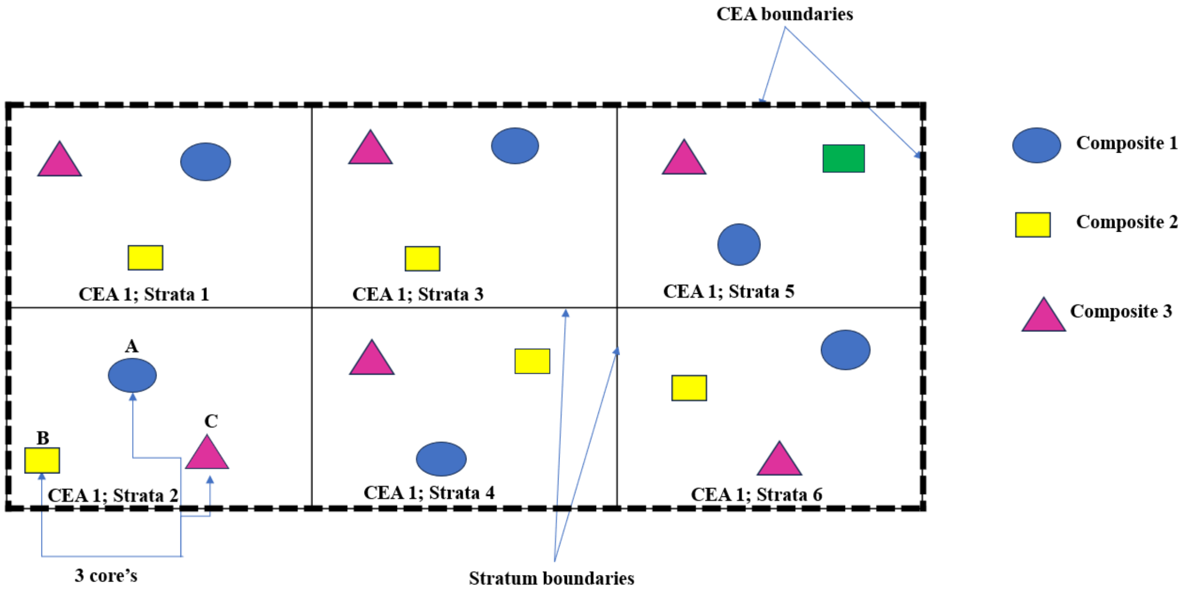


Figure 1. Composite sampling design for one CEA: 6 strata, 18 cores (3 per stratum), combined into 3 composite samples per CEA.

7.2.4. Sample preparation, analysis, and nutrient stock calculation

For each sub-farm, three composite soil samples were generated. Each composite comprised six cores, corresponding to the six distinct strata within the sub-farm. From each stratum, three soil cores (designated A, B, and C) were collected at a depth of 30 cm. Cores with the same label across all strata (all A cores, all B cores, and all C cores) were combined to form one composite sample, resulting in three composites per land-use type.

In the laboratory, individual cores were manually disaggregated and homogenized, after which the composites were air-dried and cleared of visible organic debris prior to analysis. Samples were crushed and sieved to separate the fraction <2 mm, which was used for chemical analysis. The gravel fraction (≥2 mm) was weighed and recorded. In accordance with standard soil carbon accounting procedures, the gravel fraction was excluded from the fine earth mass used to calculate SOC, TN, and TP concentrations and stocks. Total SOC and TN concentrations were determined using dry combustion analysis with an Elementar Vario MAX Cube (Elementar, Langenselbold, Germany) on samples dried at 40°C for 48 hours and ground to <2 mm using a hammer mill and sieve (Rayment and Lyons, 2011). Total P was determined using inductively coupled plasma optical emission spectroscopy (ICP-OES (Rayment and Lyons, 2011). Quality assurance and quality control procedures included the analysis of laboratory blanks, certified reference materials, and duplicate samples. Analytical replicates were performed on a subset of samples to assess precision, with results maintained within acceptable relative standard deviation limits. Instrument calibration was conducted with appropriate standards prior to sample analysis, and calibration checks were performed periodically throughout each analytical run. Detection limits for TP were determined according to standard protocols using acid digestion followed by ICP-OES analysis (Rayment and Lyons, 2011, Method 17B1). The method detection limit was <10 mg/kg, which is within the range typically reported for ICP-OES–based soil TP analysis. No significant contamination was detected in blanks, and recoveries for reference materials were within certified values.

Soil bulk density was calculated as described by Blake and Hartge (1986):

$$\mathrm{BD} = \frac{Ms}{\sum_{i=1}^{n} Vi} \tag{1}$$

Where: BD = the bulk density of the oven-dry soil sample (g/cm^3).

M_s= the oven dry mass of the soil sample (g).

V = the volume of each core (cm^3).

n = the number of cores in the sample, where the sample is comprised of one soil core, n = 1; where the sample is a composite, n = the number of soil cores in the composite.

i = each specific soil core (Blake & Hartge, 1986).

The core volume was calculated as:

$$\mathrm{V} = \pi r^2 t \tag{2}$$

Where: V= the volume of each core (cm^3).

r = the radius of the cutting head of the core (cm).

t = the actual thickness of each sample (cm) (Blake and Hartge, 1986)

To avoid systematic bias associated with differences in BD across farming systems and land-use types, SOC, TN, and TP stocks were calculated using the Equivalent Soil Mass (ESM) approach rather than a fixed-depth method (Ellert and Bettany, 1995; Wendt and Hauser, 2013). Under this approach, a reference soil mass per unit area (M_ref; Mg soil ha^{-1}) is defined as a common basis for comparison.

For each sample, the soil mass M_{sample}within the sampled depth is calculated as:

$$M_{\text{sample}} = BD \times \text{Depth} \times 10 \tag{3}$$

where BD is bulk density (g cm^{-3}) and Depth is sampling depth (cm).

When the calculated M_{sample} differs from M_ref, SOC concentrations were proportionally adjusted using adjacent soil layers so that all stocks are standardised to the equivalent soil mass. The SOC stock on an ESM basis is then calculated as:

$$SOC_{\text{ESM}} = C_{\text{conc}} \times M_{\text{ref}} \tag{4}$$

where SOC_{ESM} is the standardised SOC stock (Mg C ha^{-1}) and C_{conc} is SOC concentration (g C kg^{-1} soil).

This method ensures that differences in SOC stocks reflect actual variations in C content rather than differences in soil mass due to BD. The same procedure was applied to TN and TP.

7.2.5. Soil and Landscape Grid of Australia

The Soil and Landscape Grid of Australia (SLGA) is a continent-wide digital mapping of soil and landscape attributes at a resolution of approximately 90 × 90 m, following the GlobalSoilMap specifications (Grundy et al., 2015). The original version included 11 key soil attributes such as bulk density, SOC, TN, TP, pH (CaCl_2), texture (clay, silt and sand), effective cation exchange capacity, depth of the soil profile (A and B horizons) and available water capacity mapped to a depth of 2 m or less. An updated version, developed between 2018 and 2023, improved the accuracy of the original dataset and introduced 13 additional attributes, including available P, microbial diversity, organic C fractions (mineral-associated, particulate, pyrogenic), and pH in water (Malone et al., 2025).

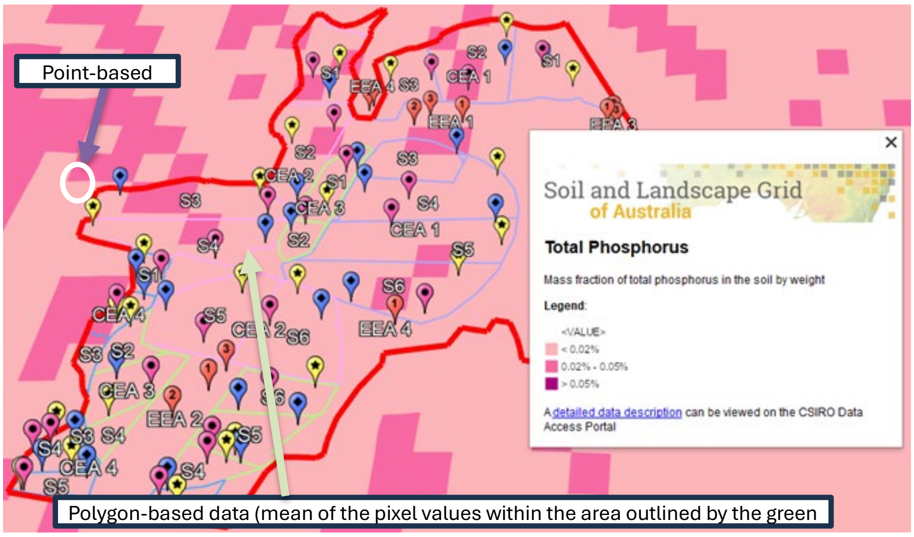
These datasets are provided in raster format (www.csiro.au/soil-and-landscape-grid). Soil organic C maps were generated using quantile regression forest models and 90,025 harmonized observational inputs, along with 57 environmental covariates representing factors such as soil, vegetation, climate, relief, and parent material, derived from gridded remote sensing and other landscape datasets (Malone et al., 2025; Wadoux et al., 2023). These covariates were projected to the WGS84 coordinate system and resampled to 30 m × 30 m and 90 m × 90 m grids. Total P and

TN were expressed as percentage of fine soil mass and were based on national datasets collected between 1950 and 2021 using machine learning and empirical modelling techniques (Malone et al., 2023, 2024) at a resolution of 3 arc sec (~90 × 90 m pixels). Total P and TN data for SLGA map calibration were derived from 11,480 sites (57,567 cases, with 49,567 used for calibration after removing 8,000 for testing) and 9,928 sites (38,124 cases, with 30,124 used for calibration), respectively (Malone et al., 2023, 2024). The SLGA maps provide soil attribute estimates across six standard depth layers (0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, and 100–200 cm) and include upper and lower confidence limits (Malone et al., 2025).

7.2.6. Data extraction from the SLGA map

Soil organic C, TN, and TP data were extracted from the SLGA using two approaches: point-based and polygon-based extraction (**Figure 2**). Both approaches were designed to align with the field sampling structure and enable comparison between laboratory-measured and SLGA-predicted values for each sub-farm. Paddock boundaries for each farm were digitized in Google Earth Pro and grouped by shared land-use types to define sub-farms, reflecting the structure described in Section 2.1. For the point-based extraction, SLGA raster values for SOC, TN, and TP were retrieved at the precise GPS coordinates of individual soil cores using R software.

However, because laboratory measurements were generated as three composite samples per sub-farm (A, B, and C), each derived from six spatially distributed soil cores, the SLGA predictions associated with each composite were also averaged across all A-labelled, B-labelled, or C-labelled core locations within that sub-farm (i.e. CEA). This means that the point-based comparison is not a strict point-to-point validation, but rather a composite-linked point extraction scheme in which both observed and predicted values represent partially aggregated spatial supports. While operationally reasonable, this approach should not be interpreted as a fine-resolution validation of individual SLGA pixels. Instead, it evaluates how well SLGA predictions correspond to the spatially averaged laboratory composites that represent small-area conditions within each sub-farm.



Total Phosphorus

Mass fraction of total phosphorus in the soil by weight

A detailed data description can be viewed on the CSIRO Data Access Portal

Figure 2. Snapshot of soil sampling points and sub-farm (Carbon Estimation Areas) illustrating the point-based and polygon-based extraction approaches used in this study. Colored pins (S1–S6) mark individual soil core locations used for point-based extraction, while shaded polygons represent sub-farms used for polygon-based extraction. SLGA raster layers used in this study have spatial resolutions of 30 m for SOC and 90 m for TN and TP, so each displayed pixel corresponds to these grid sizes. For polygon-based extraction, all SLGA pixels intersecting each sub-farm were extracted and later aggregated using a depth-weighted 0–30 cm calculation, ensuring consistency with laboratory samples collected to 30 cm. The resulting sub-farm-level means were directly compared to laboratory composite averages. The red line outlines the farm boundary, green lines indicate sub-farm and strata boundaries within the same land-use type, and blue lines denote boundaries separating different land-use types.

The SLGA provides predictions for the 0–5, 5–15, and 15–30 cm depth layers (**Figure 3**). Because these layers differ in thickness, we applied a depth-weighted aggregation to derive 0–30 cm values that are directly comparable with laboratory samples collected to 30 cm. For each soil property (SOC, TN, TP), the 0–30 cm estimate was computed as:

$$\mathrm{Value}_{0\text{–}30} = \frac{(V_{0\text{–}5} \times 5) + (V_{5\text{–}15} \times 10) + (V_{15\text{–}30} \times 15)}{30} \tag{5}$$

where: $V_{0\text{–}5}$= SLGA-predicted value of the soil property for the 0–5 cm depth layer

$V_{5\text{–}15}$= SLGA-predicted value for the 5–15 cm depth layer

$V_{15\text{–}30}$= SLGA-predicted value for the 15–30 cm depth layer

5, 10, 15 = thickness (cm) of each corresponding depth interval

30 = total depth (cm) representing the full 0–30 cm profile used for laboratory measurements

$\mathrm{Value}_{0\text{–}30}$ = depth-weighted estimate of SOC, TN, or TP for the 0–30 cm layer,

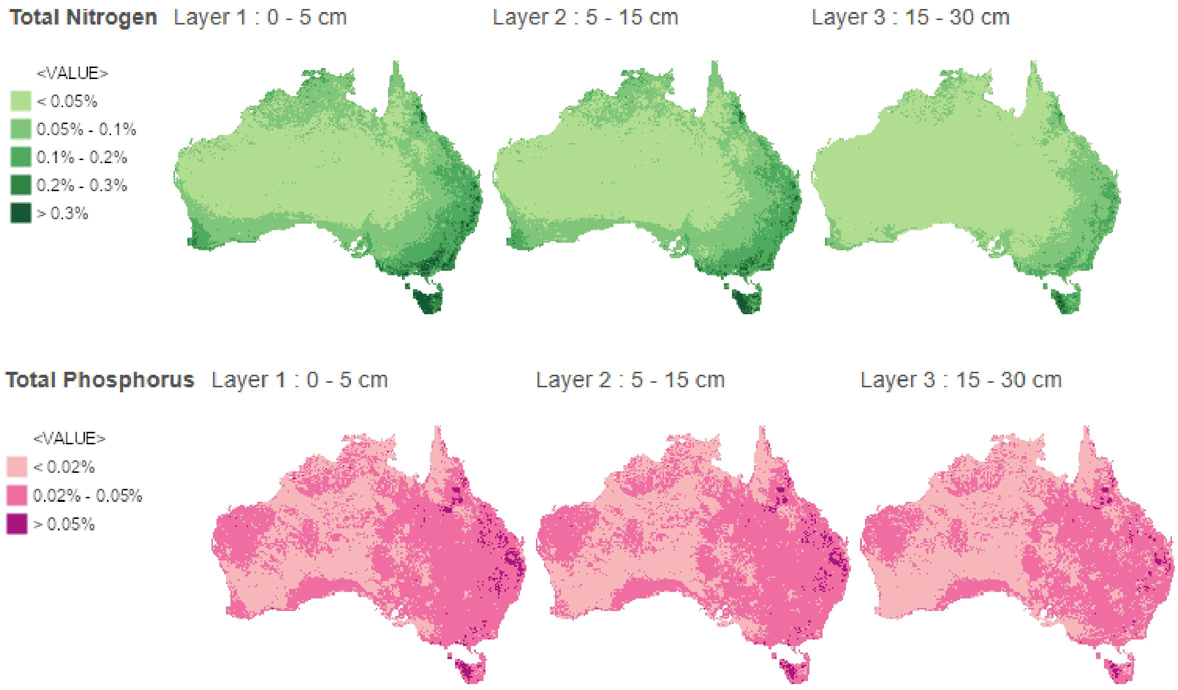


Figure 3. SLGA map layers showing TN and TP at the 0–5 cm, 5–15 cm, and 15–30 cm depth intervals. These layers are provided by SLGA at a spatial resolution of 90 m, meaning each displayed raster cell represents a 90 × 90 m pixel. Although the maps depict three separate depth layers, all analyses in this study were performed using 0–30 cm depth-weighted aggregation. This approach ensures that the visualized SLGA layers correspond directly to the values used in the statistical analyses and are fully comparable with laboratory measurements taken to 30 cm. (https://esoil.io/TERNLandscapes/Public/Pages/SLGA/ViewData-QuickView.html)

This approach ensures that each layer contributes proportionally to its thickness, avoiding the bias introduced by simple averaging. All analyses in this manuscript (descriptive statistics, model performance metrics, mixed-effects models, and comparisons across land-use types and farming systems) were calculated using the depth-weighted values. Within each sub-farm, SLGA values extracted from all A-labeled core locations were averaged and directly paired with the corresponding laboratory A composite for comparison; the same procedure was applied to B- and C-labeled cores, ensuring that each SLGA mean was compared to its respective laboratory composite. Accordingly, the spatial precision of the ‘point-based’ analysis reflects the support of composite samples, rather than true single-location point measurements. For each sub-farm, all SLGA pixels falling within the boundary were extracted and combined using a depth-weighted aggregation of the 0–5, 5–15, and 15–30 cm layers to generate 0–30 cm estimates directly comparable with laboratory samples collected to 30 cm. In this aggregation, each pixel’s contribution was further weighted according to the proportion of its area contained within the sub-farm, ensuring that irregular boundary intersections were accurately represented. The resulting

0–30 cm sub-farm level means were then compared with the corresponding laboratory sub-farm means, calculated by averaging the three composite samples (A, B, and C). In total, we analysed 146 point-based and 64 polygon-based observations at the sub-farm scale, and 9 point-based and 9 polygon-based observations at the farm scale.

7.2.7. Statistical analysis

To evaluate the accuracy of SLGA mapping products, two complementary statistical approaches were applied. First, agreement between SLGA predictions and laboratory measurements was assessed using model validation metrics. Second, statistical models were used to test whether SLGA could detect meaningful differences in SOC, TN, and TP across land use types and farming systems.

7.2.7.1. Agreement between laboratory and SLGA predictions

Model Evaluation System (MES) version 3.2.8 software was used to test the agreement between laboratory-measured and SLGA map predicted soil data (Tedeschi, 2006). Agreement between measured and predicted SOC, TN, and TP was assessed at both sub-farm and farm levels, using data derived from point-based sampling and polygon SLGA. At the sub-farm level, unweighted laboratory and SLGA values were used. Farm-level data were derived by weighing the soil property values of each sub-farm type according to their proportional area within the farm and then averaging the weighted values to obtain farm-scale concentrations and stocks per hectare. These calculated values from both data sources were used for the farm-level comparison.

Agreement was evaluated using the coefficient of determination (R^2), and Lins concordance correlation coefficient (CCC) (Lin, 1989; Isobe et al., 1990). The bias correction factor (Cb) was also reported to indicate how much the best-fit line deviates from the line of perfect agreement (i.e., where predicted values equal observed values), serving as a measure of accuracy (Lawrence and Lin, 1989). The magnitude of prediction errors was quantified using root mean square error of prediction (RMSEP), mean absolute error (MAE), and mean bias error (MBE), expressed in both absolute values and as percentages of observed values. The significance of bias was tested using paired t-tests, with results reported alongside associated p-values.

The mean square error of prediction was decomposed into its components mean bias (MB), systematic bias (SB), and random error (RE) to identify the primary sources of prediction error (Bibby and Toutenburg, 1977) and provide a nuanced understanding of whether model inaccuracies stem from bias in average predictions, incorrect slope (scaling), or random variability. All diagnostic analyses (e.g., normality via the Shapiro–Wilk test, residual analysis, and robust statistics) were computed using R software, version 4.4.3 to evaluate the distributional assumptions of model residuals and identify potential outliers or skewness. These diagnostics were used internally to support model validation and are not presented in the final tables.

7.2.7.2. Detecting nutrient variation across land use and farming systems

To evaluate whether SLGA mapping products could detect meaningful differences in SOC, TN, and TP across land use types and farming systems, linear mixed-effects models (LMMs) were fitted using the lme4 package in R software, version 4.4.3 (R Core Team, 2023). Separate models were developed for each nutrient (SOC, TN, TP) and for each spatial scale (sub-farm and farm). Model assumptions were evaluated separately for each nutrient and spatial scale using Shapiro–Wilk tests, residual plots, and Q–Q plots. Where necessary, log-transformations were applied to improve normality and variance homogeneity. Residuals were also visually inspected to confirm homoscedasticity, and no severe violations affecting inference were detected.

For the interaction of land use and farming system, the model included land use (cropping, improved pasture, mixed pasture–cropping, tree areas) and farming system (pasture-based vs. confinement) as fixed effects, with random effects for farms to account for spatial dependence. Significant differences ($p < 0.05$) are indicated in the table using superscripts a, b, c, and d. The model structure was:

$$Y_{ijkl} = \mu + L_i + F_j + (L \times F)_{ij} + u_k + \epsilon_{ijkl} \quad (6)$$

where: Y= the soil property (SOC, TN, or TP),

μ = overall mean

L = land use type (cropping, improved pasture, mixed pasture–cropping, tree areas),

F = farming system (pasture-based vs. confinement),

u_k = the random effect of farm,

ϵ = residual error.

Because natural pasture (NP) occurred only in pasture-based systems, a second LMM was fitted for this subset. This model compared cropping, improved pasture, mixed pasture-cropping, and tree areas against NP, with land use treated as a fixed effect and farm as random effects in the point-based comparison. Differences from NP are denoted by superscripts x, y, and z, and the absence of these markers indicates no statistically detectable difference. The model structure was:

$$Y_{ikl} = \mu + L_i + u_k + \epsilon_{ikl} \quad (7)$$

where: Y_{ikl} = observed soil property (SOC, TN, or TP),

μ = overall mean

L = fixed effect of land use type (cropping, improved pasture, mixed pasture–cropping, tree areas, relative to NP)

u_k = random effect of farm k,

ϵ = residual error.

To compare farming systems at the farm scale and better represent soil nutrient stocks, a separate linear regression model was applied. This analysis incorporated the proportional contribution of each land use type within farms by weighting its coverage (%) with the corresponding laboratory-measured values for SOC, TN, and TP. The resulting area-weighted values were used to estimate farm-level nutrient stocks. The model structure was:

$$Y_k = \mu + F_j + \epsilon_k \qquad (8)$$

where: Y_k = area-weighted nutrient stock for farm k,

μ = overall mean

F_j = Fixed effect of farming system (pasture-based vs. confinement)

ϵ_k = residual error.

7.3. Results and discussion

7.3.1. Descriptive Statistics of SOC, total N, and P

Descriptive statistics of SOC, TN, and TP from both laboratory analyses and SLGA estimates are presented in **Table 1**. Mean SOC was 1.19 and TP 8.7-fold greater from the SLGA compared to laboratory results, whereas TN values from laboratory estimates were similar to SLGA values. Laboratory-measured SOC stocks in this study were substantially greater than those reported by (Chan et al., 2010), who examined SOC stock under different pastures and management in the higher rainfall areas of south-eastern Australia and found SOC stocks ranging from 36 to 46 Mg C ha^{-1} in the top 30 cm of soil. Furthermore, SLGA map-derived values overestimated SOC across both measurement approaches and spatial scales. These discrepancies may be attributed to differences in land use, management practices, soil types, parent material, and local agroecological conditions of the study farms compared to the broader national dataset (Malone et al., 2025; Zhang et al., 2017). These results suggest that SLGA may need to include additional factors to increase accuracy of SOC and TP in dairy production systems.

Table 1. Descriptive statistics of soil organic carbon, total nitrogen, and total phosphorus in dairy farms, comparing laboratory analyses with Soil and Landscape Grid of Australia map-based estimates

Soil properties	Measurement scale	Data Source	Sub-farm level					Farm level				
			Mean	Median	CV	Min	Max	Mean	Median	CV	Min	Max
SOC, %	Point-based	Laboratory	1.92	1.84	37.1	0.15	4.80	2.02	2.19	31.9	1.15	2.75
		SLGA	1.99	2.02	23.6	1.03	3.22	2.13	2.23	29.1	1.21	3.03
	Sub-farm polygon	Laboratory	2.02	1.96	35.5	0.94	4.80	1.93	2.09	33.1	1.09	2.75
		SLGA	2.02	2.01	22.1	1.04	3.12	2.04	2.01	27.1	1.16	2.98
TN, %	Point-based	Laboratory	0.17	0.15	40.6	0.06	0.45	0.17	0.19	31.4	0.09	0.23
		SLGA	0.14	0.15	21.9	0.10	0.20	0.15	0.16	27.2	0.09	0.21
	Sub-farm polygon	Laboratory	0.18	0.16	40.0	0.08	0.45	0.17	0.19	36.0	0.08	0.24
		SLGA	0.15	0.15	21.1	0.09	0.21	0.15	0.15	25.0	0.09	0.20
TP, %	Point-based	Laboratory	0.008	0.004	158	0.001	0.08	0.008	0.004	141	0.003	0.04
		SLGA	0.07	0.06	36.1	0.03	0.11	0.07	0.07	37.5	0.03	0.10
	Sub-farm polygon	Laboratory	0.009	0.004	139	0.001	0.06	0.008	0.004	145	0.003	0.04
		SLGA	0.07	0.06	68.9	0.03	0.41	0.07	0.07	44.5	0.04	0.13
SOC, Mg C ha^{-1}	Point-based	Laboratory	80.8	77.4	37.1	6.39	201	84.8	91.9	31.9	48.2	115
		SLGA	85.0	86.2	24.4	43.1	146	89.6	93.5	29.1	50.6	127
	Sub-farm polygon	Laboratory	84.9	82.2	35.5	39.3	201	81.0	87.7	33.1	45.8	115
		SLGA	85.0	84.5	22.1	43.7	131	85.6	84.4	27.1	48.6	125
TN, Mg TN ha^{-1}	Point-based	Laboratory	7.02	6.30	40.6	2.65	18.7	7.20	8.01	31.4	3.93	9.52
		SLGA	6.19	6.23	22.8	3.71	9.43	6.48	6.66	27.2	3.93	8.75
	Sub-farm polygon	Laboratory	7.35	6.51	40.0	3.46	18.7	6.98	8.01	36.0	3.53	9.99
		SLGA	6.28	6.23	21.1	3.67	8.59	6.20	6.24	25.0	3.92	8.27
TP, Mg TP ha^{-1}	Point-based	Laboratory	0.35	0.16	158	0.02	3.32	0.33	0.17	141	0.11	1.57
		SLGA	2.67	2.62	36.2	1.33	4.90	2.83	2.88	37.5	1.43	4.27
	Sub-farm polygon	Laboratory	0.37	0.15	139	0.03	0.35	0.32	0.16	145	0.11	1.57
		SLGA	2.96	2.71	68.9	1.26	17.2	2.92	2.76	44.5	1.45	5.27

SOC = Soil organic carbon; TN = total nitrogen; TP = total phosphorus; Max = maximum; Min = minimum; CV = coefficient of variation; n = number of laboratory samples or sub-farms used in the comparison. For point-based data, n corresponds to the number of composites; for polygon-based data, n corresponds to the number of sub-farm polygon. “sub-farm polygon” refers to the mean of all SLGA raster pixels within each sub-farm, compared with laboratory sub-farm averages. “Point-based” refers to values extracted at the georeferenced locations of individual soil cores. Sub-farm level denotes analysis at the scale of individual sub-farms, whereas Farm level represents metrics aggregated across all paddocks within each far

7.3.2. Regression slopes, Coefficient of determination, CCC and RMSE

Table 2 presents the regression slopes, coefficient of determination (R^2), bias correction factor (Cb), root mean square error (RMSE), and concordance correlation coefficient (CCC) for the SLGA map's predictive performance of SOC, TN, and TP concentrations and stocks at sub-farm and farm scales. Both polygon and point-based measurements for SOC and TN showed moderate CCC at sub-farm scale but high at farm scale. However, TP maps showed no concordance with laboratory data. The predictive performance of the SLGA for SOC, TN, and TP was comparable between point-based and polygon-based approaches at both spatial scales. The SLGA map demonstrated improved prediction performance for SOC and TN at the farm scale relative to the sub-farm scale (Table 2), with higher agreement (CCC > 0.85 for SOC and > 0.75 for TN) and lower errors across both point-based and polygon-based measurements. The pronounced discrepancies between laboratory measurements and SLGA predictions at the sub-farm scale are likely driven by differences in sampling resolution and spatial support. The SLGA predictions represent values aggregated over 30–90 m grid cells, whereas field sampling employed a stratified design with 18 cores per sub-farm (i.e., CEA), capturing fine-scale management differences, land-use patterns, and micro-topographic variability. This mismatch introduces spatial smoothing in SLGA outputs, limiting the model's capacity to detect variation across adjacent land-use types or management zones. As a result, the map's limited sub-farm precision makes it unsuitable for paddock-level management decisions or for designing stratified carbon-sampling frameworks.

Prediction performance of SLGA maps for TP concentration was extremely poor at all scales, with $R^2 \leq 0.02$, CCC near zero, and consistent overestimation by six- to eight-fold. Such high mean bias likely reflects the limited representation of TP data in national calibration datasets and the complexity of P dynamics, which are strongly influenced by local fertiliser history, soil mineralogy, and parent material (Chang et al., 2025; Helfenstein et al., 2024).These results on TP are poorer compared to Malone et al. (2024), who reported R^2 values of 0.07 and 0.68 and CCC values of 0.13 and 0.79 for versions 1 and 2, respectively, at a depth of 0–30 cm. This may also be attributed to the large dataset and cross-validation method used in Malone et al. (2024), which included 11,480 sites with 57,567 cases containing TP information. The sub-farm polygon-based measurement at the farm scale showed better predictive performance for SOC (%) than Wadoux et al. (2023) who reported RMSE values of 1.07% and 1.14% and R^2 values of 0.48 and 0.50 at 30 m and 90 m resolutions, respectively, for the SLGA using 10-fold cross-validation on 90,025 soil samples interpolated for 0–30 cm depth. The SLGA map-derived TN concentration and stock predictions at the farm level also showed improved R^2 values relative to Malone et al. (2023), who reported R^2 values of 0.22 and 0.31 for versions 1 and 2, respectively, at 0–30 cm. However, the CCC values in the present study were comparable to the CCC values of 0.81 and 0.87 reported by Malone et al. (2023). This discrepancy could be due to the large dataset and the cross-validation approach used in Malone et al. (2023), which included 9,928 sites with 38,124 cases containing TN information.

Table 2. Performance metrics of Soil and Landscape Grid of Australia predictions for soil organic carbon, total nitrogen and phosphorus evaluated against laboratory measurements at sub-farm and farm scales.

Measurement scale	Soil physicochemical properties	Sub-farm level						Farm level					
		Intercept (±SE)	Slope (±SE)	R^2	CCC	Cb	RMSE	Intercept (±SE)	Slope	R^2	CCC	Cb	RMSE
Sub-farm polygon	SOC, %	0.19 ± 0.349^{ns}	0.90 ± 0.168^{ns}	0.32	0.51	0.90	0.60	-0.16 ± 0.426^{ns}	1.03 ± 0.203^{ns}	0.79	0.88	0.97	0.32
	SOC, Mg C ha^{-1}	8.08 ± 14.62^{ns}	0.90 ± 0.168^{ns}	0.32	0.51	0.90	25.0	-6.65 ± 17.83^{ns}	1.02 ± 0.202^{ns}	0.79	0.88	0.97	13.2
	TN, %	-0.03 ± 0.034^{ns}	1.36 ± 0.222^{ns}	0.38	0.42	0.68	0.06	-0.06 ± 0.034^{ns}	1.51 ± 0.227^{ns}	0.86	0.79	0.84	0.02
	TN, Mg C ha^{-1}	-1.20 ± 1.424^{ns}	1.36 ± 0.222^{ns}	0.38	0.42	0.68	2.34	-2.38 ± 1.435^{ns}	1.51 ± 0.225^{ns}	0.87	0.79	0.84	0.99
	TP, %	$0.01\pm0.003^{***}$	$-0.03\pm0.032^{***}$	0.01	-0.02	0.19	0.01	0.01 ± 0.010^{ns}	$-0.03\pm0.134^{***}$	0.01	-0.01	0.14	0.01
	TP, Mg C ha^{-1}	$0.46\pm0.115^{***}$	$-0.03\pm0.032^{***}$	0.01	-0.02	0.19	0.52	0.43 ± 0.430^{ns}	$-0.04\pm0.136^{**}$	0.01	-0.02	0.14	0.50
Point-based	SOC, %	0.17 ± 0.211^{ns}	0.88 ± 0.103^{ns}	0.31	0.53	0.91	0.58	0.06 ± 0.400^{ns}	0.92 ± 0.181^{ns}	0.79	0.88	0.98	0.32
	SOC, Mg C ha^{-1}	13.0 ± 8.783^{ns}	0.80 ± 0.100^{ns}	0.31	0.51	0.92	25.1	2.58 ± 16.81^{ns}	0.92 ± 0.181^{ns}	0.79	0.88	0.98	13.4
	TN, %	0.01 ± 0.020^{ns}	1.11 ± 0.137^{ns}	0.31	0.41	0.74	0.06	0.01 ± 0.044^{ns}	1.06 ± 0.274^{ns}	0.68	0.77	0.91	0.03
	TN, Mg C ha^{-1}	-0.11 ± 0.878^{ns}	1.15 ± 0.138^{ns}	0.33	0.43	0.74	2.35	0.34 ± 1.840^{ns}	1.06 ± 0.275^{ns}	0.68	0.77	0.91	1.37
	TP, %	$0.01\pm0.003^{**}$	$-0.03\pm0.047^{***}$	0.002	-0.01	0.15	0.01	0.01 ± 0.012^{ns}	$-0.03\pm0.162^{***}$	0.01	-0.01	0.13	0.01
	TP, Mg C ha^{-1}	0.14 ± 0.132^{ns}	$0.08\pm0.046^{***}$	0.02	0.02	0.16	0.55	0.43 ± 0.498^{ns}	$-0.03\pm0.166^{***}$	0.01	-0.01	0.13	0.50

SOC = soil organic carbon; TN = total nitrogen; TP = total phosphorus; SE = standard error; R^2 = coefficient of determination; CCC = concordance correlation coefficient; Cb = bias correction factor; RMSE = root mean square error; $^{ns} = p > 0.05$; $* = p < 0.05$; $** = p < 0.01$; $*** = p < 0.001$; Values expressed in percentages (%) refer to concentrations of SOC, TN, and TP, while values in Mg C ha^{-1} represent stocks per hectare; “sub-farm polygon” refers to the mean of all SLGA raster pixels within each sub-farm, compared with laboratory sub-farm averages. “Point-based” refers to values extracted at the georeferenced locations of individual soil cores. Sub-farm level denotes analysis at the scale of individual sub-farms, whereas Farm level represents metrics aggregated across all paddocks within each farm.

7.3.3. Error metrics of the SLGA map in predicting SOC, total N and TP

The performance of the SLGA map in predicting SOC, TN, and TP concentrations and stocks at the sub-farm and farm scales is presented in **Table 3**. Based on polygon-based measurement, mean bias error (MBE) values indicated that the SLGA map over-predicted ($p < 0.001$) SOC concentrations and stocks by 15% and 21% at the sub-farm and farm level, respectively. Similarly, SLGA over-predicted ($p < 0.01$) TP concentrations and stocks by 6.7-fold at the sub-farm level, and by 7.7-fold and 7.8-fold at the farm level, relative to the observed values. In contrast, TN concentrations and stocks were under-predicted by 4% at the sub-farm level ($p < 0.001$) and by 0.7% at the farm level ($p > 0.05$).

Point-based measurements over-predicted ($p < 0.001$) SOC concentrations and stocks by 19% and 21% at the sub-farm and farm scales compared to laboratory results, respectively. Total P concentrations and stocks were also over-predicted ($p < 0.001$) by 7-fold at the sub-farm level, and by approximately 8-fold at the farm level, relative to the laboratory values. Conversely, TN concentrations and stocks were under-predicted by 0.4% ($p > 0.05$) and 3% ($p < 0.01$), respectively, at the sub-farm level, and by 1% at the farm level ($p > 0.05$).

For polygon-based measurements, the absolute RMSEP and MAE values for both SOC and TN concentrations and stocks were slightly lower at the farm level than at the sub-farm level (Table 3). However, for TP concentrations and stocks, errors were slightly higher at the farm level. With point-based measurements, the absolute RMSEP and MAE values for SOC and TN concentrations and stocks were also slightly lower at the farm level compared to the sub-farm level. For TP concentrations, MAE was similar between both scales, but for TP concentrations and stocks, RMSEP were slightly higher at the farm level. Interestingly, TN was the only variable that showed no significant mean bias at the farm level with either method.

Across both measurement methods (polygon and point-based), RMSEP and MAE as percentages of observed values were slightly lower at the farm level for SOC and TN concentrations and stocks compared to sub-farm-level values, but higher for TP concentrations and stocks (Table 3). The proportional error metrics (RMSEP, MAE, and MBE % of observed values) suggest that the SLGA map provided better predictions of SOC and TN concentrations and stocks at the sub-farm level than at the farm level.

Table 3. Error magnitude and bias evaluation metrics for Soil and Landscape Grid of Australia predictions of soil organic carbon, total nitrogen, and total phosphorus concentrations (%) and stocks (Mg C ha^{-1}) at the Sub-farm level and farm levels, based on polygon and point-based data.

Measurement scale	Soil physicochemical properties	Sub-farm level						Farm level					
		RMSEP	RMSEP, % obs	MAE	MAE, % obs	MBE	MBE, % obs	RMSEP	RMSEP, % obs	MAE	MAE, % obs	MBE	MBE, % obs
Sub-farm polygon	SOC, %	0.59	29.2	0.44	21.8	-0.004^{ns}	-0.21	0.30	15.5	0.27	13.8	-0.11^{ns}	-5.66
	SOC, Mg C ha^{-1}	24.7	29.1	18.5	21.8	-0.18^{ns}	-0.21	12.5	15.5	11.2	13.8	-4.57^{ns}	-5.65
	TN, %	0.06	35.1	0.04	23.5	0.03^{***}	14.5	0.03	19.7	0.03	16.2	0.02^{ns}	10.7
	TN, Mg C ha^{-1}	2.58	35.1	1.72	23.5	1.07^{***}	14.5	1.38	19.8	1.14	16.3	0.77^{ns}	11.1
	TP, %	0.08	893	0.06	688	-0.06^{***}	-688	0.07	895	0.06	796	-0.06^{***}	-796
	TP, Mg C ha^{-1}	3.35	897	2.58	691	-2.58^{***}	-691	2.92	900	2.60	799	-2.60^{***}	-799
Point-based	SOC, %	0.59	30.5	0.44	22.9	-0.06^{ns}	-3.28	0.31	15.2	0.27	13.5	-0.11^{ns}	-5.68
	SOC, Mg C ha^{-1}	25.6	31.7	19.4	24.0	-4.16^{*}	-5.15	12.9	15.2	11.4	13.5	-4.80^{ns}	-5.67
	TN, %	0.06	36.3	0.04	24.4	0.02^{***}	13.8	0.03	19.5	0.03	16.1	0.02^{ns}	9.92
	TN, Mg C ha^{-1}	2.49	35.4	1.72	24.5	0.83^{***}	11.9	1.41	19.5	1.16	16.1	0.71^{ns}	9.92
	TP, %	0.06	752	0.06	687	-0.06^{***}	-679	0.06	814	0.06	742	-0.06^{***}	-742
	TP, Mg C ha^{-1}	2.55	726	2.34	667	-2.32^{***}	-660	2.74	824	2.49	752	-2.49^{***}	-752

RMSEP = root mean square error of prediction; MAE = mean absolute error; MBE = mean bias error; ns = $p > 0.05$; * = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$. Values in percentages (%) refer to concentrations of total nitrogen (TN) and total phosphorus (TP), while values in Mg C ha^{-1} represent stocks per hectare. "sub-farm polygon" refers to the mean of all SLGA raster pixels within each sub-farm, compared with laboratory sub-farm averages. "Point-based" refers to values extracted at the georeferenced locations of individual soil cores. Sub-farm level denotes analysis at the scale of individual sub-farms, whereas Farm level represents metrics aggregated across all paddocks within each farm. RMSEP, MAE, and MBE are also presented as a percentage of the observed mean (% obs) to standardize error magnitude relative to actual values. MBE P-values indicate whether the prediction bias differs significantly from zero

7.3.4. Error decomposition

Error decomposition of the RMSEP (**Table 4**) indicates that the relative contributions of mean bias (MB), slope bias (SB), and random error (RE) depend on soil property and spatial scale. For SOC and TN, prediction error was predominantly due to RE across both farm and sub-farm scales, and for both point-based and polygon-based measurements. In most cases, RE accounted for more than 80% of the total error, indicating that discrepancies largely reflect spatial variability and unaccounted local factors rather than systematic model bias (Kobayashi and Salam, 2000). These sources of variability likely include fine-scale management practices such as grazing intensity, fertiliser application, and irrigation, which are not fully captured by the environmental covariates used in the SLGA.

In contrast, TP predictions exhibited a markedly different pattern, with MB dominating the RMSEP for both concentration and stock, regardless of the measurement scale or method. This suggests structural limitations in the SLGA TP predictions, likely related to the strong influence of localised factors such as management history, parent material, and soil mineralogy, which are not adequately represented in national-scale models. Systematic bias was also more pronounced for TP than SOC and TN at both measurement scales and method, consistent with the strong overestimation (mean bias) observed across both scales. These mechanistic interpretations align with the patterns observed in the CCC, slope coefficients, and error decomposition, and provide a more grounded explanation for the prediction inconsistencies. The consistently poor performance of SLGA for TP can be attributed to several intrinsic challenges associated with modelling TP at national scale. Unlike SOC and TN, which are partly governed by broad environmental gradients, TP is strongly driven by highly localised management processes, including long-term fertiliser inputs, crop-specific nutrient strategies, and shifting regional hotspots (Frossard et al., 2000; Holford, 1997; Sattari et al., 2012; Sharpley et al., 2013).

Long-term gridded analyses demonstrate that P application rates and hotspot locations vary substantially among crops and regions due to differences in management history and fertiliser use (Cao et al., 2024). Additionally, P cycling operates at extremely fine spatial scales. Experimental studies show that P fertiliser is released in a rapid pulse and diffuses only a few centimetres before becoming immobilised through adsorption onto soil particles (Petroselli et al., 2021). These centimetre-scale gradients may produce sharp within-paddock patchiness that SLGA's 90 m spatial resolution cannot resolve. Spatial modelling shows that total P is significantly associated with land-use type, soil parent material, slope, pH, and distance from settlements factors contributing to heterogeneous TP distributions across agricultural landscapes (Jiang et al., 2025). Moreover, many agricultural soils including intensively managed dairy systems can exhibit substantial legacy TP accumulation from decades of fertiliser and manure inputs (Frossard et al., 2000; Holford, 1997; Sattari et al., 2012; Sharpley et al., 2013). Global analyses indicate that cropland P reserves vary dramatically by region and reflect long-term patterns of nutrient application, creating persistent spatial heterogeneity (Bouwman et al., 2017). Together, these factors demonstrate that TP is inherently more difficult to predict at national grid scales than SOC or TN because its dynamics are governed primarily by fine-scale management hotspots and mineralogical controls that are not captured by coarse environmental covariates. This may explain the low agreement metrics, high bias, and limited predictive power of SLGA TP estimates in dairy landscapes.

Overall, across all nutrients, performance differed depending on the metric considered. Agreement-based metrics (R^2, CCC, Cb) and absolute error metrics (RMSE, MAE) consistently showed substantially better performance at the farm scale than at the sub-farm scale for SOC and TN. This reflects the closer alignment between SLGA's pixel resolution (30–90 m) and the aggregated farm-level values, as well as the reduction of fine-scale variability through spatial averaging. Importantly, the proportional error metrics (%RMSEP, %MAE, %MBE) seem to support the same conclusion because these relative measures were also lower at the farm scale, reinforcing that SLGA performs more reliably when evaluated at aggregated spatial resolution. In contrast, the error-decomposition metrics (MB, SB, RE) sometimes revealed that SLGA retained some predictive structure even at the sub-farm scale, particularly for SOC and TN where RE dominated and SB was low. These results do not indicate better performance at the sub-farm scale, but rather that different statistical metrics emphasise different aspects of model behaviour.

These findings underscore the importance of interpreting DSM validation results using a suite of complementary metrics. As noted by Wadoux and Minasny (2024), CCC conflates bias and precision and may obscure underlying model properties, whereas Kobayashi and Salam (2000) caution that correlation and regression coefficients are not directly linked to error-based measures. In the present study, the low CCC and R^2 values at the sub-farm scale indicate limited precision and poor agreement with laboratory measurements, even though error-structure analysis suggests some underlying predictive capability. Moreover, the main objective of the present study was to approximate a linear relationship between observed and predicted values, ideally with a slope of 1 and an intercept of 0. In summary, all three adequacy metrics (agreement metrics, absolute error metrics, and proportional error metrics) clearly indicate that the farm scale provides the more reliable resolution of prediction for SOC and TN. Sub-farm predictions can offer complementary insights through error-decomposition analysis, but these should be interpreted cautiously and are not suitable for operational, fine-scale decision-making.

Table 4. Decomposition of Mean Square Error of Prediction (MSEP, %) for soil organic carbon, total nitrogen, and total phosphorus concentration and stock predictions using Soil and Landscape Grid of Australia map-derived polygon and point-based measurements.

Measurement scale	Soil physicochemical properties	Sub-farm level			Farm level		
		MB, %	SB, %	RE, %	MB, %	SB, %	RE, %
Sub-farm polygon	SOC, %	0.01	0.54	99.5	12.9	0.30	86.9
	SOC, Mg C ha^{-1}	0.01	0.54	99.5	13.3	0.18	86.5
	TN, %	17.1	3.34	79.5	25.3	29.6	41.1
	TN, Mg C ha^{-1}	17.2	3.40	79.4	31.2	29.0	39.8
	TP, %	59.3	34.4	2.34	79.0	16.3	2.21
	TP, Mg C ha^{-1}	59.3	34.3	2.32	78.8	16.3	2.27
Point-based	SOC, %	1.16	0.86	98.0	14.0	2.48	83.6
	SOC, Mg C ha^{-1}	2.64	2.65	94.7	13.9	2.48	83.6
	TN, %	14.4	0.41	85.2	25.9	0.48	73.7
	TN, Mg C ha^{-1}	11.3	0.74	88.0	25.7	0.47	73.8
	TP, %	81.5	12.7	4.33	83.0	12.7	2.49
	TP, Mg C ha^{-1}	83.0	12.7	4.62	83.1	12.4	2.58

SOC = soil organic carbon; TN = total nitrogen; TP = total phosphorus; MB = mean bias; SB = systematic bias; RE = random error. Values expressed in percentages (%) refer to concentrations of SOC, TN, and TP, while values in Mg C ha^{-1} represent stocks per hectare; "sub-farm polygon" refers to the mean of all SLGA raster pixels within each sub-farm, compared with laboratory sub-farm averages. "Point-based" refers to values extracted at the georeferenced locations of individual soil cores. Sub-farm level denotes analysis at the scale of individual sub-farms, whereas Farm level represents metrics aggregated across all paddocks within each farm.

7.3.5. Ability of SLGA to detect differences due to land use and farming system

To evaluate the performance of SLGA in detecting nutrient variation, SOC, TN, and TP values were compared across land-use types and farming systems using both SLGA-derived estimates and laboratory measurements (Table 5 and 6). This assessment incorporated three complementary criteria: first, whether SLGA detected statistically significant differences among land-use types and farming systems; second, whether the direction of these contrasts aligned with those observed in laboratory analyses; and third, whether SLGA reproduced the correct ranking of land-use types based on nutrient levels. Together, these components establish a rigorous framework for determining how reliably SLGA captures land-use-driven variability in soil nutrient concentrations across dairy production systems.

7.3.5.1. Interaction effect of farming system and land use type on SOC, TN, and TP

Laboratory measurements showed a significant farming-system × land-use interaction for SOC concentrations and stocks ($p = 0.001$) (**Table 5**). Interestingly, SLGA point-based SOC also detected this interaction ($p = 0.043$). The SLGA reproduced the broad direction of contrasts, specifically lower SOC in confinement cropping compared with improved pasture in pasture-based farms but compressed the magnitude of differences and did not fully replicate the laboratory

land-use hierarchy. As a result, ranking consistency was only partially achieved. In contrast, sub-farm-polygon SOC did not detect a significant interaction ($p = 0.256$) and showed limited differences between land uses, reducing alignment with laboratory outcomes.
For TN, the laboratory data indicated a significant interaction ($p < 0.001$), but SLGA did not detect such interaction in either the point-based ($p = 0.246$) or polygon TN data ($p = 0.902$). Although the numerical ordering of means was broadly similar across the two datasets, SLGA did not reproduce the laboratory grouping structure or the magnitude of differences. Consequently, SLGA did not meet the significance, direction, or ranking criteria for TN when evaluated using the interaction model.

For TP, the laboratory measurements showed no significant farming system × land use interaction for TP concentration or TP stock ($p = 0.735; p = 0.896$). In contrast, SLGA sub-farm polygon TP stock detected a significant interaction ($p < 0.001$), whereas SLGA TP concentration did not. Thus, SLGA partially met the significance criterion but failed to follow the pattern of laboratory analysis. The TP of SLGA strongly overestimated absolute values; however, the numerical ordering of land use categories in point-based TP (%) remained broadly similar to the laboratory means, satisfying the direction criterion only partially. Overall, SLGA captured some broad interaction features but did not accurately represent the laboratory-derived interaction structure for TP.

Overall, the interaction analysis demonstrated that SLGA only partially reproduced the nutrient patterns identified in the laboratory data across farming systems and land-use types. Agreement was strongest for SOC, where SLGA point-based estimates detected the interaction and captured the general direction of contrasts, but not the magnitude or ranking of land-use differences. The TN interactions were not reliably represented by SLGA because it failed to detect significant effects and did not reproduce the laboratory grouping structure. Finally, TP showed the weakest alignment between SLGA and laboratory analysis because the former either introduced a significance (in TP stocks) not detected by laboratory analysis or produced inflated values that did not reflect the underlying biological variation. This limited ability to capture nutrient differences due to farming system and land use may be partly explained by differences in data resolution and the effect of covariates within the SLGA. The SOC was available at a finer 30 m resolution, enabled by integration of the State-wide Soil Organic Carbon Map (v5) and a dedicated national 30 m environmental covariate stack (TERN Landscapes, 2022). In contrast, TN and TP were used at the standard 90 m (~3 arc-seconds) resolution because their predictive models rely primarily on national-scale soil and environmental covariates available only at coarser resolution. These differences in spatial resolution and covariate structure suggest that SLGA's current framework may be insufficient to fully capture fine-scale interaction-level nutrient dynamics, particularly for

TN and TP. Taken together, these results further strengthen the conclusion reinforced by the agreement-based metrics (R^2, CCC, Cb), proportional error metrics (%RMSEP, %MAE, %MBE), and absolute error metrics (RMSE, MAE) that SLGA performs weakly at the sub-farm scale, as it frequently fails to reproduce the laboratory-derived contrasts, directions, and land-use rankings required for reliable differentiation of soil nutrient patterns..

7.3.5.2. Effect of land use type on SOC, TN, and TP within pasture-based System

For SOC (point-based) concentration, laboratory data showed a significant ($p < 0.05$) land-use effect within pasture-based farms (**Table 5**). However, NP did not differ significantly from cropping, improved pasture (IP), mixed pasture–cropping (MPC), or tree areas (TA). The SLGA point-based SOC also detected a significant effect of land use ($p < 0.05$) but showed lower NP compared to IP, MPC, and TA. Thus, SLGA met the significance criterion and partially met the direction criterion but failed ranking consistency, as the relative position of NP differed from the laboratory pattern. For SOC (sub-farm polygon) concentration, the laboratory values showed NP significantly higher than cropping and MPC, but it did not differ from IP and TA ($p > 0.05$). The SLGA polygon determined NP had similar SOC to all other land-use types, failing to reproduce these laboratory differences and therefore failing both direction and ranking criteria. For SOC stocks, point-based laboratory and SLGA values placed NP within overlapping groupings, indicating agreement of laboratory measurement and SLGA. In contrast, polygon SOC stocks showed laboratory results of NP were significantly higher than MPC, whereas SLGA polygon data showed no such separation, failing the direction and ranking criteria.

For TN point-based concentration, laboratory values indicated a significant land-use effect ($p < 0.05$), but NP did not differ from all other land uses ($p > 0.05$). The SLGA point-based TN also detected significant differences ($p < 0.05$) but NP did not differ from all other land-use types except IP. Thus, SLGA met the significance criterion but did not maintain ranking consistency given the relative separation of IP. For TN sub-farm polygon, laboratory results showed NP had higher TN compared to cropping and MPC ($p < 0.05$). SLGA polygon TN detected significant differences ($p < 0.05$) but grouped NP together with all other categories, failing to reproduce the laboratory contrasts and therefore failing the direction and ranking criteria. For TN stocks, point-based laboratory and SLGA results placed NP in overlapping groupings with all other land uses, indicating agreement for all criteria. sub-farm-polygon TN stocks diverged, with laboratory values showing NP significantly higher than MPC, whereas SLGA did not reflect this pattern, failing the direction and ranking criteria.

For TP (point-based) concentrations, laboratory results showed significant differences ($p < 0.05$), with cropping significantly lower than NP, IP, MPC, and TA. SLGA point-based TP did not detect significant differences ($p > 0.05$) but maintained a broadly similar numerical ordering. Thus, SLGA partially satisfied direction and ranking, but failed the significance criterion. For TP (sub-farm polygon) stocks, laboratory values showed no significant differences among pasture-based land uses. SLGA polygon TP showed significant differences ($p < 0.05$), placing NP in a distinctly higher group than all other land uses. Because this pattern did not occur in the laboratory data and SLGA values were heavily inflated, SLGA failed all three evaluation criteria for polygon TP.

Across SOC, TN, and TP, laboratory measurements showed that NP generally fell within the same statistical grouping as most other land-use categories in pasture-based farms, with few meaningful separations. SLGA reproduced some of these broad patterns particularly for TN and, to a lesser extent, SOC point-based values but frequently diverged in the direction and ranking of contrasts, especially for polygon-derived estimates and all TP measurements. These inconsistencies were most apparent when SLGA placed NP in significantly different groups from land uses that were statistically indistinguishable in the laboratory data, or when it generated inflated values that altered the relative ordering of categories.

The within-system evaluation shows that SLGA provides only limited capability for resolving land-use differences at sub-farm scales, particularly where distinctions among categories are subtle. Taken together, these results further strengthen the conclusion that SLGA performs weakly at the sub-farm scale, as it frequently fails to reproduce the laboratory-derived contrasts, directions, and land-use rankings required for reliable differentiation of soil nutrient patterns. These discrepancies might be attributed to the spatial mismatch between SLGA pixel resolution (30–90 m) and the fine-scale field sampling design constrains the model's ability to resolve within-farm variation, particularly where nutrient distributions are driven by localized management or micro-topographic features.

Table 5. Interaction effects of farming system and land-use type on soil organic carbon, total nitrogen, and total phosphorus, comparing Soil and Landscape Grid of Australia predictions with laboratory measurements in dairy farms

Soil properties	Measurements scale	Data Sources	Pasture-based					Confinement				p-value
			Cropping	IP	MPC	Tree	NP	Cropping	IP	MPC	Tree	
SOC, %	Point-based	Laboratory	1.23±0.314^{axy}	2.13±0.120^{by}	1.56±0.109^{ax}	2.21±0.215^{abxy}	2.35±0.288^{xy}	1.86±0.122^{ab}	1.90±0.125^{ab}	2.07±0.191^{ab}	1.99±0.236^{ab}	0.001
		SLGA	2.05±0.234^{abxy}	2.29±0.187^{bz}	2.07±0.185^{abyz}	2.21±0.212^{abyz}	1.65±0.195^{x}	1.78±0.187^{a}	1.99±0.189^{a}	2.08±0.199^{ab}	1.87±0.210^{ab}	0.043
	Sub-farm polygon	Laboratory	1.31±0.502^{abxy}	2.21±0.155^{bxy}	1.70±0.141^{abx}	2.31±0.219^{bxy}	2.86±0.386^{y}	1.89±0.181^{b}	1.90±0.185^{ab}	2.16±0.213^{ab}	1.96±0.204^{ab}	0.063
		SLGA	1.92±0.303^{x}	2.30±0.165^{y}	2.04±0.163^{xy}	2.16±0.183^{xy}	1.94±0.210^{xy}	1.81±0.159	2.00±0.172	2.09±0.202	1.91±0.185	0.256
TN, %	Point-based	Laboratory	0.10±0.031^{abxy}	0.19±0.017^{by}	0.12±0.016^{ax}	0.17±0.023^{abxy}	0.20±0.027^{xy}	0.17±0.017^{ab}	0.18±0.017^{ab}	0.21±0.021^{ab}	0.16±0.024^{ab}	<0.001
		SLGA	0.15±0.012^{x}	0.15±0.009^{z}	0.15±0.009^{yz}	0.14±0.010^{xyz}	0.14±0.012^{xy}	0.13±0.007	0.15±0.009	0.15±0.010	0.13±0.010	0.246
	Sub-farm polygon	Laboratory	0.10±0.045^{abxy}	0.19±0.017^{byz}	0.13±0.017^{ax}	0.18±0.022^{abxyz}	0.25±0.036^{z}	0.18±0.019^{ab}	0.18±0.020^{ab}	0.22±0.027^{ab}	0.16±0.025^{ab}	0.003
		SLGA	0.14±0.015^{x}	0.16±0.008^{y}	0.15±0.008^{xy}	0.15±0.009^{xy}	0.15±0.013^{xy}	0.14±0.008	0.15±0.009	0.15±0.010	0.15±0.010	0.902
TP, %	Point-based	Laboratory	0.001±0.008^{x}	0.003±0.004^{y}	0.003±0.005^{y}	0.003±0.006^{y}	0.006±0.005^{y}	0.01±0.005	0.01±0.005	0.01±0.006	0.01±0.006	0.498
		SLGA	0.06±0.010	0.07±0.008	0.07±0.009	0.06±0.009	0.06±0.009	0.06±0.008	0.06±0.061	0.06±0.009	0.06±0.009	0.735
	Sub-farm polygon	Laboratory	0.002±0.009	0.003±0.005	0.003±0.005	0.003±0.005	0.007±0.005	0.02±0.005	0.14±0.005	0.01±0.006	0.01±0.006	0.849
		SLGA	0.06±0.011^{x}	0.07±0.007^{x}	0.07±0.007^{x}	0.06±0.007^{x}	0.17±0.026^{y}	0.06±0.007	0.06±0.008	0.06±0.008	0.06±0.008	0.896
SOC, Mg ha^{-1}	Point-based	Laboratory	51.9±13.18^{abxy}	89.8±5.040^{by}	65.6±4.550^{ax}	92.8±9.030^{abxy}	98.8±12.08^{xy}	77.9±5.094^{ab}	78.0±5.256^{ab}	87.1±8.021^{ab}	83.6±9.907^{ab}	0.001
		SLGA	89.9±11.04^{abx}	95.5±7.590^{byz}	85.5±7.438^{abxyz}	94.8±9.406^{abz}	75.1±8.691^{xy}	78.6±7.570^{a}	86.8±7.730^{ab}	93.3±8.511^{ab}	83.5±9.314^{ab}	<0.001
	Sub-farm polygon	Laboratory	55.0±21.10^{abxy}	92.7±6.491^{bxy}	71.3±5.900^{abx}	97.0±9.201^{bxy}	120±16.20^{y}	79.3±7.020^{a}	79.8±7.459^{ab}	90.7±11.496^{ab}	82.3±10.58^{ab}	0.063
		SLGA	80.5±12.73^{x}	96.6±6.945^{y}	85.5±6.840^{xy}	90.8±7.682^{xy}	81.5±8.806^{xy}	75.9±7.601	84.0±7.776	87.7±8.940	80.1±8.560	0.256
TN, Mg ha^{-1}	Point-based	Laboratory	4.25±1.311^{axy}	7.84±0.702^{by}	5.03±0.677^{ax}	7.29±0.952^{abxy}	8.45±1.109^{xy}	7.05±0.704^{ab}	7.46±0.722^{ab}	8.97±0.886^{ab}	6.88±1.012^{ab}	<0.001
		SLGA	6.51±0.586^{abx}	6.31±0.264^{axy}	5.93±0.243^{axy}	5.56±0.426^{ay}	6.05±0.541^{xy}	5.94±0.262^{a}	6.51±0.275^{a}	6.78±0.370^{ab}	8.35±0.450^{b}	<0.001
	Sub-farm polygon	Laboratory	4.32±1.891^{abxy}	8.13±0.728^{by}	5.38±0.697^{ax}	7.60±0.910^{abxy}	10.3±1.500^{y}	7.37±0.799^{ab}	7.44±0.838^{ab}	9.04±1.114^{ab}	6.93±1.034^{ab}	0.003
		SLGA	6.00±0.614^{x}	6.55±0.323^{y}	6.27±0.318^{xy}	6.31±0.361^{xy}	6.27±0.523^{xy}	5.82±0.354	6.45±0.363	6.39±0.422	6.12±0.403	0.909
TP, Mg ha^{-1}	Point-based	Laboratory	0.03±0.320	0.13±0.185	0.13±0.194	0.14±0.242	0.24±0.155	0.58±0.203	0.53±0.215	0.29±0.248	0.47±0.270	0.504
		SLGA	2.71±0.498^{ab}	2.56±0.292^{ab}	2.49±0.285^{ab}	1.82±0.371^{ab}	2.78±0.386	2.73±0.293^{a}	2.49±0.298^{a}	2.72±0.352^{ab}	3.85±0.392^{b}	<0.001
	Sub-farm polygon	Laboratory	0.06±0.358	0.12±0.191	0.12±0.203	0.14±0.216	0.32±0.228	0.64±0.212	0.56±0.228	0.34±0.262	0.47±0.241	0.619
		SLGA	2.44±0.451^{x}	2.78±0.286^{x}	2.83±0.0.284^{x}	2.63±0.306^{x}	7.27±1.087^{y}	2.58±0.313	2.65±0.317	2.72±0.348	2.57±0.338	0.920

IP= Improved pasture; MPC = Mixed pasture cropping; SOC = Soil organic carbon; CO$_{2eq}$ = carbon dioxide equivalent; TN = total nitrogen; C: N ratio = Carbon to nitrogen ratio; Log = result of log-transformed; ^{a,b,c} Means without a common superscript differ across farming systems and land uses ($p < 0.05$). ^{x,y} = Means differ from natural pasture ($p < 0.05$); “sub-farm polygon” refers to the mean of all SLGA raster pixels within each sub-farm, compared with laboratory sub-farm averages. “Point-based” refers to values extracted at the georeferenced locations of individual soil cores.

7.3.5.3. Farming System Effects

The effect of farming system (pasture-based vs. confinement) on SOC, TN, and TP at the farm scale was evaluated using area-weighted nutrient concentrations and stocks derived from both laboratory measurements and SLGA predictions (**Table 6**). This assessment tests SLGA's capacity to reproduce broad, system-level nutrient contrasts, in contrast to the finer within-farm patterns examined in section 3.5.1 and 3.5.2. As with earlier analyses, the evaluation follows three criteria: statistical significance, directional agreement, and consistency in system-level rankings.

Both laboratory and SLGA results showed significantly higher SOC concentrations and stocks in pasture-based than in confinement systems. Laboratory point-based SOC concentrations were substantially higher in pasture-based farms compared with confinement farms ($p = 0.011$). SLGA point-based SOC reproduced this contrast, with pasture-based farms similarly exceeding confinement systems ($p = 0.004$). The polygon-based estimates showed the same pattern for both datasets. All three criteria were therefore satisfied: SLGA correctly identified the significant farming-system difference, matched the direction of the contrast, and preserved the ranking of systems observed in the laboratory data. This strong agreement reflects SLGA's ability to represent broad spatial gradients in SOC, consistent with the tendency of pasture-based systems to accumulate more organic matter through residue inputs and reduced soil disturbance.

For TN, laboratory results again showed significantly higher concentrations and stocks in pasture-based systems ($p = 0.037$). SLGA point-based TN accurately reproduced this contrast ($p = 0.013$), and the polygon-based results showed a similar directional trend despite weaker statistical support ($p = 0.062$). Thus, SLGA satisfied the significance, direction, and ranking criteria for TN at the farm scale. This indicates that TN dynamics at the whole-farm level are sufficiently captured by the SLGA covariates and model structure. These results are contrasting with those reported above where SLGA did not clearly replicate differences due to land use. A plausible explanation is that confinement farms of the present study were inland and drier areas compared to pasture-based farms (Dida et al., 2026). Therefore, the environmental differences between systems are very large and SLGA shows the ability to detect such large differences, which cannot be accurately detected for land use within farms.

In contrast to SOC and TN, TP exhibited the weakest agreement between laboratory and SLGA datasets. Laboratory measurements showed no significant farming-system differences for either TP concentrations (point-based $p = 0.164;$ sub-farm polygon $p = 0.201$) or TP stocks point-based $p = 0.160;$ sub-farm polygon $p = 0.206)$, reflecting the high within-system variability typically associated with phosphorus dynamics. However, SLGA predicted significantly higher TP in pasture-based systems for both point-based and polygon values, and the SLGA TP means were substantially inflated compared with the laboratory measurements. As a result, SLGA failed all three evaluation criteria for TP: it identified significant farming-system differences where none were present in the laboratory data, the direction of contrasts did not correspond to measured TP patterns, and the ranking of farming systems was inconsistent with the laboratory results. Importantly, these TP results further reinforce the broader conclusion drawn from the agreement-based metrics (R^2, CCC, Cb), proportional error metrics (%RMSEP, %MAE, %MBE), and absolute error metrics (RMSE, MAE) namely, that SLGA performs poorly for TP and demonstrates weak predictive accuracy at the sub-farm scale.

The collective findings from this study show that SLGA offers value for broad soil assessment in dairy production systems but remains limited for detailed, site-specific applications. At the farm scale, SLGA demonstrated moderate agreement with laboratory measurements for SOC and TN, indicating its usefulness for general benchmarking. However, accuracy declined notably at the sub-farm scale, and TP was consistently overestimated, reducing confidence in its use for fine-resolution management. Although SLGA identified overall differences in SOC and TN between pasture-based and confinement systems, it did not reliably capture finer land-use contrasts or paddock-level variation observed in the laboratory data. This limits its relevance for tasks requiring high precision, such as C accounting under the Carbon Farming Initiative, where accurate SOC baselines and robust stratification are essential. Similar challenges apply to fertiliser planning, even though improved soil quality can support reductions in N fertiliser requirements (Wang et al., 2026).

As such, SLGA may therefore serve as a preliminary screening tool for identifying general SOC or TN conditions but cannot substitute for field sampling where regulatory or financial consequences are involved. This highlights the need to position DSM products not only as mapping outputs but as components of broader decision-support or decision intelligence frameworks in agricultural systems (Fan et al., 2026). The reduced predictive performance of SLGA at finer scales also limits its effectiveness for nutrient budgeting, environmental risk assessment, and process-based modelling. The substantial TP overestimation may distort nutrient stock estimates, lead to inappropriate fertiliser allocation, and misidentify P-loss risk areas, with potential implications for environmental stewardship (Fan et al., 2023). Likewise, the moderate predictive performance for SOC and TN is insufficient for supporting process-based modelling or paddock level carbon project design, where small deviations in soil inputs can propagate into large uncertainties (Zhang et al., 2025). Overall, these findings highlight the need to complement SLGA outputs with site-specific measurements whenever high spatial precision or quantitative reliability is required.

Table 6. Effect of farming system on soil physicochemical properties in dairy farms weighed by the proportional area of each land use, comparing Soil and Landscape Grid of Australia predictions with laboratory measurements in dairy farms

Soil properties	Measurement scale	Data Source	Farming system		p-value
			Pasture-base	Confinement	
Soil organic carbon, %	Point-based	Laboratory	2.65±0.252	1.35±0.281	0.011
		SLGA	2.59±0.137	1.72±0.153	0.004
	Sub-farm polygon	Laboratory	2.34±0.196	1.41±0.219	0.016
		SLGA	2.42±0.154	1.56±0.172	0.008
Total nitrogen, %	Point-based	Laboratory	0.23±0.026	0.13±0.030	0.037
		SLGA	0.18±0.011	0.12±0.012	0.013
	Sub-farm polygon	Laboratory	0.20±0.022	0.13±0.025	0.062
		SLGA	0.17±0.011	0.12±0.012	0.011
Total phosphorus, %	Point-based	Laboratory	0.005±0.003	0.01±0.003	0.164
		SLGA	0.08±0.006	0.05±0.007	0.009
	Sub-farm polygon	Laboratory	0.003±0.0047	0.013±0.005	0.201
		SLGA	0.09±0.010	0.05±0.011	0.018
Soil organic carbon, Mg ha^{-1}	Point-based	Laboratory	111±10.60	56.8±11.80	0.011
		SLGA	109±5.750	72.3±6.430	0.004
	Sub-farm polygon	Laboratory	98.3±8.240	59.4±9.210	0.016
		SLGA	101±6.470	65.7±7.230	0.008
Total nitrogen, Mg ha^{-1}	Point-based	Laboratory	9.60±1.120	5.33±1.250	0.038
		SLGA	7.45±0.440	5.24±0.492	0.012
	Sub-farm polygon	Laboratory	8.34±0.919	5.27±1.030	0.061
		SLGA	7.24±0.451	4.91±0.504	0.011
Total phosphorus, Mg ha^{-1}	Point-based	Laboratory	0.19±0.127	0.49±0.142	0.160
		SLGA	3.33±0.257	1.93±0.287	0.008
	Sub-farm polygon	Laboratory	0.14±0.199	0.56±0.222	0.206
		SLGA	3.75±0.407	1.88±0.455	0.018

Sub-farm polygon = refers to the mean of all SLGA raster pixels within each Sub-farm polygon, compared with laboratory Sub-farm polygon averages. “Point-based” refers to values extracted at the georeferenced locations of individual soil cores. Sub-farm level denotes analysis at the scale of individual Sub-farm polygon s, whereas Farm level represents metrics aggregated across all paddocks within each farm.

7.3.6. Limitations

This evaluation was conducted across nine dairy farms in New South Wales, which, although representative of the region’s production diversity, does not capture the broader range of soil types, management systems, and climatic conditions present in other Australian or international contexts. As such, the findings may not fully generalize beyond the study area. Although SLGA provides prediction-interval rasters, these could not be incorporated into the sub-farm-based extraction workflow, preventing formal quantification of spatial uncertainty. Another limitation of the current analysis is the mismatch in spatial resolution between the SOC (30 m) and the TN/TP (90 m) layers, even though all originate from the SLGA. This difference arises because SOC modelling benefited from finer-scale covariates and a state/national high-resolution C mapping initiative, whereas the TN and TP models were constrained by the resolution of the shared national covariate datasets. Consequently, direct pixel-level or fine-scale spatial comparisons of nutrient patterns across the three attributes should be interpreted with caution. The coarser resolution of the TN and TP layers also contributes to their relatively weaker predictive performance at sub-farm and paddock scales, where local variation is less well captured. These constraints are inherent to the current generation of national digital soil products and highlight the need for future harmonised high-resolution mapping across multiple soil attributes.

7.4. Conclusion

This study demonstrates that SLGA provides moderately reliable estimates of SOC and TN compared to laboratory analysis at the farm scale, making it suitable for broad baseline assessments, preliminary benchmarking, and initial screening of soil condition across dairy farming systems. However, its limited accuracy at the sub-farm scale, together with the substantial bias in TP predictions, constrains its use for operational management, nutrient planning, carbon project design, and any application requiring quantitative precision and accuracy, or within-farm stratification. Although SLGA detected significant differences in SOC and TN between pasture-based and confinement systems, it lacked sensitivity to detect differences between land uses and did not reliably capture TP variation or replicate laboratory-derived patterns. Consequently, SLGA cannot replace field sampling for applications requiring high spatial resolution or accurate quantification of SOC, TN, or TP. From a practical standpoint, these results indicate that SLGA is appropriate for broad and large differences due to farming system (e.g., identifying whether a farm is generally low, moderate, or high in SOC or TN), but is not suitable as a stand-alone tool for guiding land-use decisions, certifying C projects, or informing fertiliser allocation. Field-based measurements remain essential where nutrient estimates carry financial, regulatory, or agronomic consequences. Future improvements to national DSM products should therefore prioritise downscaling, local recalibration, and integration of management-specific covariates, including fertiliser history, stocking rates, and irrigation practices, to enhance their relevance for fine-scale agricultural applications.

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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Chapter 8: General Discussion

Overview

This chapter synthesizes the main findings of the thesis and integrates them to draw overall conclusions. It also discusses practical considerations, limitations, and future research directions. Across five studies, the thesis evaluated GHG emissions, soil C and nutrient stocks, nutrition–emissions interactions, emerging CH_4 monitoring technologies, and the predictive performance of digital soil maps. Collectively, these findings provide a comprehensive understanding of the effect of production system, management practices, and land use on the environmental footprint of confinement and pasture-based dairy farms. By combining empirical measurements, modelling outputs, and digital soil mapping, this work offers practical insights to support climate-smart dairy production in Australia.

8.1. Key Insights Across Studies

A comparative life cycle assessment (LCA) of confinement and pasture-based systems revealed similar emission intensities per unit of fat- and protein-corrected milk (FPCM) of 1.02 ± 0.038 and 1.07 ± 0.069 kg CO_2-e/kg FPCM, respectively, despite confinement farms producing 72% more milk per cow compared to pasture-based systems. Enteric CH_4 remained the dominant source in both systems, contributing over half of total emissions. Secondary sources differed by production system: manure emissions were substantially higher in confinement compared to pasture-based systems, whereas fertiliser-related and pre-farm embedded emissions were more prominent in pasture-based systems. Tree C sequestration provided modest offsets (1% in confinement and 6% in pasture-based systems), underscoring the opportunity for integrated agroforestry to complement emissions reduction strategies. These findings highlight that targeted interventions are needed to address system-specific priorities improving manure management in confinement farms, optimizing fertiliser use and supply chains in pasture systems, and reducing enteric CH_4 across both systems to advance toward net-zero emissions goals.

Analysis of concentrate supplementation across 120 commercial Australian dairy farms showed that feeding 2–3 tonnes of DM per cow annually reduced GHG emissions intensity by approximately 14% compared with ≤1 t DM/cow/year, while numerically improving gross income (+64%) and earnings before interest (+53%) per Kg of milk solid ($P > 0.05$). However, supplementation beyond 3 t DM/cow/year numerically diminished economic returns (EBIT decreased by 49% and net income by 128%; $P > 0.05$) and increased manure-derived CH_4 and N_2O emissions compared with 2-3 t DM/cow/year, illustrating trade-offs between nutritional strategies and environmental and economic outcomes. These results emphasize the importance of balanced supplementation within whole-farm frameworks that integrate feed efficiency with N management to reduce emissions from enteric to manure pathways.

Findings in chapter 3 and 4 showed that enteric CH_4 production is the main source of GHG emissions in dairy farms, highlighting the need to fast-track reduction strategies such as breeding animals for low CH_4 production and feed additives, amongst many others (Garnett and Eckard, 2024). However, these strategies need to be underpinned by tools that allow the industry measuring enteric CH_4 production in practical ways and at large scale. Innovation in monitoring technologies was explored in Chapter 5 through low-cost gas sensors (MQ-4 and MQ-8, sensitive to CH_4 and H_2, respectively) compared with the GreenFeed system (C-Lock Inc.). Tests on 28 heifers showed moderate correlations for CH_4 and H_2 detection, although repeatability and peak-capture performance were lower for CH_4 with the sensors compared to the GreenFeed. Despite these limitations, the findings highlight the potential of affordable sensor technologies (<AUD 200) compared with the cost of GreenFeed (~AUD 250,000) for scalable on-farm CH_4 monitoring, provided methodological refinements improve accuracy and enable real-time decision-making.

Soil organic C is the most important terrestrial reservoir of C, and therefore there was a need to quantify these in commercial dairy systems because research was lacking for Australia. Soil analyses revealed that pasture-based farms stored 75% more SOC and 65% more TN per hectare than confinement systems, reflecting the benefits of perennial pastures and reduced soil disturbance (cropping land uses account for only about 2% of total land area in this system). Land-use patterns reinforced these trends but only in the high-rainfall pasture-based systems where natural and improved pastures showed the highest SOC and TN. Differences between systems were partly attributed to differences in rainfall, land use and soil parent material. It is yet to be investigated the relative contribution of these factors to the differences in SOC including the potential contribution of defecation from grazing cows to SOC in perennial pastures of the pasture-based dairy systems or manure management of confinement systems including manure application within the farm. It is plausible that C, N, and P cycling through manure plays an important role in such differences where C is moved by cows to grazing paddocks but spread uniformly throughout paddocks in confinement systems. This is an important area that requires future research. In contrast, TP stocks were 3.7 times higher in confinement systems, raising concerns about nutrient surpluses and runoff risks. These findings underscore the importance of perennial vegetation and minimal soil disturbance in sustaining soil health and C sequestration. Further research is needed to quantify annual C sequestration rates for each farming system and land-use type to better assess their potential for mitigating GHG emissions.

Finally, evaluation of the Soil and Landscape Grid of Australia (SLGA) demonstrated moderate predictive accuracy for SOC and TN at farm scale ($R^2 > 0.75$; CCC > 0.75) but poor performance for TP ($R^2 \leq 0.05$). SLGA effectively captured system-level differences but lacked sensitivity to detect differences at finer scale due to land use, limiting its utility for precision nutrient management. Although SLGA offers value for baseline C monitoring, field sampling remains essential for sub-farm applications and phosphorus monitoring.

Collectively, these findings reveal that the environmental performance of dairy systems is shaped more by management design than production intensity. Although confinement and pasture-based systems exhibited similar emission intensities their secondary emission sources present distinct challenges: manure-related emissions in confinement systems and fertiliser-related emissions in pasture-based systems, which require targeted mitigation strategies. Addressing these system-specific hotspots could result in differences in the environmental footprint of milk production between them. For instance, reducing manure emissions in confinement systems may be more achievable than lowering fertiliser-derived emissions in pasture-based systems. Improving feed efficiency across both systems, enhancing manure management in confinement systems, increasing fertiliser efficiency in pasture-based systems, maintaining soil C stocks through perennial pastures and tree integration, and reducing enteric CH_4 via feed additives represent complementary pathways toward climate resilience. A whole-farm perspective that accounts for emissions, sequestration, and nutrient cycling is critical for achieving net-zero targets without compromising productivity. Overall, these interconnected findings provide producers, policymakers, and industry stakeholders with evidence-based strategies from feed optimisation and low-cost monitoring technologies to soil-focused C approaches to reduce emissions and enhance C sequestration in Australian dairy systems.

8.2. System-Level Emissions: Confinement vs. Pasture-Based

Chapter 3 assessed GHG emissions from confinement and pasture-based dairy systems using a LCA framework that incorporated C sequestration from on-farm trees. Emission intensity per unit of FPCM was similar between systems, despite 72% higher milk yield per cow in confinement compared to pasture-based systems. This counterintuitive result arises because productivity gains in confinement did not proportionately reduce the dominant animal emissions. Although, confinement farms exhibited a 13% lower enteric CH_4 intensity, they also showed a 129% higher manure-related emission intensity (CH_4 and N_2O) relative to pasture-based farms. Consequently, the reductions in enteric CH_4 associated with higher milk output were largely offset by increased manure emissions, and enteric CH_4 remained the largest single contributor to total farm emissions in both systems. Therefore, these results indicate that productivity gains alone do not substantially reduce the environmental footprint of milk production. Mitigation strategies must therefore extend beyond productivity improvements and target the dominant emission sources within each system.

Animal-related emissions dominated both systems, accounting for 85% of total emissions in confinement farms and 71% in pasture-based farms, consistent with previous studies showing that animal emissions are the primary contributors to dairy-farm GHG outputs (Gerber et al., 2013; Rotz and Thoma, 2017). Enteric CH_4 was the largest single source in both systems, but secondary contributors differed: confinement farms generated substantial manure-derived CH_4 and N_2O, whereas pasture-based farms were more strongly influenced by fertiliser-related emissions both CO_2 and N_2O and by CO_2 released from lime application, as well as pre-farm embedded emissions associated with purchased feed and fertilisers. Manure-related emissions were more than twice as high in confinement systems, highlighting the environmental burden of intensive housing when manure is stored under anaerobic conditions without additional treatment to reduce CH_4 and N_2O emissions. This study did not collect detailed quantitative data on manure management practices; however, farmer reports indicated that manure was typically stored and later applied to pasture and cropping land as fertiliser or through irrigation, with no additional treatment. Anaerobic storage is known to increase emissions and therefore, future research should explicitly characterise manure management practices to strengthen causal interpretation. Tree C sequestration provided only modest offsets 1% in confinement and 6% in pasture-based systems reflecting limited woody vegetation but underscoring the potential benefits of integrating agroforestry into dairy landscapes as a complementary mitigation strategy (Conant et al., 2001; Wuepper et al., 2020).

Table 1 below shows that confinement farms exhibited markedly higher total CH_4 emissions due to manure accumulation and anaerobic storage conditions that favour methanogenesis (Rotz and Thoma, 2017). Enteric CH_4 emissions from milking cows were consistent with total DMI and milk production, as the ADCC inventory assessment incorporates milk production into the equations for estimating DMI, which is then used to estimate enteric CH_4 emissions. This relationship is expected, as experimental studies have shown a positive correlation between enteric CH_4 production and milk yield (Hardan et al., 2022; Lovett et al., 2005; O'Neill et al., 2011; Ulyatt et al., 2002a, 2002b). Yan et al. (2010) also reported that DMI and milk production are the primary drivers of enteric CH_4 emissions. However, some research indicates substantial variation in feed efficiency among animals with similar DMI (Clark, 2013; Knapp et al., 2014; Pinares-Patiño et al., 2007). Danielsson et al. (2017) observed significant differences in daily CH_4 emissions between persistently low and high emitters despite identical DMI and milk yield, linked to differences in volatile fatty acid profiles and microbial methanogen communities. These findings suggest that biological variation influences CH_4 production in addition to DMI. Therefore, further research is needed to link feed efficiency with CH_4 production from both the rumen and manure, using direct measurements across different seasons and regions to better quantify the potential environmental gains from breeding low-emission animals.

Although enteric CH_4 emissions were higher in confinement systems, enteric CH_4 emission intensity per unit of milk (g CH_4/kg FPCM) and milk fat yield did not differ significantly between systems. This likely reflects the much higher FPCM (72%) and milk fat (74%) yields in confinement, which dilute enteric CH_4 emissions on a per-unit basis although this seemed to be counterbalanced by higher emissions arising from manure. Similarly, a 76% increase in milk protein yield reduced enteric CH_4 intensity per unit of milk protein (data not shown). Manure CH_4 emissions for confinement milking cows were approximately 8-fold higher (Table 1) due to slurry storage in lagoons, which have a high CH_4 conversion factor. In contrast, pasture-based systems lower conversion factor because direct manure excretion onto paddocks dries faster under aerobic conditions, reducing microbial activity and limiting methanogenesis, thereby lowering CH_4 emissions. Confinement diets included a higher proportion of conserved forage (silage), which had numerically lower DMD than fresh pasture in this study. Lower digestibility increases undigested fibre excreted in manure, providing substrates for methanogenesis during anaerobic storage. These interactions between roughage composition, NDF, and CP content highlight the complexity of diet effects on manure emissions. For young stock, manure CH_4 increases were smaller (78% for 2-year heifers and 3.9% for yearlings) confinement farms because most allowed heifers to graze, resulting in similar manure management practices and smaller differences in CH_4 emissions.

Table 7. Predicted Enteric and Manure Methane Emissions (g CH_4/day; mean ± SE) from Milking Cows and Replacement Heifers in Pasture-Based and Confinement Systems.

CH_4 emissions	Pasture-based	Confinement	P-value
Enteric CH_4, g CH4/day			
Milking cow (g CH_4/d per cow)	378 ± 13.70	534 ± 38.81	0.013
2-yr heifer (g CH_4/d per heifer)	160 ± 6.951	196 ± 12.80	0.046
Enteric CH_4, 1-yr heifer (g CH_4/d per heifer)	68.7 ± 1.248	79.6 ± 6.452	0.166
Manure CH_4, g CH_4/day			
Milking cow (g CH_4/d per cow)	30.0 ± 13.62	266 ± 39.53	0.003
2-yr heifer (g CH_4/d per heifer)	3.66 ± 0.271	6.48 ± 1.275	0.091
1-yr heifer (g CH_4/d per heifer)	2.57 ± 0.964	2.67 ± 0.599	0.934
Total CH_4, g CH_4/day			
Milking cow (g CH_4/d per cow)	408 ± 23.29	800 ± 53.97	<0.001
2-yr heifer (g CH_4/d per heifer)	163 ± 7.208	202 ± 13.24	0.040
1-yr heifer (g CH_4/d per heifer)	71.2 ± 1.425	82.3 ± 6.743	0.178
FPCM EI (g enteric CH_4/kg FPCM)	17.6 ± 1.263	14.2 ± 0.623	0.054

FPCM EI = Fat and protein corrected milk emission intensity; Total CH_4 = manure CH_4 (g CH_4/d) + enteric CH_4 (g CH_4/d)
Notes: The EI was allocated solely to the enteric CH_4 emissions from cows

Pasture-based farms exhibited higher direct N_2O emissions from urine and feces deposited on soil because excreta undergo nitrification and denitrification (Luo et al., 2010) (**Table 2**). However, total N_2O emissions were higher in confinement systems, primarily due to greater direct N_2O emissions from manure storage. This reflects the collection and storage of manure in confinement systems rather than its direct deposition onto paddocks. Although dietary CP concentrations did not differ significantly between systems, the numerically higher CP concentration combined with greater DMI in confinement systems likely contributed to increased N excretion and storage-related N_2O emissions. Even when CP concentrations of the diet were comparable (189 vs. 171 g/kg DM for confinement and pasture-based systems, respectively; $P = 0.281$), higher DMI could result in greater CP intake. Consistent with these results, Külling et al. (2002) reported higher N_2O emissions from manure when cows were fed high-protein diets, confirming the strong link between dietary N intake, manure N excretion, and N_2O formation. Total N_2O emissions per unit of DMI (g N_2O/kg DMI) were 30% higher in confinement systems (data not shown), a notable finding given the 41% higher total DMI and 92% higher total N_2O emissions compared to pasture-based production systems. Higher DMI increases manure N_2O emissions because greater N intake results in higher faecal N output (Nampoothiri et al., 2018). Approximately 2% of excreted N is released as N_2O (Hao et al., 2004), indicating that overfeeding protein elevates environmental N losses (Hristov et al., 2011).

In Australian pasture-based systems, nutrient balance is largely maintained through grazing, with manure deposited directly onto paddocks. This approach minimises storage-related manure CH_4 emissions but limits opportunities for CH_4 recovery. In contrast, confinement systems store manure in effluent ponds, creating both a mitigation challenge and an opportunity. Anaerobic biodigesters offer a practical solution for confinement farms by capturing CH_4 from stored manure and converting it into renewable energy. In California, incentive-based manure management and digester programs have contributed to annual CH_4 reductions of approximately 5 million t CO_2-e, placing the sector more than two-thirds of the way toward its 40 % reduction target below 2013 levels through CH_4 capture and utilisation combined with other strategies (Dairy Cares, 2025). The feasibility of similar approaches in Australia depends on policy incentives, infrastructure, and economic viability. In Australia, the adoption of biodigesters in confinement farms remains low, likely due to high establishment and operating costs relative to modest electricity returns, highlighting the need for policy incentives or subsidy schemes to improve economic viability. Accordingly, confinement systems could integrate biodigester technology with improved feed and N balance strategies, whereas pasture-based farms should prioritize optimized fertiliser use and grazing management. Further research is required to better quantify manure handling practices and evaluate the potential for effluent treatment and redistribution across both systems.

Overall, these findings emphasize the need for system-specific mitigation approaches: improved manure management in confinement systems, enhanced feed and fertiliser N-use efficiency in pasture-based operations, and enteric CH_4 mitigation in both systems. Combined with measures to increase C sequestration through tree planting, these strategies can help reduce the overall climate footprint of dairy production.

Table 8. Predicted Direct and Indirect Manure Nitrous Oxide Emissions (g N_2O/day; mean ± SE) from Milking Cows and Replacement Heifers in Pasture-Based and Confinement Systems

CH_4 emissions	Pasture-based	Confinement	P-value
Direct N_2O from urine and feces avoided to pasture, g N_2O/day			
Milking cow	2.53 ± 0.198	0.26 ± 0.107	<0.001
2-yr old heifer	1.69 ± 0.078	1.04 ± 0.333	0.123
1-yr old heifer	0.66 ± 0.030	0.38 ± 0.127	0.090
Direct N_2O from manure storage, g N_2O/day			
Milking cow	0.79 ± 0.184	7.81 ± 1.087	0.003
2-yr old heifer	0.00 ± 0.000	1.69 ± 0.898	0.132
1-yr old heifer	0.00 ± 0.000	0.61 ± 0.340	0.149
Indirect N_2O from N waste, g N_2O/day			
Milking cow	2.53 ± 0.172	3.11 ± 0.363	0.207
2-yr old heifer	1.49 ± 0.083	1.46 ± 0.094	0.793
1-yr old heifer	0.56 ± 0.033	0.53 ± 0.039	0.571
Total N_2O emissions, g N_2O/day			
Milking cow	5.85 ± 0.445	11.2 ± 1.404	0.016
2-yr old heifer	3.18 ± 0.160	4.19 ± 0.629	0.187
1-yr old heifer	1.22 ± 0.061	1.51 ± 0.245	0.302
FPCM EI (g N_2O/kg FPCM)	0.27 ± 0.032	0.29 ± 0.033	0.676

FPCM EI = Fat and protein corrected milk emission intensity; total N_2O = direct N_2O from urine and feces avoided to pasture (g/d) + direct N_2O from manure storage (g/d) + indirect N_2O from N waste (g N_2O/d)
Notes: The EI was allocated solely to the total N_2O emissions from cows.

8.3. Feeding Strategies: Concentrate Supplementation and Trade-offs

Chapter 4 examined the impact of varying levels of dietary concentrate supplementation on milk production, GHG emission intensity, and farm profitability in pasture-based commercial dairy systems. Using data from 120 farms across four major dairy regions (New South Wales, South Australia, Victoria, and Tasmania), the study found that feeding 2–3 t DM/cow/year reduced GHG emission intensity by approximately 14% compared with ≤1 t DM/cow/year, while also numerically improving gross income (+64%) and earnings before interest (+53%). These results confirm the role of nutritional strategies in enhancing productivity and environmental performance, consistent with previous studies showing that concentrate supplementation improves feed efficiency and reduces enteric CH_4 emissions per unit of output (Arndt et al., 2022; Bayat et al., 2017; Moate et al., 2020; Muñoz et al., 2017; van Gastelen et al., 2019). However, findings from Chapter 3 indicate that concentrate proportion alone does not explain the substantially higher milk yield observed in confinement systems. In Chapter 3, the proportion of concentrate in the diet differed only numerically between systems (32 vs. 38% concentrate in pasture-based compared to confinement, respectively), yet confinement farms produced approximately 72% more milk per cow. This discrepancy suggests that productivity differences were influenced not only by concentrate amount but also by differences in the nutritional quality of the feedbase and broader management factors. For example, concentrates used in confinement systems had better CP (23% vs. 16% DM) and metabolisable energy (13.2 vs. 12.9 MJ/kg DM) than those fed in pasture-based farms. These qualitative differences, combined with higher total DMI, more consistent ration delivery, reduced walking distances, and controlled environmental conditions in confinement systems, likely contributed to the markedly higher milk yield. Therefore, the results of Chapter 4 highlight the role of concentrate quantity in improving efficiency within pasture-based systems, whereas Chapter 3 underscores that in confinement systems, greater milk production arises from a combination of concentrate quality, overall diet digestibility, and management intensity, rather than concentrate proportion alone. However, it is important to highlight that Chapter 4 used a dataset consisting of milk yield and concentrate proportion, but it did not include differences in diet composition because that information was not available. In contrast, Chapter 3 collected information in diet composition of each of the case study farms. Therefore, further research is needed collecting year around information on diet quality of pasture-based systems with a spectrum of concentrate proportion in their diets.

Although higher concentrate in the diet lowers emission intensity per unit of milk, it may increase total emissions (enteric CH_4, manure CH_4 and N_2O, plus CO_2 from concentrate production). Efficiency gains from improved milk yield offset these increases, but the environmental benefits depend on balanced supplementation and should include manure emissions as well. Concentrate above 3 t DM/cow/year numerically reduced profitability and increased manure-derived emissions, with N_2O increasing quadratically and manure CH_4 linearly with concentrate feeding level likely due to higher N intake and excretion (Nampoothiri et al., 2018). Although the current study did not measure how emissions may shift between enteric and manure pathways, previous research suggests that nutritional interventions targeted at reducing enteric CH_4 can influence manure-related emissions when N-use efficiency and effluent handling are not well managed (van Gastelen et al., 2019). Likewise, although urinary N excretion and manure management practices were not measured in this study, the literature indicates that balancing concentrate feeding with dietary protein supply may reduce urinary N, a key precursor of N_2O emissions, particularly in confinement systems where diets can be tightly controlled (Cameron and Di, 2021; Mohankumar Sajeev et al., 2018). Therefore, further research is needed collecting diet quality information and manure handling systems of dairy systems feeding different concentrate levels to ascertain the effect on total GHG emissions. In addition, mitigation strategies such as storage covers, solids separation, more frequent manure removal, or acidification have been shown in other studies to reduce manure-derived CH_4 and N_2O, although these practices are less applicable in pasture-based systems where manure is predominantly deposited directly onto paddocks (Mohankumar Sajeev et al., 2018). Maintaining high-quality pastures through improved digestibility, water-soluble carbohydrate concentrations, or inclusion of legumes and herbs may support milk production; however, precise control of CP intake is challenging in grazing systems due to seasonal variability in pasture composition and selective grazing behaviour. This limits the extent to which protein-targeted nutritional strategies can be implemented compared with confined feeding systems.

Economically, the “sweet spot” seems to lie at 2–3 t DM/cow/year, where mitigation and profitability are optimised. Supplementation beyond this point continues to reduce emission intensity but erodes economic returns, although a more complete analysis is required including emissions from manure management systems. From a sustainability perspective, moderate concentrate use represents a practical near-term strategy for climate-smart dairying, particularly when combined with precision fertilisation, effluent treatment, and pasture improvement. Implementation should consider regional feed availability, price variability, and long-term nutrient cycling impacts. Overall, these findings highlight the need for holistic mitigation strategies that integrate nutritional interventions with manure and pasture management. Although concentrate supplementation can effectively reduce emissions intensity and enhance profitability, its benefits depend on system-level integration. A comprehensive LCA that includes soil and tree-based C sequestration is necessary to capture the full environmental impact. Without such a holistic perspective, effects beyond milk production and GHG emissions remain uncertain. Reliance on concentrates also influences pasture management, nutrient cycling, soil health, and long-term farm ecology, which are potential trade-offs requiring further investigation before widespread adoption.

8.4. Enteric Methane Monitoring Technologies: Low-Cost Sensors vs. GreenFeed

Chapters 3 and 4 demonstrated that enteric CH_4 is the dominant emission source across both confinement and pasture-based dairy systems, and that the effectiveness of mitigation strategies whether through productivity gains, dietary supplementation, or system-level design ultimately depends on the ability to accurately quantify CH_4 emissions at the animal level. However, the approaches used in those chapters relied primarily on inventory-based models and fixed emission factors, which, as discussed in Chapter 3 and 4, are limited in their capacity to capture biological and management-driven variation among animals. Consequently, improving empirical measurement of enteric CH_4 under commercial conditions is essential for validating system-level assessments and for supporting targeted mitigation strategies. To address this gap, Chapter 5 evaluated the potential of low-cost metal-oxide gas sensors (MQ-4, MQ-8, and MQ-7, sensitive to CH_4, H_2, and CO, respectively), with particular focus on MQ-4, for monitoring enteric CH_4 emissions in ruminants by comparing their performance with the GreenFeed (GF). Laboratory calibration demonstrated that MQ-4 exhibited the highest sensitivity and stability for CH_4 detection, making it the most promising candidate for practical applications. However, the findings from field study indicate that as these sensors could offer affordability and ease of deployment, their accuracy and repeatability are lower compared to established systems such as the GF. Correlation analyses revealed moderate agreement between MQ-4 and GF measurements, with Spearman coefficients declining from weekly to minute-level aggregation, and repeatability estimates substantially lower for MQ-4 than GF. In addition, MQ-4 produced broader, longer peaks and slower signal processing than GF, suggesting limitations in capturing rapid eructation events that characterise CH_4 release in cattle. Together, these findings point to the influence of sensor sensitivity, calibration stability, and environmental variability on measurement reliability.

Importantly, the sensor results align with the broader system-level evidence from Chapters 3 and 4: animal- and management-driven variability in CH_4 emissions that cannot be fully captured using fixed emission factors, underscoring the value of empirical monitoring. Although GF remains the most robust option for high-precision quantification, its cost and infrastructure requirements constrain widespread deployment, particularly in pasture-based systems where animals are dispersed and management is less controlled. By contrast, the low-cost sensors assessed here offer advantages in affordability, portability, and scalability, making them useful for large herds, longitudinal monitoring, and resource-constrained contexts. Even with lower precision, they demonstrated utility for detecting relative differences in CH_4 emissions among animals or across time periods. This capability is particularly relevant for applications such as screening low-emission phenotypes, assessing responses to dietary changes, or tracking seasonal trends in pasture-based systems, issues highlighted in earlier chapters as key sources of uncertainty in emission estimates. Enhancing the performance of these sensors will likely require advances in calibration protocols, sensor placement, airflow correction, and data-processing techniques, potentially supported by advanced analytics or hybrid monitoring systems. Although low-cost sensors cannot yet replace gold-standard methods like GF for absolute emission quantification, they represent a promising complement within a tiered monitoring framework. Integrated with the mitigation strategies discussed throughout this thesis (e.g., nutritional management, manure handling, and productivity optimisation), such technologies can support more accessible, data-driven approaches to enteric CH_4 mitigation. Their continued development and refinement therefore constitute a practical step toward scalable monitoring solutions that underpin climate-smart dairy systems across diverse production contexts.

8.5. Soils, Farming Systems, and Land Use: Soil Organic Carbon and Other Nutrient Profiles

The preceding chapters demonstrated that differences between confinement and pasture-based dairy systems extend beyond animal-level emissions to encompass manure handling, nutrient flows, and land-use intensity. Chapter 3 showed that manure management and fertiliser use can substantially influence CH_4 and N_2O emissions at the system level, while Chapter 4 highlighted how feeding strategies alter nutrient inputs and excretion patterns. Building on these findings, Chapter 6 examined how these contrasting management approaches translate into longer-term changes in SOC and nutrient stocks, which can represent both a mitigation opportunity and a constraint on sustainable intensification. Chapter 6 revealed marked differences in SOC and nutrient stocks between farming systems. Pasture-based farms contained 75% more SOC and 65% more TN than confinement systems. Although, these differences partly reflect regional factors such as higher rainfall and differences in soil parent material, they also reflect fundamental contrasts in land use and management. Pasture-based systems likely benefit from perennial pastures, minimal soil disturbance, and continuous nutrient cycling via grazing and manure deposition, all of which promote SOC accumulation and stabilization (Badgery et al., 2020; Conant et al., 2001; Dignac et al., 2017). In contrast, confinement systems rely heavily on annual fodder cropping (cropping accounts for 85% of land use in this system), where repeated soil disturbance, biomass export, and residue removal accelerate organic matter mineralisation, resulting in lower SOC, consistent with evidence linking intensive cultivation to SOC loss (Lal, 1997; Schlesinger and Andrews, 2000).

Building on these system-level contrasts, land-use patterns within pasture-based farms further reinforced observed trends. Natural pastures, exclusive to pasture-based farms, stored the highest SOC and TN. Although the present study lacked the data needed to identify the drivers of these differences, previous research shows that undisturbed perennial systems with continuous ground cover, minimal soil disturbance, and deep root structures typically function as effective C sinks (Conant et al., 2001; Dass et al., 2018). Improved pastures and tree-covered areas within pasture-based systems also exhibited elevated SOC and TN, reflecting the combined effects of grazing-mediated nutrient recycling and woody biomass inputs. In contrast, cropping and mixed pasture–cropping areas showed the lowest SOC and TN stocks, likely due to biomass export through silage or hay production, reduced organic matter inputs, and annual soil disturbance patterns consistent with global evidence of SOC decline following conversion to cropland (Guo and Gifford, 2002; Rui et al., 2022). Pasture soils benefit from substantial C inputs via root turnover and manure deposition, whereas cultivation and residue removal in cropping systems accelerate carbon loss through mineralisation (Six et al., 2002).

Interaction effects between farming system and land use further highlight that improved pastures and tree areas within pasture-based farms stored the most SOC and TN, whereas land-use variation within confinement farms did not translate into measurable differences in SOC or TN, underscoring the combined influence of climate and grazing-mediated nutrient recycling on soil health (Bai and Cotrufo, 2022; Lal, 2020). These confinement farms included cropping, improved pasture, mixed pasture–cropping, and tree land uses; however, livestock were confined and therefore did not graze these areas. Consequently, improved pasture and mixed pasture–cropping land uses did not benefit from continuous nutrient return through manure deposition or grazing-mediated nutrient cycling processes known to underpin SOC and TN accrual in pasture-based systems. In the absence of these processes, SOC and TN stocks under improved pasture and mixed systems were comparable to those under cropping land uses, likely contributing to the lack of statistically detectable differences among land-use types within confinement farms. Additionally, although detailed rotational information was unavailable, cropping land uses in confinement systems often included legume-based rotations or mono-cropped legumes, which can enhance soil N inputs through biological N fixation and increase below-ground biomass. These practices may partially offset SOC and TN losses associated with cultivation, thereby narrowing contrasts between cropping and non-cropped land uses such as improved pasture and tree areas. Notably, three of the four confinement farms in our study were inland, low-rainfall regions where plant productivity, below-ground biomass inputs, and microbial activity are likely constrained by limited rainfall. Numerous studies show that rainfall is one of the dominant controls on SOC formation, with low-rainfall systems exhibiting inherently reduced SOC sequestration potential regardless of management or land use (Badgery et al., 2020; van Noordwijk et al., 2023). As a result, climatic, management, and soil constraints likely contributed to the non-significant differences in SOC and TN among land-use types within confinement farming systems. However, disentangling the relative contributions of grazing exclusion, crop rotation composition (particularly legume inclusion), and climatic constraints to SOC and TN dynamics within confinement systems requires further targeted research, including detailed land use histories and long-term monitoring across rainfall gradients.

Beyond C, the study revealed important nutrient trade-offs between systems. Confinement systems exhibited significantly higher TP stocks, which may increase environmental risks such as runoff and eutrophication. Differences in soil pH and mineral concentrations between systems suggest that fertilisation regimes and parent material also influence soil properties. Patterns in nutrient distribution further illustrate how management intensity affects soil fertility. Total N and P stocks were generally higher in pasture and tree areas due to manure recycling and litter deposition, whereas cropping areas showed depleted nutrient pools. These differences have implications for both productivity and environmental risk where excess N and P in grazed systems may increase leaching potential, whereas low nutrient reserves in croplands may restrict productivity without external inputs (Bouwman et al., 2013). The spatial variability observed across land uses underscores the need for nutrient management strategies that balance productivity with soil and water protection. Soil physical properties further supported these findings. Bulk density (BD) showed an inverse relationship with SOC, suggesting that soils with higher organic matter have better structure and lower compaction. Pasture and tree-covered areas exhibited moderate SOC and low BD, demonstrating their dual role in C sequestration and soil stabilization (Sanderman and Baldock, 2010). Cropping areas, characterised by compaction, displayed the highest BD values, consistent with evidence that intensive cultivation which may degrade soil physical properties.

Overall, this chapter demonstrated that land use and management decisions strongly influence soil C, nutrient retention, and overall environmental performance in dairy farms. These findings also show that SOC differences cannot be attributed solely to farming system but instead arise from interactions among climate, soil properties, and management. Previous studies similarly report that climate, parent material, and vegetation productivity strongly mediate SOC storage (Badgery et al., 2020; McDonald et al., 2023; van Noordwijk et al., 2023). From a sustainability perspective, these results highlight the importance of maintaining and improving pasture systems, integrating trees, and minimising soil disturbance to enhance C storage and nutrient cycling. In high-rainfall pasture-based systems, transitioning from cropping to improved pastures could deliver significant gains in SOC and TN, supporting climate mitigation and soil health objectives. For confinement systems, strategies could focus on improving nutrient management and incorporating cover crops to offset C losses. However, robust evaluation of these strategies requires long-term, longitudinal studies conducted within comparable climatic and soil contexts to disentangle management effects from regional drivers and to develop system-specific pathways for improving soil health across diverse dairy production landscapes.

8.6. Digital Soil Mapping: Soil and Landscape Grid of Australia Strengths and Limits

The field measurements of SOC, TN, and TP presented in Chapter 6 revealed clear contrasts between confinement and pasture-based systems, along with substantial within-farm heterogeneity driven by land-use patterns, management practices, and climatic conditions. Although these measurements provide essential insight into soil nutrient dynamics and C stocks, collecting such high-resolution data across large spatial scales is resource-intensive and often impractical. Digital soil mapping tools such as the SLGA, therefore offer a potential alternative for estimating soil properties over broader areas. Before these tools can be applied to farm-level C accounting, nutrient management planning, or policy-relevant assessments, it is necessary to determine how well they replicate the patterns observed in measured soil data. Accordingly, Chapter 7 evaluated the reliability of the SLGA for predicting SOC, TN, and TP at sub-farm (carbon emissions area [CEA]) and whole-farm scales across nine dairy farms in New South Wales, using more than 800 laboratory measurements from Chapter 6 as benchmarks. Although SLGA provides a nationally consistent soil dataset, its predictive accuracy varied substantially among soil properties, spatial scales, and extraction methods patterns consistent with other national and continental DSM evaluations (Grundy et al., 2015). Prediction accuracy differed strongly by soil property. SLGA showed moderate accuracy for SOC and TN, particularly at the whole-farm scale, where R^2 values exceeded 0.75 for SOC and 0.85 for TN, and CCC values were above 0.75. These results indicate that SLGA can provide useful baseline estimates for SOC and TN at aggregated scales, supporting applications such as regional C auditing and nutrient management planning whereas applications such as C accounting and trading may not be possible at this stage. However, accuracy declined at the sub-farm scale, where CCC values were lower and RMSEP and MAE increased. Aggregation effects which reduce the influence of small-scale variability are widely recognised to improve DSM predictive performance (Minasny et al., 2013; Piedallu et al., 2022). This highlights the limitations of SLGA's 90 m resolution and reliance on national covariates for capturing fine-scale heterogeneity within paddocks, which is critical for precision agriculture.

Error decomposition clarified the sources of uncertainty. For SOC and TN, random error dominated at the sub-farm level, reflecting natural within-farm heterogeneity and management contrasts not captured by continental-scale predictors. In contrast, TP predictions showed extremely poor performance at all scales, with $R^2 < 0.02$, CCC near zero, and consistent overestimation by six- to eight-fold. Such high mean bias likely reflects the limited representation of P data in national calibration datasets and the complexity of P dynamics, which are strongly influenced by local fertiliser history, soil mineralogy, and parent material (Helfenstein et al., 2024).

Another key test was SLGA's ability to detect meaningful differences due to land use and farming system as clearly evident in the laboratory results. SLGA successfully detected broad differences in SOC and TN between pasture-based and confinement systems, aligning with measured data showing higher SOC and TN stocks in pasture-based farms. However, SLGA showed mixed performance in identifying nutrient differences among land uses. Although some significant interaction effects were detected for SOC and TN, the ranking of land uses often diverged from laboratory observations. These inconsistencies indicate that although SLGA captures general system-level trends, it lacks the sensitivity to represent management-driven heterogeneity at finer scales. For TP, SLGA failed to reproduce any observed land-use patterns, further illustrating its limited applicability for P assessment.

These findings carry important implications for C accounting and nutrient management. Under Australia’s Carbon Farming Initiative, accurate SOC estimation and effective stratification rely on accurate baseline data. Although SLGA may be useful for baseline assessments, its limited accuracy at sub-farm resolution makes it unsuitable for designing on-farm C projects or meeting regulatory requirements without complementary field sampling. Similarly, the strong TP bias and inconsistent land-use rankings impose major constraints for nutrient budgeting, fertiliser planning, and benchmarking regenerative practices. Overall, this chapter provided a clear assessment of SLGA’s strengths and limitations. For SOC and TN, SLGA predictions are reliable at farm scale to support broad scoping assessments. However, sub-farm predictions, TP estimates, and any applications requiring precise nutrient quantification or within-farm stratification remain compromised by prediction error and systematic bias.

8.7. Integrating Soil and Emission Dynamics

The integrated interpretation of these studies highlights the interdependence between SOC processes and GHG emission pathways. Systems that maintain higher SOC such as pastures and tree-covered areas in pasture-based systems tend to have greater potential for C sequestration but may also exhibit higher biological activity, which can enhance short-term N_2O emissions if N is not well managed (Van Groenigen et al., 2015). Conversely, confinement systems that rely on off-paddock manure storage risk substantial CH_4 and N_2O losses from effluent ponds but can recycle nutrients effectively when effluent or composted manure is applied to cropland or pastures under controlled conditions. Although detailed quantitative information on manure and effluent management was not available for all case-study farms, indicative evidence from one confinement farm suggests that integrated effluent reuse can partially offset these risks. This farm frequently irrigated cropland with effluent, which was associated with higher SOC and soil N stocks relative to other confinement farms. It also relied less on inorganic fertiliser, thereby reducing fertiliser-related CO_2-eq emissions (data not shown). While these observations cannot be generalised, they illustrate how aligning effluent management with land application can transform nutrients from a storage-related liability into a field-scale resource. This reinforces the importance of spatial and temporal coordination between animal subsystems, feed production areas, and land-based nutrient sinks within dairy farms. More broadly, these interactions demonstrate that the C balance of dairy farms cannot be assessed solely at the animal or paddock level. Tree belts and perennial pastures function as effective C sinks in pasture-based system, whereas feed production, fertiliser use, and manure storage remain emission sources. Accurately quantifying net GHG exchange therefore requires a whole-farm perspective that simultaneously accounts for emissions, sequestration, and nutrient cycling. Currently, no single model or decision-support platform fully integrates these fluxes, partly because practical, rapid, and low-cost technologies for monitoring key components particularly SOC changes at farm scale remain limited. However, emerging advances in sensing technologies, digital soil mapping, remote sensing, and process-based modelling can offer promising avenues to close this integration gap. As measurement tools and modelling frameworks evolve, future assessments could dynamically link enteric emissions, manure handling, soil and tree C sequestration, and nutrient redistribution, enabling more targeted, system-level mitigation strategies. Under such frameworks, expanding perennial pasture cover, incorporating tree belts, enteric CH_4 emission reduction, and improving effluent reuse could collectively contribute to emission reductions, although their effectiveness will depend on management intensity, spatial scale, and regional context. Enhancing SOC through improved grazing management and organic amendments may provide more durable mitigation benefits than structural changes alone, particularly when combined with strategies that reduce emissions at their source. Ultimately, transitioning toward climate-smart dairy systems will require not only improved management practices, but also the development of tools capable of capturing the full complexity of carbon and nitrogen cycling at the whole-farm level.

8.8. Implications for Sustainable Dairy Management

From a management standpoint, the results of the present thesis indicate that emissions reductions in Australian dairy systems should target the most influential sources within each production system, as emission profiles differ markedly between confinement and pasture-based farms. In confinement farms, manure-related GHG emissions contribute ~31% of total emissions (20.6% from CH_4 and 10.4% from N_2O) and are 129% higher in intensity than in pasture-based systems (0.32 vs. 0.14 kg CO_2-eq/kg FPCM). These elevated emissions reflect the concentration and anaerobic storage of manure, creating clear opportunities for mitigation through improved effluent management. A range of manure management technologies offer substantial mitigation potential. Strategies such as anaerobic digestion with biogas capture and energy conversion, frequent slurry removal, acidification, and covered storage have all demonstrated large reductions in manure CH_4 and N_2O emissions. Literature indicates potential reductions of up to 29% in CH_4 and 23% in N_2O with anaerobic digesters, 55% in CH_4 and 41% in N_2O through frequent removal, and 74% in CH_4 and up to 55% in N_2O via acidification (Mohankumar Sajeev et al., 2018; Rotz, 2018). Emerging options like EcoPond® technology, which doses effluent ponds with polyferric sulphate and sulfuric acid, can achieve over 90% CH_4 reduction from ponds (Cameron and Di, 2021). Applied to the confinement farms in this study, such interventions could reduce whole-farm emissions by approximately 8–19% (e.g., approximately 8% from anaerobic digestion alone, up to approximately 19% from frequent removal or acidification targeting both gases), equating to a potential drop in milk emission intensity from 1.02 to approximately 0.83–0.94 kg CO_2-eq/kg FPCM, while generating renewable energy (e.g., biogas) and improved digestate for fertiliser. From a C-market perspective, improved effluent management in confinement systems could also generate substantial tradable abatement under Australia's Emissions Reduction Fund (ERF). Given that the confinement farms assessed in this study averaged 15,218 t CO_2-eq per year, the estimated 8–19% reduction in whole-farm GHG emissions achievable through manure management interventions would correspond to an abatement of approximately 1,200–2,900 t CO_2-eq per farm per year. At current ACCU spot prices of approximately A$35 per t CO_2-eq (CORE Markets, 2025), this would equate to potential revenues of approximately A$43,000–101,000 per farm per year, assuming full eligibility, verification, and crediting of emissions reductions. While actual returns would depend on capital costs, operating expenses, and regulatory requirements, these values illustrate that manure-focused mitigation in confinement systems could deliver economically meaningful climate benefits when supported by appropriate policy frameworks (Christie, 2019). Although these manure management technologies offer substantial mitigation potential, their applicability in Australia remains limited by the predominance of grazing-based systems, where infrastructure-dependent solutions like digesters, covered lagoons, and acidification are more suitable for confinement systems (currently ~20% of national milk production, albeit increasing; Dairy Australia, 2024). Adoption in confinement dairies requires incentives and supportive policies to overcome costs and implementation barriers.

In pasture-based systems, fertiliser-derived N_2O is the second-largest source of emissions after enteric CH_4, contributing approximately 12% of total farm GHG outputs. Improvements in fertiliser timing, precision application, and the use of nitrification inhibitors provide effective avenues for reducing these losses, with reported mitigation potentials ranging from 30% to 57% (De Klein and Eckard, 2008; Di and Cameron, 2016; Li et al., 2018). When applied realistically to the pasture-based farms examined in this study, such strategies could lower fertiliser-related N_2O emissions by 40–60%. This translates into an overall whole-farm emissions reduction of roughly 5–7% and a corresponding decrease in milk emission intensity from the current 1.07 kg CO_2-eq/kg FPCM to approximately 1.00–1.02 kg CO_2-eq/kg FPCM, with the added benefit of potentially enhancing pasture productivity. Moreover, integrating legumes can reduce the need for synthetic N fertilisers while supporting soil fertility (Ledgard et al., 2009). The chapter on soil further reinforce that maintaining permanent vegetation, reducing soil disturbance, expanding tree cover, and improving pasture quality are essential for sustaining soil C and nutrient stocks. Practices such as rotational grazing, and targeted manure redistribution can also help preserve soil structure and C content. Tree belts and riparian vegetation can also deliver co-benefits by sequestering C, enhancing biodiversity, and improving microclimatic conditions. These strategies align with the principles of climate-smart dairy farming, which seeks to increase productivity and resilience while lowering emissions intensity (Muscat et al., 2021). From a policy perspective, incorporating both emissions and sequestration metrics into C accounting frameworks would more accurately represent the environmental footprint of dairy systems. The modest but measurable C offsets from trees (1–6% in this study) indicate that expanding agroforestry in dairy regions could contribute to farm-level mitigation targets. Incentive mechanisms such as C credits for verified sequestration or emission reductions could accelerate adoption of such practices.

8.9. Limitations and Future Directions

This thesis provided valuable insights into GHG emissions, soil C dynamics, and nutritional strategies in Australian dairy systems; however, several limitations must be acknowledged. The GHG emissions assessment in Chapter 3 was based on a small sample size (n = 10), limiting the generalizability of findings across diverse agro-ecological zones, and soil C sequestration was not included. In addition, there are many confounding factors which do not allow separating the effect of climate, farming system, land use, soil parent material, and management. Furthermore, key parameters such as actual DMI and N excretion were not directly measured for all farms, introducing uncertainty into estimates of enteric CH_4 and manure-derived CH_4 and N_2O emissions. Similarly, the analysis of concentrate supplementation in Chapter 4 relied on predicted emissions from the Australian Dairy Carbon Calculator rather than direct measurements, underscoring the need for empirical validation. Future research should incorporate on-farm measurements and process-based models to capture site-specific variability and refine estimates of manure emissions, while examining interactions among concentrate use, N cycling, and soil carbon dynamics.

Soil sampling in Chapter 6, though extensive, was cross-sectional and geographically uneven, with pasture-based farms located in high-rainfall coastal regions and confinement farms inland. This introduces confounding factors such as soil type and climate. Longitudinal studies across multiple regions are needed to quantify sequestration potential and disentangle climatic from management effects. Future work should also include deeper sampling, microbial characterization, and root turnover assessments, alongside fractionation of SOC into mineral-associated and particulate pools to better understand carbon persistence. Investigating how grazing intensity, pasture diversity, and plant–microbe interactions influence C–N coupling will further refine mitigation strategies.

Low-cost CH_4 sensors offer promise for scalable monitoring but require advances in calibration, airflow correction, data filtering, and sensor placement (Chapter 5). Integrating machine learning for signal processing could enhance their reliability across different environments. The SLGA performed moderately well for SOC and TN at the farm scale, although its accuracy for P and sub-farm resolution was poor. Future work could incorporate local calibration datasets, proximal sensing technologies, and farm-level monitoring networks to improve spatial resolution and reduce bias, broadening SLGA's utility for carbon projects, fertiliser planning, and environmental risk assessment. Finally, future research should link continuous farm-level monitoring with process-based modelling to integrate animal performance, feed efficiency, manure handling, and soil C dynamics in real time. Including socio-economic analysis could help identifying adoption barriers and ensure that mitigation strategies align with farm profitability.

8.10. Conclusion

Collectively, the five chapters in the present thesis demonstrated that the environmental performance of dairy farming systems is heavily influenced by management practices and less so by production intensity. Confinement and pasture-based systems had similar emission intensities. However, SOC and nutrient stocks were highest under permanent pastures and tree areas, reinforcing the importance of maintaining permanent vegetations. The integration of land-based C sequestration with emission mitigation offers a practical pathway toward climate-resilient dairy production. Sustainable progress will depend on holistic strategies that link animal nutrition and genetics, manure management, and soil stewardship within coherent whole-farm systems. The most credible pathway to climate-smart dairying combines a reduction in enteric CH_4 production (e.g., using feed additives), optimal concentrate supplementation, targeted manure and fertiliser management, and soil-and-tree C stewardship under whole-farm, LCA-informed decision frameworks. This integration could help reduce emissions intensity, limit leakage across sources, and support profitability delivering resilient, lower-emission dairy systems for Australia and beyond.

8.11. References

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