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Mitigation of greenhouse gas emissions from dairy systems

Thesis presented by

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Author Declaration

This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism and intellectual property.

Marion Cantillon Date 7-11-25

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Abstract

One of the most significant challenges facing modern society is feeding the world's population while minimising agriculture's contribution to climate change. This challenge is particularly pronounced in dairy production, where products' carbon footprints and mitigation costs are high relative to those of other food products. The dairy sector is under growing pressure to lower greenhouse gas emissions while remaining economically viable.

This thesis uses a farm-level optimisation model designed to assist farm managers in making strategic decisions regarding mitigation measures. Several mitigation measures are evaluated both individually and as groups of measures. The optimisation model is developed as part of a broader integrated internal modelling framework consisting of two existing Teagasc models: the Moorepark dairy systems model and the Dairy Life Cycle Assessment model. The framework is applied to data from Ireland through the National Farm Survey, split into top, middle and bottom representative farms from a profitability perspective.

The mitigation measures modelled included animal productivity, grass production and utilisation, better reproductive performance, early compact calving, reduced crude protein, decreased fertiliser N, protected urea, white clover, slurry tank cover and low emission slurry spreading (LESS). Throughout the thesis, four scenarios are evaluated: the baseline scenario, a scenario with an emission ceiling, a scenario with an individual mitigation measure, and a scenario with two grouped mitigation measures (grassland grouped, animal productivity grouped).

The results show that grassland management achieved the most significant emissions reduction while maintaining a net margin close to the baseline. Animal productivity achieved more modest emission reductions. Across all groups, both emission ceilings (10% and 25%) reduced net margin on the farm and were the least desirable measures when modelled.

This thesis shows that mitigation measures can lower emissions while maintaining economic viability, offering a practical way to steer Ireland towards a more sustainable dairy sector.

Dissemination

Journal Publications

The following publications form part of the research presented in this thesis.

Publication Manuscript 1 (Chapter 4 – Published April 2024)

Cantillon, M., Hennessy, T., Amon, B., Dragoni, F., O'Brien, D., 2024. Mitigation of gaseous emissions from dairy livestock: A farm-level method to examine the financial implications. *Journal of Environmental Management*, 352, 119904.

Publication Manuscript 2 (Chapter 5 – Submitted 2024)

Cantillon, M., Tarim, S.A., Bradfield, T., Hennessy, T., and O'Brien, D. Optimising Dairy Farm Planning: A Mathematical Programming Approach to Balancing Profitability and Emission Targets. Submitted to *Smart Agricultural Technology*.

Publication Manuscript 3 (Chapter 6 – Submitted 2025)

Cantillon, M., Tarim, S.A., Bradfield, T., Hennessy, T., and O'Brien, D. Optimising Dairy Farm Planning with Mitigation Measures: A Modelled Scenario Comparison of an Emission ceiling, Grassland Management, and Animal Productivity on an Irish Dairy Farm. Submitted to the *Journal of Agricultural & Food Research*.

Working Papers (Chapter 7)

Cantillon, M., Tarim, S.A., Bradfield, T., Hennessy, T., and O'Brien, D. 2025. Optimising Dairy Farm Planning: A Mathematical Programming Approach to Balancing Profitability and Emission Targets.

Press Article

Moran, C. (2024) 'Top dairy farmers will struggle to meet climate targets – research', Irish Independent, 2 April. Available at: https://www.independent.ie/farming/news/top-dairy-farmers-will-struggle-to-meet-climate-targets-research/a320059404.html

Kennedy, J. (2025) 'Go on, girl: the women to watch in food and farming', Irish Farmers Journal, 5 March. Available at: https://www.farmersjournal.ie/food/news/go-on-girl-the-women-to-watch-in-food-and-farming-857609

Oral Presentations

- Cork University Business School Postgraduate Symposium (2022- 2024)
- The Agricultural Economics Society Annual Conference (27 June 2024)
- University College Cork Sustainability Showcase (7 June 2024)
- Launching future disruptive tech Summit (7-8 September 23)
- Dairy 4.0 Adopting Dairy Technology (27 June 2024)
- IFC AgTech UCD (20 September 2024)
- Thrive Global Impact Summit (7 November 2024)
- Agrinext Conference: Women in Agricultural Technology (13 November 2024)
- Responsible Innovation Conference, Belfast (29 November 2024)

Conference Papers

Cantillon, M., Tarim, A., Hennessy, T., O'Brien, D., 2024. Optimising dairy farm planning: Balancing profitability and sustainability through a mathematical model on Cplex. In: Proceedings of the Agricultural Economics Society of Ireland Annual Conference, Ulster University, Belfast, UK, 25th-27th June 2024, pp. 37-39.

Cantillon, M., Chatzichristou, A.A., Herron, J., Wallace, M., Necpalova, M., Osborne, B., Tarim, A., Hennessy, T., O'Brien, D., 2024. Farm-level decision support tool to enhance economic and environmental performance in an Irish context. In: Proceedings of the Teagasc Carbon Conference - Counting Carbon: Science and Practice. Teagasc, Ashtown Research Centre, Dublin, 20th June 2024, pp. 30-32.

Open Day & Farm walks

Cantillon, M., Tarim, A., Bradfield, T., Hennessy, T. and O'Brien, D. 2025 'Dairy optimisation – balancing profitability with emission targets', Moorepark 2025 Open Day Book, Teagasc, p. 352. Available at:https://teagasc.ie/wp-content/uploads/uploads/Moorepark-2025-Open-Day-Book.pdf

Cantillon, M., Hennessy, T., Amon, B., Dragoni, F., O'Brien, D., 2024. Mitigation of gaseous emissions from livestock: A farm-level method to examine the financial implications. In: Farming for a Better Future Open Day: Resilient and sustainable farming systems open day. Teagasc, Johnstown Castle, Environment Research Centre, Co. Wexford, 16th July 2024. p102-103.

Poster Presentations

- CEJA and Macra Conference (25th January 2024) -Poster
- ISCRAES conference (25th-28th June 2024) – Poster Presentation
- AES Conference (17-21 March 2024)- Poster presentation
- CUBS Symposium (April 22/23/24/25)- Poster presentation
- AESI conference (18th June 2024)- Paper Presentation
- UCC SDG research showcase (4th June 2025) -Paper presentation

1 Introduction

1.1 Introduction

The agrifood system emitted 16.2 Gt CO_2eq globally in 2022 (FAO, 2024). Agrifood systems emissions primarily originated from crop and livestock activities, accounting for 7.8 Gt CO_2eq globally (48%). Based on analysis by the OECD-FAO (2021), over the next ten years, global emissions from agriculture are expected to rise by 4%, with livestock accounting for over 80%. Combatting climate change means that more needs to be done to reduce the emissions from the agricultural sector, especially those from livestock.

Agriculture is a significant contributor to greenhouse gas (GHG) emissions, particularly methane (CH_4), nitrous oxide (N_2O), and carbon dioxide (CO_2). Globally, livestock and fisheries are responsible for 31% of emissions from food, with the predominant share arising from ruminant animals (Ritchie, 2019). To put the consequences of climate change into perspective, a temperature increase as significant as 1.5-2°C is associated with extreme weather events that impact both natural and human systems, such as marine ecosystems, agriculture, water supply, infrastructure, and socio-economic systems. To support the green transition, the Intergovernmental Panel on Climate Change (IPCC) was set up to monitor and report on the scientific, technical and socio-economic knowledge of climate change to reduce climate change risk and slow down the rate of climate change globally. More than 100 countries had endorsed the Paris Agreement, which commits them to a maximum global warming of 2 degrees Celsius above pre-industrial levels. This agreement heightened scrutiny on the role that all sectors can play in climate change mitigation.

As a sector, agriculture is unique, being both a contributor to climate change and considerably exposed to the effects of climate change. To reduce the adverse effects of climate change on their operations, farmers needed to cut emissions and lessen their role in climate change. Additionally, they had to adapt their farm systems to increase resilience against the effects of climate change. Simultaneously, farmers must ensure that their farm businesses remain economically viable. As such, farmers face many interconnected and complex decisions, many of which involve trade-offs, while no single approach will successfully address climate change. This thesis considered the multiple options available to farmers to tackle climate change, while maintaining their economic viability, through the cost-benefit of mitigation measures for dairy farmers and developing an optimisation model to be used in an integrated internal modelling framework to assist farmers and advisors with complex mitigation decisions.

1.2 Thesis Statement

This thesis aims to evaluate the financial and environmental impacts of GHG mitigation measures at the farm level for Irish dairy farms. It introduces a new methodology approach that integrates marginal abatement cost curves (MACCs), existing Teagasc bioeconomic and life cycle assessment models, and linear programming (LP) optimisation into one single integrated internal modelling framework. The integrated internal modelling framework refers specifically to the programming (back-end) component of the decision support system described throughout this thesis.

The main goal is to determine the best farm plan that combines environmental sustainability with economic profitability, primarily by maximising net margin while adhering to emission ceilings. The integrated internal modelling framework is composed of farm-level parameters and assesses the impact of mitigation measures and emission ceilings. Through this evaluation of mitigation measures and emission ceilings across representative Irish dairy farms, this research demonstrated how tailored, scenario-specific plans could support both net margins and reduced emissions by offering a practical solution to guide customised farm-level decision-making on sustainability and financial viability. This research does not develop a complete decision support system with a user interface. Rather, it develops and formalises the optimisation backend that can be embedded within an advisory decision support system. The purpose of this research is to support Irish dairy farmers and advisors in ensuring their farms remain profitable and sustainable. Policymakers and researchers may also benefit from the framework, as it provides a transparent method for assessing the economic implications of climate policy at the farm level.

1.3 Thesis Objective and Thesis Overview

This thesis aimed to determine the optimal farm plan that balances economic profitability with environmental sustainability for typical Irish dairy farms. This research addresses the following questions:

1. What is the effect of farm type on the financial costs associated with mitigating GHG emissions from dairy production using farm-level MACC analysis?

2. What decision-support tools are currently available to farmers and advisors at the farm level, for mitigation planning?
3. How does the optimal farm plan for the middle representative dairy farm change across four scenarios when evaluated using an integrated internal modelling framework?
4. How does the optimal farm plan for all representative dairy farms reveal differences in mitigation potential and economic impact across farm types?

1.4 Structure of the Thesis

These four questions were addressed throughout this thesis in the chapters. Initially, an overview and context were provided for the agriculture sector as a whole, broadly focusing on agricultural GHG emissions, marginal abatement cost curve, mitigation measures, decision support systems, and tailored approaches to abatement in Chapter 2.

Chapter 3 outlined the research design and implementation of data used throughout this thesis and described the scenarios used for the representative farms.

Chapter 4 conducted and assessed a Marginal Abatement Cost Curve. The MACC aims to provide a quantitative framework for assessing the opportunities and costs of reducing GHG emissions. It is described in more detail in Chapter 2.2. In Chapter 4, a farm-level MACC is analysed across various representative farms, illustrating the variability in the MACC and clarifying why a more tailored approach was essential.

This continued into Chapter 5, which examined a selection of decision support systems beyond the MACC that advise farmers. This review emphasised the variation in the available systems and their differing objectives, highlighting the gap for a novel optimisation model to address the outlined research question. Chapter 5 offered a comprehensive overview of the Linear programming model, covering all assumptions, parameters, and variables used in its development.

Chapter 6 covered the application of the model within the integrated internal modelling framework. This framework includes the Moorepark Dairy Systems Model (MDSM), the Teagasc Dairy Life Cycle Assessment (LCA) model, and the LP optimisation model. A representative Irish farm was evaluated under three scenarios: an emission ceiling, the use of grassland mitigation measures, and grouped animal productivity measures. The optimal farm plan for each scenario was presented.

Lastly, Chapter 7 further application of the integrated internal modelling framework by applying it across all three representative farms under four scenarios. These scenarios included an emission ceiling of 10%, an emission ceiling of 25%, implementing all mitigation measures as separate initiatives, and two grouped mitigation measures: animal productivity and grassland measures. The optimal farm plan that balances economic viability and environmental sustainability was assessed. Chapter 8 synthesises all the findings and concludes the thesis.

This research was important in addressing climate change as it provided an integrated internal modelling framework designed explicitly for farm-level practices analysis. This framework will enable farmers and farm advisors to select the most suitable measures for their farm's economic and environmental performance while also guiding policy. While numerous decision-support systems exist for farmers to evaluate their emissions and calculate GHG reporting, few facilitate economic analysis, and even fewer support farm optimisation. This is the gap the integrated internal modelling framework aims to fill.

This thesis is structured as a publication-based thesis. Chapters four to seven consist of individual research papers, each addressing specific research questions outlined in Table 1.1. Each paper focuses on one of these questions. Chapters one to three provide the context, literature review, and methods, while Chapter eight contains the discussion and then concludes the thesis.

Table 1.1 Thesis structure and research questions

Chapters	Output
Chapter 1-3	Context building
Chapter 4	Research question 1
Chapter 5	Research question 2
Chapter 6	Research question 3
Chapter 7	Research question 4
Chapter 8	Discussion and conclusion

Chapter five describes the formation of the LP model and its application in the integrated internal modelling framework. To contextualise where the integrated internal modelling framework fits, the following chapters examine the policy environment, current decision support systems, and optimisation approaches that underpin this methodology.

2 Context

This Chapter outlines the background context of the agricultural sector in Ireland, broadly focusing on agriculture's contribution to GHG emissions, the policy requirements to reduce emissions, mitigation measures, MACC, and decision support systems that support farmers in making these reductions. The Chapter also presents the theoretical framework for the research.

The Chapter describes the Irish agricultural sector and the broader climate policy context. Following this, an introduction to the MACC, one of the key tools used in policy for assessing the cost-effectiveness of abatement options, is presented. This Chapter reviews existing decision support systems used to advise and guide farmers and advisors in farm management decisions. A discussion of mitigation measures relevant to the Irish agricultural sector follows this. Finally, the Chapter outlines the theoretical framework that links these sections and provides the basis for the research. The Chapter concludes by outlining the primary research questions explored in this thesis.

2.1 Irish Agricultural Sector

Agriculture is an integral part of Ireland’s rural economy, supporting livelihoods, shaping the landscape, and exporting produce. The agricultural sector has been a key contributor to the economy. At constant prices, agriculture, forestry, and fishing contributed €1.05 billion to GDP in Q1 2025 and €1.02 billion in Q2 2025, accounting for about 1.6% of GDP (CSO, 2025). These national statistics emphasise the importance of agriculture, not only for rural employment and regional growth but also for the expansion of Ireland’s export sector.

Agriculture remains one of Ireland's largest and oldest exporting sectors. Its products are traded from every county in Ireland to over 190 countries worldwide (DAFM,2025). In 2024, agri-food exports hit a new high of €19 billion, representing 8.6% of Ireland's total merchandise exports (DAFM, 2025). The sector is very export-focused, with as much as 90% of beef, sheepmeat, and dairy products exported yearly. Additionally, fresh or chilled beef, butter, cheese, and Irish whiskey exports all surpass €1 billion in value (CSO, 2025).

Agriculture significantly contributes to Ireland’s GHG emissions, positioning it as a key area for climate mitigation and sustainability measures.

2.1.1 Employment

According to the CSO Farm Structure Survey, in 2023, around 299,725 people worked directly in Irish agriculture (including part-time and seasonal workers), with a greater number working in agri-food employment (CSO, 2023). Employment in the sector remains regionally significant and culturally important to rural Ireland. The DAFM (2025) Factsheet confirms that in 2024, there were 169,300 people employed in agri-food as their main occupation, representing 6.1% of total national employment, with a much higher share in rural and coastal regions. When part-time and seasonal workers are included, employment rises to nearly 300,000 people working on farms (DAFM,2025).

2.1.2 Output of the Sector

The main farm types in Ireland are dairy, cattle rearing, cattle, sheep, tillage, and mixed livestock enterprises, as shown in the preliminary results of the National Farm Survey (NFS). Specialist dairy farms account for 17% (15,131 farms), cattle rearing is 18% (15,765 farms), cattle is 40% (35,283 farms), sheep is 16% (14,013 farms), and tillage is 7% (6,229 farms), with mixed livestock accounting for the remainder (Dillon et al.,2025).

Economically, there is considerable variation among systems. In 2024, dairy farms had the highest average family farm income at €108,189, mainly due to better milk prices and lower input costs. Cattle rearing farms averaged €13,547, while cattle finishing and other farms reported €18,101. Sheep farms achieved €27,796 on average, reflecting higher lamb prices, while tillage farms earned €38,685, benefiting from higher grain prices (Dillon et al.,2025). These incomes demonstrate the financial diversity of the Irish agriculture sector.

Dairy is the most economically important subsector, with higher net margins and a significant role in exports and GHG emissions. Therefore, this thesis focuses solely on dairy farms, Ireland's most commercially active and environmentally impactful farm type.

2.1.3 Agricultural Greenhouse Gas Emissions

Food production accounts for 26% of total GHG emissions globally, with livestock and fisheries accounting for 31% of emissions within this category (Ritchie, 2019). Ruminant systems, particularly beef and dairy, are the primary sources of emissions due to enteric fermentation and fertiliser-rich feed production. Agriculture accounts for 37.7% of Ireland's total GHG emissions, with ruminant systems a major contributor (EPA, 2025). The three primary sources of agricultural GHGs are methane (CH_4), nitrous oxide (N_2O) and carbon dioxide (CO_2). Over the past decade, research has primarily concentrated on quantifying and tracking these gases, although many studies tend to distinguish the physical effects of climate change from mitigation measures, instead of combining the two (Gornall et al.,2010; Jebari et al.,2023; Kamyab et al.,2023; Yuan et al.,2024). Agriculture is in a vital position in the climate change crisis, as the industry has the potential to reduce emissions, increase removals and support other sectors.

In addition to contributing to climate change, agriculture, dependent on natural resources, is also vulnerable to climate change-induced uncertainty, especially extreme weather events like flooding and drought. Changes in land and water systems are key drivers of climate risk, with farming systems facing increasing pressure from temperature changes, water shortages, soil deterioration, pests, diseases, and animal welfare issues. The impact of climate change is extensive, but the far-reaching repercussions on the agricultural sector are now plainly evident (Arora, 2019).

It is estimated that for every 1 °C warming, wheat yields fall by 3%, maize by 7%, and rice yields by 4% (Gornall et al,2010; Yuan et al,2020). Climate change increases the frequency of droughts, the demand for irrigation, and pest pressure (Kalra et al, 2020; Webb et al,2017; Shahzad et al,2021; Skendžić et al,2021). Soil organic carbon depletion further exacerbates the problem by contributing to rising atmospheric CO_2 levels (García-Palacios,2021; Kamyab et al,2023)

2.1.4 Sources and Dynamics of Agricultural Greenhouse Gas Emissions

The agriculture predominantly produces three gases: CO_2, CH4, and N_2O, each with distinct lifetimes, effects, and sources.

At the farm level, methane is primarily generated through enteric fermentation in ruminant livestock and manure management. Nitrous oxide results from fertiliser application, manure, and soil systems. Carbon dioxide is associated with land use change and soil carbon dynamics. Carbon dioxide is typically reported using carbon dioxide equivalents (CO_2eq), a metric aggregating different GHGs based on their global warming potential. While CO_2eq is useful for comparison, this aggregation may disregard the difference between the gases and their lifetimes, which could be helpful in designing targeted mitigation planning (Lynch et al.,2021).

The gases differ in atmospheric lifetime and global warming potential (GWP). CH_4 has a lifetime of around 12 years and a GWP100 estimated at 28. N_2O has a lifetime of 114 years and a GWP100 of 265. CO_2 is on the century scale. Each of the gases follows its distinct atmospheric pathway. These differences assist in gas-specific prioritisation within mitigation measures.

The key guidelines regarding emission factors and standardised methods are the IPCC guidelines and the National GHG Inventory. IPCC has a three-tiered approach. Tier 1 is the most basic method and uses default emission factors. Tier 2 builds on Tier 1 with more detail by incorporating country-specific emission factors. In contrast, Tier 3 provides the most detailed information using country-specific figures where possible, enhancing accuracy in national inventory reporting (Amaro,2024).

2.1.5 Policy, Governance and Social Policy

International and EU-level frameworks, such as the Paris Agreement and the EU Effort Sharing Regulation, have set binding emission reduction targets that Ireland must meet partly through changes in agriculture. National policies, in Ireland, containing the Climate Action Plan and the Climate Action and Low Carbon Development Bill, translate these obligations into sector-specific targets. At the national level, Ireland must achieve a 25% reduction in agricultural emissions by 2030. In practice, Ireland's 25% target is implemented through two carbon budgets: an indicative 10% reduction for agriculture from 2021 to 2025, and 25% from 2026 to 2030. These targets are incorporated into the scenario analysis in later chapters. These policy instruments together create both pressure and opportunity for the agricultural sector.

While these targets increase regulatory pressure on farmers and the agri-food industry, instruments like the Common Agricultural Policy (CAP) offer financial support and incentives to adopt more sustainable practices. Research by the Climate Council examines how farm-level behavioural changes contribute to climate resilience, highlighting the importance of adaptive capacity in adopting sustainable practices (Balaine et al.,2025). This policy environment highlights the urgent need for practical, economically viable farm-level solutions that align with environmental and productivity goals.

The following Table 2.1 outlines the policies that Irish agriculture must adhere to. It illustrates a snapshot of the policy environment with various instruments across different levels

(European or National), key targets, and the current legal status. This table shows the numerous actors and targets involved in the agricultural policy framework.

Table 2.1 Policy Framework. Source: Author's own contribution

Policy Instrument	Responsible body	Emission target	Status
UNFCCC & Paris Agreement	United Nations /National Governments	Limiting global temperature to below 2 °C, aiming for 1.5 °C	Active (International Treaty)
European Climate Law	European Union	Climate neutrality by 2050, an intermediate target to reduce GHG emissions by 55% by 2030	Legally Binding
European Union Effort Sharing Regulation	European Union/ National Governments	Aimed to set legally binding greenhouse gas emission targets for all Member States from 2021 to 2030	Implemented
National Carbon Budgets	Climate Change Advisory Council/Government of Ireland	Two five-year carbon budgets are set to reduce emissions by 51% by 2030	Legally Binding / Active
Climate Action and Low-Carbon development (amendment) Act	Government of Ireland/ Department of the Environment, Climate and Communications	Establishes legal obligation for carbon budgets and sectoral ceilings	Legally Binding
Climate Action and Low-Carbon Development Bill	Government of Ireland/ Climate Change Advisory Council	Legally binding 51% reduction in overall emissions by 2030; climate neutrality by 2050	Enacted
Ireland's Climate Action Plan	Government of Ireland (Department of Environment, Climate and Communications)	Sectoral targets, including a 25% reduction in agricultural emissions by 2030	Active (Policy in Implementation)

Numerous actors support the agricultural sector in Ireland in achieving the environmental targets set out in Table 2.1. Figure 2.1 offers a schematic overview of the range of actors and the policy framework.

Starting at the European level, the European Commission plays a key role in developing and drafting European policies. These policies are then adapted to the Irish context through two central government departments: the Department of Agriculture, Food and Marine (DAFM) and the Department of Housing, Planning and Local Government (DHPLG). From there, the policy is further divided among four independent bodies responsible for implementation, monitoring, or advancing the policy. These bodies are Bord Bia, co-operatives and agribusinesses, the Environmental Protection Agency (EPA), and research bodies such as Teagasc, the Irish Agricultural and Food Authority. At the local level, various actors govern and support policy through market, national, political, and social incentives. Additionally, a range of entities monitor and establish guidelines at this level, ultimately influencing farmers directly at the farm level.

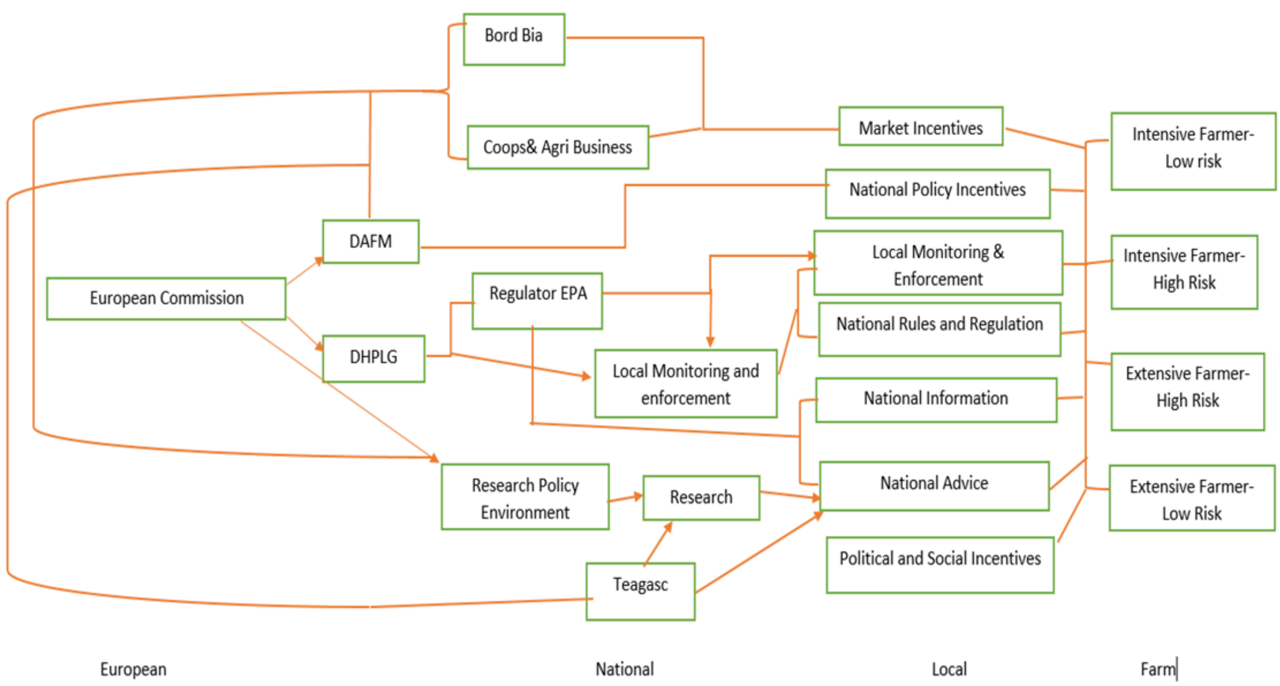

Figure 2.1 Policy and legal framework. Summary of international EU national policy instruments relevant to Irish agricultural emissions and farm-level mitigation. Sources: Author's own contribution.

2.1.6 The Role of Mitigation in Achieving Climate Targets

The policy targets for GHG reduction in the Irish agriculture sector are challenging and can only be achieved by adopting mitigation measures. Mitigation refers to actions taken within the farming and food system to reduce or prevent GHG emissions, or to enhance the removal (sequestration) of GHGs from the atmosphere. Mitigation measures in agriculture range from livestock management practices (such as more compact calving and improved breeding) to manure management, grassland management, and afforestation. These measures vary widely in terms of cost, method, and potential to reduce emissions. Mitigation measures also differ in ease of adoption, financial implications, and the level of abatement that can be delivered. The MACC is a key tool for informing mitigation decisions. It offers a structured approach to evaluating mitigation options.

The MACC aims to provide a quantitative framework for assessing the opportunities and costs of reducing GHG emissions by the non-ETS industries. It is a tool to show and compare the cost-effectiveness and potential impact of different mitigation measures. The X-axis (horizontal) on the curve represents the total potential emissions reduction (e.g. tonnes of CO_2 equivalent reduced per year) from other measures, stacked side by side. While the Y-axis (vertical) shows the marginal cost of reducing emissions (e.g. € per tonne of CO_2 equivalent abated). This indicates whether a measure saves money (negative cost) or requires extra spending (positive cost). Each bar on the curve represents a mitigation measure (such as improved fertiliser use, dietary additives for cattle, or afforestation). The width of the bar reflects the volume of emissions it could reduce; the height shows the cost per tonne of abatement.

The first MACC for Ireland, the Teagasc MACC, was developed in 2012 (Teagasc, 2012) using data on Irish Agriculture and reported in the National Climate Policy Development Consultation. A revised MACC was published in 2019 (Lanigan et al., 2019), with revisions in 2020 and 2023 (Lanigan et al., 2020; 2023). Measures were broken down into three separate groups: agricultural mitigation, land use mitigation, and energy mitigation. The revised MACC incorporated a range of mitigation measures in a top-down flow inventory approach based on the IPCC Good Practice Guidelines (IPCC, 2014). This approach is comparable to methods used for the EPA's national inventories. Measures with a net cost of zero (cost negative) are dominated by efficiency measures.

Several nations have created national agricultural MACCs in the last ten years. While these MACCs have unquestionably served as a catalyst for the sharing of scientific and policy knowledge, they have also served to highlight several restrictions and limits. Several approaches to developing MACCs and analysing GHG reduction activities can be used, with the methodology chosen depending on the assessment purpose, emission types, costs requiring calculation and available information (Isacs et al., 2016).

2.2 MACC types

There are three main types of MACC models one can use in evaluating mitigation in Agriculture:

1. Supply side (micro-economic model)
2. Equilibrium models
3. Engineering cost methods

The supply-side model encompasses the actions and behaviour of representative farmers who try to maximise their net margin under certain technological and economic limitations. The MACCs produced from these models rely on input and output costs and a specific technology.

Equilibrium models include a description of the demand for agricultural products, showing that the introduction of a mitigation measure will have both a direct effect on the supply side and an indirect effect by changing the equilibrium prices. Equilibrium models can better analyse the impact of a mitigation measure.

The most common model in the literature is the engineering technique used to assess abatement and cost. It gathers all the technical and scientific data on mitigation measures to determine the most cost-effective way to reduce emissions within a given emissions pricing. The data for each mitigation option comprises the mitigation potential per unit, the implementation rate, and the total application cost. Then, a break-even point is determined as the emission price at which a specific option becomes profitable. (Vermont and De Cara, 2010)

The Teagasc MACC, developed for the Irish situation, uses the engineering methodology and outlines the measures that are nationally cost-effective, cost-neutral, and cost-prohibited. For illustrative purposes, Figure 2.2 shows scenario one (the base case) under pathway one (adoption rates of 2018) (Lanigan et al.,2023).

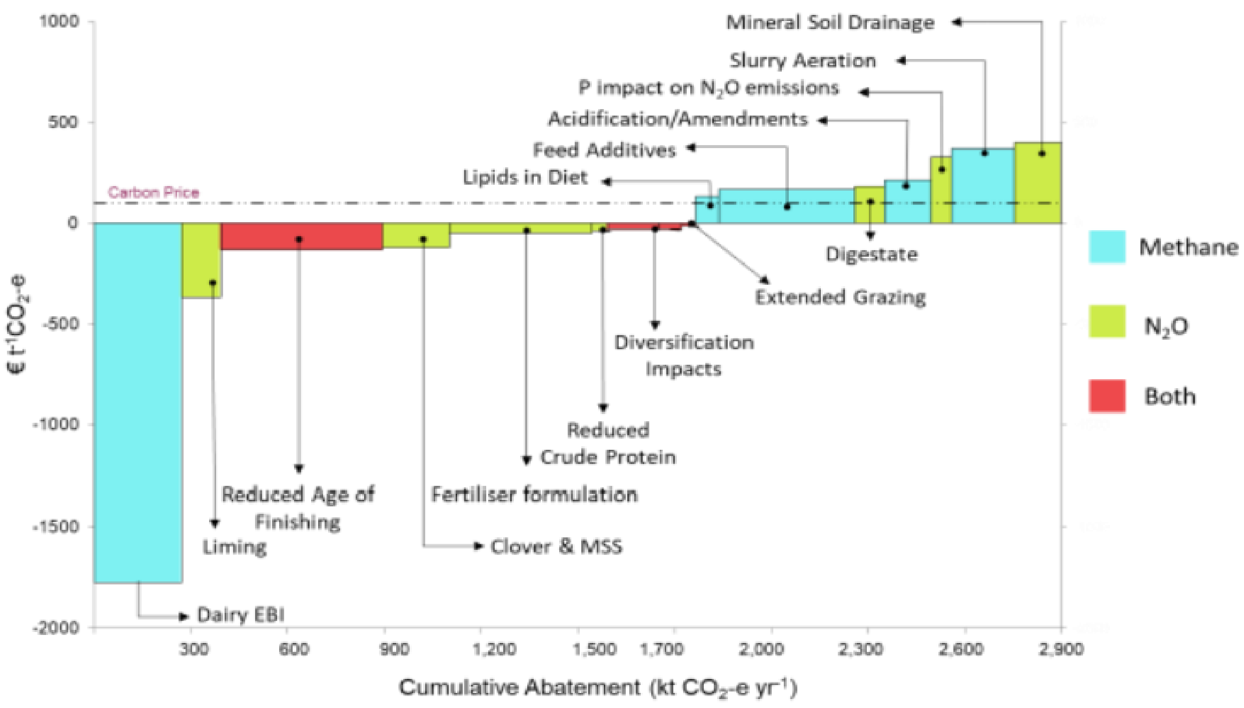

Figure 2.2 Marginal Abatement Cost Curve for agriculture measures under Scenario 1, with Pathway Source: taken from Lanigan et al. (2023), presents the Marginal Abatement Cost Curve (MACC) for agricultural mitigation measures under Scenario 1, illustrating the maximum annual abatement potential by 2030 at a carbon price of €100 per tonne of CO_2.

These results show the environmental and economic effects of various mitigation measures. The MACC analysis reveals that seven measures are cost-effective and seven are cost-neutral. This information is valuable for policy and national guidance. Most MACCs provide the abatement potential related to the boundaries of agricultural categories in the national inventories as national policy tools and as part of an economy-wide evaluation. This means that MACCs can be geographically and institutionally bound. MACCs require a wide range of data from the scientific and social sciences, whilst covering a vast array of multidisciplinary fields. Data limitations and the need to make assumptions complicate future mitigation projections inexorably (Kesicki et al., 2012). Transparency is vital as it allows for model modifications and inspections.

Moran et al. (2011) illustrated the advantages of creating a framework for the review of MACCs. They concluded that three variables must be deduced from each study's findings to calculate its potential GHG mitigation measure:

- The ability to reduce emissions should be identified/quantified,
- the total amount of emissions to which the measures apply (applicable and adopted),
- the cost of putting the measure into action.

These constraints emphasise the importance of adapting the MACC methodologies to the farm level, where management differences significantly affect costs and abatement potential. These constraints support moving from national MACCs to farm-level MACCs and eventually to prescriptive optimisation (Chapter 5).

2.2.1 Farm-Level MACC

While the MACC provides valuable information to farmers on the mitigation measures they may adopt, the national costs and benefits reported in the MACC are likely to differ across different farm types. Moran et al. (2011) argue that there is merit in deriving more regional and farm-specific MACCs to represent the variability in the abatement potential and costs. Chapter 4 of this thesis discusses the value of developing farm-level MACCs, informed by the national MACC and presents a methodology for doing so.

The whole farm approach is a valuable tool for assessing GHG mitigation measures as it considers the impacts on other environmental outcomes. For instance, Schils et al. (2005) focused only on nitrate leaching and ammonia volatilisation. Still, their work highlighted that using a single mitigation measure on the farm can influence all emissions due to the complex interlinkages between the GHGs.

Nationally, MACCs are constructed using sectoral averages, assumptions, and aggregated data, which are helpful for policy design and monitoring. However, the aggregated curves often mask the variation at the farm level. In contrast, farm-level MACCs evaluate the economic and environmental elements specific to a given farm and system. In this thesis, representative dairy farms were selected from the Teagasc National Farm survey, which provides detailed farm-level data on production, financial performance, and emissions.

The complexities of environmental trade-offs and complementarities can be considered using a farm-level MACC. While the IPCC inventory approach (national MACC) is used to document a country’s progress in reducing GHG emissions, it is not the most appropriate way to measure, inform or incentivise change at the farm level. On the other hand, a farm-level MACC may be utilised to investigate mitigation measures, given the particular characteristics of a farm. While both approaches have advantages and disadvantages, efforts to improve farm management and achieve emission reductions at the farm level can best be motivated by a farm-level MACC. The methodology described in Schils et al. (2005) could provide a framework for a comprehensive farm-wide and complete accounting approach to mitigation measures. Ogunpaimo et al. (2024) show that farm-level MACCs vary considerably across Irish sheep and dairy types, highlighting the importance of developing tailored mitigation measures. In Chapter 4, a farm-level MACC for dairy farms in Ireland is developed with a range of mitigation measures.

While MACCs can provide valuable insights into the relative cost-effectiveness and mitigation potential of different national and farm-level measures, they do not constitute a comprehensive decision-support framework. Farmers operate within complex production systems where decisions are influenced by a wide range of interrelated factors, including farm enterprise type, biophysical conditions, labour availability, managerial capacity, market signals, and evolving policy or regulatory requirements. The interaction of these factors creates significant heterogeneity in both the feasibility and attractiveness of mitigation options at the farm level. Consequently, reliance on the MACC alone risks oversimplifying decision-making contexts. More sophisticated, farm-specific decision-support systems are therefore required to account for this complexity and to assist farmers in aligning mitigation measures with both economic and environmental objectives. The following section discusses decision support systems and reviews some already available to farmers.

2.3 Decision Support Systems (DSSs)

Decision-support systems (DSSs) provide farmers with a valuable evidence-based decision-making framework to improve productivity and environmental outcomes. DSSs are often developed and designed by local stakeholders and tend to represent their national system by utilising local data. Most DSSs are primarily descriptive tools, such as calculators and scenario reports, rather than prescriptive tools that recommend specific courses of action.

DSSs were primarily developed to assist farmers with production and financial decision-making, such as the quantity of inputs used, the selection of enterprises, and the timing of sales transactions. In recent years, DSSs have been developed and adapted to consider environmental factors, and many now address the need for managing and monitoring mitigation measures (Crosson et al., 2011; Rawnsley et al., 2016).

2.3.1 Development of a back-end DSS

Several reviews have assessed DSSs and have considered their functionality, sustainability principles, usability and influences (De Olde et al., 2016; Rose et al., 2016; Arulnathan et al., 2020; MacPherson et al., 2020; Alexandropoulos et al.,2023; Taramuel-Taramuel et al., 2023). Ahumada and Villalobos (2009) developed a framework for classifying DSS under two main headings: decision scope (tactical, strategic, operational) and modelling approach (deterministic, stochastic).

Decision support systems (DSS) faced significant criticism in the early 2000s. McCown (2002) noted that DSS developed by researchers and academics to enhance farm management were often poorly received on farms, as many family farmers resisted systems they perceived as undermining or bypassing their own decision-making processes. To combat this criticism in DSS development, the idea of co-created models emerged with multiple stakeholders, actors, and users. The results and outputs are shared as a form of social learning and community benefit. Jakku et al. (2010) and McCown et al. (2009) described a conceptual framework for this approach and noted that, despite the theoretical value, their execution can be very costly and may involve competing objectives among many stakeholders. Building on this work, Hochman (2011) recommends aligning with farmers' natural decision-making processes and designing the system to accommodate their needs. The benefits to the users are to explore various options that suit them and provide support for a broader network of advisors, consultants, researchers, and marketers.

Alexandropoulos et al. (2023) reviewed thirteen commonly used DSSs from a user-friendliness perspective. Although most offer sufficient information to support their use, only four are suitable for inexperienced users, and stakeholder involvement in their development remains limited. This review highlighted broader weaknesses across DSSs, such as discrepancies in estimation methodologies and variations in results. Alexandropoulos et al. (2023) stressed the importance of DSSs in supporting farmers to meet the EU policy expectations for the agricultural sector. This review provides both a dataset of thirteen widely cited DSSs that were evaluated for their usability, which plays a vital role in adoption (Shibl et al., 2013; Akaka et al., 2024) and a relevant starting point for the DSS evaluation in this thesis.

Throughout this thesis, the Teagasc Decision Support System (DSS) is used as a base and refers to the suite of advisory and analytical tools developed by Teagasc to support farm-level decision-making in Ireland. These include production, financial, and environmental assessment tools such as the Moorepark Dairy Systems Model (MDSM) and the Teagasc Dairy Life Cycle Assessment (LCA) model, which are widely used in advisory and research contexts (Shalloo et al., 2004; Teagasc, 2019; Teagasc & Bord Bia, 2019).

While the literature on DSS development emphasises user interfaces, stakeholder engagement, and co-creation processes, the focus of this thesis is not the development of a full decision support interface. Instead, it concentrates on strengthening the internal optimisation architecture that could underpin such systems. By enhancing the backend modelling capabilities, the research contributes to the technical foundation upon which advisory DSS platforms may be built

2.3.2 Framework for Extended Review

This thesis further analyses the thirteen DSSs reviewed by Alexandropoulos et al. (2023) using an approach developed by Ahumada and Villalobos (2009) and initially applied to the supply chain literature. The decision to build on Alexandropoulos et al.'s (2023) selection was made because the DSSs were widely referenced in the literature.

The Ahumada and Villalobos (2009) framework is used to evaluate the thirteen DSSs under three main headings: scope, agriculture output, and modelling approach. For the purposes of this research, an additional heading was introduced: Environmental. This new category assesses the DSSs' environmental analysis under three main headings: scenario analysis, simulation, and calculator. The complete analysis of this extended review is described in Chapter 5.2.1, with the high-level findings presented in the next section.

2.3.3 Findings of the Extended Review

Of the 13 DSS reviewed, most were deterministic calculators or scenario simulators. Twelve models used deterministic reporting structures, and none incorporated stochastic optimisation. Only Farmscoper employed a linear programming (LP) approach, although its objective focused on minimising emissions and pollutant losses through predefined mitigation measures rather than maximising farm net margin. The remaining models, Cool Farm Tool, KSNL, SMART, RISE, BEK, Gleam, CAP 2'ER, Farm AC, Ag Balance, HOLOS, and Teagasc Moorepark Dairy Model & Dairy LCA, primarily function as static calculators or scenario/simulator tools, without any built-in optimisation engine to generate farm-specific, net margin-maximising plans under environmental constraints. Farmscoper is the only example from the DSS reviewed in Chapter Five that applied an LP element and optimised to minimise emissions. The methodology used in Farmscoper incorporates mitigation measures, including detailed physical and technical information and cost estimates. However, the system is structured to minimise emissions rather than to optimise farm profitability under an emission constraint. As such, there is a need for optimisation models that can support farmers in maximising net margin while minimising emissions, hence the latter focus of this thesis.

The extended review revealed that few DSSs were designed to optimise farm income while satisfying an emission ceiling. This creates a gap for an LP model that integrates mitigation measures with optimised farm economics, especially for the Irish agricultural sector. Addressing this gap requires developing an optimisation-based internal modelling framework that could support decision support systems that help farmers balance profitability with emissions reductions.

As part of the thirteen DSS review, two were built explicitly for the Irish agricultural sector: The Carbon Navigator for Dairy and the Carbon Navigator for Beef, which are part of the Teagasc DSS. Building on what is already available, this thesis uses the Dairy Carbon Navigator as a point of reference and core element in the integrated internal model framework. This review highlights the need for an optimisation-based approach to farm-level planning that balances profitability and emissions. To address this question, the following section outlines the development of the linear programming optimisation model that forms the core backend component of the integrated internal modelling framework that forms a core contribution of this thesis.

2.4 Optimisation at Farm Level

Decision Support Systems (DSS) and Whole-Farm Optimisation Models (WFOM) serve distinct purposes within farm management. DSS typically provide descriptive outputs, benchmarking tools, or scenario simulations that support farmer decision-making without prescribing an optimal solution. In contrast, WFOMs are prescriptive mathematical models that determine the optimal allocation of farm resources subject to defined objectives and constraints.

The research presented in this thesis develops a whole-farm optimisation model embedded within an integrated internal modelling framework. This approach is appropriate given the overall objective of identifying optimal farm plans that maximise net margin while satisfying greenhouse gas emission constraints, rather than merely simulating alternative management scenarios.

Optimisation modelling has been applied across multiple stages of the agri-food supply chain. In a systematic review of dairy supply chain optimisation, Malik et al. (2022) reported that 67% of studies focus on production and planning optimisation, 29% on inventory management, and only 15% address complete supply chain optimisation. Despite the growth of machine learning and artificial intelligence methods, mathematical modelling-based techniques remain dominant (Malik et al., 2022).

While many decision-support systems have been developed to support farm decision-making and monitor environmental performance as described above, to date, most DSS focus on emissions reporting, scenario analysis, or simulation approaches. Only a few existing models apply optimisation techniques to identify optimal farm management measures under environmental constraints. The requirement for farmers to reduce or minimise emissions while aiming to maximise the financial sustainability of the farm is complex, and supporting farmer decision-making in handling this complexity requires a model that maximises net margin while adhering to a GHG emission ceiling, choosing from a set of mitigation measures available to the farm. While models such as Farmscoper provide an embedded library of mitigation measures and calculate pollutant reduction costs (Zhang et al., 2012), their primary objective is to minimise pollutant losses rather than optimise farm income under environmental constraints. Furthermore, Farmscoper includes cost estimates for mitigation measures but does not integrate complete farm economic modelling, such as gross margins or net margin optimisation. As such, there is a dearth of models that simultaneously optimise farm profitability and environmental outcomes, specifically GHG emissions, using a prescriptive optimisation framework. Understanding how to achieve such optimisation requires a deeper evaluation of the various approaches used in agricultural systems.

2.4.1 Optimisation Techniques

Optimisation models in agriculture have been applied to diverse objectives, including maximising production (Dowson et al., 2019), maximising profit (Doole, 2013), minimising costs (Borysenko et al., 2024), optimising animal health (Ferchiou et al., 2021), and optimising feed management (Notte et al., 2020; Cecchini et al., 2022).

Recently, there has been a shift as several studies aim to integrate environmental and economic goals. Gong et al. (2025) developed a mixed-integer programming framework that optimises crop planning and dairy diets, showing that combining production and emissions objectives is achievable.

Similarly, McAuliffe et al. (2018) modified the life cycle assessment of livestock systems to incorporate the nutritional value of outputs, highlighting the trade-offs between emissions and nutritional quality. Likewise, Jones et al. (2021) analysed key industry performance indicators for a sheep system to determine which farm metrics are most valuable to monitor. These studies demonstrate that, while traditional optimisation focused on a single objective, increasingly research shows how economic and environmental outcomes can be optimised together. Optimisation techniques may be broadly classified as: (Kelemen et al., 2015)

- Intuitive methods
- Statistical and mathematical methods
- Operational research methods.

Intuitive methods rely on rules of thumb, expert judgment, and insight, often used in early decision-making without formal mathematical equations. They can help to develop more structured models. Rimbaud et al. (2019) also used heuristics and sequential use of sensitivity analysis to optimise plant disease management strategies.

Statistical and mathematical methods move beyond intuitive methods and use well-defined mathematical frameworks to guide decision-making. Numerous approaches exist, including metaheuristic algorithms, response surface techniques, and intuitionistic fuzzy optimisation. Jabed et al. (2024) reviewed different regression-based algorithms used for crop yield prediction and combined them with neural networks. Response surface methodology has been used in optimising wastewater treatment processes (Reza et al.,2024) and optimal agricultural settings (Khuri et al.,2017). Similarly, intuitionistic fuzzy optimisation has been used for agricultural production planning, particularly for plants to provide more profit to the farmer (Bharati et al.,2014). Methods can also be combined. For example, Cornelissen et al. (2003) used fuzzy evaluation and expert knowledge for the development of agricultural systems in relation to societal and public concerns.

The operational research approach includes a variety of mathematical programming approaches such as linear programming (LP), nonlinear programming, quadratic programming, multi-objective optimisation, and multi-criteria decision analysis. Recent developments also incorporate predictive analytics (Adebayo et al., 2021; Khan et al., 2019), machine learning (Liakos et al., 2018; Mirani et al., 2021), and forecasting methods (Chelliah et al., 2024).

Linear programming is an optimisation technique used to identify an optimal solution based on a linear equation (Dantzig, 1963). Objectives could be to maximise profit or minimise cost. In linear programming, the problem is framed as an objective function with a set of decision variables and constraints, which can be mathematically represented as;

$$\text{Maximise} \quad C^T x \; subject \; to \; A_x \leq b \; and \; x \geq 0$$

Where x represents the decision variables, $C$and b are vectors of the known coefficients, and A is a matrix of the coefficients (Poe & Mokhatab, 2017)

An optimisation model evaluates all feasible combinations that optimise the objective. LP can be combined with other techniques such as multi-objective programming, multi-goal programming or even weighted goal programming. Alotaibi et al. (2021) reviewed the use of linear programming to optimise agricultural solutions. They highlighted the importance of LP in helping farmers in resource allocation and decision making instead of using trial and error or heuristic techniques.

2.4.2 Whole-Farm Optimisation Models

Several whole-farm optimisation models have been developed internationally to address economic and environmental objectives in livestock production systems. These differ from the DSSs mentioned earlier, which served as simulations and benchmarking models, and partial budgeting systems without optimising the farm. In contrast, whole farm optimisation models determine the best measures by focusing on a specific objective function. Based on a recent review by Bang et al. (2023), notable models include:

- FARMDYN
- Integrated Dairy Enterprise Model (IDEA)
- DairyNZ
- FarmDESIGN
- Optimisation of Ruminant Farm for Economic and Environmental Assessment (Orfee)
- ScotFarm
- N-CyCLES
- Integrated Farm Optimisation and Resource Allocation Model (AgInform)
- Integrated Farm System Model (IFSM)

These models vary in structure, data requirements, and regional applicability. For example, FARMDYN is a bio-economic model applied to representative dairy farms and maximises farm net present value by integrating technical and economic parameters (Britz et al., 2014). Other models, such as Scotland's Scotfarm and Germany's FarmDESIGN, have built parameters for their own specific region. Scotfarm has detailed livestock (cattle, dairy, sheep) and crop modules and incorporates an emission constraint around soil CO_2 (Shrestha, 2020). While Scotfarm was built explicitly for Scotland's agriculture sector, earlier versions were applied to an Irish farm system (Shrestha, 2006).

Absent from the Bang et al. (2023) review is the SIMS_DAIRY whole-farm model (Díaz de Otálora et al., 2024), which emphasises the importance of integrating farm management, climate, and soil interactions to evaluate trade-offs in GHG and nitrogen emissions, using six case study farms across Europe, including Germany, Poland, Italy, Norway, and Ireland. Likewise, OPTIMILK employs linear programming to optimise dairy rations, assisting farmers in identifying the most cost-effective options (Mijić et al., 2024). This DSS was used in Bosnia and Herzegovina. Furthermore, Bang et al. (2025) also developed a framework to identify farm-level economic and climate-related win-win and lose-win scenarios, applying the framework to optimise management decisions economically and to estimate the associated GHG emissions in Norwegian dual-purpose cattle systems.

Despite the growing body of whole-farm optimisation models, very few of these frameworks are directly applicable to Irish farm systems, and none have been developed to integrate detailed farm-level GHG mitigation measures into LP models focused specifically on net margin optimisation under emission constraints. As such, there is a need to create such a model for Ireland

2.4.3 Linear Programming Optimisation Model

In this thesis, an LP optimisation model is created and developed for the Irish dairy system. The LP model examines the trade-off between farm profitability and GHG emissions.

This LP model is a single-objective linear programming model solved using CPLEX. The objective function is to maximise farm net margin. This model builds on two existing Teagasc models to form an integrated internal modelling framework than evaluates the farm across two time frames a five year planning horizon and ten year planning horizon.

The LP model focuses on tactical planning and represents short- to medium-term farm management decisions rather than long-term structural change. It incorporates environmental simulation outputs into the optimisation routine, ensuring that profitability and emissions are evaluated. This LP optimisation model is distinct from earlier Irish decision support systems that usually focus on simulating farm results under specific scenarios. Instead, by explicitly aiming to maximise net margin while adhering to environmental constraints, it offers a framework to assess policy measures and management tactics.

The LP model is structured into four interconnected subcategories:

1. Crop and feed production
2. Breeding and livestock
3. Environmental
4. Economic

Each subcategory is linked to decision variables that define the farm's operations over the planning horizon.

2.4.4 Integrated internal modelling framework

The LP optimisation model developed in this thesis is designed to form part of a broader Teagasc integrated internal modelling framework, while the thesis focuses on developing the LP optimisation model. The aim of the optimisation model is to support the tactical decisions that need to be made by the farm, while also providing an accurate emissions report for the farm. This will allow the farm manager to see the current state of affairs as a specific situation (baseline), thereby identifying what is relevant in meeting the targets (emission constraint).

In the context of Ireland, the Carbon Navigator Beef and Dairy LCA models are specially designed for the Irish agricultural sector but still exhibit some of the limitations addressed earlier. To address the identified gap, this thesis proposes the development of a linear programming optimisation model using the pre-existing Teagasc models to form an integrated internal modelling framework that fits within the broad Teagasc decision support system, which aligns tactical decision-making with both environmental and economic considerations.

The integrated internal modelling framework combines the MDSM, a farm-scale bioeconomic simulation model (Shalloo et al., 2004; Teagasc, 2019), with the LCA model (Teagasc & Bord Bia, 2019) and the LP optimisation model.

The MDSM provides detailed financial and production outputs at the farm level, while the Dairy LCA calculates the farm's carbon footprint and estimates total GHG emissions. Together, these two models act as feeder models, generating the economic and environmental data required for optimisation. The LP framework then integrates these outputs to identify the optimal resource allocation strategy that maximises farm gross margin while satisfying emissions and resource constraints.

Combining established Teagasc models with a formal LP optimisation model provides a more integrated and transparent method for evaluating trade-offs between profitability and emissions reduction in Irish dairy systems. Chapter 5 outlines the model formation and description. Figure 2.3 summarises the design of the integrated internal modelling framework.

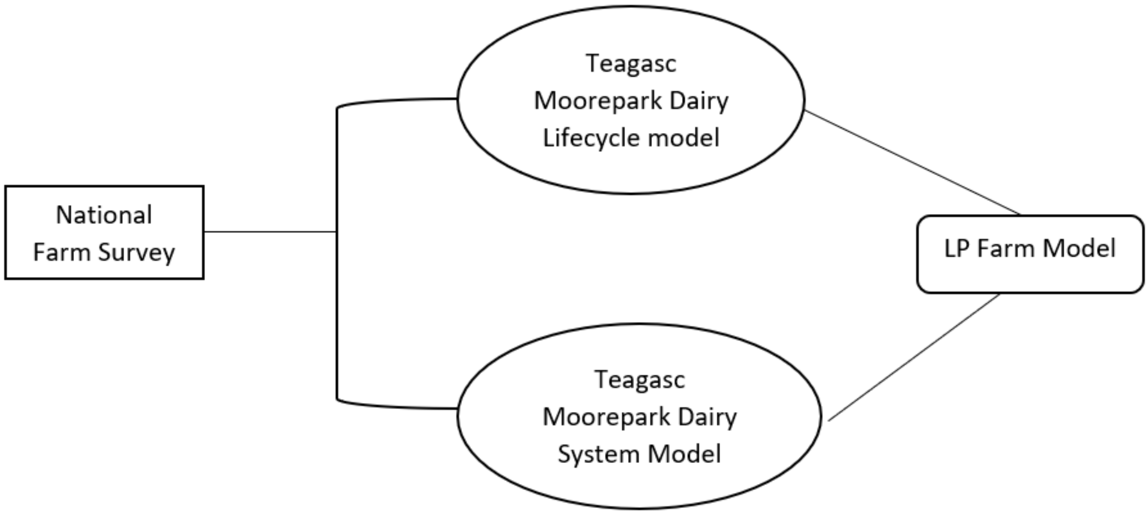

Figure 2.3 Integrated internal modelling framework design chart.

The model was used to assess mitigation measures. As numerous mitigation measures will be available to dairy farmers in Ireland, a list or library of mitigation measures needs to be developed to be included in the model's scope.

2.5 Mitigation Library

The mitigation library is a collection of mitigation measures. The selection was informed by the review of 13 models in Chapter 5.2.1 and the MACC mitigation measures outlined in Chapter 4.2.2. Based on the mitigation target, mitigation measures have been categorised under three headings: Grass, Crop, and Livestock. The full library is listed in Figure 2.4.

Grass based Systems		Crop Systems		Livestock Systems	
17	Improving pasture	32	Establish cover crops in the autumn	1	Earlier finishing of beef heifers and steers
18	Grass legume swards	33	Early harvesting and establishment of crops in the autumn	2	Improving total genetic merit of dairy cows
20	Only grass in crop rotation	34	Cultivate land for crops in spring rather than autumn	3	Lower replacement value of 20% (less young stock; older cows)
21	Incorporating straw in the soil	35	Adopt reduced cultivation systems	4	Reduce the age at first calving
24	Changing pasture quality (metabolic energy (ME) content and N content	37	Leave autumn seedbeds rough	5	Stocking rate
25	Adding wetlands or riparian strips	41	Ditch management on arable land	6	Stock Exclusion from Streams
29	Eliminate fallow	43	Use plants with improved nitrogen use efficiency	7	Wintering of stock
31	Increase grassland	44	Replace urea fertiliser to grassland with another form	8	Varying stock type, animal numbers and stock performance, including grazing off
36	Cultivate compacted tillage soils	45	Do not apply P fertilisers to high P index soils	9	Improved Live-weight performance
39	Loosen compacted soil layers in grassland fields	47	Establish new hedges	10	Improving Calving Rate/ calving date
40	Allow grassland field drainage systems to deteriorate	48	Protection of in-field trees	11	Increased Weight Gain
42	Ditch management on grassland	49	Management of woodland edges	12	EBI
46	Reduce field stocking rates when soils are wet	50	Management of in-field ponds	13	Reduce dietary N and P intakes: Dairy
57	Management of grassland field corners	30	Plant trees	14	Increase scraping frequency in dairy cow cubicle housing
58	Use high sugar grasses	22	Buffer zones	15	Additional targeted bedding for straw-bedded cattle housing
59	Monitor and amend soil pH status for grassland	23	Riparian buffers and planting	16	Washing down of dairy cow collecting yards
60	Increased use of maize silage	51	Plant areas of farm with wild bird seed / nectar flower mixtures	60	Feeding nitrate
63	Changing the grazing management	52	Beetle banks	61	Adopt phase feeding of livestock
71	Irrigation system and techniques	53	Uncropped cultivated areas	62	Feeding more fat
72	Minimise the volume of dirty water produced (sent to dirty water store)	54	Unfertilised cereal headlands	64	Nutrient Management Plan
73	Minimise the volume of dirty water produced (sent to slurry store)	55	Unharvested cereal headlands	65	Varying timing and amount of supplements feed to animals
74	Construct bridges for livestock crossing rivers/streams	56	Undersown spring cereals	66	Include feed additives in ruminant diets
75	Tile Drains	75	Use clover in place of fertiliser nitrogen	67	Feed livestock a reduced protein diet
85	Farm track management	76	Cover crops in the rotation	68	Feed livestock higher energy/ highly digestible feed
87	Calibration of sprayer	77	Nitrification inhibitors	69	Feed beef cattle more corn
88	Fill/Mix/Clean sprayer in field	78	Improved nitrogen use efficiency	70	Utilize an anaerobic digester
89	Avoid PPP application at high risk timings	81	Cultivate and drill across the slope	82	Use of wintering pads, animals shelters
90	Drift reduction methods	99	Increasing organic farming	83	Construct troughs with concrete base
91	PPP substitution	84	Re-site gateways away from high-risk areas	86	Establish tree shelter belts around livestock housing
92	Construct bunded impermeable PPP filling/mixing/cleaning area	100	Diversification opportunities	107	Allow cattle slurry stores to develop a natural crust
93	Treatment of PPP washings through disposal, activated carbon or biobeds	101	Carbon farming	104	Effluent storage
94	Leave over winter stubbles			105	Improved slurry management
95	Leave residual levels of non-aggressive weeds in crops			106	Anaerobic digestion of livestock manures
96	Use correctly-inflated low ground pressure tyres on machinery			101	Slurry acidification in the house
97	Locate out-wintered stock away from watercourses			102	using nitrate inhibitors in manure
98	Use dry-cleaning techniques to remove solid waste from yards			108	Site solid manure heaps away from watercourses/field drains
103	Changing effluent application area or methods and timing of application			109	Store solid manure heaps on an impermeable base and collect effluent
111	Use liquid/solid manure separation techniques			110	Cover solid manure stores with sheeting
112	Use slurry band spreading application techniques			116	Compost solid manure
113	Use slurry injection application techniques			128	Slurry tank cover
114	Do not spread FYM to fields at high-risk times				
115	Incorporate manure into the soil				
117	Spread liquid/ slurry manure more frequently				

118	Spread liquid/ slurry manure in spring
119	Varying timing and amount of N fertiliser applications
120	Fertiliser spreader calibration
121	Use a fertiliser recommendation system
122	Integrate fertiliser and manure nutrient supply
123	Do not apply manufactured fertiliser to high-risk areas
124	Avoid spreading manufactured fertiliser to fields at high-risk times
125	Use manufactured fertiliser placement technologies
126	Incorporate a urease inhibitor into urea fertilisers for grassland
127	Reduce synthetic nitrogen fertilizer
129	LESS

Figure 2.4 Mitigation Library Source: Author's own using data and outputs from review DSS.

2.5.1 Scope of Mitigation

While this library does not represent all mitigation options available to farms, it includes those currently embedded in the DSS reviewed in Chapter five. Incorporating measures from the MACC for Ireland (Chapter 4) and the DSSs is essential. The MACC offers a national overview of the most economically efficient mitigation options, while the DSSs show what is presently being advised and adopted by farmers. Including both ensures the library encompasses both strategic and practical perspectives on mitigation. Some new technologies and experimental measures were excluded due to insufficient data and limited farm-level analysis. Furthermore, selection was determined by data availability and whether the measures had been validated and utilised previously in the Irish agricultural system through the MACC. While only a subset of measures is used in the model developed in this thesis, the mitigation library lays a foundation for future research that may include integrating additional measures. Some new technologies and experimental measures were excluded due to insufficient empirical data and limited farm-level quantification within Irish systems. The full mitigation library represents a comprehensive catalogue of measures identified through the DSS review and MACC analysis. However, only a subset of these measures was incorporated into the LP optimisation model.

Selection of measures for inclusion in the model was guided by four criteria:

1. Data availability within the National Farm Survey dataset and compatibility with the farm-level parameters used in the modelling framework.
2. Availability of quantified emission reduction coefficients, enabling integration into the Dairy LCA model.
3. Economic parameterisation within the MDSM to allow estimation of financial impacts.
4. Relevance to Irish dairy systems under current policy targets, ensuring practical applicability.

Measures lacking sufficient quantitative data, incompatible with the structure of the MDSM or LCA models or not readily parameterised within a linear optimisation framework were excluded from the modelling application stages. The mitigation library therefore serves as a structured foundation from which feasible, data-supported measures were selected for testing.

Table 2.2 provides a high-level overview of the library's mitigation measures utilised in the LP model.

Table 2.2 Examples of mitigation measures

Measure	Category	Description
Protected Urea	Grass	Straight N fertilisers were replaced with urea fertilisers protected with an effective inhibitor.
Grass Utilisation	Grass	The annual reseeding rate was increased to the recommended rate, i.e. 10%-15%
EBI	Livestock	breeding dairy heifers and cows to top sires in the economic breeding index

Table 4.2,Chapter 4, describes a complete list of all mitigation measures included in this thesis.

2.5.2 Review Of Mitigation Measures from the Selected DSS

As is evident from the review above, many mitigation measures exist; however, those identified as having the most potential at a national level, through the MACC, for example, may not always be the most suitable at a specific farm level. Previous reviews of mitigation measures have rarely provided direct comparisons of their relative costs, yield co-benefits, and trade-offs. Given that mitigation measures can simultaneously influence multiple GHGs, it is crucial to accurately represent their synergies and interactions when formulating a comprehensive mitigation measure. Chapter 4 presents the selection of mitigation measures, while Chapters 6 and 7 detail the application of each individual measure as well as two subsets of grouped measures.

Several reviews, such as Jebari et al. (2023) and Kamyab et al. (2023), assess the technical potential of various mitigation measures across diet, manure management, soil and agroforestry. However, a limitation of these reviews is that while the technical potential of the measures is well described, the economic costs of adoption and farm-level trade-offs are generally under-reported (Leahy et al., 2020; Raihan, 2023), resulting in uncertainty when selecting suitable measures that are financially feasible for individual farms.

The economic dimension of mitigation measures is essential in decision-making (Vellinga et al., 2011; MacLeod et al., 2015). For example, one widely cited mitigation measure is manure management (Domingo et al., 2014; Wattiaux et al., 2019; Rencricca et al., 2023). under manure management options include anaerobic digesters, which require higher capital and operational costs, and slurry covers, which are less expensive but offer different abatement profiles.

Implementing an anaerobic digester requires a substantial initial capital investment to cover operation and maintenance costs. For instance, O'Connor et al. (2020) examined the cost analysis of anaerobic digestion in the Irish context, showing that while the upfront cost of anaerobic digestion is significant, farms with over 100 cows can make it economically viable, increasing returns as the farm size enlarges. Additionally, it offers considerable CO_2 reduction potential, with up to 173,237 Kg CO_2eq saved annually.

Although policy support, such as the Support Scheme for Renewable Heat and the Renewable Electric Support Scheme, and co-op communities have helped smaller dairy farmers adopt anaerobic digesters in Ireland, it would be uneconomical to do so without extra financial support. The initial costs are high, but studies have shown that farmers can recoup their investment over time (8-13 years) by saving on fertiliser and manure management, particularly with the support of policy incentives, which provide a strategic plan for developing biomethane heating systems (O'Connor et al.,2020)

A flexible slurry tank cover costs roughly €1.65 per m^3 of slurry stored (Reis et al., 2015) for the material and fitting charges. It can cut CH_4, by 40% relative to uncovered storage (VanderZaag et al., 2008; 2009; IPCC,2019). Even with these two measures, farmers must consider several factors before implementing a mitigation measures, as both focus on manure management. The variation is apparent. Table 2 in Chapter 4 provides a detailed breakdown of all mitigation measures evaluated in this thesis.

Ensuring measures are technically feasible and economically viable at the farm level is vital for implementing a mitigation plan. While the technical aspect highlights the need, approach, and potential, the economic element ensures the measure fits within the farm's budget. The challenge lies in balancing these two elements. Various tools, such as the MACC, and policy strategies have tried to address one or both of these aspects to facilitate adoption. However, the real challenge exists at the farm level, where mitigation measures must be tailored to both the environmental and economic situation of the farm. There is still a gap in the literature for the economic assessment of climate change mitigation in agriculture, with the absence of established pricing around CH4 and N2O and the potential costs and adoption barriers for low-carbon feed strategies and fertiliser (Leahy et al.,2020). To develop effective farm-level mitigation plans, this gap needs to be addressed by understanding the range of different sources and how the gases behave on the farm, which allows for a more concise approach towards mitigation. Enteric fermentation in cattle is a leading producer of methane, whereas nitrous oxide emissions are linked to fertiliser application and manure. Therefore, the mitigation measures must be targeted accordingly.

While studies on the impact of climate change, particularly on livestock farming, often present conflicting findings, this is further complicated by the different approaches to mitigation and adaptation. Crosson et al. (2011) emphasise using entire farm systems models for assessing GHG emissions and suggest that animal production and soil carbon absorption improvements can drastically lower emissions. This approach offers a thorough plan for reducing emissions and focuses on farm-level analysis. On the other hand, Wattiaux et al. (2019) emphasise targeted management strategies, such as increasing cow productivity and improving manure management, as practical and immediately implementable approaches to reducing emissions at farm level. These strategies focus on specific operational changes that can deliver measurable mitigation outcomes without requiring full system-wide optimisation. In contrast, Crosson et al. (2011) advocate for comprehensive whole-farm systems modelling to evaluate the combined effects of management changes across both economic and environmental dimensions. While both studies recognise the importance of farm-level mitigation, they differ in approach: Wattiaux et al. (2019) focus on individual, implementable mitigation measures, whereas Crosson et al. (2011) emphasise integrated modelling frameworks that assess system-wide interactions and trade-offs. Similarly, the approach to reducing GHG emissions can vary. Gerber et al. (2011) found that increasing productivity on dairy farms could decrease emissions per unit of milk, particularly in low-yield systems. This suggests that higher output could be a practical approach in reducing emission intensity. However, Van de Werf et al. (2009) noted that such productivity gains would increase environmental impacts, such as water and soil pollution, highlighting the trade-offs between intensification and environmental sustainability.

2.6 Mitigation integration into the Model

In the LP model, each measure is treated individually, with separate input sheets. As the LP model forms part of the internal modelling framework, the input data for each measure is calculated from the two feeder Teagasc models. In Cplex, each mitigation measure is assigned an executable file.

Although this thesis focuses solely on mitigation at the farm level and addresses the gap in identifying the most cost-effective option to reduce emissions, it is worth noting that these measures may not have the same effect at the regional or national levels. While some mitigation options are cost-effective at the farm level, they may not be transferable at a national level (Vellinga et al., 2011). This thesis addresses integrating policy drivers, MACCs, decision support systems, optimisation methods, and context-specific constraints. This approach provides the foundation for the theoretical framework in the next section and the methodological design detailed in Chapter 3.

2.7 Theoretical Framework

As discussed, farmers are currently facing a range of complex and interrelated challenges in meeting climate change policy targets. Specifically, farmers are required to adopt practices and implement mitigation measures that effectively reduce GHG emissions, while simultaneously striving to achieve the economic and production objectives of their farm businesses. In response to this dual challenge, the present study presents an internal modelling framework that underpins a potential decision support system designed to assist farmers in navigating this increasingly complex policy and operational environment. However, before designing such a system and selecting an appropriate methodological approach can be undertaken, it is essential to develop a comprehensive understanding of how farmers make decisions and the factors that influence these decisions. Accordingly, a review of the theoretical frameworks underpinning farmer decision-making was also conducted. Although many theories and frameworks are referenced below, not all are fully applied in the thesis. these are included to provide context for the research's theoretical and conceptual framework.

A range of theoretical perspectives has been applied to the study of farmer decision-making, including behavioural, psychological, and socio-economic models. For the purposes of this research, Normative Decision Theory, Rogers' Diffusion of Innovation Theory, and Classical Economic Theory were selected as the most appropriate foundations. These three frameworks collectively offer a comprehensive lens through which to examine the complex interplay between rational decision processes, social influences, and economic motivations that characterise farmers' responses to climate change policy. Normative Decision Theory provides an analytical basis for understanding how decisions should be made under conditions of rationality and structured choice; Rogers' Diffusion of Innovation Theory captures the dynamic process by which new practices and technologies are communicated and adopted within farming communities; and Classical Economic Theory situates these decisions within the broader context of market forces and policy incentives. While alternative frameworks such as the Theory of Planned Behaviour or Bounded Rationality offer valuable insights into behavioural intentions, the selected theories were deemed most suitable for this study due to their combined ability to integrate normative, social, and economic dimensions of decision-making relevant to the design of a farmer-oriented decision support system. The three theories are outlined in the following sections.

2.7.1 Normative Decision Theory

Normative Decision Theory provides a framework for understanding the idealised process of decision-making aimed at achieving optimal outcomes, assuming rational behaviour and access to complete information, (Małecka,2020).Rooted in principles of rational choice and utility maximisation, Normative Decision Theory assumes that decision-makers possess complete and accurate information, can evaluate all possible alternatives, and will select the option that maximises their defined objectives or preferences. Within the context of this research, the theory offers a logical foundation for the development of an optimisation model that assists farmers in balancing environmental and economic goals. By framing decision-making as a rational process of evaluating trade-offs, such as reducing GHG emissions and maintaining farm profitability, the theory supports constructing models that identify the most efficient allocation of resources under specified constraints.

In practice, this is accomplished by using linear programming to maximise net margin while complying with an emission constraint and evaluating feasibility.

While Normative Decision Theory provides a rigorous analytical basis for optimisation, it also has well-documented limitations. The assumptions of perfect information and full rationality do not reflect reality. Farmers often rely on heuristics, experiential knowledge, and local information rather than exhaustive optimisation processes. Consequently, while Normative Decision Theory justifies the use of optimisation modelling as a valuable decision-support mechanism, it must be complemented by theories such as Rogers' Diffusion of Innovation Theory and Classical Economic Theory.

2.7.2 Rogers' Diffusion of Innovation Theory

Rogers' Diffusion of Innovation theory explains how, why, and how quickly innovations and ideas spread within a population (Rogers, 2003). Using this theory to understand farmer decision making helps clarify farmers' reasons for adopting or resisting new mitigation practices and technologies in practice. It highlights key factors such as relative advantage, compatibility, complexity, trialability, and observability that influence whether these innovations are accepted.

In essence, farmers are more likely to adopt a new practice or mitigation measure when they see it as a clear improvement over existing methods (relative advantage), when it fits with their current values, beliefs, and farming systems (compatibility), and when it is not too difficult to understand or put into practice (complexity). Adoption is further encouraged when farmers have opportunities to test or experiment with the innovation before implementation (*trialability*), and when the outcomes or benefits of adoption are visible to others within their community (*observability*). Together, these factors help to explain the processes that impact the spread of new ideas and practices in farming communities, complementing the more rational and economic perspectives provided by Normative Decision Theory.

In the context of this thesis, these five factors can be linked to mitigation measures and the integrated internal modelling framework. Cost-effective mitigation measures must be compatible with Irish dairy farms for them to be adopted. Similarly, the measure and framework must offer relative advantages in terms of net margin maximisation and GHG reduction. Integration of results from the scenario analysis and the adoption of mitigation measures should not be complex. The measure and framework should be tested or experimented with before adoption, and ultimately, the results should be evident after applying the framework and mitigation measures.

This research builds on this framework by analysing existing decision support systems and identifying cost-effective mitigation measures tailored to different farm types. It aligns with Rogers' view that adoption is more likely when innovations are seen as profitable, compatible, and low-risk. This is achieved by demonstrating the criteria through reporting on margin impacts and operational changes in later chapters.

2.7.3 Classic Economic Theory

In addition to these behavioural and social dimensions of adoption, classical economic theory provides the third theoretical foundation of this study. It provides an economic perspective on how farmers allocate resources and respond to policy and market incentives in their production and mitigation decisions. This approach is based on the assumption that rational decision-makers, with the aim to maximise net margin by efficiently using limited resources. The LP modelling method is explicitly chosen to maximise net margin at the farm level, including mitigation consideration measures.

This approach enables quantifying trade-offs between economic performance and environmental sustainability. In practice farmers face real-world challenges in balancing financial sustainability with climate policy compliance.

This reflects the economic reality faced by dairy farmers, where environmental sustainability must be weighed against financial sustainability. By embedding this objective within the model, the research is firmly grounded in the theoretical principles of Classical Economic theory, which emphasises rational decision-making and efficient resource allocation (Simon, 1959). In this thesis, maximising net profit is the model's objective within the integrated internal modelling framework.

2.8 Summary

In summary, the contribution of global agriculture to GHG emissions and climate change is well recognised. As a result, a series of policy directives at both the European Union and national levels require the agricultural sector to significantly reduce its carbon footprint. Farmers face the complex task of reducing emissions while maintaining or increasing farm income and ensuring optimal returns on their assets. While a range of mitigation measures is available to support emission reductions, each involves distinct costs, benefits, and trade-offs. Consequently, farmers operate within a highly complex decision-making environment, where they must balance environmental obligations with economic objectives under conditions of uncertainty.

The literature reviewed in this study highlights numerous decision support systems designed to assist farmers in this process. However, many of these DSS lack optimisation, which involves identifying solutions that maximise profitability while satisfying emissions constraints. This is the gap in current research and practice that serves as the basis for this thesis. Which develops a linear-programming optimisation model, as part of an integrated internal modelling framework, to supports decision-making at the farm level for the Irish dairy farmer.

Guided by the theoretical frameworks discussed above, Normative Decision Theory, Rogers' Diffusion of Innovation Theory, and Classical Economic Theory, the methodological approach uses linear programming to model rational, net margin-maximising decision-making under environmental constraints.

Chapter five provides a detailed explanation of the internal modelling framework, its components, and its integration into the wider decision support system. In conclusion, this Chapter outlines the main research questions this thesis aims to address.

1. What is the effect of farm type on the financial costs associated with mitigating GHG emissions from dairy production using farm-level MACC analysis?
2. What decision-support tools are currently available to farmers and advisors at the farm level, for mitigation planning?
3. How does the optimal farm plan for the middle representative dairy farm change across four scenarios when evaluated using an integrated internal modelling framework ?
4. How does the optimal farm plan for all representative dairy farms reveal differences in mitigation potential and economic impact across farm types?

3 Research Design and Method

3.1 Introduction

This Chapter describes the research design of the thesis and includes a flow chart illustrating the study's stages. It covers identifying mitigation measures, the creation of a farm-level MACC and reviewing existing decision support systems. This chapter describes the development of the optimisation model, the use of representative farms, and the setup of scenario analysis. The chapter concludes with a summary of the data sources utilised throughout the thesis. Collectively, these components establish the methodological foundation for the results and analysis in subsequent chapters.

3.2 Research Design

The research design used in this thesis combines both secondary and primary research. The secondary research part involves a review of existing mitigation measures, the analysis of farm-level datasets, and an examination of theories of farm decision making. It includes an assessment of decision support systems and modelling approaches at the farm level. This provides the necessary context, theoretical background, and empirical evidence upon which the study is based.

The primary research part focuses on developing original models and applying analysis. Specifically, it includes creating farm-level MACCs, designing and implementing optimisation models as part of a broader decision support system, and evaluating various policy and farm-management scenarios. Overall, this combined research approach allows the study to both critically review current knowledge and generate new insights that are directly relevant for decision-making at both farm and policy levels.

Figure 3.1 presents a flow chart that demonstrates how all the elements of the research design are interconnected and progressively build on one another. It depicts how secondary research supports the primary analysis, and how model development and scenario testing contribute to the overall decision support framework, ensuring a logical and organised progression of the study.

Different colours and shapes indicate distinct categories of input, process, and output. The green ovals represent secondary research, including external data sources and inputs. Light blue rectangles denote secondary research, such as review-based elements like decision support system reviews, theoretical models, and a classification of representative farms used in this thesis. Pink rectangles and ovals symbolise the original contributions of this research, indicating methodological advancements and results. Purple octagons denote external modelling tools integrated into the framework and used during the modelling process. The pink hexagon highlights the development of the optimisation model as a specific original contribution within the integrated internal modelling framework. Arrows illustrate the flow of information, datasets, reviews, methods, and models into the framework, which ultimately produces the scenario results.

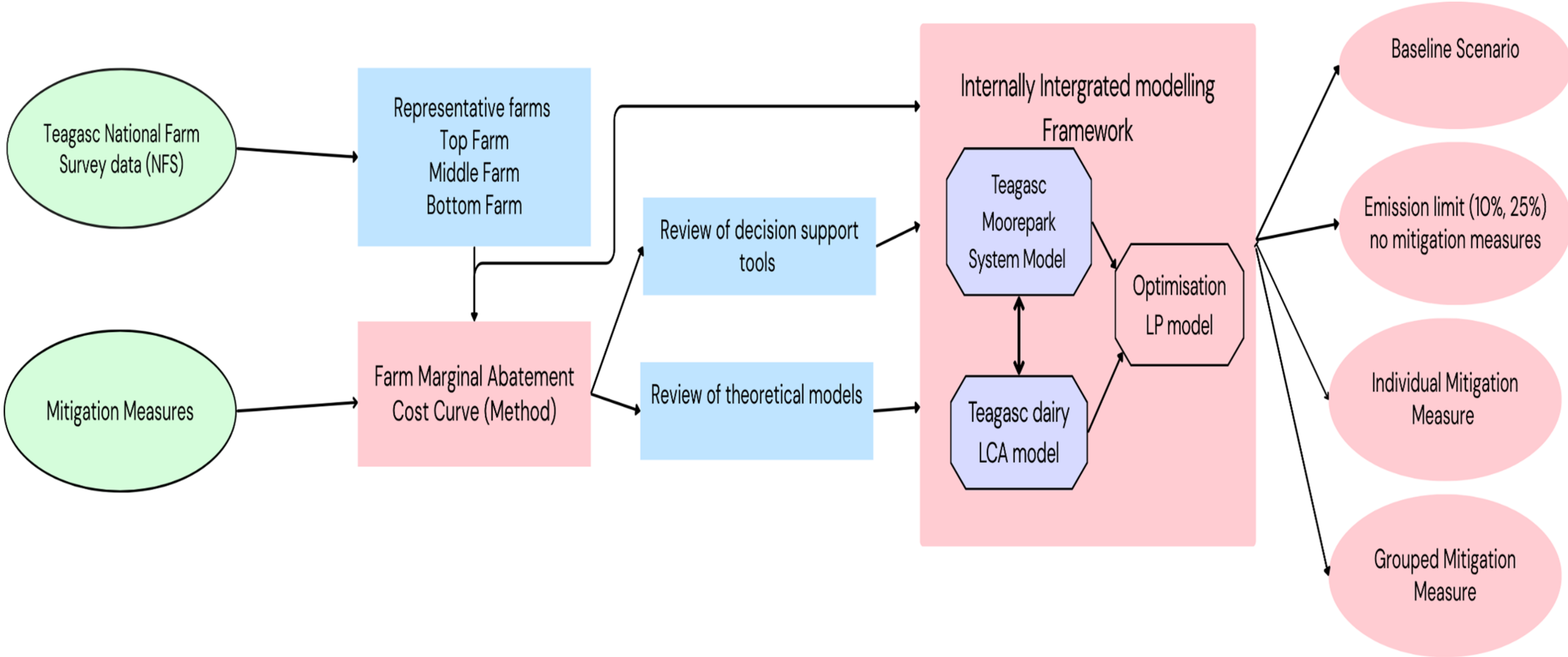

Figure 3.1 Thesis Flowchart Illustrating the Flow of Data, Methods, and Models Throughout the Thesis.

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3.2.1 Stage 1: Mitigation Measures from National MACC

Mitigation measures were identified from the GHG MACC for Irish agriculture and land use sectors (Lanigan et al., 2023). The national MACC contains a wide range of mitigation measures. Ten mitigation measures were selected as being the most suitable for dairy farms. These measures and the justification for their selection are presented in Chapter 4.

3.2.2 Stage 2: Development of a Farm-Level MACC Method

In this piece of primary research, a farm-level methodology was developed to translate broad national-level GHG mitigation measures into farm-specific MACCs. This approach enables the disaggregation of measures into outcomes that mirror the realities of individual farms, capturing heterogeneity in production systems, farm size, resource endowments, and technical performance. In doing so, the methodology offers a more precise and detailed representation of the economic and environmental trade-offs encountered at the farm level, providing valuable insights for both policymakers and farmers in evaluating the feasibility and distributional impacts of various mitigation options. Full details of this methodology and results are presented in Chapter 4.

3.2.3 Stage 3: Selection of Representative Farms

The unit of analysis in this study is dairy farms in Ireland, and the data source used is the Teagasc National Farm Survey (NFS). Bord Bia audits all Irish dairy farms approximately every 18 months, the NFS provides a detailed, nationally representative dataset. Rather than separately analysing the 17,000 dairy farms recorded by the NFS, the study employs a representative farm approach, whereby farms are grouped according to key performance characteristics, and a single farm model is constructed to represent each group. This approach captures the diversity of the sector while avoiding the complexity and redundancy of modelling every farm individually. The use of representative farms provides several benefits: it allows for detailed economic and environmental analysis at the farm level, facilitates comparisons across different systems and scales, and ensures that results remain generalisable to the broader farming population. The representative farm approach is used for the farm-level MACC analysis presented in Chapter 4 and again in the development of the optimisation model as described in Chapter 5.

3.2.4 Stage 4: Review of Existing Decision Support Systems (DSSs)

A previously published systematic review of farm-level decision support systems (Alexandropoulos et al., 2023) was used as the basis for this analysis. In that review, thirteen decision support systems were identified and selected for deeper assessment. The assessment focused on their modelling approach, scope, and environmental perspective, building on the work related to usability and functionality by Alexandropoulos et al. (2023). The review aimed not only to document the features of each tool but also to assess its strengths and weaknesses. This assessment identified methodological and practical gaps. These gaps informed the design of the primary research by highlighting where new modelling and analysis could add value to existing tools for farmers. This review is described in Chapter 5.

3.2.5 Stage 5: Theoretical Basis

A theoretical basis is required to construct a robust decision support system. To establish this foundation, various behavioural and economic theories were reviewed to better understand how farmers make decisions and which objectives they prioritise. This review is presented in Chapter 2. While each of the theories reviewed offers valuable insights, for the purpose of modelling, net margin maximisation is the primary objective guiding farmer behaviour. This assumption offers clear advantages: it is consistent with neoclassical economic theory, provides a transparent basis for modelling, and aligns with the reality that farm viability ultimately depends on financial performance. However, it is also important to note that this assumption has limitations. It simplifies the multiple objectives that farmers may have, such as risk aversion, long-term resilience and social or environmental values.

3.2.6 Stage 6: Coupling of Teagasc LCA and MDSM

Stage 6 integrates the Teagasc LCA with the MDSM to connect environmental and economic data. The LCA estimates farm-level GHG and ammonia emissions. At the same time, MDSM provides technical performance data such as herd performance and feed demand, and financial outcomes, establishing the economic baseline for Irish dairy farms. These outputs are then used in a LP model to optimise both environmental and economic objectives.

3.2.7 Stage 7: Construction of a Linear Programming Optimisation Model

A farm-level LP model was developed in the OPL language within CPLEX. The model operates by maximising net margin for each representative farm subject to several physical, financial and environmental constraints. The LP model uses the environmental outputs of the LCA and the economic outputs of the MDSM as input data. Full technical details of the LP model and its applications are presented in Chapter 5 and Appendices A and B. The overall objective of this model is to determine the optimal use of mitigation measures that maximise net margin and evaluate the net margin when emission ceilings are placed on a farm.

Stages 6 and 7 are integrated to create an integrated internal modelling framework that functions as a decision support system (DSS). The DSS enables prescriptive analysis by identifying the optimal use of mitigation strategies under varying policy and farm-level constraints. While the Teagasc models (LCA and MDSM) have been widely applied in the Irish literature, their coupling with the newly developed LP model represents a novel contribution of this thesis. This framework and the advantage of integrating these models together are demonstrated in Chapters 6 and 7, where it is applied to representative Irish dairy farms to generate optimal farm plans under different scenarios.

3.2.8 Stage 8: Scenario Analysis

The scenario analysis is a practical application of the integrated internal modelling framework by using representative farms under various scenarios, including different emission ceilings and combinations of individual and grouped mitigation strategies.

To evaluate the economic and environmental impacts of mitigation strategies, the model was applied to a set of predefined scenarios across three Irish dairy farms representing different performance levels, top representative, middle representative, and bottom representative farms based on gross margin. Each scenario was simulated over a specific period (initially five years in Chapter 6 and subsequently ten years in Chapter 7), while holding financial prices constant to focus on the effects of environmental constraints. The LP model is multi-period, and net margin is optimised for the planning horizon. Years are linked by transfer functions, with the closing inventory in one year equal to the opening inventory in the next.

The four main scenarios evaluated in this thesis were:

- Scenario 1: Baseline - no emission ceilings are applied, and the farm plan is optimised to maximise net margin.
- Scenario 2: Emission ceilings- A constraint to reduce emissions by 10% and 25% relative to the baseline is imposed, and the farm plan is optimised to maximise net margin subject to the emission ceiling.
- Scenario 3: Individual Mitigation Measures - the model is applied 10 times with separate mitigation measures, and the farm plan is optimised each time to maximise net margin, emission ceiling is relaxed.
- Scenario 4.1: Grouped Grassland Mitigation Strategy -A set of grassland mitigation measures was applied together, and the farm plan is optimised to maximise net margin, emission ceiling is relaxed
- Scenario 4.2: Grouped Animal Mitigation strategy -A set of animal mitigation measures was applied together, and the farm plan is optimised to maximise net margin, emission ceiling is relaxed.

The emission ceiling was not implemented in Scenarios 3–4.2. This approach enables an isolated assessment of both individual and grouped mitigation measures, so their impacts can be directly compared to the baseline before accounting for any interactions with emissions constraints.

In scenario three, the model simulated each mitigation strategy separately under isolated conditions to assess their effect on emissions and profitability. In scenarios 4.1 and 4.2, the grouped strategy aimed to reflect how farmers may adopt complementary measures together rather than separately.

3.3 Contribution of this Research

This thesis contributes to the literature on farm-level sustainability and decision support systems in several ways. It starts by developing a farm-specific MACC methodology tailored to dairy farming in Ireland. This approach quantifies the financial impacts of implementing mitigation measures across representative grass-based dairy farms. This differs from the national MACC, as this method emphasises the heterogeneity among Irish dairy farms. It offers the potential for a more tailored approach to help farmers in their decision-making process regarding abatement options.

The integrated internal modelling framework, which links two existing Teagasc models: The Teagasc MDSM and the Dairy LCA model, with a linear programming optimisation model, was developed in this thesis. This integration facilitates the use of detailed economic and environmental data within a farm optimisation framework. Assisting farmers and farm advisors with complex decision-making. Through scenario analysis, the economic and environmental benefits of mitigation measures are examined individually and in grouped strategies. By integrating MACC data, bioeconomic models, and an optimisation component, this thesis enhances both the theoretical framework and practical strategies for Irish dairy farmers to balance profitability with emission reductions.

3.4 Overview of Thesis

The flowchart in Figure 3.2 outlines the thesis structure, linked to the design strategy shown in Figure 3.1. Part one introduces the study: Chapter 1 discusses the motivation and goals, Chapter 2 gives background context, and Chapter 3 details the research design.

Part two builds on this methodology. Chapter 4 analyses representative farms and develops the farm-level MACC, directly answering research question one: What is the effect of farm type on the financial costs associated with mitigating GHG emissions from dairy production using farm-level MACC analysis?

Chapter 5 reviews decision support systems and presents the integrated internal modelling framework, addressing research question two: What decision-support tools are currently available to farmers and advisors at the farm level, for mitigation planning.

Chapter 6 shows scenario analysis results evaluating grouped mitigation measures and emission ceiling for the middle representative farm group, focusing on research question three: How does the optimal farm plan for the middle representative dairy farm change across four scenarios when evaluated using a linear programming model.

Chapter 7 extends this by including the top and bottom farm groups, including all individual ang grouped mitigation measures to address the final question: How does the optimal farm plan for all representative dairy farms reveal differences in mitigation potential and economic impact across farm types?

The subsequent chapters expand on this methodology by presenting farm-level MACC results and explaining the application of the LP model within the internal modelling framework.

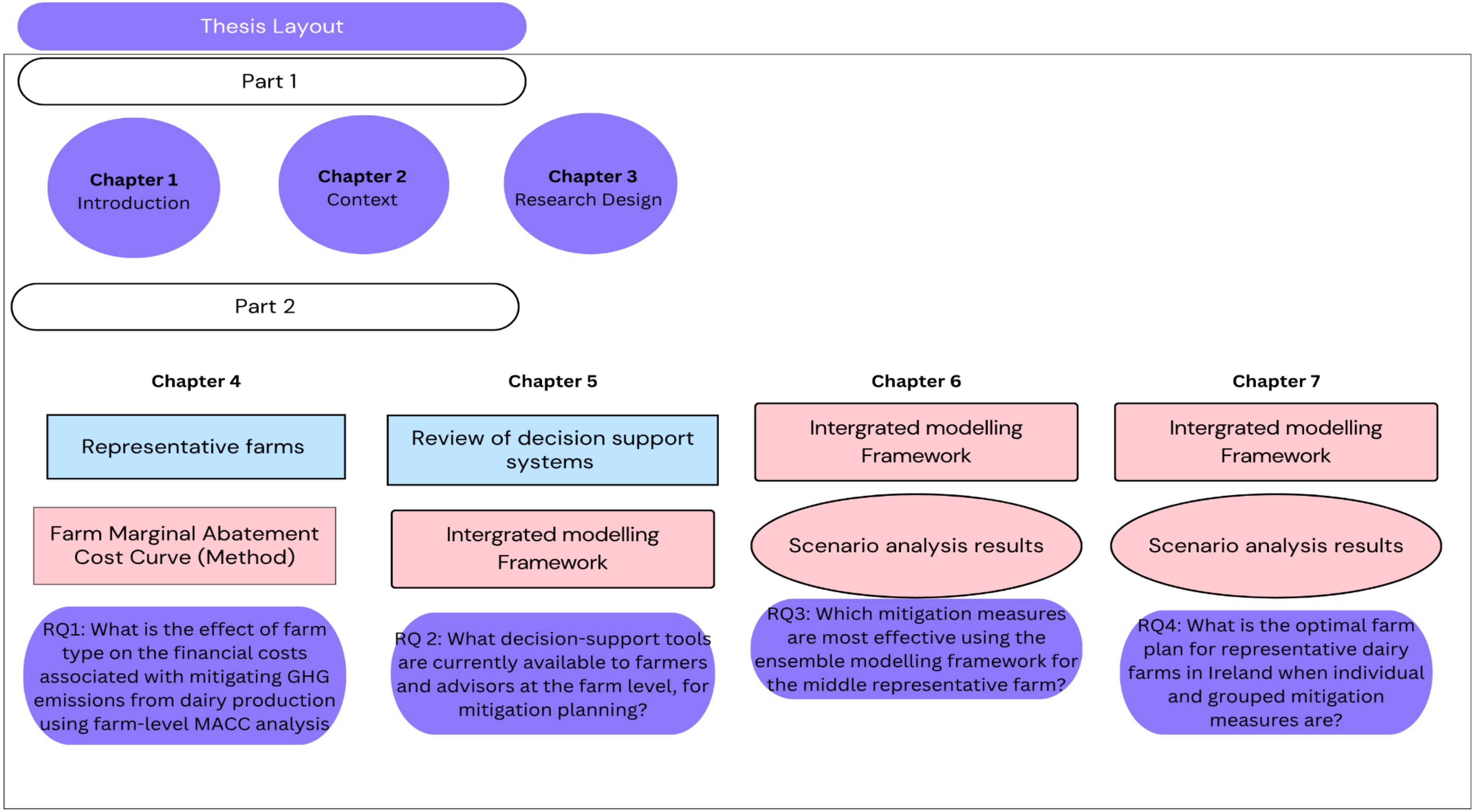

Figure 3.2 Thesis Structure.

3.5 Conclusion

In summary, this Chapter has outlined the overall research design and methodology, including both secondary and primary research elements. It established how mitigation measures, representative farms, decision support systems, optimisation modelling, and scenario analysis are integrated. This provides the methodological foundation for the results and analysis presented in the following chapters.

4 Mitigation of Gaseous Emissions from Dairy Livestock: A Farm-Level Method to Examine the Financial Implications

4.1 Introduction

Livestock are culturally and economically important to rural communities throughout the world. They not only yield a variety of valuable food products but also form the backbone of livelihoods for countless farmers. In Ireland, dairy farming holds a central position in rural life. The dairy industry is deeply woven into the country's cultural and economic fabric. It supports thousands of farming families, providing them with a sustainable source of income. Additionally, dairy farming traditions are passed down through generations, reinforcing the cultural significance of this industry. Livestock contributes significantly to biodiversity and habitat conservation. Grazing animals, including those in Ireland, play a crucial role in managing grasslands, supporting biodiversity, and ensuring the growth of native plants. Additionally, the diversity of livestock breeds raised on these farms helps safeguard genetic diversity, ensuring the resilience of livestock and local ecosystems. Mitigating gaseous emissions from livestock systems is a critical imperative in contemporary agriculture. The dairy sector, in particular, plays a pivotal role in this effort, given its substantial environmental footprint. Dairy farms, often family-owned, are at the forefront of initiatives aimed at reducing emissions and implementing sustainable practices. These efforts are integral in curbing the environmental impact and safeguarding the long-term viability of dairy farming. Traditional methods in the industry, especially those about manure management and feed efficiency, are being re-evaluated and refined to address emissions concerns while ensuring continued productivity. To sustain profitability in farming while feeding a growing population, a delicate balance is needed between sustainable practices and managing GHG emissions. Various mitigation measures have been researched, ranging from land management to animal practices. Each measure has different abatement impacts and investments.

In the EU-28, the value of animal output and livestock products was €170 billion, or 40% of all agricultural activity. Additionally, almost 4 million people are employed on European livestock farms (Peyraud & MacLeod, 2020). Growth in livestock production has multiple benefits for the economy, human health, and nutrition. However, it has the potential to harm one or more aspects of the environment.Livestock production releases nutrients into ecosystems, which cause water pollution, soil contamination, or biodiversity loss (FAO, 2009; Burchill et al., 2016). Livestock also generates gaseous pollutants, namely GHG and ammonia (NH_3) emissions, that adversely impact nearby ecosystems. GHG emissions are the primary driver of global warming and climate change, and NH_3 is a key air pollutant (IPCC, 2013; EMEP, 2019). The Paris Agreement of the United Nations (UN) on reducing GHG emissions and the UN Convention on Long-Range Transboundary Air Pollution (CLRTAP) put ceilings on NH3. The goal of the Paris Agreement is to restrict the global temperature increase to below 2°C this century, which translates into a 43% GHG emissions reduction by 2030 and net-zero levels by 2050 (UNFCCC, 2023; UN, 2023). The purpose of the CLRTAP is to avoid the exceedance of critical loads of NH_3 in sensitive ecosystems. Sensitive ecosystems might include old forests, terrestrial herbaceous areas, coastal dunes, and wetlands.

Most of the world's NH3 losses emanate from livestock farming and fertiliser N use (Ma et al., 2021; Beaudor et al., 2023). According to Beaudor et al. (2023), 78 per cent of it is attributed to soil volatilisation, which is fuelled by the application of fertiliser and manure, while the remaining per cent is attributable to interior emissions from animal housing, yarding, and storage. These sources are also the principal drivers of agricultural GHG emissions, constituting about 12% of global emissions (OECD/FAO, 2021). Decreasing gaseous emissions from livestock production is challenging, but it can be achieved by improving farming practices and agricultural technologies. Many farm practices and technologies already exist to mitigate GHG and NH_3 emissions, e.g., restoration and conservation of soil fertility and water, incorporating legumes into swards, spreading of nitrification inhibitors, extended grazing, and genetic and genomic selection of animals (Gerber et al., 2013; Pellerin et al., 2017b). The adoption of these mitigation measures by farmers depends on several factors, including ease of use, agricultural education, social acceptability, efficiency, and costs. The cost factor is among the most important for adoption and is generally assessed with MACC. This methodology estimates the abatement potential of a suite of mitigation practices and technologies relative to a baseline scenario. It ranks them according to their financial cost (Lanigan & Donnellan, 2019). The approach aims to identify the most cost-effective options to meet emission reduction targets.

MACCs are derived using either a top-down or bottom-up approach. A top-down MACC typically employs a general equilibrium model to determine the cost of emission reductions for the overall economy (MacLeod et al., 2010). Conversely, a bottom-up or engineering MACC brings together data on individual measures' costs and mitigation potential and calculates their average cost-effectiveness (Eory et al., 2018). Generally, engineering MACCs are used to determine the mitigation potential of the farming sector at a country level (Eory et al., 2018). Projected growth rates and expert judgment about costs and uptake of mitigation measures strongly influence the outputs of this approach. To overcome this issue, a limited number of MACCs have been applied to examine farms representative of a region or country (Jones et al., 2015). This analysis is helpful for visualising mitigation costs at a farm level and provides general advice on reducing emissions. This analysis is helpful for visualising mitigation costs at a farm level and for providing general advice on reducing emissions. This may also support policymakers in establishing emission strategies. However, mitigation costs are specific to each livestock farm and are potentially related to a farm's financial performance. Thus, to provide targeted advice to livestock producers about mitigating emissions, a MACC type approach is required that can estimate mitigation costs for farms with varying levels of profitability.

The primary purpose of this study was to develop a MACC methodology capable of determining the financial implications associated with mitigating gaseous emissions from livestock at a farm-level for a heterogeneous selection of representative farms. This methodology was postulated to capture heterogeneity in GHG and NH_3 abatement costs that need to be adequately accounted for in sectoral level or top-down approaches. The farm-level MACC was applied to representative livestock farms that represented the Irish dairy farm system's top, middle, and bottom averages. Applying this approach on these farms was expected to demonstrate that mitigation costs for top performing livestock farms are greater than the costs for farms with average or below-average performance. Net margin was the indicator used to determine the farm's performance. Enhancing our grasp of the expenses and advantages associated with mitigation efforts on individual farms can aid in crafting more impactful policies that foster behavioural shifts within the agricultural sector, carrying substantial policy implications. The agricultural carbon market mechanism is a concept that holds significant potential for incentivising sustainable practices within the agricultural sector. However, it is essential to acknowledge that such a market still needs to be fully developed in the Irish context. While initiatives and discussions surrounding carbon credits and offsetting have gained traction internationally, their implementation in Ireland is still in its nascent stages. The specific nuances of such a mechanism in the context of Irish agriculture, including factors like farm size, diversity of agricultural practices, and regional variations, require careful consideration. There is a need for further research, policy frameworks, and stakeholder engagement to pave the way for a robust and effective agricultural carbon market in Ireland.

4.2 Materials & Methods

4.2.1 Farm Selection

The representative farms chosen for this study were located in the Republic of Ireland. Farming in Ireland is predominantly grass-based and generally relies on livestock, particularly cattle and sheep, to convert pasture into agricultural products. The majority of Irish farms, about 55%, specialised in beef production. Specialist sheep production was the next most common farming system, with 17,435 farms, followed by specialist dairy production with 15,319 farms. Currently, the Irish agricultural sector is worth about €6 billion, with exports making up the bulk (90%) of dairy and red meat sales (DAFM, 2022). Nationally, it is also a significant source of GHG (33%) and NH_3 (98%) emissions. Beef and dairy farms are the main drivers of the country's agricultural emissions. For the purpose of this study, dairy farms were chosen.

The National Farm Survey (NFS), operated by Teagasc, estimates gaseous emissions from livestock farms in Ireland annually. The NFS aims to monitor the financial performance and sustainability of the agricultural sector. Information from the NFS is shared with the Farm Accountancy Data Network (FADN) of the European Union (Dillon et al., 2021). The NFS is undertaken annually on a nationally representative sample of farms. Generally, 900 to 1,000 farms are included in the survey. A random sampling methodology is used to select farms. The NFS weights farms according to the land area using aggregation factors from the Central Statistics Office (CSO, 2022) to ensure the survey is representative. Farms are assigned to one of the following systems based on their dominant enterprise: Dairy, cattle rearing, cattle other, mixed livestock, tillage, and sheep. The value of agricultural products in terms of standard output determines the chief enterprise(s) on a farm.

Representative livestock farms were picked from the NFS for Ireland's most valuable agricultural subsector, i.e. dairy (Bord Bia, 2022). Within the dairy category in the survey, dairy farms were ranked by gross margin and case studies were chosen from the average bottom, middle and top representative of farms. Relevant practices and technologies to mitigate gaseous emissions were applied on these farms. The cost of each mitigation strategy was calculated and represented in the financial in the MACC. The baseline year chosen for the analysis was 2020. In order to compare mitigation potential on a land use perspective, results are presented on a per hectare basis. The model is structured that the results can be expressed on per animal, per unit of output also. The farm characteristics are illustrated in table 4.1

Table 4.1 General characteristics of the top, middle and bottom representative of Irish dairy farms in terms of economic performance[a], 2020-2021 Source:(CSO, 2022; ICBF, 2022; Teagasc, 2022).

		Dairy		
Parameter	Unit	Top	Middle	Bottom
Grassland				
Area	Ha	56	56	48
Fertiliser N rate	kg N/ha	211	177	132
CAN	% fertiliser N	25	87	94
Urea	% fertiliser N	65	6	2
Protected urea	% fertiliser N	10	7	4
Fertiliser P rate	kg P/ha	16	12	11
LESS[a]	% of slurry	84	65	51
Grass utilisation	t DM/ha	10.4	8.0	5.9
Herd				
Cows	average hd[b]	119	92	61
Culling rate	% cows	18%	20%	22%
Replacement rate	% cows	19%	21%	24%
Age at first calving	Month	24	26	29
Mean calving date	Date	24-Feb	01-Mar	08-Mar
Grazing season – cows	Day	246	241	235
Concentrate feedstuffs	kg/LU[c]	1,140	1,223	1,154
Stocking rate	LU[c]/ha	2.52	2.07	1.72

Production				
Beef live weight	kg/ha	258	217	188
Milk yield	kg/cow	6,443	5,999	4,826
Milk fat and protein	kg/cow	493	455	396
Economic				
Gross output	€/ha	6,570	4,954	3,492
Variable costs	€/ha	2,140	1,812	1,451
Fixed costs	€/ha	1,790	1,365	1,168
Gross margin	€/ha	4,430	3,142	2,041
Net margin	€/ha	2,640	1,777	873

[a] Farms were ranked in terms of gross margin per hectare

[b] Low emission slurry spreading, e.g., trailing shoe.

[c] Livestock unit

4.2.2 Mitigation Measures

Multiple mitigation measures have been researched to reduce emissions from livestock farming systems (Hristov et al., 2013). The applicability of a mitigation measure to a livestock system depends on various factors, including:

- Farm location- geographical context and proximity to specific resources
- Type of production system
- Availability of activity data (i.e. farm input and output information)- presence and quality of data related to specific farming practices
- Local scientific evidence- research conducted in the specific region related to mitigation
- Environmental regulation refers to policies governing environmental impacts.
- Market conditions - economic factors affecting livestock production

Similar to O'Brien et al. (2014), these criteria were used to select mitigation measures for assessment in this study. Mitigation measures tested in farms outside of Ireland were excluded as the abatement potential and the costs of measures are known to depend on the local environmental and economic context (Pellerin et al.,2017a). Therefore, mitigation measures were restricted to scientific studies completed in Ireland. A literature review was conducted to identify mitigation measures that would be suitable for the Irish setting. It is essential to understand that not every mitigation strategy will perfectly fit each farm's structures and conditions. Each farm runs under unique circumstances, such as differing soil types, climates, and resource availability, which might affect the applicability and efficacy of particular mitigation methods. For instance, certain mitigation strategies could work better than others in areas with heavy rainfall. This review yielded several measures for decreasing emissions from livestock farming. These mitigation measures were carefully examined and filtered based on the availability of financial information, farm activity data, and the feasibility of implementation (Table 4.2). The measures selected from this process for the representative farms were:

1. Animal productivity: The productivity of the herd was improved by breeding dairy heifers and cows to top sires in the economic breeding index (EBI). The EBI measures the profitability of dairy sires across multiple genetic traits: production, fertility, and health. It was increased by an average of €15/cow per year for the bottom representative of farms, €12/cow per year for the middle representative and €9/cow per year for the top representative of farms. Selecting the best sires from this index increased fat and protein yield by 5%-10% without impairing health or fertility. Extra supplements were fed, where necessary, to meet the herd’s additional energy requirements for milk production.
2. Grass production and utilisation: The least productive pastures on a farm were targeted for renewal, i.e. reseeding. These swards were generally old, ten years or more, and contained the least amount of perennial ryegrass. To improve these swards, the annual reseeding rate was increased from 3% to 6% of the grassland area to the recommended rate, i.e. 10%-15%. A similar rate of increase was assumed for each group of dairy farms (i.e. 5 to 6 percentage points). Grazing and silage swards were renewed with the best ryegrass cultivars in the pasture profit index (PPI; Teagasc, 2014). The most suitable cultivars in the PPI were 25%-30% more responsive to N than old pastures and improved the digestibility of forage by 50-60 g/kg DM. Fertiliser rates for establishing new swards were based on Teagasc recommendations (Wall & Plunkett, 2020).
3. Better reproductive management: The delays in age at first calving for replacement dairy animals were overcome by mating heifers to easy-calving sires when they were about 14-15 months old. Heats were closely monitored with simple detection aids, and heifers were vaccinated prior to the commencement of the breeding season. Both changes reduced

age at first calving by 2 months for the middle representative of dairy farms and by 5 months for the bottom representative of farms. Replacement heifers typically calved between 22-26 months of age.

4. Early calving: The mean calving date for dairy and cattle rearing systems was brought forward by 2-weeks to early, mid and late February for the top, middle and top representative of dairy farms, respectively. Ninety percent of cows calved over a 6-week period. The breeding season was restricted to 12-weeks to tighten the calving pattern. Calving early in spring better synchronised the turnout of cows with grass supply, which decreased grass silage requirements by 35 to 45 kg DM/cow for the housing period. It also decreased concentrate supplementation by 16 to 28 kg DM/cow.
5. Reduce crude protein: Energy intake is a major factor restricting the milk yield of dairy cows offered a grass-only diet. Concentrate feedstuffs are offered to cows to overcome this restriction and to stretch feed reserves in spring and autumn. During the grazing season, the ration of dairy cows usually contains more than sufficient levels of crude protein (CP). The protein content of this ration was manipulated by replacing soybean meal with distillers' dried grains at a rate of 100 g/kg in concentrate compounds offered to grazing cows. This change decreased the crude protein content of concentrate supplements from 16% to the recommended level (14%) and had no impact on milk production.
6. Decrease fertiliser N: In line with climate policy for the Irish agricultural sector (GOI, 2023), the annual input of fertiliser N was reduced by 20%. Herbage yield was adjusted downwards by 0.8 to 1.1 t DM/ha based on the expected response to fertiliser N. The yield response to fertiliser was estimated according to the approach of Hoekstra et al. (2020). Grass silage and concentrate feedstuffs were imported to fill the grass deficit.
7. Protected urea: Compound and straight N fertilisers were replaced with urea fertilisers protected with an effective inhibitor, e.g., NBPT or NPPT. This form of N replaced 90%, 93% and 96% of the total N fertiliser for the top, middle and bottom dairy cohorts, respectively. Phosphorus, K and other nutrients were supplied with zero N fertilisers, e.g., 0-7-30.
8. White clover: Pastures dominated by productive grass species, e.g., perennial ryegrasses, were converted to grass-white clover (GWC) swards. The legume was introduced into grassland according to the steps outlined in the Teagasc management guides (Hennessy

et al., 2021). Grass-white clover swards were sown on 10%-15% of the farm in spring once soil temperature was suitable for germination. Swards received 30-40 kg P/ha and 60-90 kg K/ha at sowing to aid establishment. Fertiliser N was applied to established GWC swards in spring and mid-autumn (September). The rate of application depended on the stocking rate. The average white clover content of the sward increased from less than 5% to between 20% and 25%, which resulted in fertiliser N decreasing by 74 to 92 kg/ha.

9. Slurry tank cover: Covers were installed on above and belowground tanks for cattle slurry. The type of cover used was flexible and comprised of floating materials. Existing storage tanks were retrofitted with flexible covers, as they are as effective as rigid covers. They are also a more straightforward engineering solution. Storage tank covers increased the amount of slurry N available for application, which replaced 1 to 2 kg of fertiliser N/ha. Savings in fertiliser N were estimated using the approach described by (Buckley & Krol, 2020).
10. Low emission slurry spreading (LESS) machinery: Cattle slurry was applied with vacuum tankers fitted with LESS technology instead of conventional broadcasting equipment, i.e. splash plate. The LESS equipment selected, the trailing shoe, delivered slurry onto the soil in narrow bands, which reduced the surface area exposed to air compared to broadcasting. This technology was fully adopted. It replaced 16%, 35%, and 49% of the slurry applied with a splash plate on the top, middle, and bottom representative of farms. This resulted in better N recovery from organic fertiliser, assumed to replace fertiliser N. The fertiliser replacement value of slurry spread with a trailing shoe was determined using the approach of Wall and Plunkett (2020).

The financial costs and benefits, and approaches applied to simulate the abatement potential of the mitigation measures are detailed in the description in Table 4.2, along with references. Mitigation measures were implemented as stand-alone changes on representative dairy farms and applied as a whole to account for potential interactions between measures.

Table 4.2 Technical summary of measures applied to mitigate gaseous emissions from livestock production systems in the Republic of Ireland.

Measure	Financial costs	Abatement potential
1.Animal productivity	Based on industry reports, picking top EBI sires increased the price of artificial insemination (AI) straw by €4 relative to average sires. Factoring in repeat inseminations added a further €2.80 to the cost of AI/dairy cow. Prices for compound concentrate feeds ranged from €300-350 t/DM (CSO, 2022).	Breeding better dairy cows diluted gaseous emissions. At farm-level, the emission benefits of dilution depended on base yields. The emission benefit was computed using the methods in Irish national inventories (Duffy et al., 2022; Hyde et al., 2022).
2.Grass production and utilisation	Establishment costs for reseeded swards were estimated using standard rates for materials and agricultural contractors (Teagasc, 2014; FCI, 2021). The total cost of establishing a new pasture was estimated to be €340/ha.	Improving pasture's response to fertiliser N reduced N emissions from soils. Improving sward digestibility mitigated CH_4 emissions from cattle. Emission reductions were determined based on the aforementioned national inventory methods.
3.Better reproductive Performance	A roll of scratch cards costs €100, and the adhesive price for the cards was €20. One roll was considered sufficient for 60 heifers throughout a breeding season. Vaccines for reproductive diseases cost €5/replacement heifer.	Reductions in gaseous emissions associated with the maintenance of breeding cattle were determined according to national inventory guidelines. (Duffy et al., 2022; Hyde et al., 2022).
4. Early compact calving	Identifying empty and late-calving cows via pregnancy scanning costs €4-€5/animal. Call-out charges for scanning ranged from €50-€60.	Grazing cattle had an 18-21% lower Ym factor than cattle indoors on grass silage-based diets (Hyde et al., 2022). They also had lower CH_4 and NH_3 emission factors for manure than housed cattle (Duffy et al., 2022).
5. Reduce crude protein	Concentrate compounds offered to cows at pasture were reformulated by substituting soybean meal with distillers' dried grain at a	Nitrogen intake and excretion rates for dairy cows were decreased in line with the drop in the crude protein of

Measure	Financial costs	Abatement potential
	rate of 100 kg/t. This change decreased the price of concentrate compounds for grazing animals by about €11.5/t and reduced crude protein content by 2% points. Prices for concentrate ingredients were taken from industry reports.	concentrate compounds. The knock-on effect of reductions in N excretion rates on NH_3 and GHG emissions was calculated according to the recommended inventory approaches via the adapted emission model of Herron et al. (2021b)
6. Decrease fertiliser N	Silage production costs were based on O'Donovan et al. (2021). Transport and labour charges were included for importing silage along with feed out costs. In total, imported silage cost €231/t DM utilised. The price of concentrate feed varied from €300-€330 t/DM.	Reductions in fertiliser-related gaseous emissions were determined using country-specific loss factors from Irish emission inventories (Duffy et al., 2022; Hyde et al., 2022).
7. Protected urea	Prices for fertilisers were taken from national statistics (CSO, 2022). Per kg of N, CAN cost €1.04 and urea cost €0.83. Protecting urea with a urease inhibitor added €0.1 to the price of 1 kg of urea N.	Protected urea decreased N_2O loss by 73% relative to CAN and reduced NH_3 loss by 80% compared to straight urea (Duffy et al., 2022; Hyde et al., 2022).
8. White clover	The cost of establishing grass-white clover swards was €10-€15 greater per acre than ryegrass swards.Including white clover in the seed mix and oversowing it caused most of the rise in reseeding costs.	White clover had a similar mode of action to the measure of decreasing fertiliser N. The approach described previously to calculate emission savings for decreasing fertiliser N was applied to determine the savings in emissions caused by replacing fertiliser N with N fixed by white clover.
9.Slurry tank cover	Material and fitting charges for flexible covers were taken from Reis et al. (2015). Charges were adjusted for the baseline year (2020). This brought the overall charge for tank covers to €1.65 per m3 of slurry stored.	The NH_3 emission factor for covered tanks was 62% less than for uncovered tanks (Van der Weerden et al., 2009). Methane and N_2O emission factors for covered tanks were based on

Measure	Financial costs	Abatement potential
		inventory guidelines (IPCC, 2019). This method estimates that covering tanks reduces CH_4 emissions by 40%.
10. Low emission slurry spreading (LESS)	Spreading slurry with a trailing shoe increased application costs by 31% to €89/hr (FCI, 2021). Cattle slurry was applied with a 2500 gallon vacuum tanker by agricultural contractors.	Ammonia loss related to spreading slurry in summer was reduced by 60% by switching from splash plate to trailing. For spring and autumn, the same change reduced NH_3 loss by 13%. Fertiliser N saved by trailing shoe reduced gaseous emissions associated with using this energy intensive input.

4.2.3 Modelling Abatement

The abatement potential of mitigation measures was modelled over a 10-year period (2021 to 2030). A static approach was adopted to model abatement potential, where production levels on dairy farms were held constant over the period, i.e. dynamic adjustments that farmers might adopt were not considered. This assumption indicates that enteric methane emissions remain relatively constant throughout the ten-year period, assuming a consistent feed conversion efficiency. Mitigation measures were fully implemented on the representative farms. Positive feedback loops between economic performance and farm activity were not considered for measures that improved productive efficiency. Agricultural input (lists these inputs) and output prices were forecasted after 2021 with CSO price indexes. The value of milk increased by an average of 1% per year, and input costs went up by 0.1%-0.2% on average. The figures were based on the trend in national prices between 2015 and 2021.

4.2.4 Emission Computations

Gaseous emission and bio-economic models described in Herron et al. (2021a, b) for dairy farms were combined to quantify the cost-effectiveness of mitigation measures. In brief, these models compute emissions and environmental impacts associated with cattle production systems according to the life cycle assessment (LCA) methodology. The boundary of the emission models extends from the extraction of raw materials to the sale of dairy and beef products from the farm, i.e., cradle to farm gate. For this analysis, gaseous emission models were adapted to consider only agricultural sources of emissions that arise within national inventories and the perimeter of a dairy farm. In other words, the national inventory method (NIM) for simulating emissions from the agricultural sector was applied at a farm scale. The term "national inventory methods" refers to the Intergovernmental Panel on Climate Change (IPCC) protocols used by nations to calculate and report GHG emissions and carbon dioxide (CO_2) removals from the atmosphere. The specific emission sources attributed to livestock farms with this method are agricultural soils, manure management, and enteric fermentation. The NIM was deployed within the models to calculate NH_3 loss and the primary GHG emissions, namely CO_2, methane, and nitrous oxide. These gaseous losses were quantified as described by Herron et al. (2021a, b) with emission factors from the Irish national inventory (Duffy et al., 2022) and emission data from the NFS (Dillon et al., 2021). The tiers in the NIM classification system for emission estimation methodologies are defined based on the level of detail, where higher tiers indicate a more accurate approach to estimating emissions. Emission estimations specific to Irish livestock farms, classified as tier-2 in the NIM, were used to quantify NH_3 and CH_4 emissions from manure management. Ammonia and N_2O emissions related to spreading synthetic fertilisers in agriculture and N_2O from manure deposited by grazing cattle were determined using tier 2 emission estimations. For the remaining sources, default tier 1 emission factors reported in emission inventory guidelines (EEA, 2019; IPCC, 2019) were used to estimate ammonia and GHG emissions. The gaseous emission models converted GHGs to CO_2 equivalents (CO2-e) based on their 100-year global warming potentials using factors from the IPCC (2013): CO2 = 1, CH4 = 28, N_2O = 265. Gaseous emission models operated on a monthly time-step and reported annual NH_3 and GHG on a per-hectare basis. The impact of each mitigation measure on annual emissions was simulated for each representative farm and compared to the base situation (without measures).

4.2.5 Economic Analysis

Standard economic metrics, i.e. gross output, gross profit, and net profit or loss, were determined using financial records collected on livestock farms for the period 2019-2021. Monthly receipts for milk, livestock, and forage sales were added to quantify the gross output or revenue of a farming system on a yearly basis. Gross profit or loss was measured as gross output less the variable cost of production. Consumables items, e.g., feedstuffs, fertilisers, lime, livestock, and medicines, were included in the variable cost category, as well as service costs for providers of materials and skills, e.g. agricultural contractors and veterinarians. Fixed costs were added to variable costs to determine the total cost of production. The expenses included under fixed costs were maintenance fees for buildings and machinery, depreciation, casual labour charges, electricity, telephone, insurance, and sundry expenses. Fixed costs were taken from gross margin to determine net profit or loss. This financial metric, along with gross profit or loss and gross output, was related to the area and outputs of livestock systems.

Marginal costs related to the abatement of gaseous emissions were determined for each mitigation measure applied to livestock farms. Technical information from research studies and price data from agricultural handbooks and national databases were used to derive marginal abatement costs. The agricultural input and output prices considered in the analysis were forecasted beyond 2021 using the aforementioned CSO price trend observed between 2015 and 2021. For each abatement measure, the marginal cost was computed by taking the financial benefits, i.e. cost savings and income gains of a measure from the extra capital, maintenance, and running costs incurred. Financial costs and benefits were converted to net present value (NPV) by annualising them over a 10-year period and discounting at a rate of 4% per year (Equation 1),

$$\sum_{t=0}^{n} \frac{Cost_t - Benefit_t}{(1+r)^t} \qquad \textbf{(1)}$$

Where $Cost_t$ is the additional cost of the measure in year t, $Benefit_t$ is the revenue or cost-saving benefit in year t, r is the discount rate, and t is the time in years. The NPV for each abatement measure was related to the quantity of GHG avoided in CO_2-e. Individual measures were then categorised based on their costs. Three cost categories were defined: 1) cost beneficial, 2) cost effective, and 3) cost prohibitive. Practices and technologies that simultaneously improved financial margins and reduced emissions were termed cost beneficial. Mitigation measures that cost less than the shadow price of carbon or NH_3 were considered cost effective, and measures above these prices were categorised as cost prohibitive. The shadow carbon price was estimated at €50/t CO_2-e (Lanigan et al., 2019), and the shadow price of NH_3 was €17.5/kg (Bruyn et al., 2018). Total abatement costs for a livestock system were quantified by estimating the costs of implementing several mitigation measures simultaneously.

4.2.6 Sensitivity Analysis

The sensitivity of the representative farms' mitigation costs to major changes in economic conditions was tested using national statistics on agricultural prices (CSO, 2022). The output prices and the prices of major agricultural inputs, i.e. fertiliser, feed, fuel, buildings and machinery, were increased to the extreme levels observed in 2022. The annual rate of increase in input costs was also increased from an average of under 0.2% to 5% (Buckley et al., 2023). Output prices were not assumed to match the general inflation rate, increasing by an average of 2% per annum. For the NPV of investments, the discount rate was changed from 4% to 8%.

4.3 Results and Discussion

4.3.1 GHG Mitigation Potential

Over the 10-year commitment period, the cumulative GHG abatement potential of standalone (implemented on their own) measures for dairy farms ranged from an average of 2.0 t CO_2-e/ha per year for the top representative of farms to 2.8 t CO_2-e/ha per year for the bottom representative of farms (Figures 4.1-4.3). Similar to MacLeod et al. (2010) and Lanigan et al. (2019) MACC analyses of agricultural GHG emissions, the majority (54%-86%) of the abatement potential on dairy farms could be realised with cost beneficial and net-zero cost measures. Cost savings were greatest for the bottom representative of dairy farms, followed by the middle and top representative of farms. Regarding the cost-effectiveness of GHG mitigation measures, there was little difference between the three groups of dairy farms. Cost-effective measures constituted 89% of the GHG mitigation potential for the top representative, 90% for the middle representative, and 93% for the bottom representative of farms. Cost-prohibitive measures accounted for a greater share of the aggregated GHG abatement potential on the top representative of dairy farms than the middle or bottom representative farms. They tended to be technological interventions (Figure 4.1-4.3)

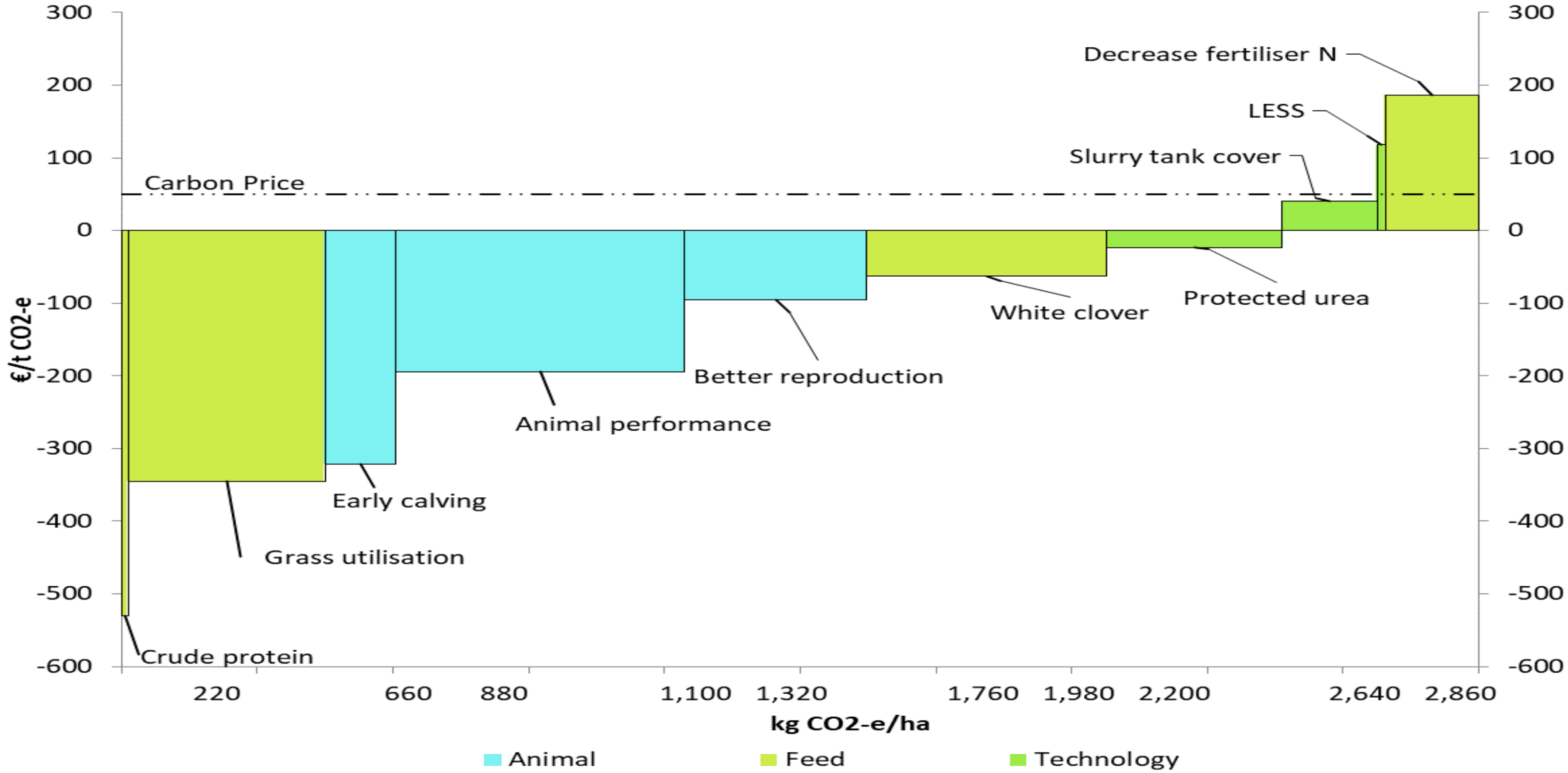

Figure 4.1 Marginal abatement cost curve of greenhouse gas mitigation measures for the bottom representative of Irish dairy farms in terms of gross margin.

Abatement potential corresponds to the annual average for the period 2021-2030. Colours indicate the type of mitigation measure. The dashed line represents the shadow price of carbon. The width of each block represents the total CO_2 saving per annum of the Mitigation strategies. The height of the block shows the cost per unit of CO_2 saved, over the lifetime of the project. Savings are shown as negative costs. These mitigation strategies that are cost prohibited are above the horizontal (x) axis, which means that they will require a net investment.

Figure 4.2 Marginal Abatement cost curve of greenhouse gas mitigation measures for the middle representative of Irish dairy farms in terms of gross margin.

Abatement potential corresponds to the annual average for the period 2021-2030. Colours indicate the type of mitigation measure. 78% to 6.8 kg NH3/ha. The dashed line represents the shadow price of carbon. The width of each block represents the total CO_2 saving per annum of the Mitigation strategies. The height of the block shows the cost per unit of CO_2 saved, over the lifetime of the project. Savings are shown as negative costs. These mitigation strategies that are cost prohibited are above the horizontal (x) axis, which means that they will require a net investment.

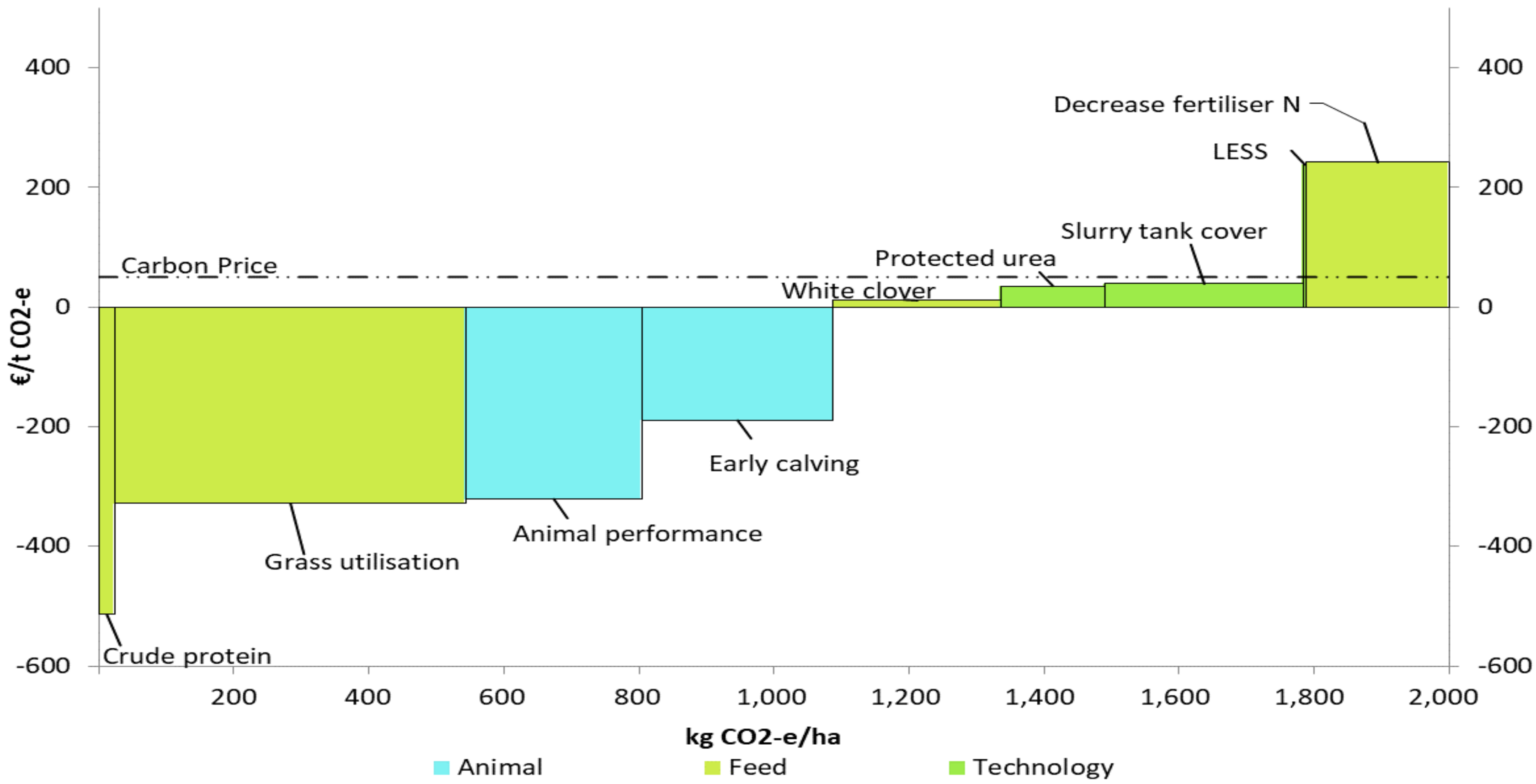

Figure 4.3 Marginal abatement cost curve of greenhouse gas mitigation measures for the top representative of Irish dairy farms in terms of gross margin. Abatement potential corresponds to the annual average for the period 2021-2030. Colours indicate the type of mitigation measure. The dashed line represents the shadow price of carbon. The width of each block represents the total CO_2 saving per annum of the Mitigation strategies. The height of the block shows the cost per unit of CO_2 saved, over the lifetime of the project. Savings are shown as negative costs. These mitigation strategies that are cost prohibited are above the horizontal (x) axis, which means that they will require a net investment.

The bulk of the benefit in terms of costs and GHG mitigation on dairy farms resulted from animal and feed-related improvements. These measures increased productive efficiency, decreasing the intensity of livestock production's emissions by improving the input-to-output ratio (Capper et al., 2009; Wiedemann et al., 2015). The main reason the abatement potential was lower for the top representative of farms than the middle and bottom representative of farms was that this group operated at a relatively high efficiency level. Reducing the CP content of concentrate supplements offered to grazing cows was the most cost-beneficial way (i.e. first measure) to mitigate GHG emissions from dairy farms. This mitigation measure decreased feed costs and N excretion during the grazing season, without impairing animal performance. Decreasing N excretion reduced gaseous emissions from soils, roadways and collecting yards. Coupling emission reductions from these sources with feed cost savings resulted in the CP reduction measure having the lowest GHG mitigation costs (-€513 to €530/t CO_2-e).

Improving grass utilisation and productivity by increasing reseeding rates to the recommended levels, i.e. 10%-15% of the farm/year was the second most cost beneficial mitigation measure in terms of GHG emissions. The abatement cost for this practice change was between €328 and €345/t CO_2-e and t resulted in more digestible forage, which decreases methane emissions associated with the digestion of feed by ruminants (IPCC, 2019). Additionally, productive ryegrass swards respond better to fertiliser N and thus reduce the likelihood of nitrous oxide losses from agricultural soils. Unlike the CP and grass utilisation measures, the financial ranking of other feed and animal-related GHG mitigation measures tended to vary across dairy farms. Early calving was the third most cost-beneficial for the bottom and middle dairy groups but ranked fourth for the top group of farms. Likewise, animal performance ranked as the third best measure in terms of costs for the top group but was the fourth best option for the middle and bottom groups. All of these results are based on the assumptions of unchanged animal numbers.

Some feed and technology-related mitigation measures shifted from cost-beneficial to cost prohibitive in the GHG MACCs for dairy farms (Figures 4.1-4.3). Protected urea and white clover were cost-beneficial or cost saving for the bottom and middle representative of dairy farms (-€22 to -€63 t/CO_2-e) and cost prohibitive for the top representative of farms (€35 to €36 t/CO_2-e). The heterogeneity in costs for these mitigation measures was largely explained by the quantity and type of replaced fertiliser. For the bottom and middle dairy groups, protected urea and white clover primarily substituted CAN, but urea was the main fertiliser replaced for the top dairy group. Urea fertiliser is generally cheaper than CAN and protected urea per unit of N (CSO, 2022). Thus, replacing it with protected urea increased fertiliser costs for the top group. Fertiliser expenditures for the top group were significantly reduced for white clover when 38% to 40% of the N was replaced with biological N that is carbon neutral. However, it was insufficient to outweigh the greater establishment costs for the top dairy group. Similar replacement of fertiliser N by white clover for the middle and bottom dairy groups led to greater savings in fertiliser costs because CAN was primarily replaced instead of urea. These savings more than compensated for the rise in establishment costs for white clover and thus resulted in white clover being cost-beneficial for the bottom and middle dairy groups.

Decreasing fertiliser N was the most cost prohibitive option for each dairy farm group, ranging from €175 to €242/t CO_2-e. This measure partly replaced a relatively inexpensive form of forage, grazed pasture, with a more expensive form, grass silage. Consistent with O'Donovan et al. (2021), the cost of producing grass silage was 2 to 2.5 times greater than grazed grass. Technologies to mitigate GHG emissions from manure also increased production costs and were consistently cost prohibitive for the LESS measure. Covering slurry tanks was generally cost effective, with GHG mitigation costs varying from €39 to €44 t/CO_2-e. Applying all GHG mitigation measures simultaneously on dairy farms was cost-beneficial. Financial savings were similar for each dairy group, averaging -€284 to -€274 t CO_2-e. Generally, mitigation measures had synergistic relationships; combining them increased GHG abatement. However, abatement potentials for GHG mitigation measures were not additive. Interactions among measures, on average, decreased the annual GHG mitigation potential for all of the measures applied to 1.7 t CO_2-e/ha, 1.8 t CO_2-e/ha and 1.4 t CO_2-e/ha for the bottom, middle and top dairy groups, respectively. The existence of interactions between mitigation measures agrees with previous MACC analyses, e.g. Eory et al. (2018) and Wagner et al. (2015). Both authors highlighted the importance of accounting for interactions to give a more accurate estimate of the total GHG mitigation potential (Table 4.3).

Table 4.3 Greenhouse gas abatement potentials and mitigation costs for the bottom, middle and top representative Irish dairy farms in the Teagasc national farm survey. Note: Farms were ranked in terms of gross margin/ha.

Mitigation Measure	**GHG Abatement Potential (kg CO_2-e/ha)**			**GHG Mitigation Costs (€/t CO_2-e)**		
	Bottom	Middle	Top	Bottom	Middle	Top
Improve animal performance	603	404	261	-194	-232	-321
Increase grass utilisation	412	485	522	-345	-332	-328
Crude protein	15	20	25	-530	-517	-514
Better reproduction	380	205	NA	-95	-93	NA
Early calving	147	199	284	-321	-326	-189
Decrease fertiliser N	195	249	214	186	175	242
Protected urea	366	454	154	-23	-22	35
White clover	503	369	249	-63	-30	11
Slurry tank cover	199	255	295	41	44	39
LESS	18	18	4	118	100	238
Total	1,709	1,805	1,389	-184	-185	-202

Source: Author's own contribution.

Overall, combining mitigation measures decreased GHG emissions by 23%, 19% and 12% below 2020 levels for the bottom, middle and top dairy groups, respectively. For the bottom and middle representative of dairy farms, this level of GHG mitigation potential was in line with the current emission ceiling put on the Irish agricultural sector. Under the Climate Action Plan 2023, agriculture needs to decrease GHG emissions by 10% 2025 and 25% by 2030 to meet its emission ceiling targets, with 2020 as the base year (GOI, 2023). Based on our analysis, the top group of dairy farms will need help to achieve the latter target with existing technologies and practices. Further accelerating improvements in productive efficiency may address some of the GHG mitigation gaps for this cohort. However, more is needed to meet the 2030 and future GHG reduction targets, e.g., climate neutrality by 2040 or 2050. Therefore, new mitigation measures must be developed and/or deployed on the top dairy group and the bottom and middle representative of farms. Developing strategies to reduce

GHG emissions from livestock should focus on the principal emission sources, mainly methane from the enteric fermentation of feed in ruminants (Hristov et al., 2013). Dietary supplements that inhibit methane, such as 3-NOP and halides, are promising mitigation options (Cummins et al., 2022) that are likely to aid the sector in meeting medium-term targets. Our study excluded these due to insufficient data to draw firm conclusions for grass-based systems. Offsetting of GHG emissions will also be needed to achieve the sector's long-term net-zero emission goals. Several practices are reported to offset GHG emissions via enhancing carbon stocks in soils and vegetation (Soussana et al., 2010) but modelling these practices with appropriate biogeochemical models was outside the scope of this study.

4.3.2 Ammonia Mitigation Potential

Consistent with the GHG MACC analyses for dairy farms, the bulk of NH_3 mitigation potential was achieved with cost beneficial measures (Figures 4.4 to 4.6). The share of the cumulative NH_3 abatement potential of cost beneficial or saving measures varied from 83% for the top representative of dairy farms to 87% for the bottom representative of farms. For the top dairy group, all of the mitigation measures examined were below the estimated price of NH_3 and, therefore, cost effective. As regards the middle and bottom dairy groups, all but one of the NH_3 mitigation measures, decreasing fertiliser N, were categorised as cost effective. Buckley & Krol (2020) and Wagner et al. (2015) results generally corroborated our findings about the cost-effectiveness of NH_3 mitigation measures. However, the ranking of NH_3 mitigation measures varied between studies and farm groups. For the middle and top dairy groups, improving grass utilisation and productivity was the most cost beneficial measure for reducing NH_3. Still, for the bottom group, white clover was slightly more cost beneficial. Improving animal performance was the second best option in terms of NH_3 mitigation costs for the middle and top representative of dairy farms and ranked third for the bottom representative group. Early calving reduced mitigation costs as well, and followed better animal performance in the cost rankings for each dairy group.

White clover ranked fourth in terms of cost saving for the middle group of dairy farms (-€17.1/kg NH_3 but shifted to cost positive for the top dairy group (€0.3/kg NH_3). The reasons for the fluctuation in costs for this measure were the same as described for the GHG MACC analysis, i.e. white clover primarily replaced a cheaper form of fertiliser N for the top dairy group compared to the other dairy groups. Differences in the type of fertiliser N replaced also caused protected urea to fluctuate between cost beneficial and cost positive. Better reproduction was a more cost effective option than protected urea, albeit it was not an option for the top representative farm as this group were already calving all replacement heifers at 24 months of age. Decreasing the CP content of concentrate feed was a cost beneficial NH_3 mitigation for dairy farms (-€14.9 to -€17.3/kg NH_3). Ammonia mitigation costs for the CP reduction measure were similar to those of Buckley & Krol (2020). However, in contrast to Buckley & Krol (2020), decreasing the CP content of dairy diets ranked among the least cost beneficial mitigation measure for the bottom, middle and top representative of farms. The difference in ranking was partly due to the mitigation measures examined, e.g. early calving and better grass utilisation were not considered by Buckley & Krol (2020). The discrepancy may also have been caused by different reductions in the crude protein content of diets, and the reduction may have been applied at alternative times of the year, such as only during the grazing season, for this analysis.

Combining mitigation measures over the period resulted in the total NH_3 abatement potential ranging from an average of 9.9 kg NH_3/ha per year for the bottom representative of farms to 12.0 kg NH_3/ha per year for the middle representative of farms. For the top representative of farms, the total NH_3 abatement was, on average, 31 kg NH_3/ha per year. The disproportionate potential to abate NH_3 losses from the top dairy group was caused by the more significant amount of urea applied on the top representative of farms relative to the other groups. Protecting this form of fertiliser N with effective urease inhibitors substantially decreases NH_3 losses (Forrestal et al., 2016). This measure accounted for about half of the NH_3 mitigation potential for the top dairy group. Protected urea made a minor contribution to NH_3 mitigation potential for the bottom and middle representative of dairy farms, as it primarily replaced CAN fertiliser instead of urea. The rate of NH_3 loss from CAN application is similar to spreading urea with a urease inhibitor. Thus, the potential emission savings were minor. LESS equipment had the greatest capacity to mitigate NH_3 loss from the bottom and middle representative of farms. However, its share of NH_3 mitigation potential was well below the 60% estimate of Buckley & Krol (2020) because a large share (51%-84%) of the slurry was already applied with LESS in 2020 (base year). Consequently, animal and feed-related measures were also essential contributors to NH_3 mitigation for dairy farms, along with the covering of slurry tanks. White clover was particularly important for the top dairy group, but the NH_3 mitigation potential for this measure, like protected urea, was sensitive to the form of fertiliser N it replaced. Substituting urea fertiliser with CAN for the reference year led to white clover making a small (2% to 3%) contribution to NH_3 mitigation for all dairy groups. It also decreased the mitigation potential for the top group by 78% to 6.8 kg NH3/ha and increased GHG emissions. This observation highlights the importance of examining gaseous emissions in an integrated way, as Wagner et al. (2015) reported.

The total NH_3 abatement potential, with interactions taken into account, for each dairy group exceeded the reduction targets currently set out in the national emission ceilings directive (European Commission, 2016) and was cost beneficial. The total cost of NH_3 abatement varied from €-34/kg NH_3 for the bottom representative of farms to €-9/kg NH_3 for the top group. This finding somewhat supports the hypothesis that abatement costs rise as farm profitability increases, even though the measures were still cost saving. For the bottom and middle groups, NH_3 abatement was at the lower end of the range recommended by the CLRTAP for regions with high livestock densities and nearer to the upper end of the range for the top group. Replacing urea with straight CAN fertiliser in the base year resulted in all of the groups falling outside of the CLRTAP range. It also results in the top group having the least abatement potential for NH_3, which was more in line with the results for GHG abatement. None of the mitigation measures assessed for NH_3 led to greater GHG emissions or vice versa. This issue, known as pollution swapping, can be a problem for some mitigation measures, particularly those related to organic and inorganic N applications, as Buckley & Krol (2020) pointed out. The risk of pollution swapping is potentially increased by having separate policy instruments for mitigating air pollution and climate change. Combining these policies, as suggested by Wagner et al. (2015), and harmonising them would reduce this risk and help policymakers establish appropriate sectoral emission ceilings for NH_3 and GHG.

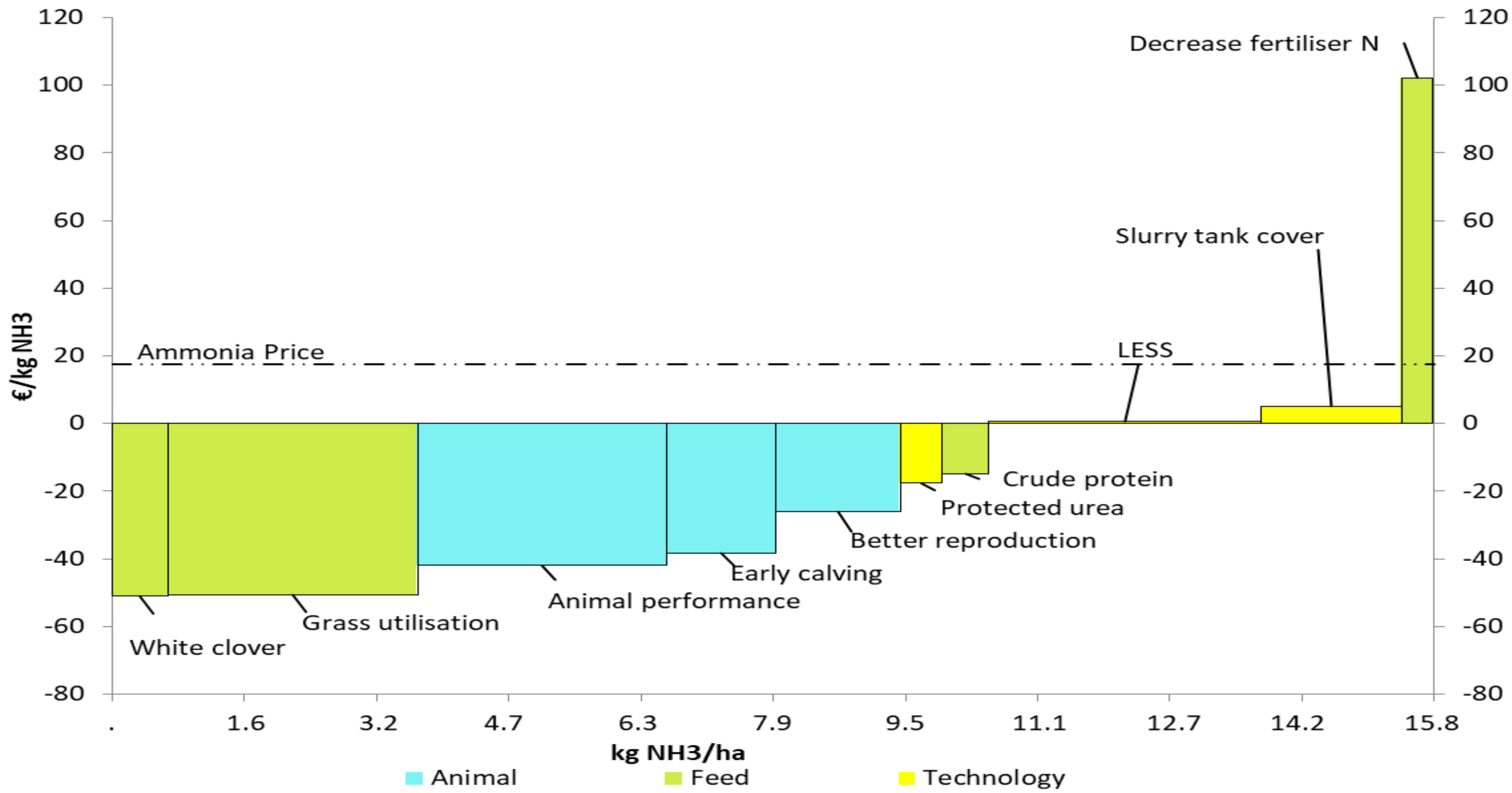

Figure 4.4 Ammonia (NH3) marginal abatement cost curve for the bottom representative of Irish dairy farms in terms of gross margin. Abatement potentials correspond to the annual average for the period 2021-2030. Colours indicate the type of mitigation measure. The dashed line represents the shadow price of NH_3.

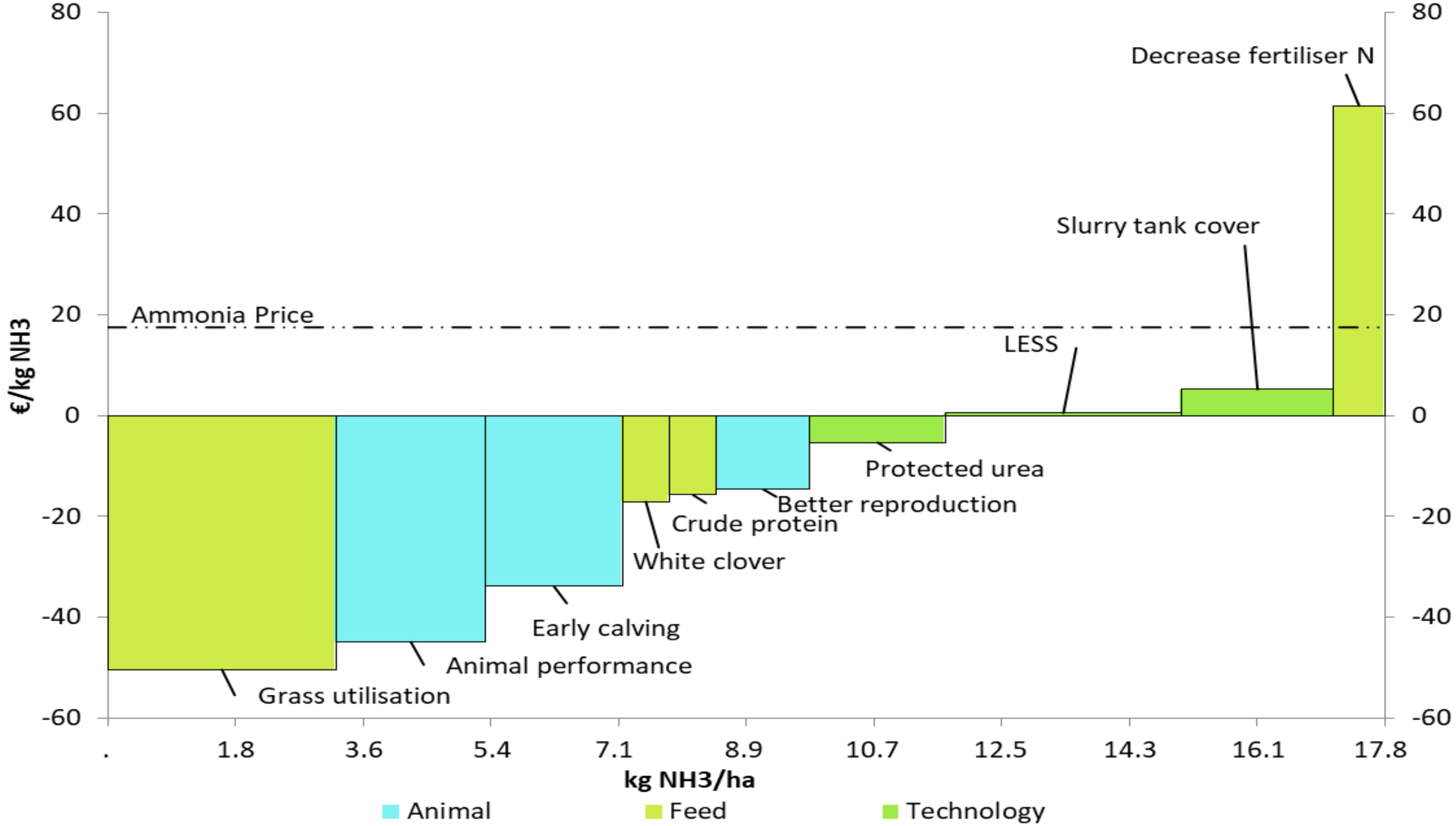

Figure 4.5 Ammonia marginal abatement curve for the middle representative of Irish dairy farms in terms of economic performance. Abatement potentials correspond to the annual average for the period 2021-2030. Colours indicate the type of mitigation measure. The dashed line represents the shadow price of NH_3.

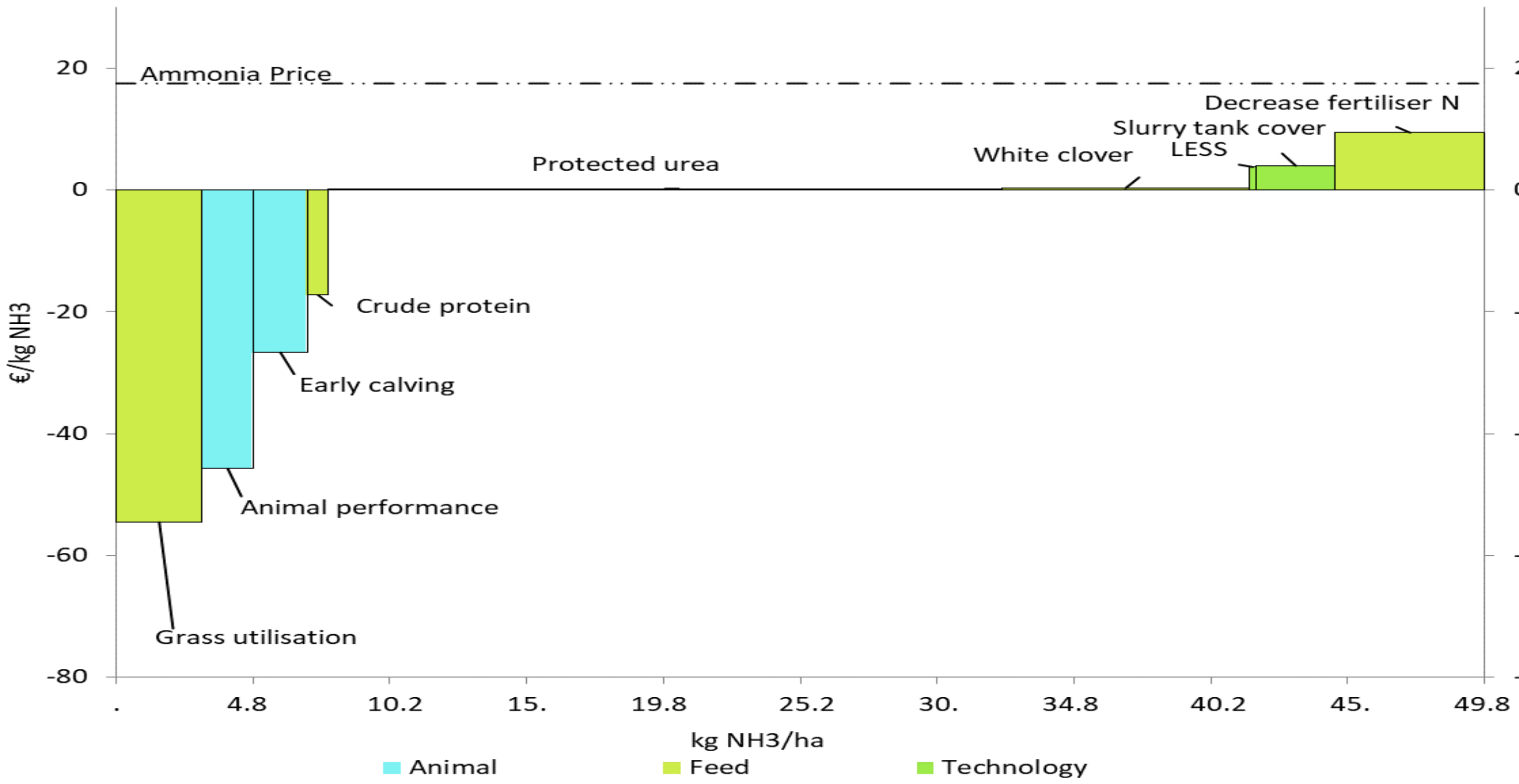

Figure 4.6 Ammonia marginal abatement cost curve for the top representative of Irish dairy farms in terms of economic performance. Abatement potentials correspond to the annual average for the period 2021-2030. Colours indicate the type of mitigation measure. The dashed line represents the shadow price of NH_3.

4.3.3 Sensitivity Tests

Rising input and output prices decreased GHG mitigation costs for each dairy farm group in Table 4.4. For the bottom representative of dairy farms, cumulative GHG mitigation costs decreased from -€184 to -€294 t/CO_2-e. The decrease for the middle representative of dairy farms was -€110 t/CO_2-e and -€104/t CO_2-e for the top representative of farms. GHG mitigation costs were lower for the bottom and middle representative of farms compared to the top group. The bulk of the benefit in terms of mitigation cost resulted from animal and feed related measures. Technological measures also contributed, specifically protected urea. The cost benefit of this technology was substantially greater than the initial analysis due to the two and half to threefold rise in the cost of N fertilisers in 2022. This resulted in a larger price differential between CAN and protected urea and was the driver of the significant decrease in GHG mitigation costs for white clover. The rise in fertiliser costs also brought cost prohibitive measures closer to the shadow price of carbon.

Consistent with GHG emissions, increasing prices to 2022 levels reduce NH_3 mitigation costs across representative dairy farms. The reduction in cumulative NH_3 mitigation costs was greatest for the bottom representative of dairy farms, €-20.1/kg NH_3. Ammonia mitigation costs decreased by a similar amount, €-16.6/kg NH_3, for the middle representative of farms; the decrease in NH_3 mitigation costs was substantially less for the top representative of farms (€-4.8/kg NH_3). This can be explained by the greater use of urea on these farms, which resulted in less cost savings for protected urea or white clover compared to the other farms. For NH_3 and GHG emissions, the steep increase in fertiliser price caused protected urea and white clover to move from cost effective to cost beneficial for the top dairy group. The majority of NH_3 mitigation measures were cost beneficial or cost effective. In line with the initial analysis, none of the selected NH_3 mitigation measures were cost prohibitive for the top dairy group. The only cost prohibitive measure for the bottom and middle groups was decreasing fertiliser N.

Table 4.4 Sensitivity of greenhouse gas and ammonia (NH3) mitigation costs for the bottom, middle and top representative Irish dairy farms in the Teagasc national farm survey to elevated agricultural input and output prices in 2022.

Mitigation Measure	**GHG Mitigation Costs ($€/t\ CO_2$-e)**			**NH_3 Mitigation Costs ($€/kg\ NH_3$)**		
	Bottom	Middle	Top	Bottom	Middle	Top
Improve animal performance	-269	-312	-414	-58.1	-60.5	-59.0
Increase grass utilisation	-475	-432	-415	-69.7	-65.6	-69.0
Crude protein	-575	-562	-559	-16.1	-17.1	-18.7
Better reproduction	-149	-132	NA	-40.8	-20.9	NA
Early calving	-382	-388	-230	-45.5	-40.4	-32.4
Decrease fertiliser N	107	97	191	58.6	34.0	7.4
Protected urea	-157	-156	-104	-119.7	-37.6	-0.7
White clover	-251	-221	-213	-203.6	-124.6	-5.9
Slurry tank cover	29	32	27	3.7	3.8	2.8
LESS	124	68	397	0.7	0.4	6.3
Total (including interactions)	-294	-295	-306	-53.7	-44.5	-14.1

Note: Farms were ranked in terms of gross margin/ha

<u>Limitations</u>

The representative farms in this study only partially represent the agriculture industry. The findings discussed here are based on particular case studies and may not be generalisable to the farming industry. It is important to note that this assessment only offers an “average” representation and does not adequately consider the significant variety that distinguishes Irish farms. The national MACC provide a clear understanding and representation of mitigation costs. However, it is crucial to recognise that the depth of our study does not allow for a thorough examination of the relative costs, labour costs, or the particular costs related to implementing mitigation measures. It’s crucial to emphasise that even if this paper offers various mitigation techniques, the adoption rate of these mitigation strategies is a limitation. Instead, this study emphasises the opportunity for mitigation, highlighting the significance of these choices in the larger context. It is critical to recognise that different farm management techniques might affect the success of certain mitigation strategies. For instance, modifications to crop rotation or irrigation practices may affect how well some mitigation measures work. The understanding of implementing new techniques and the readily available information affect farmers' decision-making processes on mitigating measures. Although the direct mitigation effects may be the main emphasis of this study, it is important to recognise the possible external advantages, such as changes in ecosystems and water quality, which call for consideration for future research projects. Farmers need a customised decision-support tool to help them determine which mitigation strategies are best for their type of farm, farm investment, and farm structure. Our analysis demonstrates the possibility for mitigation in three separate groups: the top, middle, and bottom representative of Irish dairy farms.

In addition to these factors, it is crucial to understand that risk perception and management techniques can also impact the success of mitigation strategies. Our research concentrated on a static assessment of farms at a particular moment and did not thoroughly assess dynamic feedback effects between pasture/feed availability, yield, and total production factors. These feedback loops may have a significant impact on profitability. Further research may include dynamic programming models such as CPLEX to address this research question.

4.4 Conclusions

Farm-level MACCs are useful for understanding the capacity to reduce gaseous emissions from specific agricultural systems or farms. The approach illustrates that the potential to reduce GHG and NH_3 emissions from different farms varies significantly. It demonstrated that combining mitigation measures resulted in a decrease of 23%, 19%, and 12% in GHG emissions below 2020 levels for the bottom, middle, and top dairy groups, respectively. This implies the top dairy group will struggle to achieve its 2030 and future GHG reduction targets with existing technologies and practices. It is important to note that emission reduction targets are assessed at the national level; therefore, underperformance within a specific farm group does not in itself constitute a legal compliance issue, provided that aggregated sectoral emissions meet national commitments.These findings indicate that new GHG mitigation measures must be developed for dairy farms. However, from both an efficiency and equity perspective, reliance on other farm groups to compensate for limited mitigation potential within high-performing dairy systems may not represent a balanced long-term strategy.The knowledge generated by the farm-level MACC is helpful because it enables advisors and livestock farmers to choose the most affordable mitigation strategies for achieving air quality and climate change goals. The approach highlights that some farms have greater potential for abatement than others and that the most economically effective mitigation measures vary by farm. Farm-level MACCs can account for variability in GHG and NH_3 mitigation potentials and costs that are often missed at the sectoral or country level. This suggests that the potential to mitigate GHG and NH_3 emissions from the agricultural sector is over or underestimated and needs to be quantified with a more detailed approach at regional or local scales.

5 Optimising Dairy Farm Planning: A Mathematical Programming Approach to Balancing Profitability and Emission Targets

5.1 Introduction

Farm planning is a crucial decision-making process for any farm business, regardless of the system. With the ever-increasing demands on the sector, including the need to increase food production due to population growth while adhering to climate change targets within limited resources, having effective agricultural management is vital. Farm planning has been in practice for centuries. However, it has undergone significant changes and evolved from a traditional form of judgment based on experience and intuition (Nuthall et al., 2018) to a more modern and sophisticated approach using mathematical modelling (Zhai et al., 2020; Tedeschi et al., 2020). Technological advancements and the increasing desire for specialised production systems have significantly influenced this evolution.

Mathematical models enable farmers to simulate different scenarios and assess outcomes before deciding. These models take into account market prices, input use, crop rotations, grassland management, irrigation, drainage, and environmental factors. Through mathematical optimisation, farmers can determine the most efficient allocation of resources, such as land, labour, and capital, to meet their production goals whilst ensuring environmental sustainability. A comprehensive review by Ahumada and Villalobos (2009) of the tools used in agricultural decision-making focuses on various aspects of the supply chain associated with production to distribution, varying from mixed integer programming whole farm tools to linear programming crop rotation models. Most tools in this review focus on maximising revenue or minimising cost. More recently, models are being adapted to minimise adverse environmental impacts or maximise positive outcomes (Díaz de Otálora et al., 2024; Del Prado et al., 2013), which align with broader sustainability goals.

Optimisation tools are pivotal in modern farm planning, offering farmers data-driven means to maximise productivity, minimise costs, and mitigate risks (Walter et al., 2017). These tools have various approaches, from simple spreadsheets to complex algorithms and software solutions. These tools enable farmers to navigate the complexities inherent in agricultural management. Sustainable farming practices are essential for achieving the balance between net margin maximisation and the minimisation of environmental damage (Rawnsley et al., 2016). Furthermore, concerns are increasing regarding the impact of climate change on agriculture, emphasising the importance of optimal farm planning in reducing its effects. Several agricultural techniques and technologies have already been developed to address climate change by lowering GHG emissions or improving carbon sequestration. Several factors, including cost, efficiency, social acceptability, ease of use, and agricultural education, affect farmers' adoption of these GHG mitigation measures (Olum et al., 2020; Farstad et al., 2022).

The Paris Agreement of the United Nations (UN) aims to limit global temperature rise to 2°c. above pre-industrial levels this century, which translates into a 43% reduction in GHG emissions by 2030 and net-zero levels by 2050 (UNFCCC, 2023; UN, 2024). Decreasing gaseous emissions from livestock production is challenging, but it can be achieved by improving agricultural practices and technologies. With increasing market demands and rising prices, farmers are under pressure to meet these demands while being sustainable. As such, it is vital to find a balance between economic objectives and environmental considerations. With the ability to account for many constraints and an objective simultaneously, farm models can help achieve this intricate balance between being economically viable while also ensuring environmental sustainability.

This paper presents a Linear Programming (LP) model to optimise the financial performance of a representative (average) Irish dairy farm, while also calculating annual GHG emissions. The representative farm is considered under two scenarios. The first is effectively a simulation of the status quo or baseline, and the second scenario includes a constraint to reduce GHG emissions by 10% relative to the baseline. The second scenario is intended to test the impact of a GHG ceiling that may be imposed on farms to satisfy national environmental objectives.

This paper aims to address the gap in research in optimising farm profitability and emissions by focusing on optimal farm planning and financial viability. The integrated internal modelling framework developed in this thesis currently generates financial results along with GHG emission estimates, while the model reported here may be used to incorporate mitigation strategies, which are essential for advancing sustainable agricultural practices; these are not considered in this paper. The model estimates an economically optimal farm plan across a five-year period.

The paper is organised as follows: Section 5.1 discusses the fundamentals of farm planning. Section 5.2 outlines the evaluation of thirteen decision support systems identified from the literature. Next, Section 5.3 describes the model formulation, while Section 5.4 highlights the model constraints and working sets. Section 5.5 focuses on the application to a representative farm. Section 5.6 presents the results of the representative farm from both scenarios. The paper concludes with a discussion of the results and the model's limitations.

5.1.1 Farm Planning Optimisation Fundamentals

Farm planning optimisation refers to using mathematical models and algorithms used to find the optimal plan for managing a farm's resources, such as land, labour, and capital, to maximise profitability and productivity (Nott, 1977).

Adopting technology for sustainable agricultural systems entails risk and trade-offs (Kanter et al., 2018). Given the scarcity of resources, there are unavoidable trade-offs or conflicts in reaching sustainability goals. Farm planning optimisation is about finding the best ways to allocate resources, make decisions, and implement measures that maximise profitability and productivity while also considering sustainability factors such as environmental impact, resource conservation, and long-term financial viability (Taheri et al., 2024; Rendel et al., 2013)

5.1.2 Decision Support Systems

Given the complexity of the issues farmers face and the vast array of mitigation and production decisions, decision-support tools help address the sometimes competing goals of reducing GHG emissions from the farm while also maintaining farm profitability. Many of the choices farmers face in this regard are complex, and Decision-Support Systems (DSSs) may help farmers select appropriate measures.

DSSs provide farmers with a valuable evidence-based decision-making framework to improve productivity and environmental outputs. DSSs are often developed and designed by local stakeholders and tend to represent their national system. There have been numerous reviews of farm-level decision-support systems, from their sustainability principles and assessment (Arulnathan et al., 2020; De Olde et al., 2016; MacPherson et al., 2020; Bartke & Schwarze, 2015; Lindblom et al., 2017) to DSSs useability and influences (Rose et al., 2016)

(Alexandropoulos et al.,2023) (Taramuel-Taramuel et al., 2023) (Ara et al., 2021) (Zhai et al., 2020).

Currently, a vast array of farm-level decision-support systems are available. For example, Alexandropoulos et al. (2023) evaluated thirteen decision-support systems from a user-ability perspective. The thirteen tools were selected under three key requirements (a) their frequent citation in search results; (b) recommendations from expert modellers in the European Research Area Network (ERA-NET) project “MELS”; and (c) the authors’ ability to access and personally use the tools for evaluation (Alexandropoulos et al, 2023). The review presented here builds on the work of Alexandropoulos et al. (2023) by evaluating the same tools with a focus on the composition of the tools, their scope and approach. The details of the thirteen tools are provided in Appendix C.

Many tools have a principal focus on GHG emission management, and several studies have addressed the need for managing and monitoring mitigation strategies (Crosson et al., 2011). In this paper, thirteen decision support systems are reviewed and outlined in more detail in Appendix C. The following section presents a review of existing decision-support systems and makes the case for the development of the linear program model presented here.

5.2 Background

5.2.1 DSS Review

The thirteen selected tools are evaluated using the approach of Ahumada and Villalobos (2009), initially developed for supply chain literature. Ahumada et al.(2009) evaluated DSS under three main headings: scope, agriculture output, and modelling approach, illustrated in Figure 5.1, and then a number of subheadings. This paper has modified this template for farm-level decision support systems by adding a new category: Environmental. This new category assesses the tools' environmental analysis under three main headings: scenario analysis, simulation, and calculator.

Agriculture output is divided into two categories: perishable and non-perishable products. This template was originally used for DSS in supply chains, and it accounts for non-perishable agricultural goods like beans and wheat. As this paper focuses on DSS in dairy systems, all the tools reviewed here are categorised as agricultural perishable goods.

Scope includes strategic, tactical, and operational to differentiate the type of decisions the tool can consider. Strategic planning represents any long-term planning activities. These decisions may take several years to complete and may involve distinct levels of commitment, but they will be aligned with the overall long-term goals of the firm, for example, implementing new sensory monitoring technology or farm expansion. Tactical planning is any medium-term decisions made on a farm focused on improving operations and dealing with the allocation of resources. These decisions may be made seasonally or annually. While operational are the short-term decisions the farm will make to allow it to run efficiently.

Modelling approaches are categorised based on their handling of uncertainty and unpredictability. Models can be initially classified as deterministic or stochastic. This is further refined by the mathematical programming approach. Stochastic methods, including stochastic programming (SP) and stochastic dynamic programming (SDP), and deterministic methods, such as linear programming (LP) and dynamic programming (DP). There are many other forms of modelling, like multi-objective and multi-criteria and predictive analysis, as well as time series analysis (Adebayo et al., 2021; Khan et al.,2019); machine learning (Liakos et al., 2018; Mirani et al.,2021) and forecasting (Chelliah et al., 2024) that have grown in popularity in the agricultural sector in recent years. This review follows the same template as Ahumada et al. (2009) and looks at four types of modelling, namely stochastic programming, stochastic dynamic programming, linear programming (LP) and dynamic programming. For this review, an additional subheading of reporting was added into the modelling category to account for the DSS's that are used as a reporting tools as illustrated in Figure 5.1.

Environmental includes three sections: scenario analysis, simulator and calculator. In the context of this paper, scenario analysis involves creating conditions or assumptions about farm operations and environmental factors. The modeller predetermines these conditions, allowing users to evaluate various scenarios and address "what if" questions. For example, scenario analysis can be used at the farm level to assess potential outcomes, such as implementing specific policy targets.

A simulation model charts the farm system over time and provides a detailed understanding of environmental and management changes affecting farm productivity and sustainability measures. It allows users to change their data to show how the farm will run under changing conditions. A calculator is a static analysis of a farm's operations; it is used as a benchmark and can well represent the current farm's status.

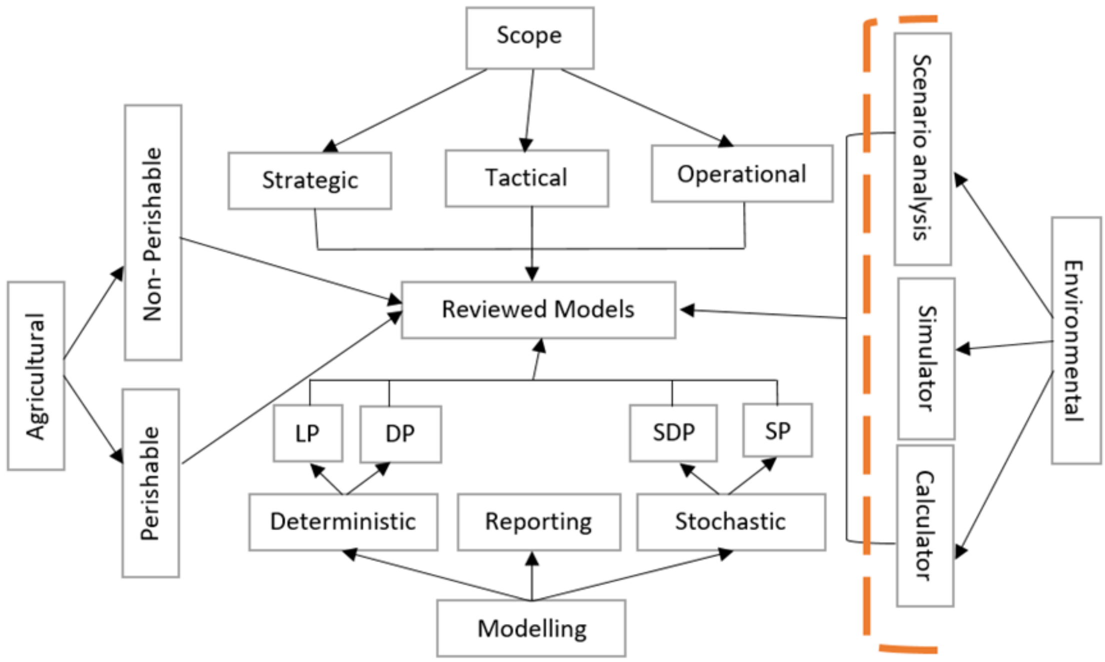

Figure 5.1 Adoption of Ahumada and Villalobos (2009) review template for decision support systems.

The following Table 5.1 present a review of the aforementioned 13 decision support systems using the approach of Ahumada and Villalobos (2009) is presented in the following tables.The review of the thirteen decision support systems was conducted based on publicly available documentation, including peer-reviewed publications, technical reports, and user manuals where available. In some cases, limited access to the full backend structure of the tools was available; therefore, the assessment is based primarily on reported functionality, documented methodologies, and observable outputs from the user interface. While this approach provides a consistent basis for comparison across tools, it may not capture all underlying model complexities where full documentation was not accessible

Scope				Deterministic			Stochastic		Environmental		
Model	Strategic	Tactical	Operational	Liner Programming	Dynamic Programming	Reporting	Stochastic dynamic programming	Stochastic programming	Scenario Analysis	Simulator	Calculator
Cool Farm Tool			X			X					X
Farm AC	X					X			X		
MDSM & LCA		X				X			X	X	
KSNL			X			X					X
SMART			X			X					X
RISE			X			X					X
BEK			X			X					X
Ag Balance	X					X			X		
Overseer	X					X				X	
HOLOS	X					X			X	X	
Gleam		X				X					X
CAP 2’ER		X				X			X	X	
Farmscoper		X		X					X		

Table 5.1 DSS Evaluation: Scope, Modelling and Environmental analysis.

The Cool Farm Tool is used for operational decision-making, Farm AC is applied strategically, and the MDSM and Dairy LCA and SMART tools are utilised for tactical decision-making. KSNL, RISE, BEK, and Gleam focus on operational aspects. Ag Balance and HOLOS are used strategically, and CAP 2'ER and Farmscoper serve tactical purposes.

The majority of models (12) in this review are classified under the deterministic reporting column. This classification is selected as these models are deterministic in their composition. These models are given a specific set of input parameters, which are then processed through established equations. None of these models incorporated randomness or probability elements into these calculations, ruling out the stochastic processes approach.

An LP model requires an objective function, where all relationships are linear. The objective function is a min or max equation around a certain problem under given constraints. None of the models maximised or minimised an objective function except for farmscoper. Instead, these models are either static calculators (6) or scenario/simulators that simulate emission cycles and nutrient flows, with predefined management practices and advice based on the results.

For DP, the models should break the problems into smaller sub problems and solves repetitively over time. These models are usually complex with sophisticated mathematically methodologies. From the 13 models reviewed, none of them fall under dynamic programming.

No model was identified for stochastic processes. A model is considered a stochastic program if it considers multiple uncertain outcomes in scenario evaluations.

Seven models calculate environmental issues: Cool Farm Tool, KSNL, SMART, RISE, BEK, Gleam, and CAP 2'ER. Additionally, four-scenario analysis models, including Farm AC, Ag Balance, HOLOS, and CAP 2'ER, evaluate various farming strategies and their outcomes. Three hybrid models, HOLOS, CAP 2'ER and MDSM & Dairy LCA, combine both scenario analysis and simulation, allowing users to run different scenarios and change the input data while also changing the conditions.

Table 5.2 DSS Economic Analysis.

Model	Economic Analysis
Cool Farm Tool	Standard farm financials –Income, expenditure, and profit
Farm AC	Not reported
MDSM & Dairy LCA	Standard financials in MDSM only
KSNL	Not evident
SMART	Not reported
RISE	6 headings for economic assessment: Liquidity, stability, profitability, Indebtedness, and livelihood security
BEK	Not evident
Ag Balance	Cost analysis: profit, gross margin, net value added, and total production cost are all calculated
Overseer	Standard farm financial and cost analysis
HOLOS	Not reported
Gleam	Not evident
CAP 2'ER	Not evident
Farmscoper	Detailed cost analysis with mitigation costs

While the degree of cost analysis varies significantly across all decision support systems as highlighted in Table 5.2, it ranges from not apparent to basic cost functions (revenue, expenditures, and profit) to a complete cost breakdown of mitigation strategy costs and economic impact on farms. Farmscoper and Ag balance are the models that produced the most detailed cost analyses. While both environmental analyses of these models are scenario analyses, limited simulators run economic analyses at the farm level.

While many decision-support systems have been built to monitor and evaluate emissions and sustainability, gaps remain. From the model review above, none of the models reviewed optimise farm income under environmental constraints. One of the models reviewed is Farmscoper, which is a tactical, linear scenario decision support system. Farmscoper has a library of mitigation strategies embedded in the model. However, the main objective is to provide an optimal set of mitigation measures to minimise pollutant losses while considering the associated costs. With the main objective set at minimising emission and measuring pollutant losses farmsoper has elaborate cost analysis of each mitigation measure however it does not include standard farm. Therefore, this thesis proposes an optimisation model as part of an integrated internal modelling framework that maximises net margin as the main objective while satisfying emission targets. This approach allows the farm to work in a financially optimal manner first, while satisfying emission targets.

While the review above highlights limitations within existing decision support systems, it is important to recognise that a range of optimisation models have been developed in the wider literature. However, many of these models are not embedded within operational decision support frameworks or lack integration with detailed farm-level economic and environmental models used in advisory contexts.

Within Ireland, Teagasc has developed a suite of decision support tools, including the Teagasc MDSM and the LCA model, which provide detailed economic and environmental assessments but do not inherently perform optimisation. The contribution of this research is not to replace these models or develop a standalone system, but to enhance their functionality through the development of an optimisation-based backend that integrates these existing models within a unified framework.

In this context, the novelty of the approach lies in combining farm-level economic modelling, life cycle assessment, and linear programming optimisation to identify optimal farm plans that maximise net margin while satisfying greenhouse gas emission constraints. This integrated approach provides a prescriptive tool that extends beyond scenario analysis or simulation, and represents a methodological advancement within the Irish dairy context, with relevance to broader international research on farm-level optimisation under environmental constraints.

Furthermore, by linking marginal abatement cost curve (MACC) insights with farm-level optimisation, the research contributes to bridging the gap between policy-level mitigation analysis and practical farm-level decision-making, particularly within the Irish dairy sector while maintaining relevance to broader international research on farm-level optimisation under environmental constraints.This approach aligns with broader international research on whole-farm optimisation models (e.g. FARMDYN, IFSM), while extending their application through integration within an operational advisory context.

model. This model focuses explicitly on prescriptive analytics, allowing the user to benefit from the results while highlighting the consequences of each decision option for the decisionmaker and recommending the optimal course of action (Lustig et al., 2010). The gap this paper aims to address is the optimisation of farm planning from both an economic and environmental perspective

Agricultural management involves various tasks and decisions to improve productivity and profitability while minimising adverse environmental impacts. While many decision-support systems are available from academic and commercial sources, the critical objective of this LP farm model is to provide the optimal farm solution to maximise net margin while limiting emissions. This model is unique as it simultaneously produces the optimal net margin and emission level a farm can attain every year. An optimal target can be set for net margin and or emission reduction. This is useful as it allows the user to see the financial impact on the farm while achieving a set emission target. The result of the model is an optimal farm plan (economic and environmental report) for the specific farm across a specific time frame.

5.3 Data and Modelling Approach

5.3.1 Representative farm

The representative farm was taken from the Irish National Farm Survey (NFS), run by Teagasc. This survey serves the purpose of monitoring the financial performance and the sustainability of the farm sector in Ireland. The National Farm Survey (NFS), operated by Teagasc, estimates gaseous emissions from livestock farms in Ireland annually. Information from the NFS is shared with the Farm Accountancy Data Network (FADN) of the European Union (Dillon et al.,2021). The NFS is undertaken annually on a nationally representative sample of farms. A random sampling methodology is used to select farms. The NFS weights farms according to the land area using aggregation factors from the Central Statistics Office (CSO, 2024) Census of Agriculture to ensure the survey is representative. Farms are categorised into different systems based on their main enterprise, as measured by standard gross output, such as dairy, cattle rearing, cattle other, mixed livestock, tillage, and sheep.

For this study, livestock farms were selected from the NFS, focusing on Ireland's most valuable agricultural subsector as measured by output value, dairy farming (Bord Bia, 2024). Within the dairy category, farms were ranked by net margin, and the average of farms was chosen to be representative of each subgroup. Using an average provides a simplified and tractable representation of farm systems, allowing consistent comparison across groups and facilitating integration within the modelling framework. The use of representative farms derived from survey averages is common in agricultural economics and farm-level modelling studies, particularly when integrating environmental and economic models (e.g. Crosson et al., 2011; Moran et al., 2011). However, this approach may mask variability within each subgroup, including differences in management practices, stocking rates, and system intensity. Despite this limitation, the use of representative average farms is appropriate for the objectives of this study, as it enables the analysis of general trends and trade-offs between economic performance and emissions while maintaining computational efficiency.

5.3.2 The Model

The representative farm has been modelled using linear programming, with a tactical scope and environmental simulation, to optimise resource allocation, improve operational efficiency, and assess the farm's emissions. The model produces an optimal farm plan that satisfies an emission target while maximising net margin.

The integrated internal modelling framework developed in this thesis couples a Teagasc bioeconomic model, the MDSM model with LCA model to perform economic and emission analysis, which the LP model then utilises for optimisation (Shalloo et al., 2004) (Teagasc, 2019) (Teagasc & Bord Bia, 2019). The dairy LCA model completes the carbon footprint assessment for the farm and generates an emission estimate for the farm.

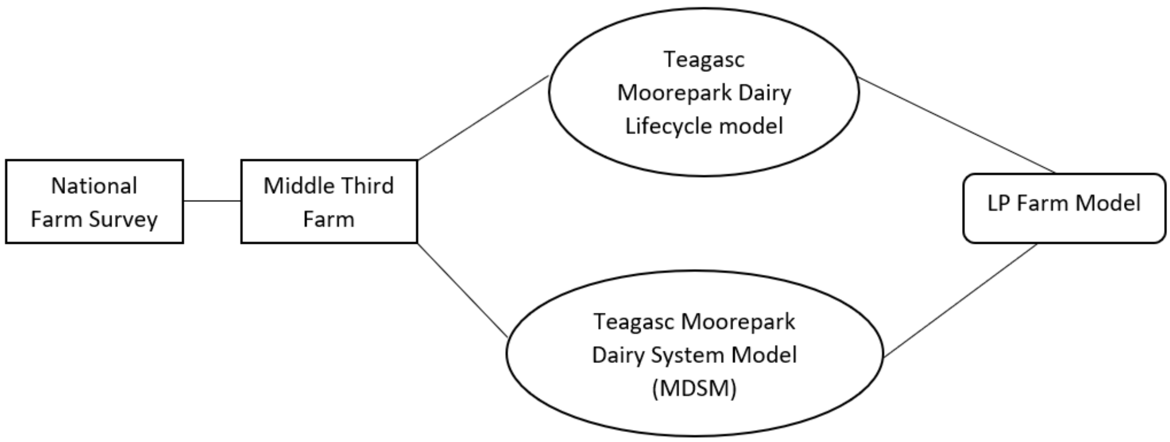

Figure 5.2 The flow chart of the integrated internal modelling framework for the middle representative farm.

The dairy LCA and MDSM models serve as feeder models for the LP optimisation model as illustrated in Figure 5.2. Individually, both Teagasc models compute very different perspectives of the farm. The dairy LCA model focuses on GHG emissions, namely methane, nitrous oxide and carbon dioxide, and determines ammonia losses. This results in a detailed emission output for the farm. Meanwhile, the MDSM focuses on the farm's economic side and generates financial statements: Profit & Loss statement and balance sheet (Shalloo et al., 2004). Both systems run on Microsoft Excel Solver. Each input and component were evaluated and calculated within its own Excel sheet, each with specific parameters to assess the granularity and complex relationships involved.

While both models accurately represent the farm's status, this is used as a baseline for the model. The MDSM uses a suite of scenarios with different mitigation strategies to build a tailored farm sustainability action plan. However, it has limited optimisation ability. The MDSM and dairy LCA model may be used to assist the decision-making process, but do not inherently optimise for specific/multiple objectives, i.e. cost minimisation, efficient resource allocation or yield maximisation, thereby making it difficult to account for trade-offs while implementing different measures.

The modelling framework adopts a static, partial equilibrium approach and does not incorporate dynamic feedback loops between system components or across time periods. In particular, interactions such as market price adjustments, biological feedbacks beyond herd transition equations, or sector-level supply responses are not endogenously modelled. Instead, key inputs from the feeder models (Teagasc MDSM and Dairy LCA) are treated as fixed parameters within the optimisation. While this approach enables tractable optimisation and clear interpretation of results, it represents a limitation of the model and should be considered when interpreting outcomes.

The addition of LP provides several advantages to the existing modelling environment primarily the ability to optimise one or multiple objectives on the farm. The LP model has been built using a mathematical framework that can optimise across numerous objectives or one main objective with a suite of constraints. This allows the user to make decisions while satisfying the desired objective, i.e. maximise net margin while considering a range of constraints around labour, land, budget or environmental targets. The LP model allows for the efficient allocation of resources on the farm throughout a planning horizon, allowing for the most efficient and effective use of farm resources.

Having the LP model as an additional element to the existing Teagasc modelling architecture facilitates more informed action plans based on one primary objective while satisfying a suite of constraints, including environmental constraints.

The output data from both feeder models (Teagasc MDSM and Dairy LCA) are extracted and used as parameter inputs into the LP optimisation model. These outputs are treated as static inputs rather than dynamically linked variables, meaning that the feeder models and the LP model do not update iteratively during the optimisation process.The model formulation is programmed in Optimisation Programming Language. The model framework comprises four main sub-categories: crop and feed production, breeding, environmental, and economic (Figure 5.3).

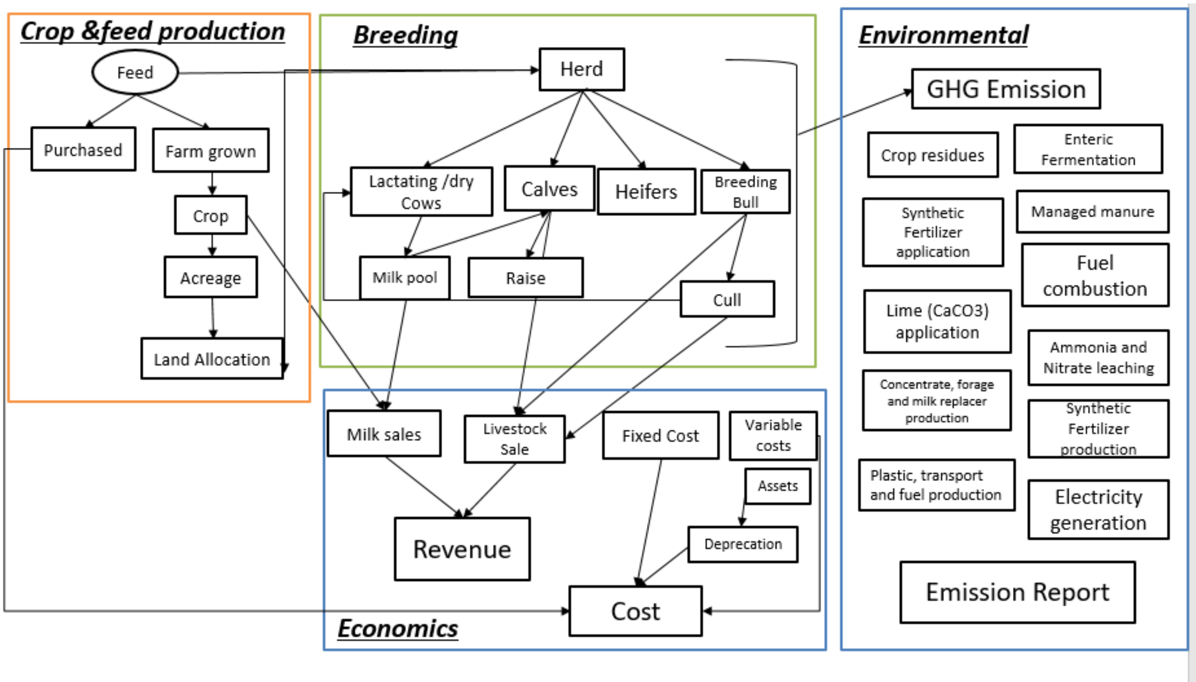

Figure 5.3 Model framework.

Each subcategory has relevant key elements that contribute to its overall function. Each of these key elements is tied to a decision variable in the LP model, making it crucial to monitor and run the farm model.

The following is the mathematical framework of the LP model. In Appendix A, Table 10.1 defines the sets used; Table 10.2 and Table 10.3 highlight the parameters for the farm, while Table 10.4 lists the variables used in the model.

5.3.3 Empirical model

The objective function of the model is to maximise net margin over the planning horizon while satisfying an emission ceiling of a 10%, in the scenario. The emission constraint is applied on an annual basis, with emissions in each year of the planning horizon required to remain below the specified emission limit. This is the main objective function of the model. In this case, t represents the time period of the model. Net margin is expressed as an average annual value over the planning horizon, discounting is not applied, as the model is designed for tactical farm planning rather than long-term investment appraisal.

$$\boldsymbol{max\ \frac{1}{T}\ \sum_{t=1}^{T}\left(revenue[t]-cost[t]\right)} \qquad (\mathbf{1})$$

The model is run annually to allow for an overall view of the farm's economic viability. The objective function determines the farm's annual net margin over the planning period. In this paper, the planning period is five years.

5.4 Economic Analysis

The economic subcategory of the model comprises two main sections: revenue and cost. as the representative farm is a dairy, revenue is calculated from milk sales, crop sales, livestock trade or culls, and the sale of farm assets. All prices are taken from the NFS and held constant over the five years, as the primary focus is on the environmental constraints. The model includes costs (variable and fixed) associated with the farm, livestock, and assets acquired as well as fodder production and feedstuffs. All the equations for the model are outlined in appendix B.

5.4.1 Revenue Calculation

As illustrated in Figure 5.2, the farm's revenue comes from the sale of milk, crops, livestock, and the farm's assets. Revenue from milk production is calculated by multiplying the milk price by the milk yield per animal. The table on dairy cows shows the yield produced by each animal and its corresponding age, (Appendix B, formula E1). Revenue from crop sales is determined by multiplying the crop price by the yield per hectare of each crop grown. For the first example, two crops are taken into consideration: wheat and barley (Appendix B, Formula E2). Grasslands comprise almost 62% of the total land cover in Ireland (CSO, 2024). They contribute significantly to Irish dairy herds by providing a large proportion of the feed requirements for ruminant livestock. In Ireland, the most proficient feed for dairy herds based on grass is grazed grass (Cashman et al., 2024). Grass is consumed by the herd as grazed grass and as silage or hay. This representative farm uses grass silage as the winter feed and grazed grass. The following table 5.3 is based on the Teagasc MDSM model and represents the amount required by each livestock throughout the year.

Table 5.3 Forage requirements of dairy cattle by category in kilograms of dry matter (DM) per year.

Livestock type	Grazed Grass	Grass silage	Forage
Calves	543	316	859
Yearling	1414	845	2259
2 year-old[a]	685	670	1355
Cows	2904	1172	4076

[a] Heifers were in 2-year-old category for two to three months

Grazing management: The rotation and stocking of grazing animals is considered under grazing management. The model uses the same stocking rate in Teagasc Pasturebase: (Hanrahan et al., 2017). Silage production represents the cost associated with the harvest and maintenance of silage as winter feed and is present in the model as silage.

For livestock, the model uses the stocking rate values outlined in the Department of Agriculture, Food and Marine for each age category of livestock. This stocking rate is assigned a specific livestock unit, (DAFM, n.d). Livestock sales are as follows:

- Revenue from trading livestock; selling cows, transfers, and calves, is calculated based on the prices for each category. (Appendix B, formula A1)
- Cull sale: Revenue from culling livestock is evaluated based on the respective prices for each category. (Appendix B, formula A2)

Farm assets are grouped under three headings: Buildings, Machinery and Land. The revenue from selling farm assets are calculated in (Appendix B, formula A3).

5.4.2 Cost Calculations

The feed cost represents the cost associated with the feed needed on the farm to sustain the herd. This formula describes the feed concentrate (Appendix B, Formula A4). The cost associated with growing, maintaining and harvesting the crop on the farm, on the required land (formula A5). The assets used in the model are land, land improvements, buildings, machinery, and new fixed assets. A 7%, and 8% depreciation rate is taken annually for buildings, machinery, and new fixed assets. (Appendix B, formula A6). While the variable costs are calculated within the LP model and associated with the decision variables, the fixed costs are added as a lump sum. This is taken into account to represent the net margin and costs on the farm. The following variable and fixed costs are described in Appendix D.

5.4.3 Environmental

In the environmental subcategory, Figure 5.3, emissions are calculated with the Dairy LCA model. The boundary of the emission model is defined at the farm level, consistent with the National Inventory Method (NIM) approach described in Chapter 4. However, it incorporates selected upstream emission sources associated with key farm inputs, in line with farm-level life cycle assessment requirements, including concentrate feed, fertiliser production, and energy use. The specific emission sources considered include enteric fermentation, manure storage, and spreading, manure deposited by grazing cattle, concentrate feedstuffs, N fertiliser application, lime application and fossil fuels. Each source is listed by GHG type, under the three main gas types: carbon dioxide, methane, and nitrous oxide. The data is further divided by the associated animal age category, illustrated in Table 5.4.

Table 5.4 Detailed breakdown of greenhouse emissions by source in kg CO_2 equivalent.

	Dairy heifers (0 to 12 months)			
	CO_2	**CH4**	**N2O**	**Total**
Enteric Fermentation		2386.70		2386.70
Managed manure		292.2	202.0	494.24
Manure deposited on pasture.			183.2	183.16
Synthetic Fertilizer application	197		242.5	439.65
Crop residues	1.40	4.51		5.91
Fuel combustion			87.26	87.26
Lime (CaCO3) application			58.35	58.35

Ammonia and Nitrate leaching	25.00	80.64	30.74	136.38
Synthetic Fertilizer production	51.13	164.89	62.86	278.89
Concentrate, forage and milk replacer production	22.41	72.26	27.55	122.22
Electricity generation	0.00	0.00	0.00	0.00
Plastic, transport and fuel production	17.76			17.76
Lime (CaCO3) production	4.73	15.24		19.97

A similar emission calculation is created for the crops produced, see Appendix B**,** Formula A8.

In the scenario, all the emission calculations are less than or equal to an emission ceiling.

5.4.4 Breeding

The breeding subcategory illustrated in Figure 5.3 represents the structure of the herd on the farm. The LP model considers the specific characteristics of the dairy herd, such as milk yield, feed requirements, and reproductive performance, to ensure that the farm's production goals are aligned with its resources and constraints. The breeding subcategory is linked with the decision variable associated with buying, selling, culling, and the milk yield of the herd. The initial distribution of cows is reflected in Appendix B, Formula B1.

The max-age represents the age at which dairy cows are no longer effectively productive; this max-age is predetermined by the user for their herd. In the representative farm, the max age limit for a dairy cow is set at six years old. The trading dynamics of the herd are represented in Formulas B2 to B5. These jointly illustrate the dynamics of the herd population over time, incorporating initial herd structure, births, deaths, purchases, sales, and culling processes.

5.4.5 Crop and Feed Production

The model's crop and feed subcategory in Figure 5.3 follows the lifecycle of the herd. The MDSM evaluate the herd's diet by calculating the daily concentrate intake per head and the number of feeding days. This allows for an accurate count of the total amount of concentrates fed. This feed budget is evaluated in the MDSM.

The LP model uses the yearly average of the consumption amount and the associated costs of feeds over the year to run the analysis.

For crop production, the model considers growing costs, the labour required, and the yield of each crop in Formula C1. The LP model focuses on the economic effect of growing and harvesting the crop. The crops can be sold at markets or used on farms for animal consumption in Appendix B, Formula C2.

The dairy LCA, which calculates the emissions associated with each crop and computes an emission footprint, nutrient losses and other environmental impacts.

5.5 The Empirical Model: Constraints and Feasible Set

Several constraints are embedded into the LP model to represent a real-life farm structure. The constraints from formulas D1 to D4 are outlined in Appendix B. A full description of all decision variables and constraints used in the model is outlined in Appendix E.

5.6 Application to a Representative Farm

A dairy farm from the middle representative farm of the population in terms of gross margin was selected from the National Farm Survey following the approach of Cantillon et al. (2024). The representative farm is a dairy enterprise with one breeding bull brought in every three years. Input data was taken from both the NFS, the Teagasc Dairy LCA model and MDSM and combined into one input sheet. The representative farm is described in the table below.

The following Tables 5.5 -5.6 present the physical and financial characteristics of the farm in the baseline year, which is 2020.

Table 5.5 Farm Description characteristics.

Parameter	Unit	Dairy Farm
Farm size, ha	Ha	56
Grass utilisation	t DM/ha	8
Concentrate feed	kg/LU	1223
Stocking rate	LU/ha	2.07
Milk produced	kg/cow	5,999
Milk fat and protein	kg/cow	455
Milk price	€/L	€0.34

Table 5.6 Average number and valuation of dairy cattle in the herd by animal category.

Animal category	Female	Male	Sell price €	Buy Price €	Cull price €
Calves	26		336	302	0
Yearlings	20		635	578	0
Two-year-olds	3	1	1140	1026	0
Three-year-olds	45		1140	1026	772
Four-year-olds	46		0	1026	772
Five-year-old	0		0	1026	772
Six-year-old	0		0	0	772
Culls	18				
Cows died	1				

Buy and sell prices are derived from the model input parameters and reflect the cost of purchasing and selling animals at different age categories, enabling the model to capture replacement and trading behaviour within the herd. Animals in older age categories are assumed to exit the system through culling rather than market sale; therefore, sell prices are recorded as zero and cull values are applied.

5.2 Assets

The opening livestock numbers are taken from the middle representative farms in NFS from the MDSM, these livestock number are listed above in Table 5.6. The farmland allocated in this model is 56 hectares, this is held constant for the five year period. The assets are divided into two categories: buildings and machinery. For the purpose of the model, eight items are under buildings and nine under machinery. The types of buildings included are milking parlours, cow cubicle houses, calf sheds, bullpen, calving boxes, cattle crush, and slurry tanks or dungstead. Similarly, under machinery is fertiliser spreader, yard scraper, front scraper, front-end loader, unit pipeline plant, bulk tank, yard wash pump, trailer and electric fence. The initial fixed cost and variable costs are outlined in Table 5.7.

Table 5.7 Fixed and Variable cost.

Fixed Cost	€	Variable cost	cent/litre milk
Car use	2865.5	Fertiliser, Lime & Reseeding	2.90
Electricity	4281.61	Machinery Hire	0.41
Labour	13946.4	Silage making	2.07

Machinery Operation & Repair	4258.31	Vet, AI and medicine	1.81
Phone	456		
Insurance, transport, Sundries	4393.73		
Interest repayments	9498.09		

5.7 Result

In the baseline, the results of the model generate an estimated average net margin for the farm of €80,437. In scenario 2, where an emission ceiling of 10% is implemented in the model, the average net margin for the farm was €71,340. This represents a 11.5% reduction in net margin due to the imposition of the emission ceiling, assuming no mitigation measures are adopted. The following section of the paper describes the results in more detail, including herd dynamics in the two scenarios.

5.7.1 Emission Report

Table 5.8 shows the emission results for the average farm across the five-year period, with baseline figures alongside the 10% emission ceiling figures. The specific breakdown of each emission source is listed above. The results show the collective of CO_2, CH_4, and N_20 for each year, comparing. Comparing both the baseline and scenario 1 side by side.

Table 5.8 Emission report for the middle representative farm.

Period	Unit	S1: Baseline	S2: 10% reduction
Year 1	$KgCO_2$ eq	531,285	474,512
Year 2	$KgCO_2$ eq	530,723	475,010
Year 3	$KgCO_2$ eq	531,078	474,744
Year 4	$KgCO_2$ eq	530,977	474,759
Year 5	$KgCO_2$ eq	530,898	474,882

5.7.2 Herd dynamics

5.7.2.1 Herd Dynamics Baseline

The herd dynamics represent the average number of dairy cattle on the farm per year. The herd dynamics for the representative farm are described in Table 5.9. The herd is split into six distinctive groups: calves, dairy heifers (12-24 months) and the milking dairy cows from three and six years old.

Table 5.9 Herd dynamics for baseline.

Herd	Unit	Year 1	Year 2	Year 3	Year 4	Year 5
Calves	average number/year	25.4	16	26.3	19.7	21.6
Dairy Heifer (12m - 24m)	average number/year	0.00	0.00	0.00	0.00	0.00
Dairy Cows (2-6 yrs)						
2-3 yr	average number/year	28.6	73.0	36.5	54.7	52.8
3-4 yr	average number/year	14.1	20.2	29.9	15.2	27.8
4-5 yr	average number/year	45.5	13.9	20	29.6	15.1
5-6 yr	average number/year	0.00	0.00	0.00	0.00	0.00

The herd structure fluctuated annually.

- For the calves group, the average number ranged from 26.3 (Year 3) to 15.9 (Year 2). The calves figure stabilised at around 19 and 21 after year 4.
- Dairy Heifers (12m-24m): There are no 12-24 month old calves in any of the years of the planning horizon. The model focuses on older animals that contribute to the milk pool.
- 2- 3 Year-Old Dairy Cows: This group ranged from 28.6 in year 1 to a high in year 2 of 73.1. The 3 year old stabilised in the low 50's after year 4.
- 3-4 Year-Old Dairy Cows: This group ranged from 14.1 in year 1 to a high in year 2 of 29.9. The average began to stabilize at 20.2, and this stabilisation continued into Year 4 with an average of 15.2 and 27.9.
- 4-5 Year-Old Dairy Cows: This group fluctuated the most throughout the five year horizon with a high of 45.5 in year one to a low of 13.9 in year 2. Finally finishing in year 5 with 15.1.

- 5-6 Year-Old Dairy Cows: As the max productive age is set to seven in the model, there are no six year olds kept in the herd.

The herd dynamics show the fluctuation of the herd throughout the five years. The main trend in the model is to keep a strong milking pool between three-year-old and five year old cows, whilst the dairy heifers seem to be consistently maintained at zero.

While the model results indicate that selling calves and purchasing replacement animals can improve farm-level efficiency by reducing unproductive emissions associated with rearing heifers, this strategy is not intended to represent a sector-wide equilibrium outcome. At a national level, such behaviour would not be feasible if adopted universally, as the supply of replacement animals must be sustained within the herd.

This modelling assumption reflects a partial equilibrium, farm-level perspective, where the representative farm optimises its own performance given existing market conditions, including the availability of replacement livestock. The objective of the model is therefore to evaluate optimal farm-level decisions rather than simulate sector-wide herd dynamics.

While the representative farm captures structural characteristics of Irish dairy systems, the results should be interpreted with caution when extrapolating to the national level, particularly where system-wide feedbacks and herd sustainability constraints are not explicitly modelled.

5.7.2.2 Herd Dynamics Scenario 2

Table 5.10 Herd dynamics for S2 emission reduction.

Herd	Unit	Year 1	Year 2	Year 3	Year 4	Year 5
Calves	average number/year	25.4	14.1	23.47	19.9	18.9
Dairy Heifer (12m - 24m)	average number/year	0.00	0.00	0.00	0.00	0.00
Dairy Cows (2-5 yrs)						
2-3 yr	average number/year	21.7	67.4	40.1	52.2	53.1
3-4 yr	average number/year	14.1	15.3	28.7	8.1	28.9

4-5 yr	average number/year	45.5	13.9	15.12	28.8	8.1
5-6 yr	average number/year	0.00	0.00	0.00	0.00	0.00

- For the calves group, average numbers ranged from 25.4 (Year 1) to 14.1 (Year 2). The calves figure stabilised at around the low 20's.

- Dairy Heifers (12m-24m): There is no 12-24 months in any of the years of the planning horizon. The model focuses on older animals that contribute to the milk pool.

- 2-3-Year-Old Dairy Cows: The 2 to 3 year old group ranged from 21.7 in year 1 to a high in year 2 of 67.4. A decline in year 3 to 40 and the number stabilises around the low 50's in year 4.

- 3-4-Year-Old Dairy Cows: This group fluctuated a lot throughout the five years. This group ranged from 8.1 in year 4 to a high of 28.9 in year 5.

- 4-5-Year-Old Dairy Cows: This group also fluctuated throughout the five-year horizon with a high of 45.5 in year two to a low of 8.1 in year five.

- 5-6-Year-Old Dairy Cows: As the max productive age is set to six in the model, there is no six year olds kept in the herd.

Overall, the baseline maintained a larger herd than S2. The most notable difference occurred in year four, where the baseline had 15.2 four-year-olds compared to only 8.1 in S2. This continued into year 5 as five year olds. This marked a significant gap in the age group. In years four and five, the baseline showed higher numbers for four-year-olds. After year three, both groups' numbers stabilised, with S2 consistently remaining slightly lower than the baseline. Both systems have no six year olds. The baseline system had a higher stocking rate throughout the five years compared to S2. This in turn had an impact on the milk yield. The average for the baseline is 561,133 litres, compared to 517,646 litres for scenario 2. This reflects an average drop in milk production of 8%. A drop in milk production could have wide reaching effects on food security.

5.7.3 Economic Performance

5.7.3.1 Economic Performance Baseline

For scenario 1 an economic overview is presented in Table 5.11 with assets outlined in Table 5.12.

Year one has the highest revenue of € 269,258 This is due to a combination of high milk sales of €212,213.93 and livestock sales of €57,043.

Overall, the revenue varied slightly over the five years, starting at €269,257 in Year 1 and decreasing to €238,644.31 in Year 2. A recovery was observed in Year 3 (€257,027), followed by slight declines in Year 4 (€252,550) and Year 5 (€247,586). Costs showed a downward trend overall, starting at € 207,424 in Year 1 and reducing to €162,799 by Year 5. Significant reductions were observed in Year 2 (€144,276) and a slight increase in Year 3 (€180,650), before stabilising in the following years. The increase in cost in Year 3 and year 1 are due to the high purchasing rate in both years. The net margin varied annually, showing improvement in Year 2 (€94,367) from Year 1 (€61,832). This upward trend continued into Year 3 (€76,376) and remained relatively stable in Year 4 (€84,609) and Year 5 (€84,787).

Table 5.11 Scenario 1 Economic overview.

	Year 1	Year 2	Year 3	Year 4	Year 5
Revenue	€ 269,257	€ 238,644	€ 257,027	€ 252,550	€247,587
Cost	€ 207,424	€ 144,277	€ 180,651	€ 167,960	€162,799
Net margin	€ 61,833	€ 94,368	€ 76,377	€ 84,590	€84,788

Table 5.12 Scenario 1 Assets.

Investing in Assets	**Initial Value**	**Y1**	**Y2**	**Y3**	**Y4**	**Y5**
Machinery	31,550					
Euro Increase in Capital Investment		14637	0	3985	1862	2224
Euro decrease in Capital Investment		0	0	0	0	0
	Initial Value	**Y1**	**Y2**	**Y3**	**Y4**	**Y5**
Buildings	11321.83					
Euro Increase in Capital Investment		11200	11200	11200	11200	11200

Euro decrease in Capital Investment		0	0	0	0	0
	Total	**€25,837**	**€11,200**	**€15,185**	**€13,062**	**€13,424**

5.7.3.2 Economic Performance Scenario 2

For scenario 2 an economic overview is presented in Table 5.13 and asset breakdown in Table 5.14.

Year one has the highest revenue of €247,025. This is due to a combination of high milk sales of €191,230 and livestock sales of €55,793. Overall, revenue varied slightly over the five years, starting at €247,025 in Year 1 and decreasing to €230,977 in Year 5. A decrease was observed in Year 2 (€226,640), followed by a slight incline in year 3 (€236,322) and year 4 (€235,322) with a drop in year 5 (€230,977). Costs showed a downward trend overall, starting at € 184,088 in Year 1 and reducing to €152,205 by Year 5. Between year two and four the cost ranged from €150,610 to €165,016. The high cost in Year 1 is due to the high purchasing rate and increase in capital investment.

The net margin stabilised around seventy thousand with the exception of year 1. With a low start in year 1, it shows a significant improvement in Year 2 reaching a high of €76,030 from Year 1 (€62,936). The low net margin in year one is due to the high costs previously mentioned and illustrated in Table 5.13. An upward trend continued into year 5, reaching another peak at €78,771 with a slight decline in year 3 and 4 to € 71,367 and €70,305, respectively.

Table 5.13 Scenario 2 Economic overview.

	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
Revenue	€247,025	€ 226,640	€ 236,384	€ 235,322	€230,976
Cost	€ 184,089	€150,610	€ 165,016	€ 165,017	€ 152,205
Net margin	€62,936	€76,030	€ 71,368	€ 70,306	€ 78,771

Table 5.14 Scenario 2 Assets.

Investing in Assets	**Initial Value**	**Y1**	**Y2**	**Y3**	**Y4**	**Y5**
Machinery	31,549					
Euro Increase in Capital Investment		12,209	0	3,090	4,363	676

Euro decrease in		0		0		
Capital Investment			0		0	0
	Initial Value	**Y1**	**Y2**	**Y3**	**Y4**	**Y5**
Buildings	11,321					
Euro Increase in Capital Investment		3,347	16,302	8,360	9,861	12,775
Euro decrease in Capital Investment		0	0	0	0	0
	Total	**€15,556**	**€16,302**	**€11,451**	**€14,225**	**€13,451**

The revenue for the baseline remained consistently higher than scenario 2 across all five years. Year two is the year that this gap narrowed with S2 revenue at €226,640 and baseline revenue of €238,644. Costs fluctuated for both baseline and scenario 2. Both costs peaked in year 1 due to the high purchasing rate and investment in capital. Baseline generally had higher costs apart from year 2. The optimal net margin for the baseline is €94,367 (year two) while the optimal net margin for scenario two is €78,771 (year five). While the baseline did tend to have a higher net margin throughout the five year period. In year 1,3 and 5, both the baseline and scenario 2 exhibited close net margins. Consistently, the baseline had a higher milk production compared to scenario 2, which is due to the higher stocking rate.

The baseline spread the machinery investment across the five years whereas S2 had a higher initial machinery investment in year 1 with little investment throughout the five year period. For building investments, it is fixed and higher in the baseline than in S2.

5.8 Limitations of the Model

The model outlined above shows how a farm plan can be optimised to maximise net margin while subjected to environmental constraints. While the model is a useful decision support system, it should be acknowledged that there are a number of limitations. The model assumes all the relationships are linear, that the constraints and objective function are constant and all prices are held constant through time. Currently, the prices are set in this model and require one input sheet. The model can easily be adjusted to include dynamic prices that can change over time, but it was chosen to go with set prices to get a baseline scenario for an average Irish dairy farm and illustrate the impact of a 10% emission ceiling.

Furthermore, the model does not consider feedback loops as outlined in 5.3.2, which could present a challenge, particularly when looking at the supply and demand of farm products. This could be overcome by introducing a recursive LP model or having a simulation, allowing for a feedback mechanism to be incorporated (Nasyrov et al., 2024).

The application presented here demonstrates the cost to a farm of an environmental limit. While the costs of a GHG limit could be alleviated through the implementation of mitigation strategies, such as more efficient fertilisers or better genetics, for example, this has not been included in the model. The model could however be adapted to include such measures for a future analysis.

As this LP model is planned to be part of an overall Teagasc decision support system, having a hybrid approach of an LP model and the existing Teagasc dairy LCA and MDSM model can combat many of the linear programming limitations, (Shalloo et al., 2015) (Teagasc, 2019).

The model also has limitations around specific time measurements, as it only evaluates yearly; other variations could consider seasonal changes.

Another limitation of the model is that it does not consider different soil types, land variations and land restrictions. This will impact the decisions around crop types and land allocation. To overcome this the LP model could be coupled or another feeder model added with a mapping geographical informatics system or sensor analysis for soil to allow for the optimal selection of crops (Mathenge, et al., 2022; Rötter, et al.,2012).

The model evaluates the financial and environmental impact of maintaining and managing the herd within an emission ceiling. It is crucial to recognise while the model has limitations, the main objective was to assess the optimal net margin of an “average” dairy farm under a certain emission ceiling.

5.9 Conclusion

As farmers face increasing pressure to sustainably feed the growing population, new tools are needed to assist them in navigating a complex set of choices. Sustainability requires achieving a balance between economic goals and environmental targets which involves many trade-offs. Understanding the full ramifications of farm production decisions on these trade-offs is challenging for farmers, hence making the case for the use of decision support systems.

This model is unique as it simultaneously estimates the optimal net margin and levels of emission produced by a farm each year. This allows for the optimisation of farm planning from both an economic and environmental perspective. This LP model is built to be used as part of the wider Teagasc decision support systems as it uses two key feeder models.

For the representative farm as a baseline, the average net margin of €80,791 was achieved with a total emission of 531,000KgCO_2eq. When a 10% reduction ceiling was implemented on emissions, the net margin of the representative farm was €71,482. When the 10% emission ceiling was activated, the stocking rate and milk production dropped compared to the baseline.

Ultimately, the model aims to optimise farm management strategies, balancing revenue generation with resource constraints, environmental considerations, and regulatory requirements. While the model in its current form does not consider any mitigation measures, it can be adapted to consider a range of such measures and can be used to select the optimal measures that both minimise emissions and maximise net margin. This would be a useful and interesting extension of the model.

6 Optimising of Grass-Based Dairy Production Through Mitigation Measures: Scenario Modelling of Emission Ceilings, Grassland Management, And Animal Productivity

6.1 Introduction

Dairy farming is a vital component of Ireland's agricultural sector, making a substantial economic contribution. Irish dairy exports to the European Union (EU) increased by 6% to €2.4 billion in 2024 (Bord Bia, 2024). The agriculture sector makes an essential contribution to the Irish economy and holds cultural and societal importance, supporting around 18,000 farming families (CSO, 2018). As the global population expands and resources remain limited, dairy producers are under pressure to boost production while improving environmental sustainability and economic growth. Ireland's is unique with a grass-based, pasture-centric system. Along with a temperate climate and an extended grazing season, this combination requires a different model than the more widespread total mixed ration systems prevalent in many parts of Europe and North America. This research adds to the international discussion on sustainable dairy farming by exploring mitigation strategies within a grass-based system, offering insights that could be useful for other temperate, pasture-focused regions aiming to reduce emissions and maintain farm profitability.

Amid growing environmental concerns, sustainable dairy farming must achieve a balance between productivity and climate impact. The potential for GHG reduction in the dairy sector is well-acknowledged, supported by a proliferation of research on mitigation measures, farmer adoption rates, and environmental effects (Moerkerken et al., 2020; Adenaeuer et al. 2023; Rencricca et al., 2023; O'Donoghue et al., 2024). For Ireland, official sectoral GHG ceilings were established in the carbon budget for 2022, including a 10% emissions reduction goal for 2025 and a 25% emissions reduction goal for 2030 (DECC, 2023; Oireachtas, 2024). Farmers can reduce emissions through various methods including feed management (Contosta et al., 2021; Lahart et al., 2021; Ouatahar et al., 2021; Ma et al., 2024), breeding (de Haas et al., 2021; Lahart et al., 2021; Richardson et al., 2022), enhancing precision farming (McNicol et al., 2024; Neethirajan, 2024) and utilising nitrification inhibitors and grassland management (Herron et al., 2021b; Hennessy, 2022; Garnett et al., 2024), among others.

These measures differ in their emission reduction potential and approaches, and vary in their economic implications for the farm.

Ensuring that farms are economically viable while meeting these ambitious GHG reduction targets will be challenging. Decision support systems can help address the often competing goals of reducing GHG emissions from the farm while also maximising farm profitability. Data-driven decision support systems will be vital in reducing GHG emissions from the livestock sector. Approaches range from machine learning, data analytics, modelling, and/or simulations. These can be combined with optimisation techniques to enhance the decision support functionality (Niloofar et al., 2021).

Optimisation models have already been successfully implemented in the agri-food sector, spanning from supply chain to farm-level tools (Taşkıner et al., 2021; Malik et al., 2022). At the farm level, optimisation tools range from minimising production costs and maximising profitability to reducing GHG emissions through improved nutrient management in the landscape (Milne et al., 2020), optimising health management (Ferchiou et al., 2021), and optimising feed management (Cecchini et al., 2022). Cantillon et al. (2024) analysed the cost-saving potential and the environmental outcome of various mitigation measures for a representative Irish dairy farm. The analysis considered multiple mitigation measures and concluded that the optimal combination of mitigation strategies varied from farm to farm.

The study by Cantillon et al. (2024) highlights the need for a tailored decision-support tool to assist farmers in identifying the best mitigation strategy for their farms. Although optimisation models have demonstrated success, most focus either on economic outcomes or environmental impacts separately. There is a lack of studies that combine mitigation strategies to optimise net margin while reducing emissions at the farm level. While some Irish models have examined the effects of agricultural mitigation, few have used optimisation techniques across the entire farm to evaluate the economic and environmental trade-offs of practical, implementable options. This research seeks to address that gap.

In this Chapter, linear programming optimisation modelling is used to select appropriate mitigation measures that maximise the profitability of grass-based milk production systems while constraining GHG emissions. For this study, two groups of mitigation measures, animal productivity and grassland management, are included in the model and net margin is maximised subject to an environmental limit over a five-year period. These measures are described in detail in section two.

The Chapter begins by describing the model used in this evaluation and then providing a detailed overview of the representative Irish dairy farm. Next, the mitigation measures considered in the model are described. The Chapter concludes with a discussion of the optimal approach to maximising farm net margin while minimising GHG emissions.

6.2 Materials & Methods

6.2.1 Optimisation Model

The concept of optimisation farm modelling is not new and has featured in the literature since the late 1940s. According to Kelemen et al. (2015), optimisation techniques can be classified under three main approaches: intuitive methods, statistical and mathematical methods, and operational research methods. The approaches differ based on the problem being addressed by the optimisation model. For example, operational research typically consists of non-linear, linear and square programming but there are also many other forms of modelling approaches that can utilise optimisation, such as multi-objective and multi-criteria and predictive analysis, as well as time series analysis (Adebayo et al., 2021; Khan et al., 2019); machine learning (Liakos et al., 2018; Mirani et al., 2021) and forecasting (Chelliah et al., 2024), that have grown in popularity in the agricultural sector in recent years.

Optimisation techniques can be implemented at any stage of the agri-supply chain. According to a review of optimisation techniques used in the dairy supply chain by Malik et al. (2022),67% of studies focused on production and planning optimisation, and 29% focused on inventory management, while only 15% addressed the entire supply chain optimisation. This illustrates how optimization techniques can be applied to every phase of the dairy supply chain. The focus on production-level optimisation is directly aligned to this study, which models farm-level decisions up to the farm gate. This review confirms that mathematical modelling-based techniques are still dominant, but AI and machine learning techniques are growing which could offer complementary tools for future on farm decisions.

Numerous decision support systems exist for dairy farming. Optimisation techniques at farm level have centred around maximising production (Dowson et al., 2019), maximising net margin (Doole, 2013), minimising costs (Borysenko et al., 2024), optimising health management (Ferchiou et al., 2021), and optimising feed management (Notte et al., 2020; Cecchini et al., 2022). Nevertheless, few decision support systems have integrated optimisation methods that simultaneously address economic and environmental objectives. Notable examples include Van Middelaar et al. (2013; 2014), who used linear programming and life-cycle assessment (LCA) to evaluate trade-offs between emissions and profitability in Dutch indoor farms. While their system differs from Irish pasture-based farms, their approach offers valuable insights as a benchmark.

A recent European wide modelling study by Díaz de Otálora et al. (2024) used the SIMS DAIRY framework to assess mitigation options like reducing protein feed, slurry injection, anaerobic digestion, and fertiliser selection across six European production systems. These results illustrate that economic and environmental impacts differ significantly across systems, highlighting the importance of developing tailored mitigation strategies.

Together, these studies guided the creation of our pasture-based optimisation model, highlighting the need to evaluate emissions and economics concurrently within specific scenario conditions.

Various whole farm optimisation models have also been developed based on a recent survey by Bang et al. (2023); seven DSSs are whole farm optimisation models. A full description of the models is included in Appendix F.

- FARMDYN
- Integrated Dairy Enterprise Model (IDEA)
- DairyNZ
- FarmDESIGN
- Optimization of Ruminant Farm for Economic and Environmental assessment (Orfee)
- ScotFarm
- N-CyCLES (nutrient cycling: crops, livestock, environment, and soil)
- Integrated Farm Optimisation and Resource Allocation Model (AgInform)
- Integrated Farm System Model (IFSM)

While simulation models are valuable, their methodologies differ from optimisation models. Optimisation models are mathematical models centred around a specific objective function or a set of objective functions (multi-objective) that is either minimised or maximised. To date optimisation models have not been applied to optimise mitigation measures on Irish dairy farm systems. Hence, we developed this optimisation model which focuses on prescriptive analytics and creating a deterministic linear program that runs a farm optimisation to maximise farm net margin, while satisfying emission constraints.

6.2.2 The Model

The objective function of the model is to maximise net margin over the planning horizon with an emission constraint that can be activated or relaxed. In this case, t represents the time period of the model.

$$\boldsymbol{max\ \frac{1}{T}\ \sum_{t=1}^{T}\big(revenue[t]-cost[t]\big)} \qquad (\mathbf{1})$$

The model is run annually to provide an overall view of the farm's economic viability. The objective function calculates the farm's annual net margin over the planning period, which in this paper is five years.

The model is run annually to provide an overall view of the farm's economic viability, and the objective function calculates the farm's annual net margin over the planning period. For the purpose of this paper, the model applied to a number of scenarios. A full description of the optimisation LP model and associated formulas is outlined in Chapter five, as well as Appendix A and B.

The Teagasc MDSM and dairy LCA models serve as feeder models into the LP optimisation model providing distinct perspectives on farm performance. The dairy LCA model focuses on GHG emissions, namely methane, nitrous oxide, and carbon dioxide, and calculates ammonia losses, generating detailed emission data. On the other hand, the MDSM examines the farm’s financial side, generating profit and loss statements and balance sheets. The LP model integrates data from both Teagasc models, forming a framework with four sub-categories – crop and feed production, economics, breeding and environmental. The model is run annually to provide an overall view of the farm's economic viability, and the objective function calculates the farm's annual net margin over the planning period. For the purpose of this paper, the model is applied to a number of scenarios. A full description of the optimisation LP model and associated assumptions is available in Chapter 5.

6.2.3 Representative Farm

A representative farm approach is used. The representative farm was taken from Ireland's National Farm Survey (NFS) data, collected by Teagasc. This survey serves the purpose of monitoring the economic performance and the sustainability of the agricultural sector, and it satisfies Ireland's reporting requirements as part of the Farm Accountancy Data Network (FADN) of the European Union (Dillon et al., 2021). The NFS is undertaken annually on a nationally representative sample of farms selected using a random stratified sampling approach. Each farm is assigned an aggregation factor from the Central Statistics Office (CSO, 2022) to ensure the sample is nationally representative.

Following the approach of Cantillon et al. (2024), that identify a representative dairy farm from the middle representative of the population in terms of gross margin performance. Input data was taken from the middle third of NFS, data . Input data was sourced from the NFS, the Teagasc Dairy LCA model, and the MDSM and combined into one input sheet. Table 6.1 presents the physical and economic characteristics of the farm in 2020, the baseline year.

Table 6.1 Farm Description characteristics of the middle representative farm from 2020.

Parameter	**Unit**	**Dairy Farm**		
Farm size, ha	Ha	56		
Grass utilisation	t DM/ha	8		
Concentrate feed	kg/LU	1223		
Stocking rate	LU/ha	2.07		
Milk produced	kg/cow	5,999		
Milk fat and protein	kg/cow	455		
Milk price	€/L	€0.34		
Animal category	**Female**	**Male**	**Sell price €**	**Cull price €**
Calves	26		336	0
Yearlings	20		635	0
Two-year-olds	3	1	1140	0
Three-year-olds	45		1140	772

Four-year-olds	46	0	772
Five-year-old	0	0	772
Six-year-old	0	0	772
Culls	18		
Cows died	1		

6.2.4 Mitigation Measures Used

Cantillon et al. (2024) evaluated ten farm-level mitigation strategies applicable to grass-based dairy farms under temperate climatic conditions. Seven animal and grassland-related strategies analysed by Cantillon et al. (2024) were included in the optimisation model. The specific strategies added to the model were as follows.

1. Animal productivity – Genetic gain in dairy cattle was accelerated to improve the productivity of the herd. This was accomplished through breeding dairy heifers and cows to top sires in the economic breeding index (EBI). The EBI is a single profit index representing several genetic traits, e.g., production, survival, and fertility (ICBF, 2023). The rate of genetic gain as measured via EBI was increased by an average of €12/cow per year over the course of the planning period. Improving dairy EBI enhanced fat and protein yield and improved cow longevity. Furthermore, increasing EBI by 10 units decreased the methane conversion factor for enteric fermentation by 0.32% (Lanigan et al., 2023). The mitigation effect from improved herd genetics (EBI) was phased in over the 5-year horizon using a 20% annual replacement rate. The full mitigation potential was 4.9% for the middle representative farm.

2. Grass production - Unproductive pastures were renewed with ryegrass to increase grass production and utilisation. The annual reseeding rate was increased from 3% to 6% of the grassland area to the recommended rate, i.e. 10%-15%. The top ryegrass cultivars in the pasture profit index (PPI) were selected for reseeding. They improved the digestibility of forage by 50-60 g/kg DM and increased response rates to N fertiliser by 25%-30% relative to older swards (Teagasc, 2014). Fertiliser rates for establishing new swards were based on Teagasc recommendations (Wall & Plunkett, 2020).

3. Reproductive management aimed to reduce the age at first calving by closely monitoring heats and matching heifers with easy-calving sires.

4. Reducing fertiliser nitrogen, leading to a reduction in annual fertiliser input while adjusting herbage yield downwards. In line with climate policy for the Irish agricultural sector (GOI, 2023), the annual input of fertiliser N was reduced by 20%.

5. Use of protected urea in place of conventional CAN and nitrate-based compound to reduce nitrogen losses. This form of N replaced 93% of the total N fertiliser.

6. Incorporation of white clover into grassland swards to lower fertiliser nitrogen usage. White clover was added into grassland according to the steps outlined in the Teagasc management guides (Hennessy et al., 2021). The annual reseeding rate increased to 10% of the farm area.

7.Cattle slurry was applied using Low Emission Slurry Spreading (LESS) equipment such as trailing shoes. To delivered slurry onto the soil in narrow bands, to improve nutrient efficiency.

More detail on these measures is available in Cantillon et al. (2024) in terms of costs, benefits, and abatement potential. A worked example showing how the Protected Urea measure is parameterised and passed through the modelling chain is provided in Appendix G and a step-by-step narrative worked example is provided in Appendix H. An important contribution of this research is the integration of mitigation costs derived from the farm-level MACC (Chapter 4) into the Teagasc MDSM model. This ensures that both the economic and environmental impacts of mitigation measures are consistently represented within the modelling framework.

For the purposes of this study, animal productivity and grassland management were the mitigation strategies considered in our model.

Animal productivity and grassland management were chosen due to their lower barriers to uptake and the robust scientific literature on their application to the Irish dairy system (Palma-Molina et al., 2023; O’Donovan et al., 2022; Mulkerrins et al., 2022; Ryan, 2022)

In this case, grassland management is a collective of four measures: protected urea, white clover, ryegrass, and LESS. While animal productivity is a combination of breeding animals based on the economic breeding index with the addition of an earlier calving date.

All grassland-related measures were combined into a single category to account for their complementary effects. Similarly, all animal productivity measures were combined into the animal productivity category. This coupling ensured that interactions between these measures were appropriately considered, as these practices would be implemented simultaneously, annually. For instance, integrating grassland-related measures led to a slight increase in fertiliser relative to the white clover measure, but together, the measures reduced baseline fertiliser N usage from 177 to 112 kg N/ha. The measures also improved milk yield/cow due to a more digestible grass white clover sward.

These measures were initially modelled separately and processed through the dairy LCA and MDSM models, which served as feeder models for the LP optimisation model. The results of these individual models are also included below.

6.3 Scenario analysis

Four scenarios are modelled: S1 is the baseline scenario for a representative average Irish farm this is the farm without any active constraints and mitigation measure, S2 is the same farm operating with a 10% emission ceiling (active emission constraint), S3 is the farm implementing grassland management as a mitigation strategy, and S4 is the farm implementing animal productivity as a mitigation strategy. Each scenario is modelled across a five-year time frame.

All 4 scenarios include prices from the NFS that are held constant over the five years across all scenarios, as the main focus is on the environmental constraints and the impact of mitigation measures on the farms' profitability. All scenarios are outlined in Table 6.2.

Table 6.2 Scenario explained.

Name	Description	Abbreviation
Scenario 1	Baseline of the middle representative Irish dairy farms taken from the NFS.	S1
Scenario 2	Baseline with an activated constraint to reduce GHG emissions by 10% relative to the baseline.	S2
Scenario 3	Baseline line with grassland measure; This comprises a combination of four individual measures: grouped-grass	S3

	utilisation, protected urea, white clover and reduced fertiliser nitrogen	
Scenario 4	Baseline with animal productivity measures, comprises of the use of EBI and early calving dates.	S4

The implementation of mitigation measures occurs at the feeder model stage (Teagasc MDSM and Dairy LCA), where parameter adjustments reflecting each mitigation strategy are applied prior to optimisation. The resulting economic and emission outputs are then passed to the LP model as fixed input parameters. As such, the LP model does not endogenously select mitigation measures, but rather optimises farm decisions conditional on the predefined mitigation scenario.

Mitigation measures are analysed as two distinct scenarios: grassland and animal productivity. However, both could be adopted simultaneously in reality. This approach was adopted as the model employs linear programming, which excels at optimisation under fixed, linear constraints but is limited in handling intricate decision combinations. Incorporating both mitigation strategy measures into a single scenario would require mixed integer programming (MIP). This method can handle more complex decision-making by combining both continuous and discrete variables, enabling the model to recognise trade-offs and determine the best strategy independently. However, implementing MIP introduces considerable complexity and computational requirements. Consequently, choosing separate linear programming scenarios is a strategic decision aimed at keeping the model simple and clear, even though a unified MIP approach might offer a more cohesive solution perspective.

6.4 Results

For the baseline, the average net margin was €80,437. In S2, with the emission ceiling of 10% the average net margin for the representative farm was €67,507. In S3, the combined grassland measure had an average net margin of €80,436, while in S4, the EBI measure had an average net margin of €78,630. Grassland management also excelled in reducing farm emissions, achieving the lowest average emissions at 445,000 kgCO_2eq. This reflects a 16% decrease compared to the baseline. Overall, both S3 and S4 exhibited lower yearly emissions than S1 and S2, as illustrated in Figure 6.1.

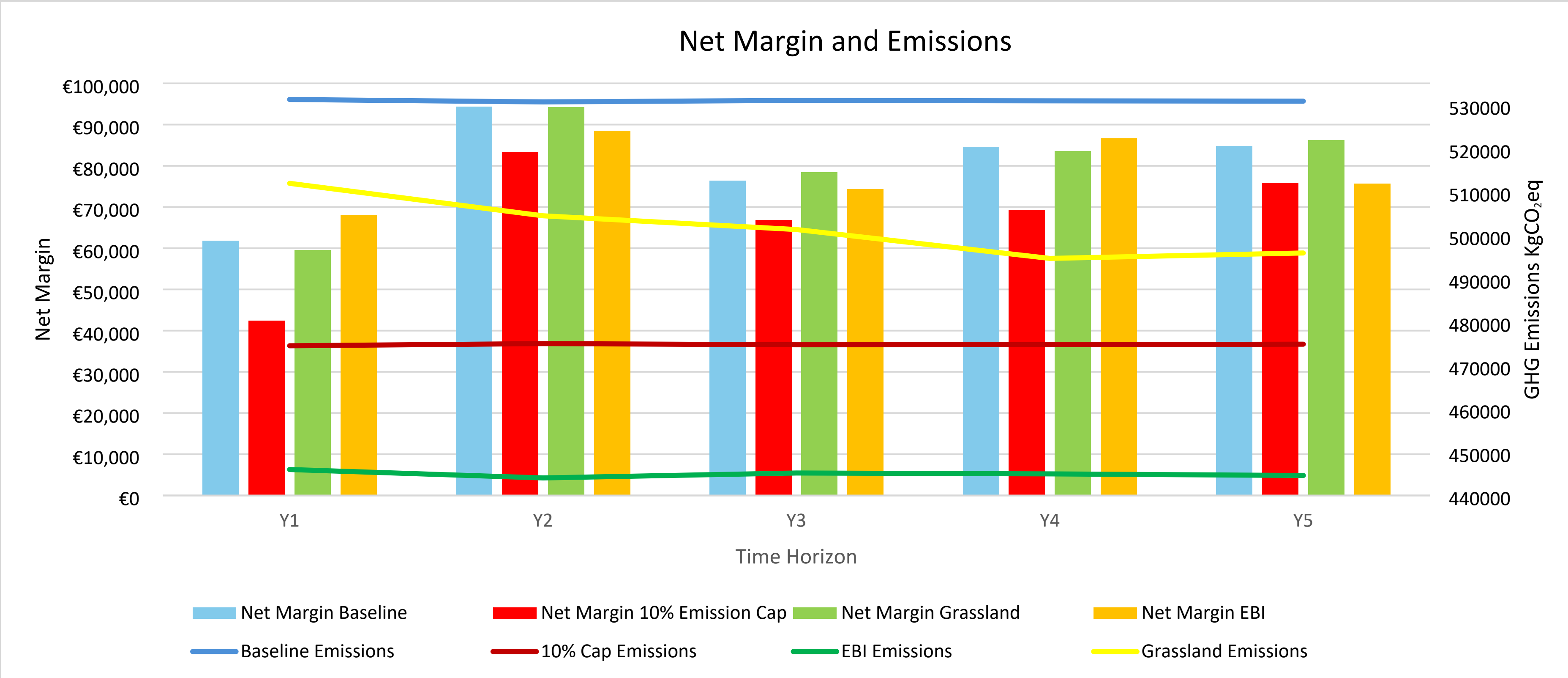

Figure 6.1 Net Margin and emission comparison graph for Middle representative farm for the Baseline, Emission Ceiling, Grassland group, Animal Productivity.

Figure 6.1 presents the comparison of net margin and emissions for the baseline and mitigation scenarios across the five-year planning horizon. The figure has been revised by adjusting the emissions axis scale and including markers for each year to better reflect the underlying variation in the data.

Each marker represents the calculated emission value for an individual year. Although herd composition varies across years, total emissions remain relatively stable because the overall herd size changes only modestly and emissions are calculated using fixed coefficients for each animal category.

The following section of this Chapter describes the results in more detail, including an emission report, economic report and breakdown of the herd dynamics.

6.4.1 Emission Reporting

The results in Table 6.3 show the collective CO_2, Ch_4, and N_2O for each year, comparing the baseline and the three scenarios.

Table 6.3 Emission report for baseline and scenarios for middle representative farm.

Period	Unit	S1: Baseline	S2: 10% reduction	S3: Grassland Management	S4: EBI
Year 1	$KgCO_2$ eq	531,285	474,512	445,984	511,955
Year 2	$KgCO_2$ eq	530,723	475,010	444,046	504,476
Year 3	$KgCO_2$ eq	531,078	474,744	445,180	501,306
Year 4	$KgCO_2$ eq	530,977	474,759	444,978	494,652
Year 5	$KgCO_2$ eq	530,898	474,882	444,606	495,900

The baseline emissions fluctuated from a low of 530,723 $KgCO_2$eq in Year 2 to a high of 531,285 $KgCO_2$eq in Year 1. All mitigation measures show lower emissions than the baseline, though the extent varied. Grassland management consistently achieved lower reductions throughout the planning horizon. S2 had an average percentage reduction from the baseline, of 10%, while S3 had an average decrease of 16.2% and S4 achieved an average decrease, of 5.5%.

6.4.2 Economic Results

Regarding the economic results of the representative farm, Table 6.4 presents the farm's results over five years. Year 1 consistently recorded the highest revenue across all scenarios, attributed to high milk yield and livestock sales.

While, S2 has the lowest revenue on average across the five years, at €228,493, illustrating that a strict emission ceiling impacts negatively on farm net margin. S3 and S4 maintain average revenues of €233,873 and €246,608, respectively. S1 shows slightly higher average revenue of €253,013. In this case, implementing mitigation measures is more beneficial for farm income than imposing strict ceilings.

The average baseline cost is €172,576. S3 achieves the lowest costs over the five years, indicating that it is the most cost-competitive strategy. S2 also maintains a lower cost on average at €160,985, most likely due to the reduced stocking rate and milk volume. S4 had a higher average cost of €167,978, exceeding both S2 and S3 but still close to the baseline. Indicating that while productivity-focused strategies may incur higher costs, they can still compete with the baseline in terms of overall efficiency.

Net margin is used as a key profitability indicator. The average across the five-year planning horizon for the baseline is €80,437. S3 is closest to the baseline with an average net margin of €80,436. The lower net margin in S2 of €67,507 is likely due to the lower revenue. S4 had an average net margin of €78,630, just slightly below the baseline. Overall S3, emerges as the most profitable mitigation measure.

The average milk yield for the baseline farm is 561,133l and an average low of 508,000l occurred in S2 due to a low stocking rate, whilst a high of 558,879l is achieved in S4. This is slightly reduced in S3 to 521,483l. S4 produced the highest milk yield, making it an effective mitigation measure compared to the baseline. The emission ceiling (S2) is the least favourable strategy for this farm, as it reduced average revenue by 9.7% and milk yield, resulting in the lowest on-farm net margin.

Table 6.4 Economic Report for the middle representative farm.

	S1 Baseline					S2 Emission ceiling 10%					S3 Grassland Management					S4 Animal Productivity				
	Y1	Y2	Y3	Y4	Y5	Y1	Y2	Y3	Y4	Y5	Y1	Y2	Y3	Y4	Y5	Y1	Y2	Y3	Y4	Y5
Revenue	€ 269,258	€238,644	€ 257,027	€ 252,550	€247,587	€248,375	€212,293	€230,362	€230,630	€220,805	€252,355	€217,976	€237,029	€234,669	€227,340	€252,485	€239,652	€250,416	€241,721	€ 248,768.67
Cost	€207,378	€144,239	€180,607	€167,899	€162,759	€205,994	€129,001	€163,504	€161,413	€145,015	€192,762	€123,755	€158,569	€151,043	€141,062	€184,525	€151,129	€176,075	€155,101	€ 173,060.00
Net Margin	€61,880	€94,405	€76,420	€84,652	€84,828	€42,381	€83,291	€66,857	€69,218	€75,790	€59,593	€94,221	€78,460	€83,626	€86,278	€67,960	€88,523	€74,340	€86,620	€ 75,708.67
Milk yield (Litres)	624,158.62	503,167.22	579,686.28	557,725.76	540,926.15	586,211.20	441,916.68	517,360.63	514,473.72	478,460.56	593,360	457,464	536,986	522,801	496,806	583,406	530,577	574,100	538,885	567,425.25

Table 6.5 Herd Dynamics.

Herd	Unit	S1 Baseline					S2 10% Emission Ceiling					S3 Grassland Management					S4 EBI				
Calves	average number/year	16	26	20	22	23	12	25	18	18	21	13	25	18	19	21	16	20	17	20	17
Dairy Heifer (12m -24m)	average number/year	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dairy Cows (2-6 yrs)																					
2- 3yr	average number/year	73	37	55	53	49	73	29	43	51	41	71	31	47	50	43	22	12	20	13	19
3-4 yr	average number/year	20	30	15	28	16	14	33	13	24	17	16	31	14	25	16	42	35	40	36	40
4-5 yr	average number/year	14	20	30	15	28	14	14	33	13	24	13	16	30	14	25	33	41	35	40	36
5-6 yr	average number/year	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

6.4.3 Herd Dynamics

Herd dynamics indicate the annual average number of dairy cattle on the farm. Table 6.5 outlines the herd dynamics for the representative farm for each scenario. The herd is categorised into six distinct groups: calves, dairy heifers (aged 12 to 24 months), and milking cows aged three to six years.

Overall, S2 maintained the lowest herd numbers across all age groups, highlighting the impact of the emission constraint. However, S1 generally had a larger number of younger cows over the five years, while S4 illustrated a higher number of mature cows, resulting in different herd structures than the baseline. Beginning in year three, all scenarios started to stabilise. On average, S3 maintained 26.4 four-year-olds, while S4 had 37, both significantly higher than S2's figure of 19.2. Additionally, calf numbers in S2 were somewhat lower at 18.4 per year, compared to 21.3 in S1 and 21.2 in S3. All scenarios excluded dairy heifers, as the model prioritises older animals that contribute to the milk pool; similarly, the five to six-year-old group is absentsince the model's maximum age is set to six.This reflects a structural assumption of the model rather than an empirical finding, as the optimisation prioritises animals that directly contribute to milk production and net margin.

Although Table 6.5 shows notable variation in the distribution of animals across age categories, the total herd size remains relatively stable across the planning horizon. For example, in the baseline scenario, total animal numbers (including calves) range from 113 to 123 head, representing only modest variation. As emissions in the model are primarily driven by total livestock numbers and dominated by emissions from productive animals, these relatively small changes in overall herd size result in limited variation in total emissions. Furthermore, emissions are calculated using fixed coefficients for each animal category, meaning that shifts between adjacent age groups have only a marginal impact on aggregate emissions. This explains why emissions appear relatively stable across years despite changes in herd composition.

6.5 Discussion

These results illustrate that grassland management (S3) is the optimal mitigation strategy for the middle representative farm, resulting in a higher net margin and a lower level of total annual emissions over a five year period.

Compared to the baseline (S1), S3 achieved significant reduction in emissions (16.2%) while maintaining a competitive net margin. Although animal productivity (S4) also contributed to emissions reductions, it was slightly less effective than grassland management, achieving a 16.2% reduction and demonstrating efficiency gains in milk production per animal. In contrast, the 10% emission ceiling (S2) resulted in a smaller herd and decreased milk output, leading to a reduction in total revenue and overall efficiency when the farm did not implement any mitigation measures. While it moderately reduced emissions by 10%, the negative economic impacts were significant.

In terms of economic performance, S3 maintained a high net margin, averaging just 0.14% below S1, while achieving an average emission reduction of 16.2%. S4 showed a slight average decrease in emissions of 5.52% and a slight net margin increase of 0.77% relative to the baseline.

However, in S4, net margin varied from year to year, ranging from a 9.8% increase in year 1 to a 10.8% decrease in year 5. this variation emphasises the sensitivity of the scenario to changes in herd composition. It suggests that, within the structure of this model, productivity improvements can be cost-effective under certain conditions. However, S2 had the lowest economic performance, with an average net margin reduction of 16.94%, illustrating the negative impact of an emission ceiling on a farm that does not adopt mitigating measures.

Milk yield and stocking rate were also evaluated. The baseline scenario, with no emission ceiling, maintained the highest stocking rate, resulting in the highest total milk yield. S3 maintained a strong level of milk yield. S2 had the lowest milk yield out of all scenarios evaluated.

To conclude, grassland management (S3) appears to be the ideal measure, as it reduces emissions while maintaining economic performance relative to the baseline. The key reasons include improved pasture quality, better animal nutrition, and maintaining productivity per hectare. These findings are consistent with recent Irish research indicating that farms utilising grassland management technologies, such as improved fertiliser strategies and decision support systems, achieved better environmental and financial results than those that did not (Palma-Molina et al., 2023).In the same way, Cashman et al. (2024) demonstrated that grassland-based systems employing reduced nitrogen inputs and clover swards can maintain profitability while reducing emissions. In this scenario, herd dynamics have minimal impact, allowing the farm to maintain a stable production system.

While animal productivity (S4) is also beneficial, it improves efficiency with lower costs and generates a slightly higher net margin than the baseline. Its approach also reduces emissions by 5.52%, outperforming S2. However, S4 required adjustments in herd structure, which seemed to stabilise by year 5. These echoes earlier work by Lopez-Villalobos et al. (2020), who showed that profit-based sire selection strategies can differ from conventional indices, emphasising that breeding choices must be evaluated in economic terms. In this chapter, by incorporating emission ceilings, the logic is extended to include environmental trade-offs. These outcomes correspond with Irish studies showing that higher EBI cows tend to have better fertility, higher survival rates, lower replacement rates, and reduced emissions intensity (Dillon et al., 2018; O'Sullivan et al., 2020).

These findings underline the importance of tailoring mitigation strategies to specific farm objectives. S3 demonstrates strong performance in both emissions reduction and profitability, making it ideal for farms aiming for climate benefits without significant economic sacrifice. S4, which offers a modest net margin increase alongside emission reduction, might be more suitable for farms focusing on transitional strategies where moderate reductions are acceptable with minimal operational impact disruption. Given S3's high performance in both emissions and net margins, targeted support for grassland management strategies may yield strong returns on climate investments. Conversely, emission ceiling systems like S2 may require economic compensation to offset potential losses and encourage adoption. Similar findings are reported by KPMG (2021), indicating that stricter environmental constraints, particularly those requiring herd adjustments or limiting production without providing compensation, can decrease farm profitability by 25% to 40%. The results of this study are consistent with those of Van Middelaar et al. (2014), who demonstrated that when emissions-focused techniques, like reducing feed protein, are applied in isolation, they often minimise farm profitability. Economic consequences were also observed in S2, as the emissions ceiling alone led to an average net margin reduction of 16.9%.

While S2 was the least favourable scenario in this incident, promoting the adoption of measures remains essential. Research indicates farmers are more motivated to adopt actions that improve profitability, efficiency, or reduce costs, viewing environmental benefits as secondary rather than the primary goal of adoption (Farstad et al., 2022). However, various obstacles can hinder adoption. Farmers point to policy-related barriers like unpredictable government strategies, landowner bias, tenancy restrictions, and bureaucratic hurdles, particularly within environmental schemes, which foster uncertainty. Similarly, commercial challenges like supermarket price pressure, labour shortages, and rising input costs cause hesitation. Interpersonal issues, such as succession concerns, contribute to uncertainty about the farm's future (Whitton et al., 2024). Education level greatly influences farmers' attitudes, intentions, and efforts to adopt sustainable practices (Zachariou et al., 2025). Policy support, targeted financial aid, and farmer-oriented education and advisory services are crucial to foster wider adoption of mitigation measures.

6.6 Limitations

While total milk yield is considered, milk fat and protein variations are not explicitly modelled in the LP optimisation model. This is a limitation of the model because milk pricing and market value depend on quality, not just quantity. Whilst the LP in its current form does not consider fat and protein yield, milk quality metrics should be integrated into the evaluation for a more precise economic impact. However, the MDSM feeder model calculates that the milk price varies depending on fat and protein content.

As with any LP model, a set of modelling assumptions exists. In this case, the model does not account for fluctuations in milk price, input costs, or climate variability, which could impact long-term sustainability. As previously mentioned, the prices are held constant solely to accurately capture variations in emissions and net margins due to the mitigation strategies. The model assumes all the relationships are linear and that the constraints and objective function are constant. While this is consistent with the linear programming framework, several farm processes are inherently non-linear. For example, milk yield and fertiliser response typically exhibit diminishing marginal returns, meaning the model may overestimate the benefits of increased input use. Similarly, biological processes such as herd dynamics and emission responses may not scale proportionally, potentially biasing results. Currently, the prices are set in this model and require one input sheet. The model can easily be adjusted to include dynamic prices that can change over time. Still, it was chosen to control prices to determine a baseline scenario for an average Irish dairy farm and illustrate the impact of the different scenarios. In each scenario concentrate, milk, and input costs remained constant.While these assumptions improve tractability and interpretability, they may favour more extreme or simplified optimal solutions. Therefore, results should be interpreted with these limitations in mind. It is crucial to recognise that while the model has limitations, the main objective was to assess the optimal net margin of an "average" dairy farm under an emission ceiling and with specific mitigation measures.

Incorporating both mitigation measures into a single scenario would require mixed integer programming (MIP). With MIP, more complex decision-making scenarios can be analysed by integrating continuous and discrete variables, allowing the model to independently identify trade-offs and the optimal strategy for the farm. However, implementing MIP introduces considerable complexity and computational requirements. Consequently, choosing separate linear programming scenarios is a strategic decision to preserve model simplicity and clarity, even though a unified MIP approach might offer a more cohesive solution perspective. This model has evaluated a particular set of mitigation measures and identified an optimal measure for the representative average farm. Future developments of this integrated internal modelling framework could include evaluating other farm types and mitigation strategies under MIP. Building on the mitigation strategies and including dynamic pricing could allow the model to run a more elaborate approach. Similarly, other model iterations could examine policy implications, such as emission reduction incentives.

While these findings offer valuable insights, it is essential to recognise that the results may not universally apply to all Irish dairy farms. Differences in land, herd size, grass growth capacity, and farmer goals can affect mitigation strategies. These findings demonstrate the potential of targeted strategies to help Ireland meet its climate goals by achieving significant emission reductions with minimal economic impact. Future improvements to this model could include national inventory systems, enhancing its usefulness as a decision-support tool for policymakers and farmers

7 Optimising Dairy Farm Planning with Mitigation Measures: An Irish Representative Study

7.1 Introduction

The agricultural sector faces the dual challenge of ensuring food security while reducing its environmental impact. Especially, the dairy sector as it is under increasing pressure to satisfy growing demand for high quality products whilst achieving climate targets. Ireland is now legally required to achieve climate neutrality by 2050, under the Climate Action and Low-Carbon Development Act. The Climate Change Advisory Council developed a programme aligned with the carbon budgets outlined in Chapter two, to help Ireland achieve this goal. The Carbon budgets each cover five years, and each budget has a set emission target based on 2018 emission levels (Climate Change Advisory Council, 2024). The first carbon budget for 2021 to 2025 sets a cumulative emission ceiling of 106 Mt CO2eq for agriculture, with a 10% reduction target relative to 2018 levels. The second budget between 2025 and 2030 aims for a 25% reduction relative to 2018, equating to 17.25 Mt CO_2eq by 2030. While these environmental goals are ambitious and require considerable GHG mitigation efforts, it is essential to keep the sector profitable during this transition.

The agricultural sector contributed to 37.8% of Ireland's GHG emissions in 2023, mainly due to enteric fermentation (63%) and manure management (11.8%) (EPA, 2024). Bovine agriculture is the largest source of GHG emissions in Ireland's agriculture. The Irish dairy sector has been an essential driver of growth in its GHG emissions over the past decade. The agricultural market is highly profitable, with exports estimated at €6.3 billion in 2024. In addition to strong financial performance, it serves as a significant source of employment in Ireland, with nearly 18,000 family farms (CSO, 2018), especially in rural communities. Given the dairy sector's considerable economic and physical presence in the Irish landscape, it must attain both environmental sustainability and financial viability. Ensuring that the dairy sector stays economically resilient throughout the transition to climate neutrality will be crucial, considering policy targets, labour demands, and economic pressures (Fitzgerald, 2019). As the dairy industry is an integral part of the Irish landscape, it supports high skilled employment and commercial investment, particularly in rural communities (Lawton et al., 2024). 2024 marked the first year since 2009 that there had been a decline in dairy cow numbers, by

1%. Milk output also ended the same year with a similar decline (Teagasc, 2025). Hence, dairy farms were chosen for this scenario analysis to examine the competitiveness and optimisation of dairy farms going forward.

As farmers tend to work within narrow financial margins, making strategic decisions on the farm is crucial to achieving environmental and economic goals. Various methods exist to reduce emissions on the farm, although these measures differ in their potential for emission reduction and their mitigation costs. Additionally, the financial impacts of these measures vary from farm to farm. At a national scale, the Teagasc MACC informs policymakers and advisors on mitigation measures and their impacts across different scenarios (Lanigan et al., 2023). Although the MACC is crucial for illustrating the total abatement potential, it may insufficiently represent costs and potential abatement at the farm level (Cantillon et al., 2024). Given that numerous variables like farm structures, sizes, and resources differ, the effectiveness of mitigation measures and economic viability can also vary significantly among dairy farms. This variability underscores the need for a customised approach to support farmers' decision-making.

Decision support systems have been evolving to cater for this tailored farm-level approach. The DSSs assist in balancing often conflicting objectives. Data-driven decision support systems will be crucial in helping farmers curb GHG emissions within the livestock sector (Niloofar et al, 2020; Thumba et al, 2020; Neethirajan et al, 2024)

Optimisation models have been successfully utilised within the food sector, covering everything from supply chains to tools used at the farm level (Taşkıner et al., 2021; Malik et al., 2022). For farm level optimisation, these tools range from minimising production costs and maximising profits while also decreasing GHG emissions through better nutrient management across the landscape (Milne et al., 2020), enhancing health management (Ferchiou et al., 2021), and refining feed management practices (Cecchini et al., 2022). Despite the success of optimisation models, it remains crucial to evaluate mitigation measures that balance profit maximisation with emissions reduction at the farm level.

This Chapter focuses on determining how different measures impact the representative farm's profitability and emissions. By identifying which methods are most effective in reducing emissions while maintaining and/or improving financial performance. This paper utilises the National Farm Survey (NFS), divided into distinct representative farms based on net margin. These farms serve as representative dairy farms, enabling us to model and develop optimisation measures.

7.2 Materials and Methods

7.2.1 Classification Criteria for Farms

Given the pressing need to fulfil Ireland's environmental objectives, and the significant contribution of beef and dairy farms to the nation's agricultural emissions, this scenario study proposed an effective mitigation plan for Irish dairy, categorised into three types: Top, Middle and Bottom representatives based on gross margin performance. It analysed the impacts of two emission ceilings, set at 10% and 25%, applied across all three representative farm categories, alongside a scenario that applies a collection of mitigation measures. The goal was to simulate the farm's physical structure, financial performance and emissions-related operations.

All scenarios in this study were modelled over ten years. This research addressed the following questions: What is the effect of an emission ceiling on representative Irish dairy farms? What is the optimal farm plan while achieving emission reduction?

The study utilised a linear program optimisation model, which forms part of the integrated internal modelling framework, to assess the optimal farm plan relative to the baseline. This forms part of the backend programming element of a larger Teagasc based decision support system.

The framework used the National Farm Survey (NFS) data collected by Teagasc. The NFS aims to monitor the financial performance and sustainability of the agricultural sector. Using NFS data, gaseous emissions from livestock farms in Ireland can be estimated. Information from the NFS is shared with the Farm Accountancy Data Network (FADN) of the European Union (Dillon et al., 2021). The NFS is undertaken annually on a nationally representative sample of farms. Generally, 900 to 1,000 farms are included in the survey. A random sampling methodology is used to select farms. The NFS weights farms according to the land area using aggregation factors from the Central Statistics Office (CSO, 2022) to ensure the survey is representative. Farms are assigned to one of the following systems based on their dominant enterprise: Dairy, cattle rearing, cattle other, mixed livestock, tillage, and sheep. The value of agricultural products in terms of standard output determines the chief enterprise(s) on a farm.

For the purposes of this study, milk producers were ranked by gross margin, and case studies were selected from the average Bottom, Middle, and Top representative of farms. The data taken from NFS for each group was an average across 2019 to 2022. The representative farms used in this study were dairy enterprises with one breeding bull. Table 7.1 presents the physical and financial characteristics of the representative farms initially used to run the model.

Table 7.1 Farm Characteristics.

Parameter	Unit	Bottom	Middle	Top
Farm size, ha	Ha	48	56	56
Grass utilisation	t DM/ha	6.0	8	10.4
Concentrate	kg/cow	1078	1135	1054
Stocking rate	LU/ha	1.75	2.07	2.55
Milk produced	kg/cow	4,826	5,999	6443
Milk price	€/L	€0.34	€0.34	€0.34
Animal category				
Calves		19	19	26
Yearlings		15	15	20
Two-year-olds		6	6	3
Three-year-olds		30	30	45
Four-year-olds		31	31	46
Five-year-old		0	0	0
Culls		14	14	18
Cows died		1	1	1

7.2.2 Mitigation Strategies

For this study, ten mitigation measures were selected to illustrate the variation between measures and farm types. Mitigation costs and abatement rates (€/t CO_2eq) are reported in Chapter 4 (Tables 4.3–4.4), while Chapter 6 reports the resulting farm-level economic outcomes (revenue, costs and net margin) under the mitigation scenarios for the middle representative farm. A worked example showing how a mitigation measure is translated from MACC inputs into model parameters and propagated through the modelling chain is provided in Appendix G.This research builds on this work by adding the Top and Bottom categories and applying the same mitigation measures.

The measures were chosen based on their practicality for short-term implementation and effectiveness in reducing GHG emissions. They were selected due to their lower barriers to uptake and the robust scientific literature on pasture-based Irish dairy systems. The measures are listed in Table 7.2. For this analysis, grassland management comprises four measures: protected urea, white clover, ryegrass, and LESS. Animal productivity is a combination of breeding animals based on the EBI and an earlier calving date. The aim was to function as close to a genuine farm as possible, and the presence of two collective mitigation groups facilitated the simultaneous implementation of practices on the farm throughout the year.

7.2.3 Optimisation Model

The optimisation model is an additional element to the existing Teagasc bioeconomic models. It is outlined in detail in Cantillon et al. (2024). The primary objective function of the model is to maximise net margin over the planning horizon according to equation 1 while satisfying emission ceilings.

$$\boldsymbol{max\ \frac{1}{T}\ \sum_{t=1}^{T}\big(revenue[t]-cost[t]\big)} \qquad (\mathbf{1})$$

In this case, t represents the time period of the model. The model is run annually to provide an overall view of the farm's economic viability. The objective function calculates the farm's annual profit over the planning period, which in this study is 10 years. Input data was taken from the NFS. The Teagasc Dairy LCA model and MDSM are combined into one input sheet linked to the LP model.

7.2.4 Scenario Definitions

In this analysis, the model was run four separate times with four different constraints and working environments. The model had a baseline for each representative farm type: Top Baseline (TBL), Middle Baseline (MBL) and Bottom Baseline (BBL). All results were compared with the baseline representative farms to assess the effectiveness of each strategy. All scenarios are described in Table 7.2. The standalone measures were applied individually to each representative farm and represented by S3.x depending on the measure. Emission ceilings were relaxed for both the stand-alone and combined measures to allow the model to fully explore the potential impact of each scenario. Resulted in an output of 45 results.

Table 7.2 Scenario definitions.

Types	Description
Baseline (TBL)	Top (TBL), Middle (MBL) and Bottom (BBL) baseline average
Scenario 1 (S1)	Examines the emission ceiling set at 10% (carbon budget one; 2021-2025)
Scenario 2 (S2)	Examines the emission ceiling set at 25% (carbon budget two; 2025-2030).
Scenario 3 (S3)	Stand-alone mitigation measures are individually applied (10)
S3.1	Animal productivity: Economic Breeding Index
S3.2	Grass production and utilisation
S3.3	Reduced Crude Protein
S3.4	Better reproductive management
S3.5	Early calving
S3.6	Decrease fertiliser N
S3.7	Protected Urea
S3.8	White clover
S3.9	Slurry Tank Cover
S3.10	Low Emission Slurry Spreading (LESS)
Scenario 4 (S4)	A collection of measures under grassland management (4) and animal productivity measures (2) are applied as two distinct groups:
S4.1	Grassland management (grouped grassland)
S4.2	Animal productivity (grouped animal)

7.3 Results

Each scenario was modelled over a ten-year planning horizon. The results show the average net margin and average emissions for each scenario. A full herd distribution is per representative farm is outlined in appendix J.

7.3.1 Top Representative Farm

The baseline average for the Top representative farm exhibited a high net margin (€ 101,509) and emissions of 632,692 kg CO_2eq.

Although none of the measures improved net margin, four measures successfully reduced emissions while maintaining financial performance within a 10-12% of the baseline (Table 7.3). These measures were improved animal performance, increase grass utilisation, decreased fertiliser N and LESS.

Both emission ceilings, S1 and S2, were undesirable options for the Top representative farms, as both scenarios lowered net margin (by 16% and 35%). The grouped measures reduced emissions but did not outperform the baseline. While Grassland grouped measure had a net margin of €89,827 and reduced emissions by 112 t CO_2eq.

Table 7.3 Annualised Net Margin and Emission results for the Top representative farm Group.

Measures	Net Margin (€)	Emission (kg CO_2eq)
TBL	€101,509	632,692
S1	€84,988	569422
S2	€66,350	477,682
S3. 1 Improve animal performance	€91,532	619,056
S3.2 Increase grass utilisation	€86,871	596,967
S3.3 Reduced crude protein	€89,398	614,251
S3.5 Early calving	€89,333	610,738
S3.6 Decrease fertiliser N	€89,451	606,484
S3.7 Protected Urea	€89,420	613,551
S3.8 White Clover	€89,438	604,557
S3.9 Slurry tank cover	€89,423	601,854
S3.10 LESS	€89,780	615,071
S4.1: Grassland grouped	€89,827	520,555
S4.2: Animal productivity	€99,917	609,920

S3.4 (Better reproductive management) was not applied to the Top representative farm, as this group already operates at high reproductive efficiency, limiting further scope for improvement within the model assumptions.

In the optimisation model, margins initially declined with the introduction of EBI, grass utilisation, crude protein reduction, and early calving. However, this was due to the model's dynamic adjustment of herd size and stocking rate, which resulted in higher revenues alongside increased costs. The optimisation model does not model the genetic and physiological improvements linked to EBI, such as milk solids or reduced replacement, similar to the MACC. To enable comparability with the MACC framework presented in Chapter 4, a constant-output approach is applied. The constant output Table 7.4 is used to align the outcomes with the fixed output framework used in Chapter 4.

Under this constant-output approach, farm output (e.g. milk production) is held fixed, allowing the direct economic and environmental effects of each mitigation measure to be isolated from structural adjustments within the optimisation model , the four measures identified as cost beneficial in Chapter 4 were recalculated while holding output constant, which resulted in negative net costs and emission reductions..As shown in Table 7.4, all four measures remain cost-beneficial, with grass utilisation delivering the highest abatement and largest cost saving, reinforcing its importance as a key mitigation strategyThe results confirm that improving animal performance, increasing grass utilisation, crude protein, and early calving remain consistent with the MACC findings, with negative net costs alongside positive emission reductions.

Table 7.4 Comparison of Chapter 4 (MACC) results, optimisation model results and constant-output recalculations for the Top representative farms..

Measure	Abatement (t CO_2eq/yr)	Constant-output Net Cost (€/yr)	Constant-output Cost (€/ha)	Cost Beneficial
Improve animal performance	13.6	-4,377	367	Yes
Increase grass utilisation	35.7	-11,718	148	Yes
Crude Protein	18.4	-9,977	397	Yes
Early Calving	22	-4,149	337	Yes

7.3.2 Middle Representative Farm

The middle representative farm's baseline net margin is €80,746 with emissions of 527,571kg CO_2eq. Two individual measures improved the net margin compared to the baseline in Table 7.5.

One grouped strategy, grassland management, enhances the net margin slightly, by 0.2%, while reducing emissions by 83 t CO_2eq, (16% below baseline). Among individual measures, better reproductive management achieved the highest net margin, while grass utilisation offered the strongest emissions reduction (19%) among single measures. Protected urea slightly improved net margin by 0.4% and reduced emissions by 3%. Both decreased fertiliser N and slurry tank cover had lower net margins and reduced emissions slightly. The final grouped strategy, animal productivity, had a lower net margin (-1% lower) and a 6% emissions reduction. Like the Top representative farms, the middle representative farms also had emission ceilings, falling among the least desirable measures regarding average net margin and emissions.

Table 7.5 Annualised Net Margin and Emission results for the Middle representative farm.

Measures	Net Margin (€)	Emission (kg CO_2eq)
MBL	€80,746	527,570
S1	€70,091	467,787
S2	€57,533	395,930
S3. 1 Improve animal performance	€71,862	503,869
S3.2 Increase grass utilisation	€77,486	425,502
S3.3 Reduced crude protein	€76,865	527,044
S3.4 Better reproductive management	€87,693	535,855
S3.5 Early calving	€84,220	520,201
S3.6 Decrease fertiliser N	€78,834	517,697
S3.7 Protected Urea	€81,067	510,588
S3.8 White Clover	€81,078	511,736
S3.9 Slurry tank cover	€77,193	516,422
S3.10 LESS	€77,193	529,710
S4.1: Grassland grouped	€80,919	444,958
S4.2: Animal productivity	€79,845	498,465

7.3.3 Bottom Representative Farm

The most promising results were seen in the bottom representative farms, with most measures giving better results than the baseline in Table 7.6. The lower baseline net margin is €40,774, while the emissions are 398,810 kg CO_2eq. The highest performing strategy for this representative farm is protected urea, generating a net margin increase of 42% and a 2% emission reduction. Similarly, age at first calving also had similar gains in net margin, this is a 37% increase in net margin and a reduction of 2% in emissions. Decreasing fertiliser N resulted in a modest 12% reduction in net margin with a 2% emissions reduction. White clover increased net margin by 28% and reduced emissions by 3%. Increasing grass utilisation boosted margins by 22% and reduced emissions by 14%, making it a highly attractive option for lower-performing representative farms. The grouped grassland strategy exceeded the baseline, achieving a 37% higher net margin and a 19% decrease in emissions. This is the highest emission reduction for the bottom representative farms. In line with the other two representative farms, protected urea increased margins by over 40% while reducing emissions, and grassland measures achieved nearly 20% abatement with a 37% margin increase. The grouped animal productivity increased net margin by 9%, relative to the baseline and reduced emissions by 16%. The emission ceilings S1 and S2 are the least desirable measures.

Table 7.6 Annualised Net Margin and Emission results for the Bottom representative farm.

Measures	Net Margin (€)	Emission (kg CO_2eq)
BBL	€40,773	398,809
S1	€34,338	358,953
S2	€26,443	295,443
S3. 1 Improve animal performance	€36,162	357,145
S3.2 Increase grass utilisation	€49,755	344,722
S3.3 Reduced crude protein	€53,165	408,035
S3.4 Better reproductive management	€53,019	405,438
S3.5 Early calving	€56,124	391,027
S3.6 Decrease fertiliser N	€35,753	389,160
S3.7 Protected Urea	€58,017	389,425
S3.8 White Clover	€52,008	384,930
S3.9 Slurry tank cover	€54,622	398,898
S3.10 LESS	€56,220	409,118
S4.1: Grassland grouped	€55,691	323,544
S4.2: Animal productivity	€44,491	336,417

Across all representative farms, the grouped measures (S4) either matched or exceeded the performance of the 10 individual measures (S3) in abatement efficiency, while maintaining a greater margin, especially for middle and bottom representative farms. This underscores the practical benefit of combining measures into effective packages. Showing the farmer the benefits of each individual measure and the grouped measures give them options and aids in farm decision-making.

7.4 Discussion

The purpose of this paper was to evaluate the performance of different measures over a ten-year planning horizon across three representative farms. The objective of the model was to maximise the farm's net margin, with a constraint on GHG emissions. The representative farms were separated into Top, Middle, and Bottom categories based on gross margin in the NFS. The aim was to determine how different measures affect profitability and emissions across the representative farms, identifying which methods are most effective in reducing emissions while maintaining and/or improving financial performance.

7.4.1 Different Representative Farms Responses

7.4.1.1 Scenarios

Notably, across all representative farms, the emission ceilings (S1 and S2) were consistently less effective in achieving a desirable balance between profitability and emission reductions. The emission ceilings imposed a hard emission constraint on the model, resulting in lower yields and reduced net margins. While these emission targets are based on carbon budgets, emission intensity varies widely across farms and livestock systems. As shown by McAuliffe et al. (2018), the emissions intensity of beef systems in the UK varies widely across animals and farms, due to variations in management practices, feed composition, and productivity. This supports the current findings that mitigation strategies should be system and farm specific, targeting efficiency improvements rather than uniform emission caps across the sector.

A comparison between Scenario 3 (individual measures) and Scenario 4 (grouped measures) reveals that grouped approaches can achieve similar emission reductions with fewer impacts on net margin. This aligns with existing literature by Jebari et al. (2025), which showed practical measures such as clover, inhibitors, and anaerobic digestion can deliver significant reductions in carbon footprints within a beef system.

Overall, emission ceilings alone should not be the only emphasis when striving for farm sustainability. Although they can provide guidance, they should complement measures that promote increased flexibility and efficiency, such as optimising fertiliser use, enhancing grassland management, and improving animal productivity. Strict emission ceilings add an additional burden to the agricultural sector, which is already under increasing pressure. These findings reinforce the policy implications of a targeted system specific approach.

7.4.2 Policy Implications

The findings highlight the importance of having policy flexibility in achieving environmental and financial goals for the dairy sector. The results suggest that emission ceilings (S1 at 10% and S2 at 25%) will result in lower farm income unless farmers adopt mitigation measures. Policy programmes that encourage tailored emission reduction measures on the farm, which will enable farmers to select and implement a combination of measures that best suit their farm's characteristics and operational targets, will be a more suitable approach. This aligns with Yang et al. (2024), who indicated that local policymakers should carefully tailor agricultural development policies based on local needs.

Future policies and knowledge transfer programmes should embrace a more flexible carbon budgeting framework that allows farms to meet emissions targets through customised, scalable measures. This framework should encourage farms to adopt effective combinations of mitigation measures that align with their economic and environmental objectives. Similar agricultural frameworks are being developed to support sustainable farming practices (O'Keeffe et al., 2025).

While policy heavily relies on the MACC approach, this method offers effective decision-support tools for guiding and analysing farmers. By having a strong focus on financial and environmental elements at farm level, it creates a data-driven decision-support system that supports farm management, helping farms optimise their financial and environmental objectives. This approach may also help tackle the financial challenges and policy targets that farmers often encounter (Martin et al, 2025).

A flexible and supportive policy framework is essential to support sustainability and long-term economic viability for farms. This framework will motivate farms to adopt appropriate mitigation measures tailored to their specific circumstances and a personalised, achievable model for their own operations.

7.4.3 Limitations and Assumptions of the Model

As with any linear model, it relies upon a set of economic assumptions. The model does not consider fluctuations in milk prices, input costs, or climate variability, which could affect long-term sustainability. It assumes all relationships are linear and that the constraints and objective function remain constant. Currently, the prices in this model are set and require one input sheet. While total milk yield is considered, milk fat and protein variations are not explicitly modelled. This is important because pricing and market value depend on quality, not just quantity. Although the LP element does not consider milk's fat and protein ratio, milk quality metrics should be integrated into the evaluation for a more precise economic impact. However, both feeder models calculate the yield and value of milk based on its constituents. In addition, emission ceilings within the model are applied independently of mitigation adoption. In practice, farmers are unlikely to respond to emission constraints solely through reductions in herd size or output, but instead by adopting cost-beneficial or cost-effective mitigation measures to maintain profitability. As a result, the model may overstate the negative economic impact of emission ceilings when implemented in isolation. Future research could address this by integrating emission constraints and mitigation measures within a single optimisation framework

As this LP model is intended to be part of an overall Teagasc decision support system, adopting a hybrid approach that combines an LP optimisation model with the existing Teagasc Dairy LCA and MDSM model can address many of the limitations of linear programming (Shalloo et al., 2015; Teagasc, 2019).

7.4.4 Enhancing the Optimisation Model

It is crucial to recognise that, while the model has limitations, the main objective was to assess the optimal profits of a range of dairy representative farms under an emission ceiling and specific mitigation scenarios. This model has evaluated a particular set of mitigation measures and has identified an optimal strategy for the representative farm.

The model incorporates only a limited number of mitigation measures and is therefore not exhaustive. There is scope to expand the model to include a broader range of mitigation strategies,such as, dietary interventions including feed additives (Gholami et al.2025; Ni et al. 2025), and changes in current practices such as the surge in anaerobic fermentation (Wang et al. 2025) , growth in biodiversity programmes, water management practices (Bhat et al. 2025) and integration of Internet of Things and Artificial Intelligence into farming systems (Alawode et al.2024), which all show promising results and a drive towards a new age of farming.

The trend of stress, long working commitments and working conditions seems to be growing issue for dairy producers and results in them leaving the industry (Holmes et al. 2025). While the model developed here is centred around profit maximisation, there is scope for future iterations to widen the system analysis by including some social and behavioural goals by using multi-goal objectives. The establishment of tools and systems that evaluate the wider system and social objectives as well as the economic and environmental, such as incentivisation for reducing biodiversity loss may help improve work-life balance for farmers.

This model is currently a linear programming model. Future research could enable it to utilise mixed integer programming, allowing the model to determine a combination of measures and select the optimal suite of measures. According to Byfuglien et al. (2025), numerous countries have initiated programs aimed at promoting the adoption of sustainable farming practices.

A local farm-level perspective influences perceptions of mitigation practices, as noted by Evans et al. (2014). They emphasise that climate change affects local regions and that discussing adaptation measures may indirectly promote behaviours to mitigate climate change by first highlighting its impact in the local area.

7.5 Conclusion

Measures for emission reduction and improving net margins show that different representative farms respond variably to various mitigation measures. While emission ceilings are generally less effective, measures such as grassland utilisation, protected urea, and animal productivity are promising, particularly for the middle and bottom representative farms. Customising measures based on representative farm characteristics and herd dynamics is key to achieving economic and environmental sustainability for pasture-based milk producers.

Using the optimisation model in conjunction with the Teagasc bio-economic model, the optimal mitigation strategy for each representative farms that maximises net margin and reduces emissions can be determined. While this paper has evaluated a small set of mitigation measures, expanding the mitigation measures to include some new technologies and different approaches will allow for a more elaborate mitigation plan.

The model generates an ideal farm mitigation plan that maximises net margin, providing farms with a realistic and achievable goal for their sustainability journey. Accurately modelling farm measures identifies each representative farm group's most cost-effective and environmentally sustainable approaches and practices. This tool’s ability to balance financial goals with emissions reductions will be invaluable in guiding farm decisions.

8 Discussion and Conclusion

This final Chapter aims to consolidate and align all prior results through the lens of integrated internal modelling framework developed in this thesis. The framework connects three components the farm level MACC, the review of DSS, and the linear programming optimisation model to offer a comprehensive overview of the optimised mitigation measures for representative Irish dairy farms.

In this Chapter, Figure 3.2 is revisited, updated to Figure 8.1. This figure summarises how the chapters address the research questions, the analytical methods, and the main findings. The Chapter concludes with a synthesis of contributions, policy implications, and suggestions for future research.

This Chapter revisits the research questions in Chapter one and includes a combined discussion of the results of chapters 4, 5, 6, and 7. Each subsection focuses on one of the four research questions. The Chapter concludes with a summary of the overall results in the context of farm-level decision-making, the policy context, and potential future developments.

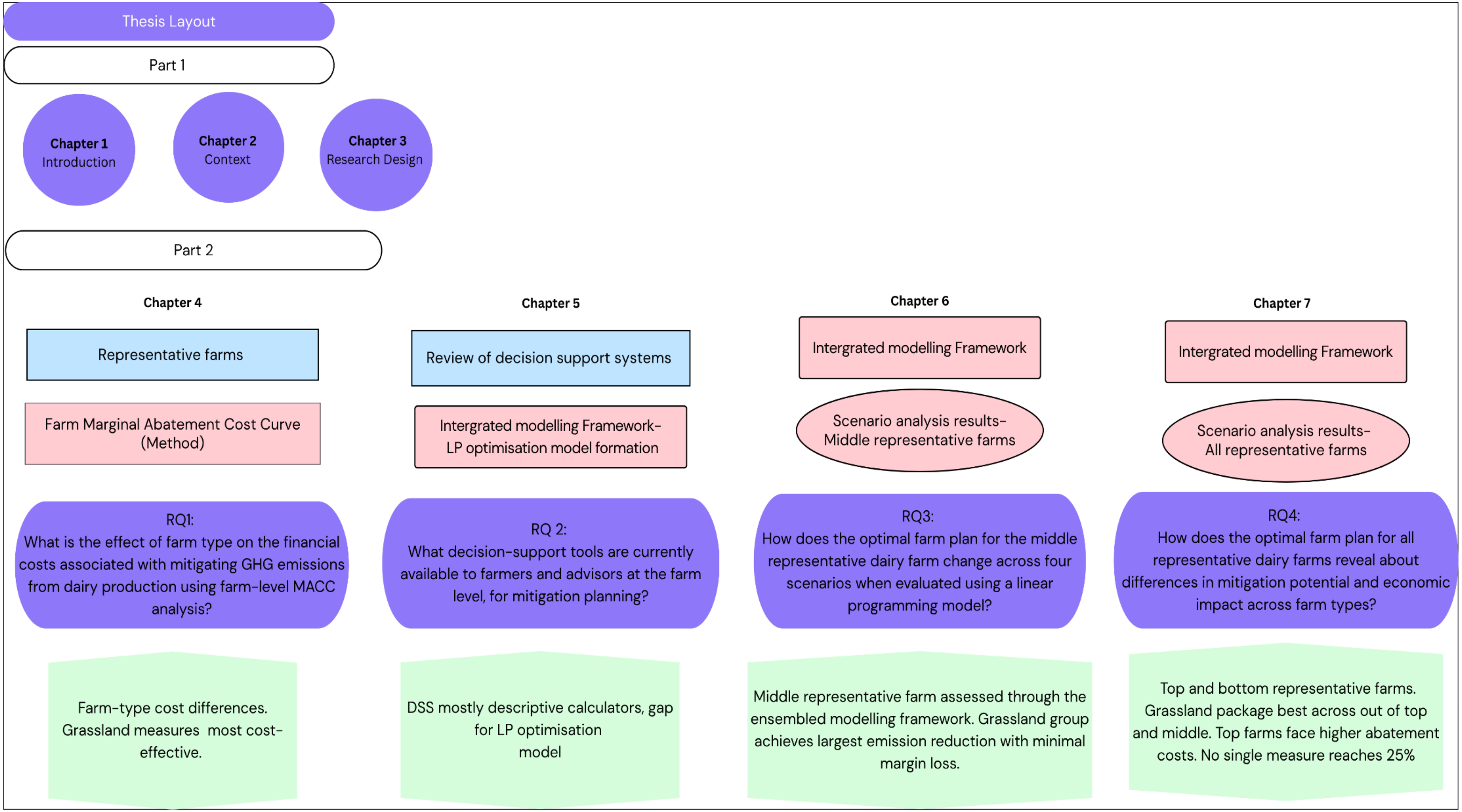

Figure 8.1 Thesis layout. Thesis structure showing how each Chapter aligns with the research questions, methods, and key findings. RQ3 and RQ4 both apply the integrated modelling framework across different scenario.

8.1 The Internally Integrated Modelling Framework

8.1.1 Farm Level Variability

The first component of the framework addresses the cost-benefit of GHG and ammonia mitigation measures across representative Irish dairy farms. Mitigation measures such as animal-related measures (improved animal productivity, better reproductive management and early calving) and grassland and feed related measures (grass utilisation, decreased fertiliser N, protected urea, white clover) and manure management measures (reduced crude protein, slurry tank cover and LESS) were considered. The results outlined in Chapter 4 show significant variation in the cost-benefit of mitigation measures between top, middle, and bottom representative farms, illustrating the varying degrees of abatement potential.

The results presented in Chapter 4 showed that over half of the total abatement potential for both GHG and ammonia emissions identified across all representative farms was realised through cost-effective, cost-beneficial measures. Cost-beneficial fall underneath the zero cost line, and cost-effective measures are those that fall below the shadow price of carbon on the MACC curve. Animal and feed-related mitigation measures that increased efficiency also drove the abatement of GHG emissions. For example, measures of variation can be seen in the level of abatement and the cost per ton of CO_2 for animal performance and grass utilisation.

The variation in the cost-effectiveness of mitigation measures across different farm types is not evident in the national MACC, where national average dairy data is applied, and as such, justifies the approach used here to examine the cost-effectiveness of mitigation measures at the farm level. The analysis presented in chapters 6 and 7 confirms earlier work by Lanigan (2018) and Schulte & Donnellan (2012), which found that mitigation measures can be cost-neutral or beneficial, and extends this work by quantifying variability across farm types.

This is also echoed in the international literature. Olthof et al. (2025) emphasise scale-driven variation in the cost-benefit of mitigation measures in US dairy systems. Similarly, in Australia and New Zealand, Garnett et al. (2024) highlighted the variation in land management, while Baudracco et al. (2013) and López-Villalobos et al. (2024) illustrated how local conditions, genetic merit and market assumptions drive heterogeneous outcomes. This strengthens the point that abatement and local farm circumstances are context specific. By extending these insights by explicitly linking farm-level estimates of emission abatement potential to changes in financial performance.

The results indicate that dairy farmers and advisors cannot assume the highest mitigation measure in the national MACC will automatically be the best choice for their farm type. Advice should be customised to the farm, and mitigation plans should be tailored to the farm, as measures that perform well nationally or internationally may not always be transferable to every farm. Since determining precise mitigation costs for each individual farm is often impractical due to data and resource limitations, developing mitigation strategies at the representative farm-type level used in this framework offers a more efficient and scalable approach. Our results confirm that farm-level MACCs for gaseous emissions allow farmers to receive practical and precise actionable guidance. Customisable abatement pathways at a farm level are crucial to ensure the sustainability and resilience of the sector.

8.1.2 Decision Support Systems and Integration

The second components involve evaluating the existing decision support systems that are already available and the advice or results they provide for farmers and advisors. This review is presented in Chapter 5 and includes the systems reviewed, which placed emphasis on emission reporting and benchmarking rather than on the farm level profitability. This was a key conclusion from the review of thirteen current decision support systems.

While emission reporting and benchmarking are helpful for the end users, only a limited number of DSS have evaluated the economic impact of mitigation measures on the farm. A limited number of systems combined economic and environmental outcomes, while fewer utilised optimisation methods to consider environmental and economic outcomes in a single framework. Regarding whole farm optimisation modelling, the review presented in Chapter 5 revealed that numerous comprehensive farm optimisation models have been created, such as FARMDYN in Germany, IDEA in France, ScotFarm in Scotland, and the United States' Integrated Farm System Model (IFSM). Unlike most decision-support systems that offer reporting or scenario analysis, these models are designed to optimise or simulate farm performance by integrating biological and management interactions so that both economic and environmental impacts are considered.

One notable study, Rotz et al. (2025), modelled pathways toward net zero for US dairy farms using the IFSM framework, highlighting how technical synergies across feed, manure, and energy systems could substantially reduce emissions. While this analysis captured complex biophysical interactions, it did not optimise farm profitability or tailor solutions to farm-type heterogeneity.

This distinction reveals a significant gap: existing DSS tools mainly focus on reporting or benchmarking, whereas whole-farm models offer system-level analysis but are not customised to the Irish context. None of the identified models accurately represent Irish pasture-based dairy farming systems or align with the national mitigation framework.

This review highlighted a particular gap in the literature. Our model, the linear program optimisation model, was specifically built to address this gap in the literature, building on the previous DSSs used for Irish dairy farming to create an integrated internal modelling framework that considers profitability and emission reductions to generate an optimal farm plan. This appears to be the first integrated internal modelling framework that allows optimisation of profitability while adhering to emission limits in Irish dairy farming.

8.1.3 Optimisation and Integrated Modelling

The third components focus on an optimal farm plan for the middle representative farm through the integrated modelling framework. This builds on the first research question by using the same representative farm data and analysing it in an optimisation manner through the integrated internal modelling framework. The four scenarios used for the middle representative farm are the baseline, a 10% emission limit and the two grouped measures: grassland and animal productivity. The findings in Chapter 6 build on those presented in Chapter 4, as each scenario demonstrates the measures, herd structure, and economic performance alongside the farm's emissions when the farm's net margin is optimised. Unlike the MACC analysis in Chapter 4, which considered mitigation measures as marginal changes with a fixed pasture-based production system, the optimisation approach in Chapter 6 enables the farm to adjust herd structure and management strategies to maximise net margin in each scenario. The baseline scenario (S1) establishes the farm’s optimal configuration without emission limits or mitigation measures. Here, the LP model maximises net margin.

When a 10% emissions limit (S2) is imposed, the LP model responds by reducing herd size and adjusting stocking rate. This results in lower milk production and total revenue. In this case, the optimal farm plan prioritises compliance over profitability, illustrating how rigid GHG emissions limits can reduce economic performance in the absence of mitigation measures.

In S3 (grouped grassland measures), by using protected urea, white clover, lowering fertiliser nitrogen, and improving grass utilisation, the farm can keep a similar herd size and stocking rate as the baseline but with lower emissions per unit of output otherwise known as emission intensity, (Lahart et al, 2021). This approach allows for high milk production and profitability while reducing total farm emissions by 16.2%.

In S4 (grouped animal productivity measures), the model includes genetic improvements (EBI) and earlier calving dates, causing a gradual shift in herd structure with enhanced reproductive performance. Although the net margin is slightly higher than the baseline, the abatement effect is smaller at 5.52% compared to S3. The optimal farm plan in this scenario emphasises biological efficiency gains while keeping the overall scale of production similar.

The integrated internal modelling framework shows that the nature of the grouped mitigation measure shapes the optimal farm plan. The emission limit alone reduced output and profit, while the grouped mitigation measures, in the case of grouped measures, allowed the farm to improve net margin compared to the baseline.

These results align with previous Irish studies (Palma-Molina et al., 2023; Cashman et al., 2024), which demonstrated that pasture-based systems that use nitrogen fertiliser more efficiently and incorporate white clover can maintain profitability while reducing emissions.

Building on the middle representative farm analysis presented earlier in Chapter 7, the integrated internal modelling framework is extended to the top and bottom representative farms to examine how (10) mitigation measures and (2) grouped mitigation measures vary by dairy farm type.

In Chapter 7, two grouped measures were used: combining individual grassland mitigation measures to form the grouped grassland measure and combining animal mitigation measures to form the grouped animal productivity measure. A comparison between individual and grouped measures shows that grouped approaches can deliver comparable GHG emission reductions while achieving a greater net margin for the middle and bottom representative farms. This finding informs the constructive recommendation that combining complementary mitigation measures may encourage wider adoption, delivering more optimal outcomes.

For the emission limit scenarios (S1, S2), the results were consistent across all representative farm types in that they reduced herd size and total milk output to meet the emission target. This scenario alone reduced activity levels on the farm and consistently delivered a lower net margin than the baseline.

Several standalone mitigation measures (S3.1-S3.10), such as Protected urea, improved grass utilisation, and improved breeding methods like EBI enhancements, achieved significant emissions reductions while preserving or boosting net margins particularly for bottom and middle representative farms. In contrast, for the top group these measures reduced net margin slightly and reduced emissions. Slurry covers and white clover provided modest emission reductions at low cost. Measures with limit impact on farm structure, such as slurry covers, white clover resulted in small but positive abatement at an economic gain.

The different impacts of mitigation measures on the representative farm were evident. The bottom representative of farms exhibited the most significant potential for net margin improvement from adopting mitigation measures. These findings confirm that the cost–benefit of mitigation cannot be universally applied, as the baseline characteristics of each farm influence it.

For top representative farms operating close to their technical and economic limits, the potential for additional margin gains through mitigation is limited. The LP model shows that while efficiency improvements can result in small reductions in emissions, they do not increase net margins beyond baseline levels. This builds on the results presented in Chapter 4, as four mitigation measures are cost-effective for the top representative farms: increasing grass utilisation, reducing fertiliser N, using protected urea and adopting LESS. However, their effect on net margin was different under the integrated internal modelling framework in Chapter 7. While all four mitigation measures reduced emissions by 13% to 25% relative to the TBL, none increased the net margin of the baseline (€101,509). This difference occurred because the MACC analysis considers each measure as a marginal change while keeping the rest of the system constant. In contrast, the LP model allows the herd size and milk production to adjust yearly, re-optimising the farm in response to the mitigation measures. As the LP model reallocated resources across the whole system, the margin gains are absorbed within the existing optimal structure of the farm.

For the middle representative farm, better reproductive management increased net margin but increased emissions slightly. Protected urea improved both economic and environmental outcomes, while grass utilisation reduced emissions by 19%. The grouped grassland management delivered the largest emission reduction with a minimal impact on net margin.

The bottom representative farm had the greatest potential to increase net margin and reduce emissions through measures such as protected urea, decreased fertiliser N, white clover, and grass utilisation. Similarly, the grouped grassland measure delivered a reduction in emissions and a significant net margin improvement.

Mitigation effectiveness relies not only on the measure itself but also on the type of farm implementing it. Across all representative farms, grouped measures generally achieved better emissions reductions than individual actions, often resulting in more favourable economic results. This demonstrates the synergies created when complementary practices are implemented together, enabling the LP model to re-optimise the farm system more efficiently than with single measures. Even for top farms with limited margin gains, grouped measures improved abatement compared to isolated actions. For middle and bottom representative farms, grouped grassland measures yielded more substantial economic and environmental benefits. However, in the middle group, increasing grass utilisation alone achieved a slightly greater emissions reduction than the grouped strategy. This highlights the importance of customised advice and optimisation to balance emissions reduction with profitability.

Internationally, the work of Kankanamge et al. (2025) in New Zealand whose study focused on environmental emissions from dairy systems primarily methane and nitrous oxide. The study highlighted how the effectiveness of mitigation measures depends on the context of the farming system and how the interaction between mitigation measures must be carefully considered to avoid double-counting. Interaction effects between mitigation measures were considered indirectly by employing grouped scenarios (S4.1 and S4.2), created using external feeder models. These grouped measures, such as grassland and animal productivity, were pre-aggregated to represent their combined impacts and prevent double counting emission reductions during the LP model simulation. The LP model then optimises the farm for each scenario.

This thesis expands on existing knowledge in two ways: first, by including farm-level differences among the top, middle, and bottom representatives of Irish dairy farms; and second, by linking mitigation results not only to environmental impacts but also to net margins through optimisation modelling. This shows that interactions are important both biologically and economically, affecting farm-level decision-making regarding emissions limits. Farmers rarely adopt measures in isolation for farm decision-making, and policy frameworks should support bundled packages of measures rather than isolated mitigation measures. Grouped approaches reflect real-world practice and improve economic outcomes, and they are essential if farms are to meet the agriculture sector's short to medium-term GHG reduction targets.

8.1.4 Integrated Framework Outcomes

Overall, this thesis sets out to determine the optimal farm that is both economically viable and environmentally sustainable for Irish pasture-based dairy systems. It addresses this through four main research questions.

The analysis demonstrates that farm-level heterogeneity matters in evaluating the potential to mitigate gaseous emissions. The farm-level MACCs showed significant differences among the top, middle, and bottom farms. These results confirm that “one-size-fits-all” advice from national MACCs can be misleading; emission abatement measures are specific to each farm type and depend on the context. While this analysis uses representative farm groupings (top, middle, and bottom), which simplifies the full spectrum of farm-level diversity, it still highlights important differences in mitigation potential across farm types.

It is essential that farmers and farm advisors consider the context of the farm when selecting mitigation measures. Furthermore, the results also confirmed that combining different mitigation measures can alter the overall performance, which is clear from the grouped measures versus the standalone measures. This suggests that support should be provided for farmers to adopt “bundles” of mitigation measures, as this will lead to more optimal outcomes. The analysis shows that some grouped measures can lead to significant “win–win” outcomes. In contrast, others present challenging trade-offs, stressing the need for optimisation systems that explicitly balance profitability with emissions reductions. However, it is important to note that the representation of farms using top, middle, and bottom groupings provides a simplified view of farm-level heterogeneity. While this approach captures variation in economic performance, it does not fully reflect the diversity of farming systems, such as low-input or alternative management systems that may not align with this classification. Therefore, the results should be interpreted as indicative of broader trends rather than a complete representation of all farm-level variability.

Table 8.1 Summary of mitigation outcomes across top, middle, and bottom farms (10-year average results).

Farm Group	Measure	Net Margin (€/farm)	Change vs Baseline	Emissions (kg CO_2eq)	Change vs Baseline
Top	Baseline	€ 101,509	-	632,692	-
	Grass Utilisation	€ 86,871	-14%	596,967	-6%
	LESS	€ 89,780	-12%	615,071	-3%
	Grouped Grassland	€89,827	-12%	520,555	-18%
	Grouped Animal	€ 99,917	-2%	609,920	-4%
Middle	Baseline	€80,747	-	527,570	-
	Grass Utilisation	€77,486	-4%	425,502	-19%
	LESS	€ 77,194	-4%	529,710	0%
	Grouped Grassland	€ 80,919	0.2%	444,958	-16%
	Grouped Animal	€79,845	-1%	498,465	-6%
Bottom	Baseline	€40,773	-	398,809	-
	Grass Utilisation	€49,755	+22%	344,723	-14%
	LESS	€56,220	+38%	409,118	3%
	Grouped Grassland	€55,691	+37%	323,544	-19%
	Grouped Animal	€44,491	+9%	336,417	-16%

The review of decision support systems revealed a gap between emission reporting and optimisation. Analysis of Irish and international systems revealed that most are focused on emissions reporting, with fewer integrating profit alongside environmental goals. Platforms like FARMDYN and ScotFarm showcase robust environmental accounting but seldom optimise economic trade-offs. IFSM is one of the more comprehensive process-based models, capable of evaluating both economic and environmental outcomes and used across Australia and New Zealand, encompassing various systems (Sejian et al, 2018; Rotz et al., 2016)

The research presented here fills this gap by applying farm-level MACC data in an LP model developed as part of an integrated model framework, explicitly balancing emissions and profitability for the Irish dairy sector. This methodology provides a transparent and computationally efficient foundation. This approach is novel within an Irish context, as existing decision support systems and their underlying modelling frameworks have not incorporated optimisation of mitigation measures within an integrated framework for pasture-based dairy farms. Further advances of this work could include using multi-objective programming or mixed integer approaches to capture more complex combinations of measures.

The results highlighted the effectiveness of grouped measures for the middle representative farm. Results showed that some grouped measures, such as grassland management, had a significant impact on net margin. In contrast, grouped animal productivity did not give the same increase in net margin; however, both reduced emissions for the baseline. The analysis of single measures also reveals that there is no silver bullet to eliminate dairy emissions. At the same time, there is no immediate quick-fix solution for the dairy sector. The integrated internal modelling framework can support Irish dairy farmers in addressing the long-term goal to have a climate-neutral agri-food system by 2050.

This work applies both decision support systems and optimisation approaches. DST platforms are generally built to clearly display indicators such as emissions, nutrient balances, and profit to farmers and advisors, aiding informed decision-making. Optimisation models, in contrast, determine the mathematically optimal farm plan given specific constraints and a set objective. By integrating the strengths of both perspectives, this thesis develops an optimisation-based backend within an integrated modelling framework, using LP to generate optimal solutions while showing how results presented through grouped or standalone measures can enhance a DSS-style interface.

These findings highlight that practical climate advice for Irish dairying should extend beyond national MACCs and reporting systems. Farmers and advisors need evidence that is specific to their context and economically sound. The integrated modelling framework approach presented here offers such a solution. Its novelty is connecting environmental reductions with farm profitability, while its value lies in providing customised, scenario-based farm plans.

A useful benchmark for interpreting these results is a proportional (homothetic) reduction in farm activity. Under such a scenario, a 10% reduction in all inputs and outputs would be expected to result in an exactly 10% reduction in both emissions and net margin. However, the results of this study show a disproportionate reduction in net margin relative to emissions. This reflects the presence of structural constraints within the farm system, including fixed costs, biological herd dynamics, and resource allocation limitations, which prevent proportional adjustment. As a result, simple operational contraction is not an economically efficient strategy for achieving emission reduction targets, highlighting the importance of optimisation-based approaches.

In the future, creating a dashboard-style interface on a digital sustainability platform such as AgNav could make this optimisation model a practical decision-support system. This would enable farmers and industry to assess the effects of specific mitigation measures or grouped measures and to see their impact on farm profit and GHG emissions instantly (Teagasc,2025). It would also bolster advisory efforts and help the sector meet the Irish agriculture 25% GHG reduction goal in an environmentally, economically, and sustainably viable manner.

Mitigation measures and farms are often bound by their local context and specific farm structure, making it very challenging to generalise abatement across a nation.

Mitigation measures were used to apply and test the LP model and internal modelling framework. With ongoing research in GHG mitigation, the focus here was on 10 mitigation measures and two grouped mitigation packages. Having two elements, the grouped mitigation and the individual measures, allowed for detailed results and prioritisation for different farms. As farms operate on tight financial margins and with limited labour forces, assessing options thoroughly is essential for optimising resource use for economic and environmental benefits.

Determining the most effective farm plan is vital for farmers to be able to work towards a realistic benchmark for their own farm that is tailored to their specific structure.

8.2 Contributions of the Framework

The thesis contributes to the methodological literature by advancing farm-level analysis and the foundations of farm-level optimisation modelling. This thesis contributed to the existing research on MACCs by developing a novel farm-level MACC approach specifically for the Irish dairy farming systems. Through the development of an integrated internal modelling framework that couples existing Teagasc bio-economic and LCA models with an optimisation LP model. It is a unique approach for the Irish dairy system. This thesis makes four main contributions.

8.2.1 Theoretical contributions

While the primary focus of this thesis was on developing the LP model to identify cost-effective mitigation measures across different scenarios, Rogers' Diffusion of Innovation theory offers a valuable perspective on this work (Rogers, 2003). The key factors that drive adoption are relative advantage, compatibility, complexity, trialability, and observability. These factors were kept in mind throughout the development of the LP model and the integrated modelling framework.

Throughout this thesis, a clear economic advantage (relative advantage) is demonstrated, ensuring that mitigation measures are customised to the representative farm (compatibility) and supported by a transparent and adaptable internal modelling framework (reducing complexity). This approach aims to aid farmer decision-making. Future versions of the internal modelling framework could facilitate trial and demonstration projects (trialability) across multiple farms, allowing these farm trials to serve as scenario analyses to evaluate the impact of measures at the farm level (observability).

Future work could expand on this foundation by using the model in advisory settings, such as knowledge transfer groups, to explore how farmers respond to these results in practice.

8.2.2 Farm Level Advisory

It was important in the thesis to be able to utilise the findings with the people who need it most, the farmers. This thesis contributes to the farming community and sector by evaluating the impact of different emission ceilings, mitigation measures, and mitigation bundles on farms. The route of the internally integrated modelling framework was chosen because the decision was made to build on two existing, sophisticated Teagasc models that had already been developed and validated. Adding an optimisation element allowed the model to optimise based on a specific objective. For this thesis, the aim is to maximise net margin. From the results outlined earlier, each scenario generates a specific economic and environmental report for the farm and scenario. In practice, this will allow the farm to evaluate each option and see the impact on the farm. Providing this information at the farm level will enable the farm to make informed decisions regarding economic status and environmental goals.

Darnhofer et al. (2010) demonstrated that farmers' learning, flexibility, and diversity can be improved through tailored information, which is crucial for adapting to change and maintaining farm survival. They emphasised the importance of farmers learning via experimentation and monitoring, indicating that information customised to their specific farm conditions could be invaluable. The model could support farmers in making sustainable, long-term strategic decisions about their farm as an enterprise. This could be done by allowing the farmers to test different mitigation pathways and how they impact overall profitability over time. Of course, the model would have to change from fixed to dynamic market pricing, but this would allow the farmer to plan and support investment decisions.

Similarly, co-operatives, banks, advisors, and consultants could benefit from the model, especially in awarding incentives for specific practices or in identifying cost-effective mitigation options. This will also help the co-ops as it can support and provide the information needed to comply with the corporate sustainability reporting directive (KPMG,2024).

8.2.3 Sector and Policy Benefits

Utilising farm-level optimisation models could potentially feed into a wider sector-level outputs database that would improve the accuracy of emission projections and could be used to inform national inventories. The model outputs could support and enhance the sectoral roadmaps for achieving environmental targets (Teagasc, 2024). Sector aggregation can enhance evidence-based climate policy by providing more precise bottom-up GHG inventories and projections.

While national MACCs are useful for national comparison, implementation and guided advice require farm-level analysis. Utilising a farm-level MACC showed the variation between farms and the abatement potential of different measures. This shows how farms should be treated differently when it comes to abatement and why customised advice is needed to achieve the climate targets.

Meeting the climate goal for the dairy industry will require tremendous effort. Having a benchmark specific to the farm that allows it to maintain its profits while meeting the environmental goals forms a blueprint for the farm to operate on. This thesis demonstrated the effect of bundled and stand-alone measures across three farm types. Policies should recognise the role of mitigation measures (individual/grouped) and support their coordinated adoption.

Having robust farm-level modelling systems will support changes in national or EU-wide policies, especially if agricultural emission trading schemes are implemented, as discussed by Matthews et al. (2025). If Ireland were to introduce a carbon pricing system for agriculture unilaterally, following a carbon levy and rebate model, it could be effective. However, adopting such a levy/rebate system at the EU level faces political challenges, making an agricultural emissions trading scheme more probable.

8.3 Limitations and Future Developments

As with any modelling approach, this thesis has a number of limitations. These limitations illustrate methodological choices to balance model complexity, scope and feasibility at this stage of development. These areas are currently presented as limitations but offer an excellent opportunity for future growth and expansion.

8.3.1 Data Limitation

Throughout this thesis, representative farms are used; these are derived from the NFS and split based on their gross margin into three groups: the top, middle and bottom representative farms. By using only a subset of representative farms, these results do not fully represent all Irish dairy farms, and they cannot be generalised to the agricultural industry.

The ‘average farm’ approach simplifies the diversity of farm structures and does not capture the risk perception of individual farmers or farm management differences

8.3.2 Method and Model Limitations

The optimisation model is based on linear programming, which assumes linear relationships, fixed constraints and constant prices. The model is limited as it does not consider price variability, dynamic market pricing and response as well as feedback loops.

As the model assumes a static price, this simplifies the real system's behaviour to have an accurate representation of the current market; the model would have to use market costing and temporal pricing.

The model is currently running annually for 5 years and 10-year periods. This doesn’t account for seasonal variation, while the two feeder models can account for the seasonal variation, the LP itself does not.

Similarly, land structure and land types are not taken into account in this thesis, even though various land constraints exist across the country, such as elevation and aspect, which can limit the available space for the herd in the model. Similarly, soil type variations across the country are evident and will have different effects on yields, nutrients, and drainage. While this was out of the scope of this thesis, it is worth noting for future iterations.

Milk production is reported in the model as litres; it is not broken down into the fat/protein content of the milk, while this will significantly impact the price the farmers receive, the LP is not yet able to do this. The two feeder models can break milk yield into fat/protein content; the optimisation model does not.

8.3.3 Implementation and Behavioural Considerations

The model assumes a 100% adoption rate of the mitigation measures and group measures; this, of course, is not an accurate representation of the current sector. But this allows the farmer to work towards their own goals. The model currently doesn’t take the farmers' decision-making behaviour and their thought process in adopting new measures and technologies, as well as the lead time and lag time associated with that.

Another area that the model has not accounted for is social factors, including stress and work-life balance in the agricultural industry. The mental status and balance on the farm will impact the farm's overall efficiency and are crucial to take into consideration when advising farms.

8.3.4 Mitigation Measures

The analysis is limited because optimisation was only applied to a subset of measures; a joint optimisation of all 10 standalone and two grouped mitigation measures was not feasible without risking double-counting or complex interactions. Nevertheless, presenting the complete set of results individually remains useful. Farmers and advisors can compare each measure (and groupings) to assess their economic and environmental impacts. Another limitation is that the model assumes static farm conditions and does not yet account for longer-term dynamics like soil carbon sequestration or adoption costs.

Incorporating mitigation strategy measures into a single scenario would necessitate MIP. This approach can manage more complex decision-making by integrating continuous and discrete variables, allowing the model to independently identify trade-offs and develop the optimal strategy. However, implementing MIP introduces considerable complexity and computational requirements. Consequently, opting for separate linear programming scenarios is a strategic decision to maintain model simplicity and clarity, despite a unified MIP method potentially providing a more cohesive perspective. This model has evaluated a particular set of mitigation measures and has shown an optimal strategy for the representative average farm. Potential future developments of this model could include evaluating other farm types and mitigation measures. Building on the mitigation measure and including dynamic pricing could allow the model to run a more elaborate approach. Similarly, other model iterations could examine policy implications, such as emission reduction incentives.

While these limitations do not undermine the value of the findings, they can identify future pathways for the model to evolve into a framework that fully reflects the complexity of Irish farming.

8.4 Future Research

Future research in this area could include broadening the scope by assessing other farming systems. Although the model is designed for dairy farms, future versions could include beef, which would be a logical next step. Since beef and dairy are among Ireland's most significant agricultural sectors, including them in the model would significantly enhance its benefits. As the model is developed to sell bull calves, incorporating dairy cross calves, suckler cows, and finishing cattle would enable it to represent the entire beef and dairy sectors effectively.

While this thesis was limited to 10 mitigation measures and two grouped mitigation packages, the results showed that each farm type differs and that the optimal plan varies from farm to farm. As this model and framework develop, utilising the complete mitigation library and advancing the model to an MIP or multi-goal model will allow for more elaborate plans and results that will enable the farmer to make a well-informed decision.

This extension would be interesting to see, especially in evaluating the cross-farm spillovers like contact rearing. Extending the framework in this manner would allow the assessment of mitigation measures at a more integrated, system-wide level, rather than solely at the individual farm scale. One area that could strengthen the model is MIP or multi-objective programming The model is in its infancy and has proven a clear proof of concept by building on this foundation by advancing the modelling into MIP or multi-objective programming involving some key social factors regarding the mindset and health of the farmers, such as burnout, loneliness and or pressure, as well as societal goals like improved biodiversity and agricultural settings. While the model is initially built as an LP optimisation model, moving to mixed-integer programming or multi-objective programming will involve handling more complex situations, especially when considering other motivators for farmers, such as social and environmental goals, as mentioned in the limitations section. This would enable consideration of how farmers balance economic, environmental, and social objectives simultaneously, rather than concentrating solely on profit maximisation.

This shows the evolving role of farm decisions by coupling social and environmental objectives, reflecting the move of the model from a single economic optimiser to a multi-objective sustainability framework. Building on Antle et al. (2017), this study highlighted the importance of considering various sustainability outcomes and the need to understand the trade-offs among economic, environmental, and social dimensions in farm decision models.

Similarly, future work on the model would incorporate dynamics and resilience, especially relating to pricing. Incorporating climate variability and uncertainty into the model would move it into the realm of stochastic programming, making it more realistic for current farm practices.

Decision support advancement, with the current formulation of the integrated modelling framework, investing in building a user-friendly front end in a dashboard style would allow advisors and farmers alike to use the models results.

8.5 Final Conclusion

With the combination of evaluating individual and grouped mitigation measures across three farm types, developing this model to include a front-end dashboard would provide invaluable information to support farmers and advisors in meeting the climate targets.

This thesis offers a practical, scalable pathway to align profitability with environmental goals, supporting Ireland's transition toward a more sustainable dairy sector.

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10 Appendix

Appendix A

Model sets and parameters and variables

Table 10.1 Sets.

Symbol	Sets	Index
S	Sex [s]	Gender of livestock
F	Fy	Feed and yield associated with each livestock
C	Capitaltypes	Capital Investment types (Land, Machinery, Building)
B	Bs	Set of cow transaction (buy/sell)

Table 10.2- Parameters farm.

Symbol	Description	Unit
T	Length of the planning horizon	Year
n_c	Number of possible crops grown	Ton/year
n_b	Number of possible biodiversity alternatives	Number/year
n_a [s]	Maximum possible age of cows for each sex ,$s \in S$	Year
Maxage	Maximum age at which a cow is no longer productive	Year
n_e	Number of different emission types	Number
$n_e s$	Number of emission sources	Number
A_0	Initial land area	Hectares
P_h	Price per hectare	Euro
M_0	Initial Machinery value	Euro
B_0	Initial building value	Euro
H_{max}	Maximum labour hours	Number
C_u	Cost of utilities for each time period	Euro
U_c	Utilities consumption for each time period	Units

Table 10.3 Parameters herd.

Symbol	**Description**	**Unit**
I_{is}	Initial number of cows by age *i* and sex *s*	Number of animals
T_{if}	Attributes of cows by age *I* and feature f ∈ {feed,yield}	Various
d_c	Mortality rate of cows	Percentage rate per year
K_{cc}	Percentage of herd kept	Percentage
$b_c[i]$	Birth rate of cows by age *i*	Percentage rate per year
$P_c[I,b,s]$	Price of cows by age *I,* transaction type *b* ∈ {buy,sell} and sex *s*	Euros per cow
$C_c[i,s]$	Slaughter price by age *I* and sex *s*	Euros per cow
F_c	Unit feeding cost	Euros
$L_c[i]$	Land required per cow by age *i*	Hectares
K_c	Conversion factor for buildings vs. number of cows	Factor
D_c	Cost of dairy concentrate	Euro
$\delta_c[c]$	Depreciation cost as a percentage by capital type c∈{Land,Machinery,Building}	Percentage
M	Price of milk	Euros per litre
K_m	Litres of milk produced per euro of machinery investment	Litres per euro
Y_{ci}	Crop yield per hectare	Tonne per hectare
P_{ci}	Crop price	Euros
C_{ci}	Cost of growing crops per hectare	Euros per hectare
S_{ci}	Cost of seeds	Euros
$L_h[i]$	Land requirements by each hectare of crops	Hours
F_{fert}	Cost of fertiliser, lime & reseeding	Euros
S_{silage}	Cost of making silage	Euros
m_h	Cost of machinery hire	Euros
v_m	Veterinary cost	Euros
C_{car}	Car cost	Euros
E	Electricity cost	Euros
L	Labour cost	Euros

m_r	Machinery/repair cost	Euros
P	Phone cost	Euros
I	Insurance cost	Euros
i_r	Repayments term loan	Euros
e_{lim}[e]	Emission limits by type *e*	Kg CO_2eq
$e_{ci}[i,e,s]$	Emission profiles for cows by age *I,* emission type *e,* and source *s*	Kg CO_2eq
e_{cr}[i,e]	Emission profiles for crops by type *e*	Kg CO_2eq

Table 10.4 Variables.

Symbol	**Description**	**Unit**	**Domain**
A_{ti}	Area allocated to each crop in period *t*	Hectares	Non-negative real numbers
C_{tis}	Number of cows by age *I* and sex *s* at the end of year *t*	Number of cows	Non- negative real numbers
C_{timf}	Number of female (f) cows at age *i*, in period *t*, that produce milk *m*	Number of cows	Non-negative real numbers
L_t	Land used for cows in period *t*	Hectares	Non-negative real numbers
S_{tis}	Number of cows sold by age *I* and sex *s* in period *t*	Number of cows	Non-negative integers
B_{tis}	Number of animals bought by age *I* and sex *s* in period *t*	Number of animals	Non-negative integers
K_{tis}	Number of cows culled by age *I,* and sex *s,* in period *t*	Number of cows	Non-negative real numbers
I_{tc}	Capital investment by type *c* at the end of period *t*	Euro	Non-negative real numbers
$^{inc}_{tc}$	Increase in capitqal investment by type *c* at the start of period *t*	Euros	Non-negative real numbers
$^{dec}_{tc}$	Decrease in capital investment by type *c* at the start of period *t*	Euros	Non-negative real numbers
	Revenue at the end of period *t*	Euros	Non-negative real numbers
	Cost at the end of period *t*	Euros	Non-negative real numbers
	Total milk production in period *t*	Liters	Non-negative real numbers

Appendix B

Appendix B Model Formulation

The following expressions represent the components of the objective function and constraints used in the linear programming model. Where applicable, these expressions are incorporated within the full model formulation.

A1.Livestock trade

$$\sum_{t=1}^{T} \sum_{i=1}^{maxage} \sum_{j=1}^{n_s} \sum_{k\epsilon\{F,M\}} (P_c\,[i,sell,k] * S_{t,i,k})$$

A2. Livestock trade

$$\sum_{t=1}^{T} \sum_{i=1}^{maxage} \sum_{k\,\in\{F,M\}} \left(C_{ci}\,[i,k] * \; K_{t,i,k}\right)$$

A3.Farm Asset

$$\sum_{t=1}^{T} \sum_{i\epsilon c} (\,\Delta I_{tic}^{dec}\,)$$

A4. Feed Purchased

$$\sum_{t=1}^{T} \sum_{i=1}^{maxage} (f_c * T_{i,feed} * C_{t,i,f})$$

A5.Crop production

$$\sum_{t=1}^{T} \sum_{i=1}^{n_c} (C_{ci} * A_{ti}) \; * \; \sum_{t=1}^{T} \sum_{i=1}^{n_c} (S_{ci} * A_{ti})$$

A6. Assets

$$\sum_{t=1}^{T} \sum_{i\in c} (\,\delta\mathrm{c[i]} * \; I_{tc} + \; C_{cs}[i,cost] * \Delta I_{tc}^{inc})$$

A7. Livestock equation:

$$\sum_{t=1}^{T} \sum_{i=1}^{maxage} \sum_{j=1}^{nbemissionsources} \sum_{k\epsilon\{F,M\}} (E_{i,e,j} \; * \; C_{t,i,k}\,)$$

A8. Crop formula:

$$\sum_{t=1}^{T}\sum_{i=1}^{n_c}(E_{i,e} * A_{ti})$$

B1. Initial Cows Distribution:

$$\forall \mathrm{i} \in \{1,\ldots,\mathrm{maxage}\}, \forall \mathrm{k} \in \{\mathrm{F,M}\}, \mathrm{C}_{0,i,k} = \mathrm{I}_{i,k}$$

B2. Newborn calves:

$$\forall \mathrm{t} \in \{1,\ldots,\mathrm{T}\}, \forall \mathrm{k} \in \{\mathrm{F,M}\}, C_{t,1,k} = \sum_{i=1}^{maxage} 0.5 \times B_i \times (1-D) \times C_{t-1,i,f}$$

B3. Cow Aging Process:

$$\forall t \in \{1,\ldots,T\}, \forall i \in \{1,\ldots,maxage-1\}, \forall k \in \{F,M\}, C_{t,i+1,k} = (1-D) \times C_{t-1,i,k} + B_{t,i,k} - S_{t,i,k} - U_{t,i,k}$$

B4. Selling of Cows:

$$\forall \mathrm{t} \in \{1,\ldots,\mathrm{T}\}, \forall \mathrm{k} \in \{\mathrm{F,M}\}, \mathrm{S}_{tis} = (1-D) \times C_{t-1,maxage,k}$$

B5. Selling and Culling Constraints

$$\forall t \in \{1,\ldots,T\}, \forall i \in \{1,\ldots,maxage\}, \forall k \in \{F,M\}, S_{t,i,k} + K_{t,i,k} \leq (1-D) \times C_{t-1,i,k}$$

C1. Crop formula $\sum_{t=1}^{T}\sum_{i=1}^{maxage}(Fc \times I_{i,feed} \times C_{t,i,F})$

C2. Crop growth

$$\sum_{i=1}^{n_c}\sum_{t=1}^{T}((C_{ci}[i] + S_{ci}[i] + L_h[i] \times At_{t,i}))$$

D1. Land Allocation Based on Acreage Constraint

$$\forall t \in \{1,\ldots,T\}, \sum_{i=1}^{n_c} At_{t,i} + Lt_t \leq \frac{Itc_{t,\text{"}land\text{"}}}{Ph}$$

D2. Land Available for Cows:

$$\forall t \in \{1,\ldots,T\}, \quad \sum_{i=1}^{maxage} \sum_{k \epsilon S} L_c\,[i] \times C_{land(t,i,k)} \leq Lt_t$$

D3. Yield Based on Parlour Capacity:

$$\forall \mathrm{t} \in \{1,\ldots,\mathrm{T}\}, \quad \sum_{i=1}^{maxage} T_{i,"yield"} \times C_{timf} \leq Km \times I_{t,m}$$

D4. Number of Cattle Based on Housing Available:

$$\forall t \in \{1,\ldots,\mathrm{T}\}, \quad \sum_{i=1}^{maxage} \sum_{k \in sex} Ctis_{t,i,k} \leq Kc \times Itc_{t,"building"}$$

E1. Milkrevenue $\sum_{t=1}^{T} \sum_{i=1}^{maxage} (m * T_{i,yield} * C_{t,i,m,f})$

E2. Crop revenue

$$\sum_{t=1}^{T} \sum_{c=1}^{n_c} P_{ci} * Y_{ci} * A_{tc}$$

Appendix C

Appendix C Decision support systems description

1. Cool Farm Tool v2.0, developed by the University of Aberdeen and the Cool Farm Alliance, offers an intermediate-level approach focusing on livestock and crop production (Cool Farm Alliance, 2023).
2. FarmAC by Aarhus University provides a quantitative approach to simulate carbon and nitrogen flows on arable and livestock farms, aiding in emission quantification and soil carbon sequestration (Aarhus University, 2023a, b)(Hutchings et al, 2018.)
3. Overseer, developed by Overseer Ltd., extends the scope to nutrient flow management, assisting farmers in analysing the impact of management practices on nutrient cycles within the farm system (Overseer Limited,n.d).
4. AgNav for beef and dairy production, developed by Teagasc and Bord Bia, offers farmers online tools for monitoring GHG emissions and assessing mitigation options (Teagasc & Bord Bia, 2019).
5. KSNL (Kriteriensystem Nachhaltige Landwirtschaft) enables comprehensive sustainability analyses for agricultural businesses, incorporating environmental, economic, and social dimensions (KTBL, 2016).
6. The CAP2ER model, developed by the French Livestock Institute, aims to quantify the impacts of milk and beef production in France and provide recommendations for mitigating these impacts. The model employs two levels of analysis to assess a farm's sustainability (CAP'2ER, 2023).
7. SMART—Sustainability Monitoring and Assessment RouTine, created by the Research Institute of Organic Agriculture (FiBL), performs sustainability assessments of farms and agricultural food companies. It is structured based on the FAO's guidelines for the Sustainability Assessment of Food and Agriculture Systems (fiBL, 2017).
8. Rise- Response-Inducing Sustainability Evaluation, created by HAFL - University of Agricultural, Forestry and Food Sciences, monitors and assesses farm sustainability. (Bern University of Applied Sciences, 2022).
9. BEK—Berechnungstandard für einzelbetriebliche Klimabilanzen in der Landwirtschaft—is the standard calculation for carbon footprints at the farm level in Germany; it enables firms to calculate GHG emissions for various industrial processes (Effenberger et al., 2021).
10. AgBalance®- BASF created the AgBalance® Model 2009 2010 to analyse farming sustainability using the ISO 14040 Life Cycle Assessment framework principles. (Saling et al., 2014).

11. HOLOS- Holos is a software application and a whole-farm model that calculates GHG emissions based on data entered for individual farms. in Canada. Holos was created as an exploration tool for evaluating potential GHG reduction scenarios before implementation (Little et al., 2017)
12. GLEAM 2.0 (GLEAM-I)- GLEAM-i is an open-source programme for calculating GHG emissions from various livestock species and production systems around the globe. GLEAM-i is a Tier 2 GHG calculator explicitly designed for the cattle industry. (FAO, 2017; Mac Leod et al., 2017)
13. Farmscoper (Farmscoper v4) is a tool primarily used to examine multi-pollutant farming systems in England and Wales. It can evaluate the environmental impacts of standard agricultural activities in terms of emissions and biodiversity (Zhang et al., 2012).

Appendix D

Appendix D Variable costs

The variable costs represented in the model are:

- Concentrates- the unit price of the concentrate brought on the farm for each animal category
- Silage purchases- this is the unit cost of silage bought throughout the year
- Fertilizer, lime, and reseeding- these activities are grouped and represent the cost of grass production and management
- Land rental- unit price per hectare of land rented throughout the year
- Livestock purchases- the unit price of livestock sold associated with each age group
- Machinery hire- price to hire any machinery needed throughout the year
- Milk replacer- unit price used for calves throughout the year
- Silage making- the cost associated with the silage process on the farm
- Vet. AI & Medicine- any animal medical and vet costs throughout the year.

The fixed costs represented in the model are:

- Car usage - the cost associated with the farm car throughout the year
- Electricity - all electricity used associated with the farm activities for the year
- Labour & living expenses- the cost of the labour force and living expenses on the farm
- Machinery Operation & Repair- all maintenance and repairs associated with farm machinery
- Phone
- Sundries
- Loan interest
- Interest repayments
- Bank Charge

Appendix E

Decision variables, constraints and factors

Decision Variables:

- **cropland:** Decision variable representing the allocation of land to different crops.
- **biodivland:** Decision variable representing the allocation of land to different biodiversity alternatives.
- **cowland:** Decision variable representing the total land used for cows.
- **cows:** Decision variable representing the number of cows in each age category, differentiated by milk or beef and gender.
- **sellcows:** Decision variable representing the number of cows sold in each age category, differentiated by milk or beef and gender.
- **buycows**: Decision variable representing the number of cows bought in each age category, differentiated by milk or beef and gender.
- **capinvest:** Decision variable representing capital investment at the end of each year for different types (tractor, milk parlour, housing).
- **inccapinvest**: Decision variable representing an increase in capital investment at the start of each year.
- **deccapinvest**: Decision variable representing a decrease in capital investment at the start of each year.

Objective Function:

The objective is to maximise gross margin over the planning horizon.

Constraint:

1. **Revenue Calculation Constraint:**
   Ensures that the total revenue is calculated accurately based on milk production, crop yield, livestock prices, and capital investments.

Factors:

- Milk yield
- Crop yield and prices
- Capital investments
- Number of cows bought and sold
- Prices of milk, meat, and crops

2. **Cost Calculation Constraint:**
   Ensures that the total cost is calculated accurately, considering various factors such as feed costs, crop costs, equipment costs, breeding animal costs, labour costs, veterinary service costs, utility costs, salvage costs, and costs associated with buying and selling cows

Factors:

- Feed costs for milk and beef production

- Crop costs
- Seed costs
- Equipment costs (currently commented out)
- Breeding animal costs (currently commented out)
- Labor costs (currently commented out)
- Veterinary service costs (currently commented out)
- Utility costs (currently commented out)

3. **Salvage costs for capital investments**
- Buying and selling costs for cows
- Dairy feed concentrate costs

4. **Land Allocation Constraint:**
   Ensures that the total land allocated for crops, and cows does not exceed the available land area**.**

Factors:

- Land allocated to crops
- Land allocated to cows
- Available total land area

5. **Assets Constraint:**
   Ensures the correct tracking of the values of various assets (capital investments) over time, considering depreciation or increase

Factors:

- Initial capital investments (tractors, milk parlour, housing)
- Increase and decrease in capital investments over time

6. **Cows and Equipment Utilisation Constraints:**
   Ensures that land is utilised appropriately for cows and crops, and that tractor hours do not exceed the available capacity

Factors:

- Land per cow
- Tractor hours required per crop
- Milk parlour capacity
- Housing capacity for cows

7. **Livestock Capacity Constraints:**
   Ensures that the milk parlour's capacity is not exceeded by the milk production of cows.

Factors:

- Milk production capacity based on milk parlour capacity

8. **Cattle Housing Constraint:**
   Limits the number of cattle based on the available housing capacity

Factors:

- Housing capacity for cows

9. **Initial Cows Constraint:**
   Sets the initial number of cows in each age category, differentiated by gender.

Factors:

- Initial number of cows in each age category and gender

10. **Transition Equations for Cows:**
    Governs the dynamics of the number of cows over time, considering buying and selling

Factors:

- Buying and selling of cows over time

11. **Environmental Emission Constraints:**
    Enforces limits on environmental emissions from cows, crops, and overall environmental limits

Factors:

- Emission profiles for cows and crops
- Limits on overall environmental emissions

Appendix F

Source; Taken from Bang et al,(2023).

FARMDYN is a dynamic mixed-integer bioeconomic whole farm optimization and simulation framework with environmental accounting modules and more (Britz et al, 2014). It is designed for German beef and dairy farming, among other things, and applied by Kokemohr et al. (2022) and Kuhn et al. (2019), among others.

Integrated Dairy Enterprise Model (IDEA) is a deterministic dynamic nonlinear bioeconomic whole farm optimization model for dairy production in New Zealand farms. A detailed outline of the model can be found in Doole and Romera (2013). This model is applied by Doole (2015), as well as in other studies before our time frame.

DairyNZ is a deterministic dynamic nonlinear bioeconomic whole farm optimization model. Like IDEA, this is also designed for dairy farms in New Zealand. More details about the model can be found in Gregorini et al. (2014), and an application in Gregorini et al. (2016).

FarmDESIGN is a deterministic dynamic nonlinear bioeconomic whole farm optimization model for dairy farms. The model is described by Groot et al. (2012) who apply it in the context of the Netherlands. Applications in other countries include Tanzania by Paul et al. (2020) and Mexico by Cortez-Arriola et al. (2016).

Optimization of Ruminant Farm for Economic and Environmental assessment (Orfee) is a deterministic mixed-integer static linear whole farm optimization model for beef, dairy, and mixed farms, tailored to applications in France. The model is presented and evaluated by Mosnier et al. (2017) and applied in Diakité et al. (2019).

ScotFarm is a deterministic dynamic linear whole farm optimization model for beef, dairy, and mixed farms, designed for Scottish conditions (SRUC, 2023), applied to Scottish farms in Shrestha et al.(2018). Other applications have also been tailored to farms in England and Ireland.

N-CyCLES (nutrient cycling: crops, livestock, environment, and soil) is a deterministic dynamic mixed-integer linear whole farm optimization model (DairyNutrient, 2019). It is applied by Ouellet et al. (2021) and Fournel et al. (2018) and Pellerin et al. (2017a) in the context of Canadian farms.

Integrated Farm Optimization and Resource Allocation Model (AgInform) is a deterministic static linear whole farm optimization model for beef and sheep farms. It is tailored for applications in New Zealand. The model is used in Dominati et al. (2019), among others.

Addis et al. (2021b) put forward a deterministic multistage whole farm optimization model for beef and sheep farms. Like AgInform, this model is also tailored to New Zealand, and an application is reported in Addis et al. (2021a).

Integrated Farm System Model (IFSM) is a dairy forage system model considering all major processes on dairy farms (USDA, 2020). Among others, this model is used by Rojas-Downing et al. (2018) who deal with a multiobjective optimization problem in USA

Appendix G

The following table provides a detailed example for the Protected Urea mitigation measure, illustrating how the practice is translated from the Marginal Abatement Cost Curve (MACC) into model parameters. These parameters are processed through the Teagasc MDSM and LCA models and ultimately optimised within the Linear Programming (LP) model. The row documents the baseline values and associated outcomes, including greenhouse gas emissions, revenues, costs, milk production, and net margins. Abatement and efficiency metrics are subsequently derived between environmental and economic performance. This structure guarantees transparency among the empirical MACC inputs, the optimisation process, and the farm-level outcomes reported.

Method description

Compound and straight N fertilisers were replaced with urea fertilisers protected with a urease inhibitor (e.g., NBPT, NPPT). This form of N replaced 93% of the total fertiliser N for the representative (middle) dairy farm. Phosphorus and K were supplied via zero-N fertilisers (e.g., 0-7-30).

- *Parameter changes – Dairy LCA:*
  Adoption rate of protected urea set at 93% of N fertiliser. N_2O emissions reduced by 73% relative to CAN; NH_3 losses reduced by 80% compared to straight urea (Duffy et al., 2022; Hyde et al., 2022).

- *Parameter changes – MDSM:*
  Fertiliser costs updated from CSO (2022): CAN €1.04/kg N; urea €0.83/kg N; inhibitor +€0.10/kg N.

- *LP inputs:*
  Decision variable x_protected_urea_share = 0.93. Constraint set as inactive for this run (emissionlimit not binding).

Appendix G1.1 Step by Step Approach

Step 1: The measure is identified from the MACC (Protected Urea). Its characteristics are defined in terms of adoption rate, cost, and emission factors.

Step 2: These characteristics are configured into the model parameters suitable for the Teagasc MDSM and LCA models. The MDSM generates economic outputs (profit and loss statement, balance sheet), while the LCA calculates environmental outputs (methane, nitrous oxide, carbon dioxide, ammonia losses). At this stage, results reflect the standalone performance of the measure.

Step 3: Outputs from the MDSM and LCA are combined into a single input sheet for the LP model. This provides key farm-level data such as land, herd, costs, and emission profiles.

Step 4: The optimisation model is programmed to maximise net margin over the planning horizon while adhering to emission constraints that can be activated or relaxed. The LP allocates land, feed, labour, and capital based on the new parameters

Step 5: The LP model generates optimised farm plans with two sets of outputs: (a) economic (gross margin, costs, revenue), and (b) environmental (total farm GHG emissions).

Appendix G.1.2 Worked Example Table

Each calculation is directly linked to the optimisation model equations (see Appendix B), ensuring transparency in how outputs are derived. Protected Urea (Middle representative farm)

Table 10.5 Worked Example Protected Urea.

Column		Value	Formula location
Measure		Protected Urea	MACC measure 7
Farm Area (ha)		56	Input parameter
Baseline GHG (Kg CO_2eq)		527,555	A7 (livestock) + A8 (crops) baseline
With Measure GHG (Kg CO_2eq)		510,588	A7 + A8 with updated PU Data sheet
Baseline Revenue €		252,279	E1 (milk revenue) + E2 (crop revenue)
Baseline Cost €		171,532	A4 + A5 + A6 + D1–D4 + C1–C2
With measure Revenue €		252,074	E1 + E2 with PU data sheet
With measure Cost €		171,007	A4 + A5 + A6 + D1–D4 + C1–C2 with PU data sheet
Annual Abatement (Kg CO_2eq/yr)	527,554.9934−510,588.0711	16,967	Baseline − With measure (A7 + A8)

Annual Abatement (Kg CO_2eq/ha)	16,966.9223 / 56	303	Abatement ÷ Farm Area
Baseline Milk (L/yr)	551,908×1.03	551,908	E1 (milk litres)
With measure Milk (L/yr)	557,715×1.03	557,715	E1 (milk litres) with PU data
Milk density (kg/L)		1.03	Input constant
Baseline Output (kg/yr)		568,465	Milk L × density
With measure Output (kg/yr)		574,446	Milk L × density
Farm €/t CO_2e	(80,746.63−81,067.715)/16.9669223	-18.92	ΔMargin ÷ (Abatement/1000)
Baseline Margin	252,278.99−171,532.36	80,747	Revenue – Cost
With- measure Margin €	252,074.336−171,006.621	81,068	Revenue – Cost (PU data)
Margin per kg milk (€)(baseline)	80,746.63/568,465.24	0.142	Margin ÷ Output (baseline)
Margin per kg milk (€) (with measure)	81,067.715/574,446.45	0.141	Margin ÷ Output (PU)
Constant-output abatement Net Cost (€/yr) (F.1)	(80,746.63−81,067.715)+(0.141123189×5,981.21)	523	Appendix G1 formula
Constant-output abatement cost €/t CO_2eq (F.2)	523.00243/16.9669223	30.82	Appendix G2 formula

Data sources; CSO (2022); Duffy et al. (2022); Hyde et al. (2022); Teagasc MDSM and Dairy LCA outputs (internal data files, 2025) were used for baseline and with-measure scenarios, OPL input data and results file (11 Aug 2025)

Appendix G1.3 Additional Formulas

The following adjustment formulas (F.1–F.2) are applied consistently across all measures to ensure comparability to the teagasc output where milk in help constant.

A constant-output cost adjustment was used to enable comparison across scenarios with varying milk outputs. This separates the economic cost of abatement from production volume changes.

Formula 1: Constant-output Net Cost (€/yr)

Constant-output Net Cost=

$$(C_{with} - C_{base}) + \left(\frac{Q_{with} - Q_{base}}{Q_{base}}\right) x\, R_{base})$$

Where:

- C_{with},C_{base} = total farm costs with and without the measure (€)
- Q_{with},Q_{base}= farm milk output with and without the measure (kg)
- R_{base} = baseline farm revenue (€)

Formula 2: Constant-output Abatement Cost (€/tCO_2e)

Constant-output €/t CO_2e = $\frac{Constant\text{–}output\ Net\ Cost\ (€/yr)}{Annual\ abatement\ (tCO2e/yr)}$

Where:

- Annual Abatement = GHG_{base}–GHG_{with} (expressed in tonnes CO_2e)

Appendix H

Worked Example

The following section demonstrates how this process works in practice by providing a detailed example of one mitigation measure through the whole modelling process.

Worked Example -Reference PU example

This thesis features a worked example of one mitigation measure to clarify how it transitions from the initial MACC assessment to the LP model. The aim is to demonstrate the connections between the mitigation data in MACC, the parameter settings in the Teagasc models, and the outputs produced by the LP optimisation model.

The worked example is a step-by-step pathway illustrating how one measure is initially parameterised, how the changes are incorporated into the feeder models and how the output is processed by the optimisation model.

To support this worked example, a master table is provided in Appendix I. It summarises key information about the mitigation measures and offers a clear overview. The table features headings such as the measure, the method, the parameters altered in the Teagasc models, the abatement costs, the impact on emissions, and the effect on net margin. This detailed overview demonstrates how mitigation measures progress through the modelling process.

The first step is the MACC, which identifies the technical abatement potential and the financial implications of the individual mitigation measures. Each measure is expressed as its abatement effect in reductions in CO_2eq per hectare or per cow, with the cost of implementation.

In this example, one measure is selected to demonstrate the methodology. Its characteristics are then configured into the model parameters suitable for the Teagasc MDSM and LCA models in step two. These adjustments ensure that the feeder models accurately simulate the measure in line with farm practices and MACC assumptions. The MDSM model generates economic outputs, including a detailed profit and loss statement and a balance sheet. Meanwhile, the LCA model calculates environmental impacts, such as GHG emissions (methane, nitrous oxide, and carbon dioxide) and ammonia losses. At this point, these outputs reflect the standalone performance of the mitigation measure, providing an initial estimate of its impact on farm net margin and emissions.

The outputs from the MDSM and LCA models are then combined into a single input sheet, marking step three. This sheet contains key information needed for the LP model to operate, such as basic farm characteristics, economic data, and emission figures. The economic and environmental impacts of the measure are evaluated using the complete set of farm resources.

In step four, the LP model is programmed to maximise the net margin over the specified planning horizon whilst adhering to certain emission constraints that can be activated or relaxed depending on the scenario. The LP model considers trade-offs by determining the best allocation of land, feed, labour, and capital based on the new parameters. The LP model builds on the descriptive outputs of the feeder models and creates an optimised farm plan.

In step five, the LP model generates a solution set which is split into two sets of outputs. The first includes economic outputs such as gross margin, costs, and revenue. The second encompasses environmental outcomes, such as total GHG emissions produced on the farm for the specific year and timeframe. Separating the outputs in this way allows for direct comparison across economic and environmental data and follows the same structure that Teagasc already operates in. Each mitigation measure has its own data file, with the LP model enabling specific changes or adjustments to be made, whilst the model file remains consistent for all farms.

The example illustrates the entire process, from collecting mitigation data to developing optimised farm plans. It shows how measures are initially defined with the MACC, then transformed into parameter changes, modelled using the Teagasc MDSM and LCA models, and optimised with the LP model. The detailed master table in Appendix I documents each step clearly, and the formula column explains how each figure is calculated. The example improves understanding of the optimisation process by presenting both economic and environmental outputs and comparing individual measures with grouped measures.

This example demonstrates how the methodology works and prepares for the final section, which highlights this approach's unique contribution.

Appendix I

Master table

Table 10.6 Master Table of results.

Farm	Measure	P1 per-ha mitigation (kg/ha)	P1 per-ha cost (€/ha)	P1 €/t CO2e (ratio)	P1 farm mitigation (kg/yr)	P1 farm cost	Baseline Profit (€)	Baseline Emissions (kg CO2e/yr)	With-measure Profit (€)	With-measure Emissions (kg CO2e/yr)	Δ Profit (€/yr)	Δ Emissions (t/yr)	Abatement (t/yr)	Cost per t (€/t)	Baseline Milk (L/yr)	With-measure Milk (L/yr)	Constant-output Net Cost (€/yr)	Constant-output €/t CO2e
Top	Baseline						101509.3013	632692.693	€ -	0	-101509.3013	-632.692693	632.692693	160.4401354	613202.2767		5008.257799	42.40662667
Top	10%								€ 84,988.78	569422	-16520.5222	-63.270693	63.270693	261.1086021				
Top	15%								€ 73,799.60	537753	-27709.7023	-94.939693	94.939693	291.8663567				
Top	25%								€ 66,350.90	477682.36	-35158.4013	-155.010333	155.010333	226.8132751				
Top	Improve animal pe	261	-84	-321	14616	-4704			€ 91,532.06	619056.5532	-9977.2451	-13.6361398	13.6361398	731.6766509		581627.5474	5008.257799	367.2782674
Top	Increase grass utili	522	-171	-328	27144	-8892			€ 86,871.18	596967.8667	-14638.1262	-35.72482633	35.72482633	409.7466021		553534.5493	5273.930954	81.30258534
Top	Crude protein	25	-13	-514	1400	-728			€ 89,398.32	614251.0282	-12110.9823	-18.44166482	18.44166482	656.7184915		582073.2438	7329.997702	397.4694137
Top	Early calving	284	-54	-189	15904	-3024			€ 89,333.00	610738	-12176.29763	-21.954693	21.954693	554.6102436		582073.243	7398.805943	337.0033889
Top	Decrease fertiliser	214	52	242	11984	2912			€ 89,451.37	606484.4684	-12057.9317	-26.20822464	26.20822464	460.081973		582073.2431	7274.109865	277.5506531
Top	Protected urea	154	5	35	8624	280			€ 89,420.97	613551.5932	-12088.3361	-19.14109982	19.14109982	631.5382196		581870.8298	7273.370167	379.9870559
Top	White clover	249	3	11	13944	168			€ 89,438.43	604557.8977	-12070.8736	-28.13479533	28.13479533	429.0371925		581870.8397	7254.968984	257.864644
Top	Slurry tank cover	295	12	39	16520	672			€ 89,423.33	601854.7952	-12085.9736	-30.8378978	30.8378978	391.9195037		582005.769	7292.729822	236.4859586
Top	LESS	4	1	238	224	11			€ 89,780.53	615071.5255	-11728.7733	-17.6211675	17.6211675	665.607049		582075.039	6927.640029	393.143078
Top	Grassland Mgmt (grouped)								€ 89,827.93	520555.1864	-11681.3729	-112.1375066	112.1375066	104.1700788		553534.5493	1998.45726	17.82148828
Top	Animal productivity (grouped)								€ 99,917.31	609920	-1591.98694	-22.772693	22.772693	69.90771535		596053.3625	-1282.71113	-56.32672124
Middle	Baseline						80746.632	527570.6067			-80746.632	-527.5706067	527.5706067	153.0536974	551908			
Middle	10%								€ 67,507.00	474795.7532	-13239.632	-52.7748535	52.7748535	250.8700853				
Middle	15%								€ 61,439.52	451318.1536	-19307.1151	-76.25245306	76.25245306	253.1999211				
Middle	25%								€ 57,533.36	395930.7618								
Middle	Improve animal pe	476	-164	-345	24728	-8536			€ 77,486.53	425502.7144	-3260.1064	-102.0678923	102.0678923	31.94056748		540701.3379	7430.125369	315.0167925
Middle	Increase grass utili	485	-241	-498	27156	-13518			€ 77,486.00	425,503.45	-3260.632	-102.0671567	102.0671567	31.94594721		564427.87	-6502.049471	-108.1723421
Middle	Crude protein	20	-16	-772	1126	-869			€ 76,865.87	527044.013	-3880.762	-0.5265937	0.5265937	7369.556453		545745.1398	2901.159442	5677.63351
Middle	Better reproductio	205	-28	-139	11486	-1591			€ 87,693.30	535855.4982	6946.6678	8.284891482	0			527100.953	6778.003422	160.4181567
Middle	Age first calving	199	-96	-481	10943	-5260			€ 84,220.54	520201.2182	3473.9083	-7.369388518	7.369388518	-471.3970897		536062	-3738.423196	-508.351237
Middle	Decrease fertiliser	249	65	262	13959	3653			€ 78,834.11	517697.288	-1912.525	-9.8733187	9.8733187	193.7063978		562120	3344.694502	339.29747
Middle	Protected urea	454	-15	-33	25408	-844			€ 81,067.72	510588.0711	321.083	-16.9825356	16.9825356	-18.90665844		557715	523.00243	30.82482614
Middle	White clover	369	-17	-45	20690	-936			€ 81,078.86	511736.709	332.2248	-15.8338977	15.8338977	-20.98187107		557715.3147	512.0238927	
Middle	Slurry tank cover	255	17	65	14273	929			€ 77,193.97	516422.6093	-3552.666	-11.1479974	11.1479974	318.6819904		558503.3577	4368.022265	392.3707829
Middle	LESS	18	3	149	994	148			€ 77,193.97	529710.6117	-3552.6584	2.140005	0			558403.2684	4450.56586	
Middle	Grassland Mgmt (grouped)								€ 80,919.20	444958.736	172.5692	-82.6118707	82.6118707	-2.088915292				
Middle	Animal productivity (grouped)								€ 79,845.85	498465.9868	39072.1714	99.6562871	0					
Bottom	Baseline						40773.68	398809.6997			-40773.68	-398.8096997	398.8096997	102.2384361	378066.69			
Bottom	10%								€ 34,338.87	358953.1848	-6434.8139	-39.8565149	39.8565149	161.4494874				
Bottom	15%								€ 31,259.72	339860.548	-9513.9619	-58.9491517	58.9491517	161.3926855				
	25%								€ 26,443.97	295443.85	-14329.715	-103.3658497	103.3658497	138.6310376				
Bottom	Improve animal pe	709	-206	-291	30505	-8874			€ 36,162.69	357145.9089	-4610.99437	-41.6637908	41.6637908	110.6715035		331365.41	-485.6260261	-11.65582912
Bottom	Increase grass utili	412	-213	-516	16469	-8506			€ 49,755.12	344722.6267	8981.4415	-54.08707303	54.08707303	-166.0552327		320202.3112	-17972.78571	-332.2935538
Bottom	Crude protein	15	-12	-791	699	-552			€ 53,165.11	408035.7606	12391.4292	9.2260609	0			371194.0946	-13375.77214	
Bottom	Age at first calving	380	-54	-142	17865	-2538			€ 53,019.49	405438.6737	12245.8107	6.628974027	0			331365.41	-485.6260261	
Bottom	Better reproductio	147	-70	-475	6637	-3155			€ 56,124.84	391027.2482	15351.16	-7.782451518	7.782451518	-1972.535256		365231.47	-14109.05876	-1812.932432
Bottom	Decrease fertiliser	195	54	278	9243	2568			€ 35,753.29	389160.5379	-5020.3933	-9.6491618	9.6491618	520.2932031		378817.2005	-15099.70332	-1564.872021
Bottom	Protected urea	365	-13	-35	17533	-605			€ 58,017.43	389425.545	17243.747	-9.3841547	9.3841547	-1837.538654		384317.6281	-16300.09176	-1736.98029
Bottom	White clover	503	-47	-94	24139	-2268			€ 52,008.53	384930.3582	11234.8516	-13.8793415	13.8793415	-809.4657517		371194.0946	-12197.7807	-878.8443385
Bottom	Slurry tank cover	199	12	61	9544	580			€ 54,622.91	398666	13849.2313	-0.1436997	0.0884751	-156532.5306		372060.4361	-14731.02104	
Bottom	LESS	18	3	176	849	150			€ 56,220.81	409118.8956	15447.1288	10.30919586	0			382075.2274	-14857.2889	
Bottom	Grassland Mgmt (grouped)								€ 55,691.21	323544.8416	55691.2092	323.5448416	0			341667.5965	-20850.51656	-277.0285774
Bottom	Animal productivity (grouped)								€ 44,491.74	336417.268	44491.7409	336.417268	0			304273.3682	2019.110029	32.35931814

Appendix J

Herd distribution broken down by age and farm group from Chapter 7.

J.1 Bottom Representative Farm

For calves, the Bottom baseline average is 18.7 per year. Several strategies had slightly higher calf numbers than the baseline: Protected urea, reduced crude protein, slurry tank cover, and white clover had the highest average calf numbers at 18.9 per year. Meanwhile, age at first calving averaged at 17.7 and animal productivity averaged at 16.8 both slightly lower averages than the baseline. For the grouped measures, grassland grouped (S3) had an average of 16.9, and animal productivity (S3) grouped averaged 14.5, both falling below the baseline. In Figure 10.1, the 25% ceiling (S2) had the lowest average calf numbers at 12 per year, indicating a notable drop compared to the other strategies.

For the three-year-old group, the baseline average is 45.6, with grassland management being the strategy that exhibited the most extensive range over the ten years, from 28.1 to 47.3. Meanwhile, LESS, crude protein, protective urea, slurry cover, and white clover all remain consistent around the figure of 45-45.3. For the grouped measures showed that grouped grassland(S3) averaged 40.6, and animal productivity (S3) averaged 37.6, both values below the baseline. In Figure 10.2, both S1 and S2 recorded the lowest averages, at 40.6 and 29 per year. For four-year-olds, the baseline average is 17.7 per year, with grassland management showing the highest average at 15.9, but exhibiting a wide range from 9.4 to 21.6, as illustrated in Figure 10.3. Age at first calving also has a broad range of 13.7 to 20.5, with the average nearly matching the baseline of 17.9. Similar to the three-year-old category, LESS, crude protein, protective urea, slurry cover, and white clover all remain consistent at around 18.5 to 18.8. For the grouped measure, S3 averaged 17.6, slightly below the baseline. The 25% emission ceiling had the lowest average compared to all other strategies at 10, with the 10% emission ceiling (15.7) and EBI (16.4) exhibiting slightly higher averages than the 25% limit, yet still falling short compared to the different approaches. For five-year-olds, the baseline average is 16.9 per year. Grassland, LESS, crude protein, protective urea, slurry cover, and white clover performing consistently above the baseline, with averages of 17.5 to 18.1, with AFC averaged at 16.6 and EBI 14.9. For the grouped measures, S3 animal productivity averaged 15.8, slightly below the baseline, while S3 grouped grassland averaged 11.9, notably lower than the baseline in Figure 10.4. The 25% emission ceiling had the lowest average at 9.8, with the 10% ceiling higher at 15.

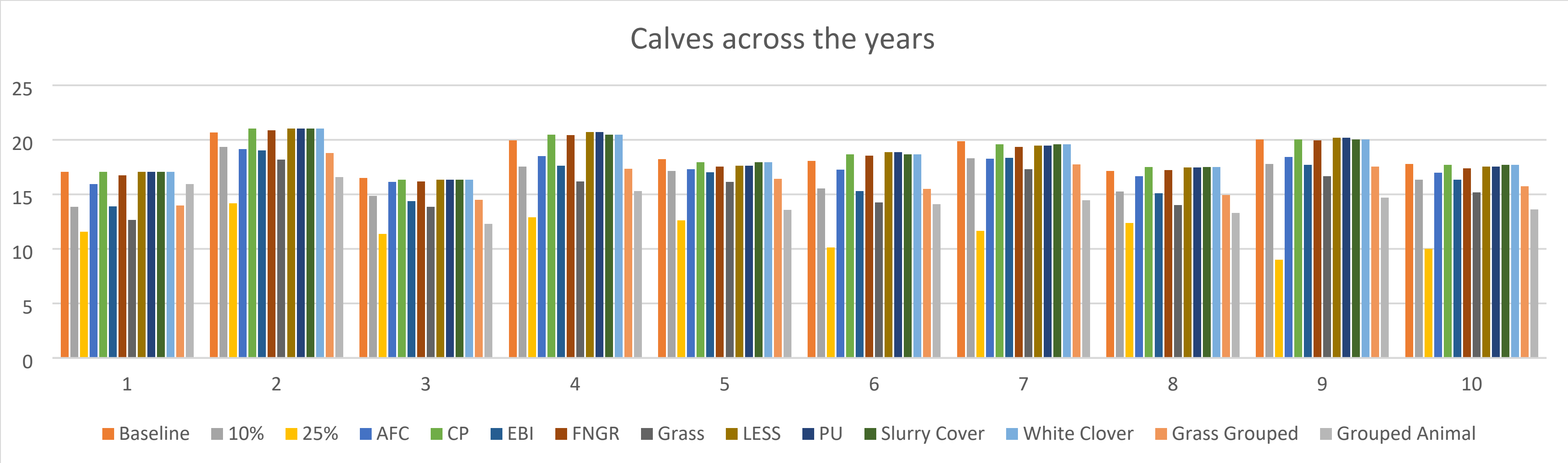

Figure 10.1 Bottom Calves across the years.

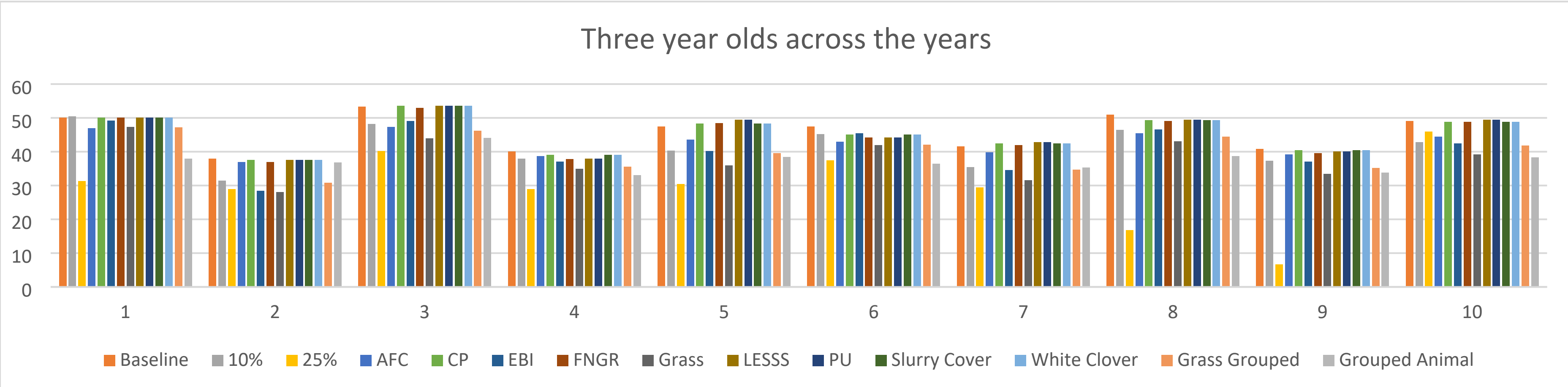

Figure 10.2 Bottom Three year olds across the years.

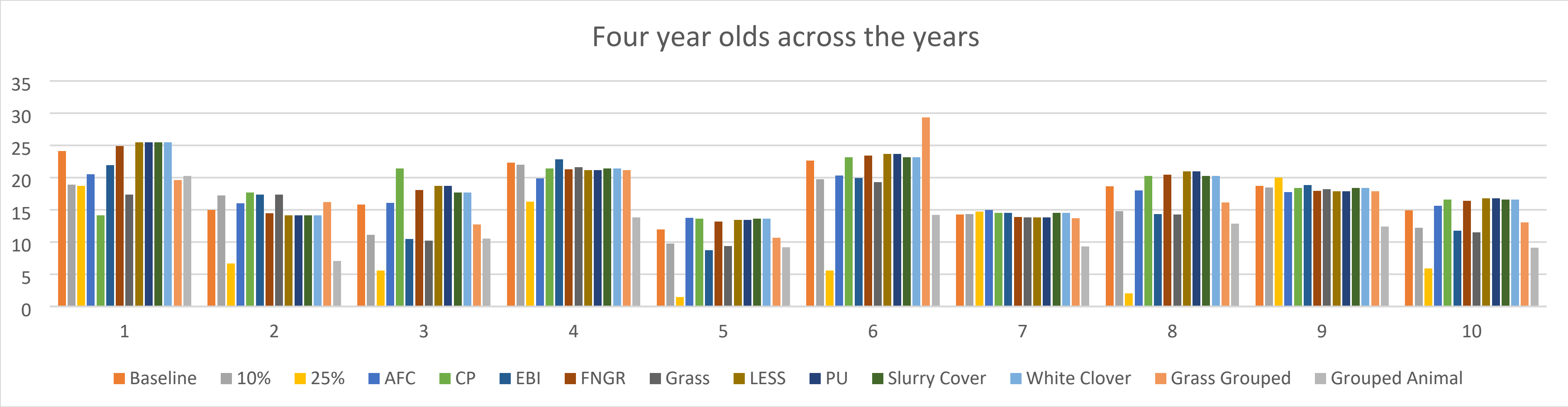

Figure 10.3 Bottom Four year olds across the years.

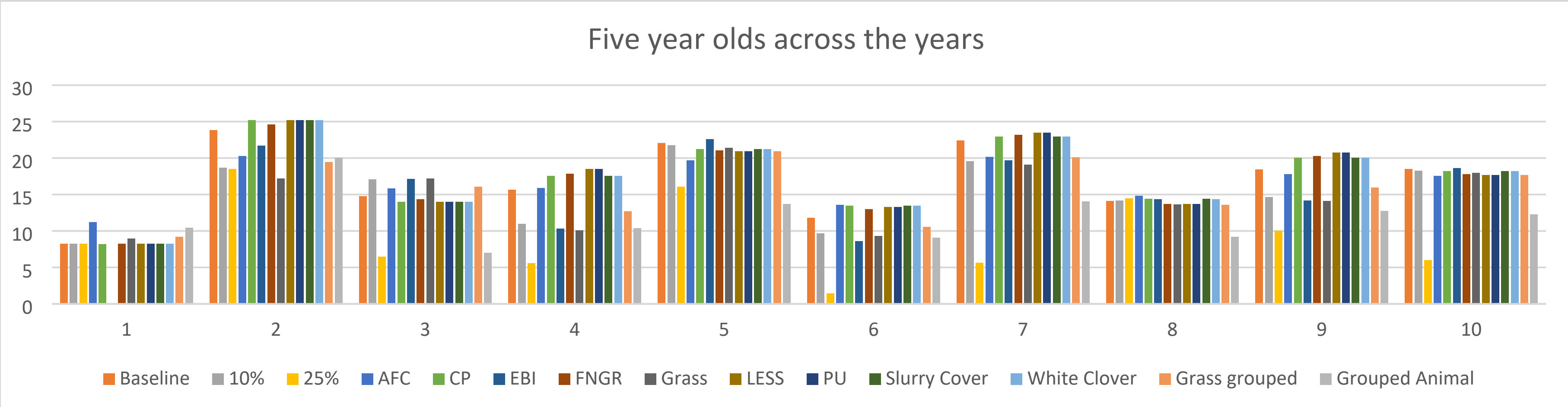

Figure 10.4 Bottom Five years olds across the years.

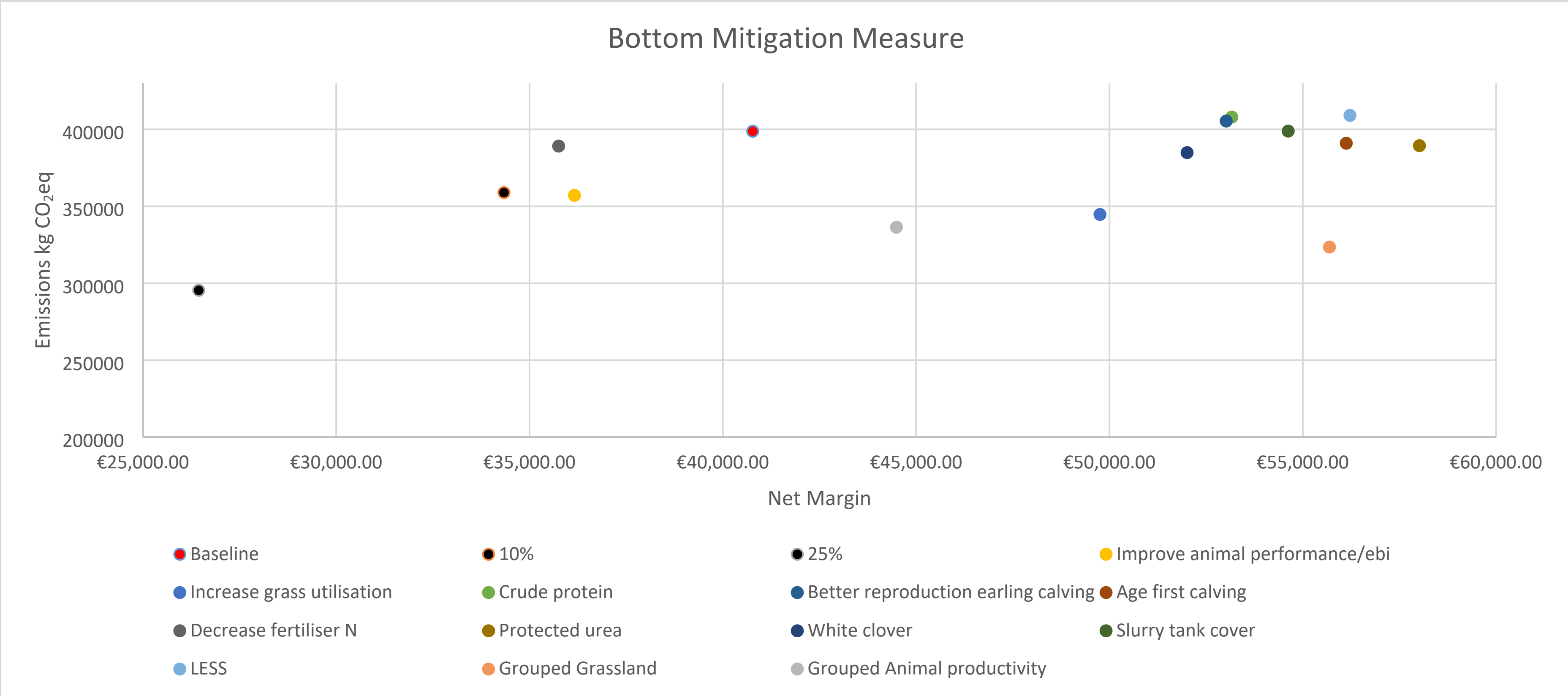

Figure 10.5 Bottom Mitigation Measures.

J.2 Middle Representative Farm

For calves, the middle baseline average is 21.2 per year. Five strategies had slightly higher calf numbers than the baseline: LESS, protected urea, reduced crude protein, slurry tank cover, and white clover, with the highest average calf numbers at 23.6 per year. Meanwhile, age at first calving showed slightly lower figures compared to the baseline, at 23.6, while grouped animal productivity and grouped grassland showed below baseline figures at 18.4 and 19.9, respectively. In Figure 10.6, the 25% ceiling (S2) had the lowest average calf numbers at 16 per year, indicating a notable drop compared to the other strategies. Grassland had the highest average at 21.7, but it also showed the most significant variability in its range.

For the three-year-old group, the baseline average is 52.2, with grassland management being the strategy with the highest average of 52.9. Meanwhile, LESS, crude protein, protective urea, slurry cover, and white clover all remain relatively consistent around the figure of 52.7. In Figure 10.7, S2 (25%) recorded the lowest averages at 38. Three strategies remained close to the baseline throughout the years: EBI at 49.7, and the 10% emission ceiling at 43.7 and grassland at 52.9. For the grouped measures, the combined grassland average was 46.6, which is slightly below the baseline, while animal productivity averaged 16, lower than the baseline.

For four-year-olds, as illustrated in Figure 10.8, The baseline average was 21.5. Grassland management had the highest average at 21.7, with a wide range from 13.6 to 30.6. Similar to the three-year-old category, LESS, crude protein, protective urea, slurry cover, and white clover all remain consistent at around 21 to 22. The 25% emission ceiling had the lowest average compared to all other strategies at 15, while the 10% emission ceiling and EBI exhibited slightly higher averages than the 25% ceiling, of 20.1 and 20.9 respectively, but still below the baseline. For the grouped measures, animal productivity averaged at 38.7, above the baseline while grouped grassland was slightly below the baseline at 19.9.

For five-year-olds, in Figure 10.9, the data followed a similar pattern to the other two groups, with a baseline average of 22 per year. Grassland, LESS, crude protein, protective urea, slurry cover, and white clover performing consistently close to the baseline with averages of 20.9 to 21, while EBI averaged at 19.8. The 25% emission ceiling had the lowest average at 15, while the 10% emission ceiling averaged 18.7, both slightly below the baseline. For grouped measures, animal productivity averaged 38.2, above the baseline, while grouped grassland averaged 20.5 below the baseline.

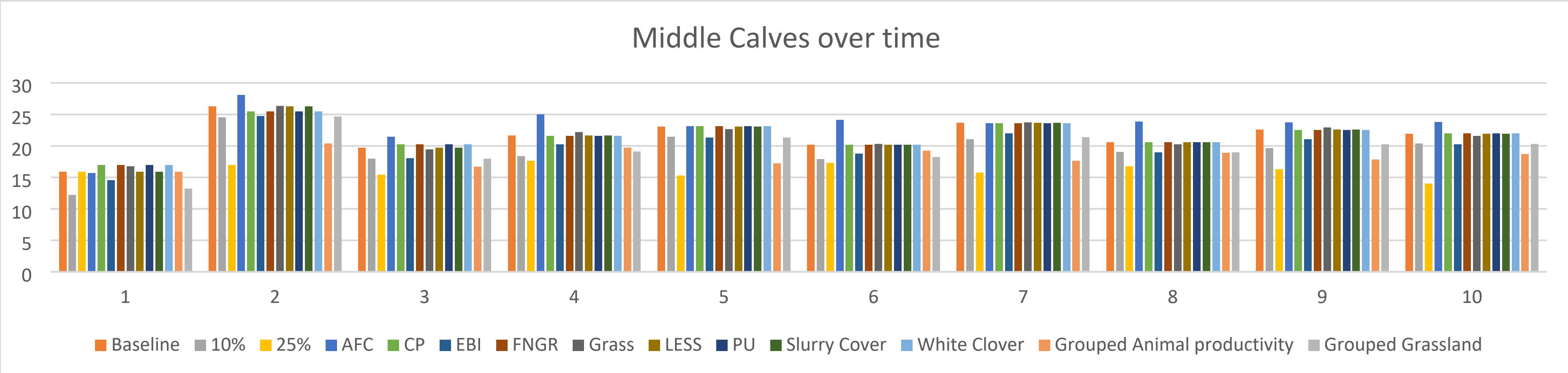

Figure 10.6 Middle calves over time.

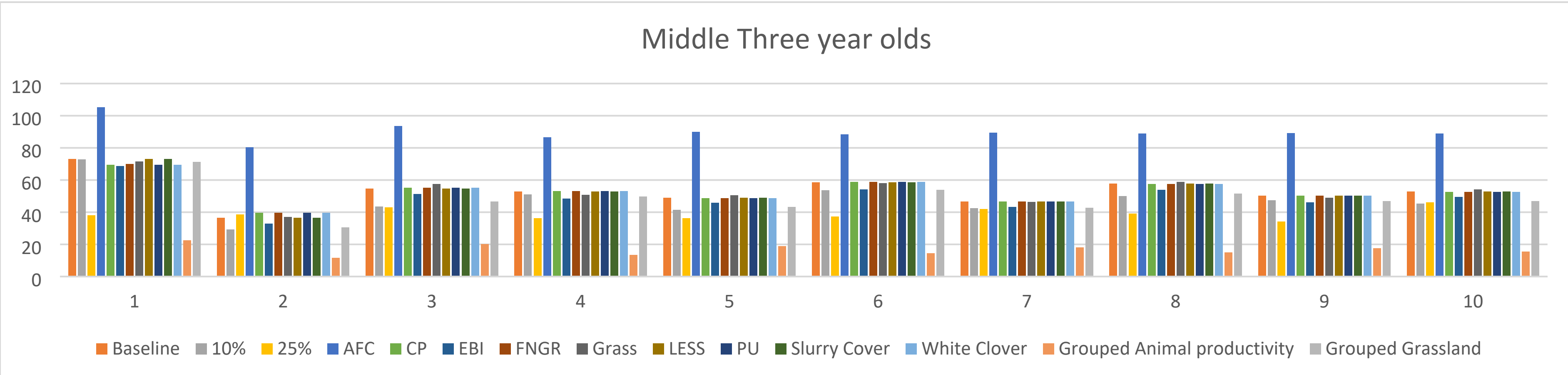

Figure 10.7 Middle three year old.

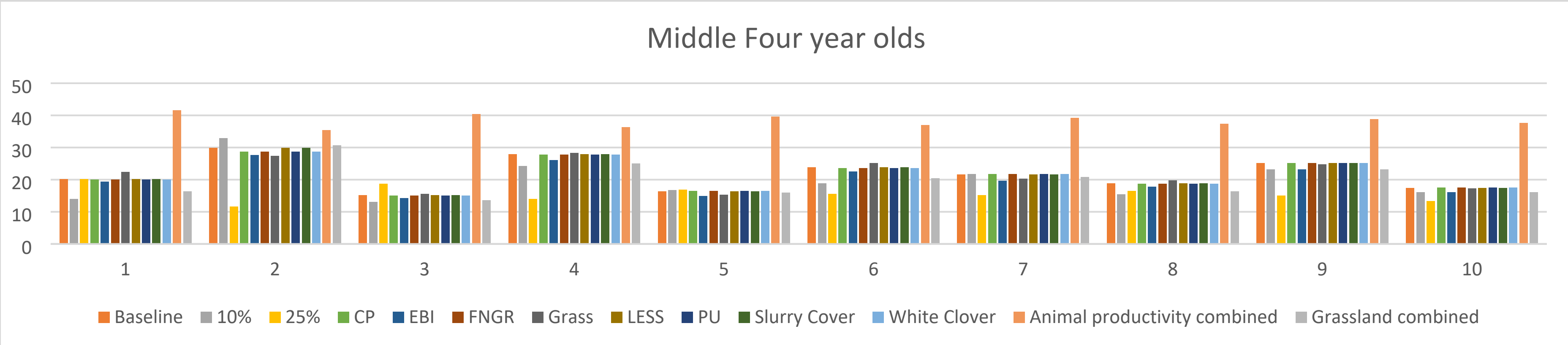

Figure 10.8 Middle four year olds.

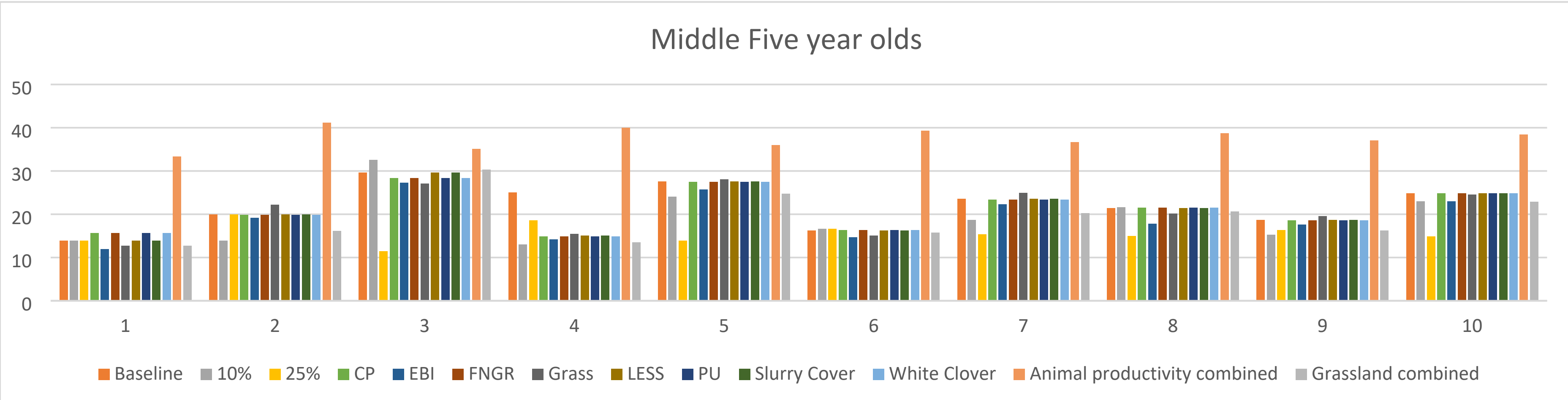

Figure 10.9 Middle five year old.

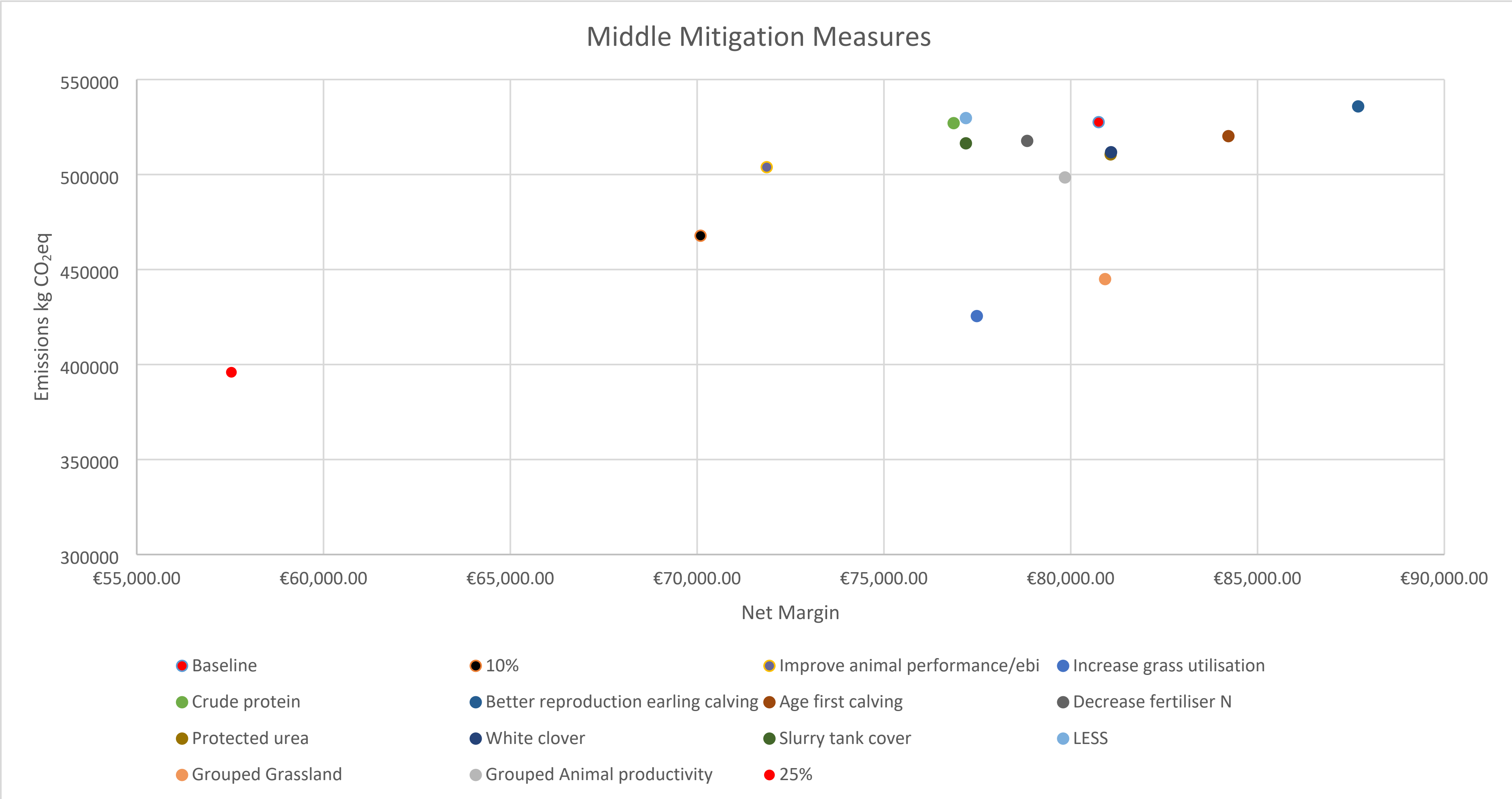

Figure 10.10 Middle Mitigation Measure.

J.3 Top Representative Farm

The Top group demonstrates remarkable consistency across several mitigation measures. For calves, strategies like Grass Management, LESS, CP, and Slurry Cover achieved steady averages between 20.6 to 21.5 nearly mirroring the baseline at 21.9, illustrated in Figure 10.11. In contrast, the 25% ceiling underperforms, with an average of approximately 16, while the 10% ceiling averages 19.1, both below the baseline. Grouped measures are also near the baseline, with animal productivity averaging 21.6 and grassland at 20.6.

In Figure 10.12, the Top Three-Year-Olds exhibit variability. Most mitigation measures performed consistently near or above the baseline. The baseline average was 59.4, while AFC, CP, EBI, FNGR, LESS, PU, slurry cover, and white clover all had averages around 61.5–62.2, slightly exceeding the baseline. Grassland averaged 58.7, close to the baseline, while grouped animal productivity averaged 60.4 and grouped grassland 57.3, both aligning with expectations. Conversely, the 25% ceiling underperformed at 44, and the 10% ceiling averaged 51.0, both significantly below the baseline.

Results for the top four-year-olds vary significantly. The baseline average was 16.4, with AFC and CP slightly higher at 17.8, while EBI stayed close to the baseline at 16.8. Grassland averaged 16.4, close to the baseline, whereas LESS, protected urea, slurry cover, and white clover all averaged around 17.8 consistently. Grouped data indicated that both animal productivity and grassland measures averaged 16.5, just above the baseline. In contrast, the 25% ceiling had the lowest average at 12, with the 10% ceiling slightly higher at 15.6, both below the baseline in Figure 10.13.

The Top five-Year-olds, in Figure 10.14, demonstrate a slightly higher average of 18. Mitigation measures like AFC and EBI, which maintain averages close to the baseline at 16.6 and 16.1, while grassland averaged at 15.8, slightly below the baseline. LESS, protected urea, slurry cover, and white clover all had consistent average values around 16.0, close to the 25% ceiling. The 10% ceiling averaged 15.9, slightly below the baseline while it peaked in year 2 this was not sustain throughout the planning horizon. While the 25% ceiling averaged at 14.Grouped data indicated that animal productivity averaged 17.3, while grassland grouped averages were 17.0, both below the baseline but still relatively close. This highlights the importance of examining the herd dynamics across a period of time not just isolated years.

Overall, 25% remains the lowest performer resulting in reduced stocking rates, while AFC, CP and EBI consistently surpass the baseline, especially in the older categories, with Grassland showing a strong performance too.

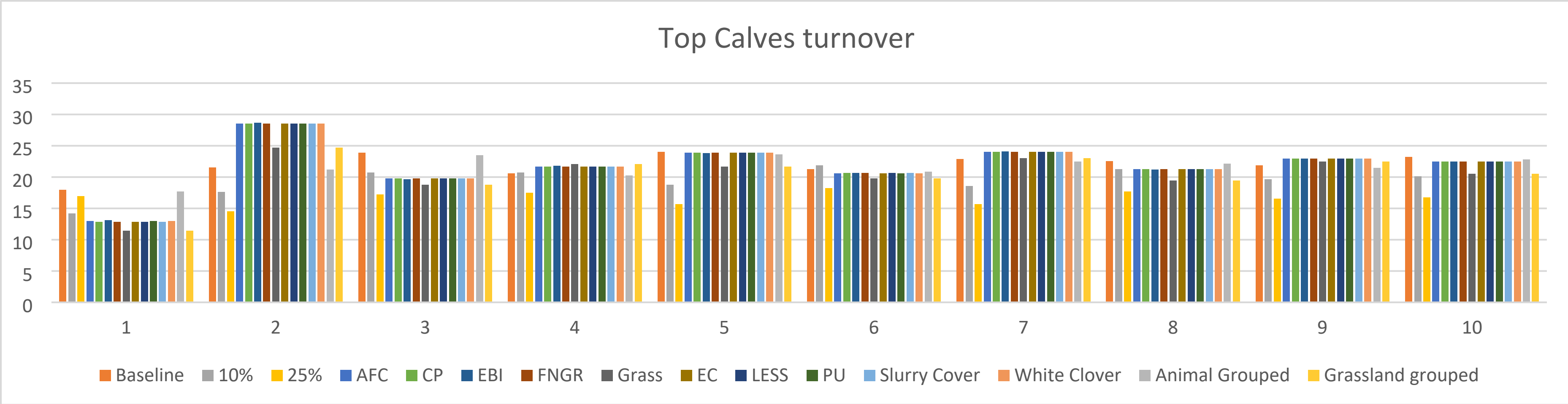

Figure 10.11 Top Calves across the years.

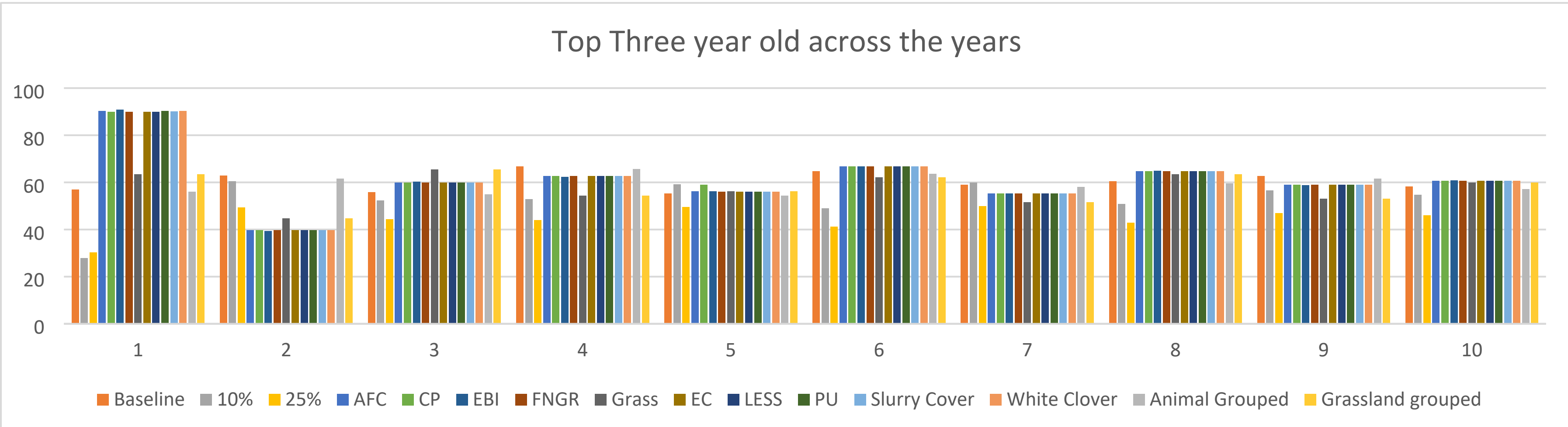

Figure 10.12 Top Three year olds across the years.

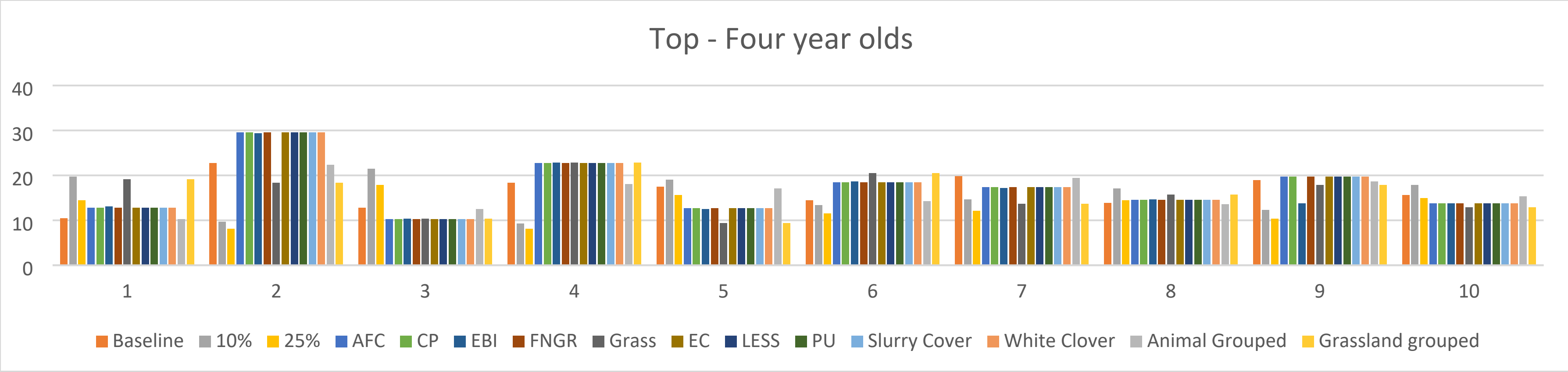

Figure 10.13 Top Four year olds.

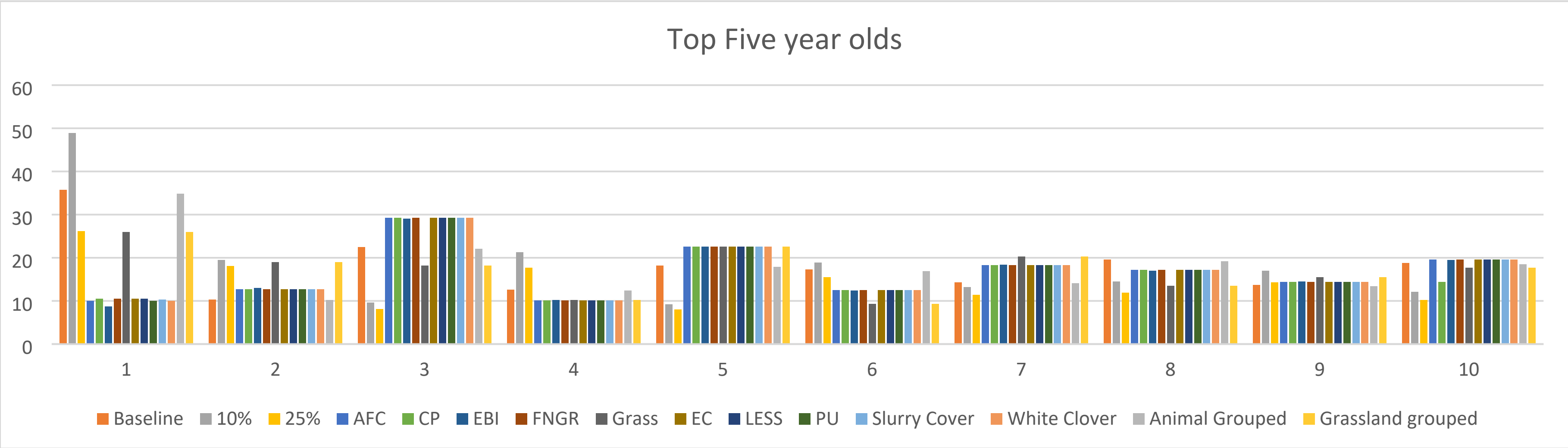

Figure 10.14 Top Five year olds across the years.

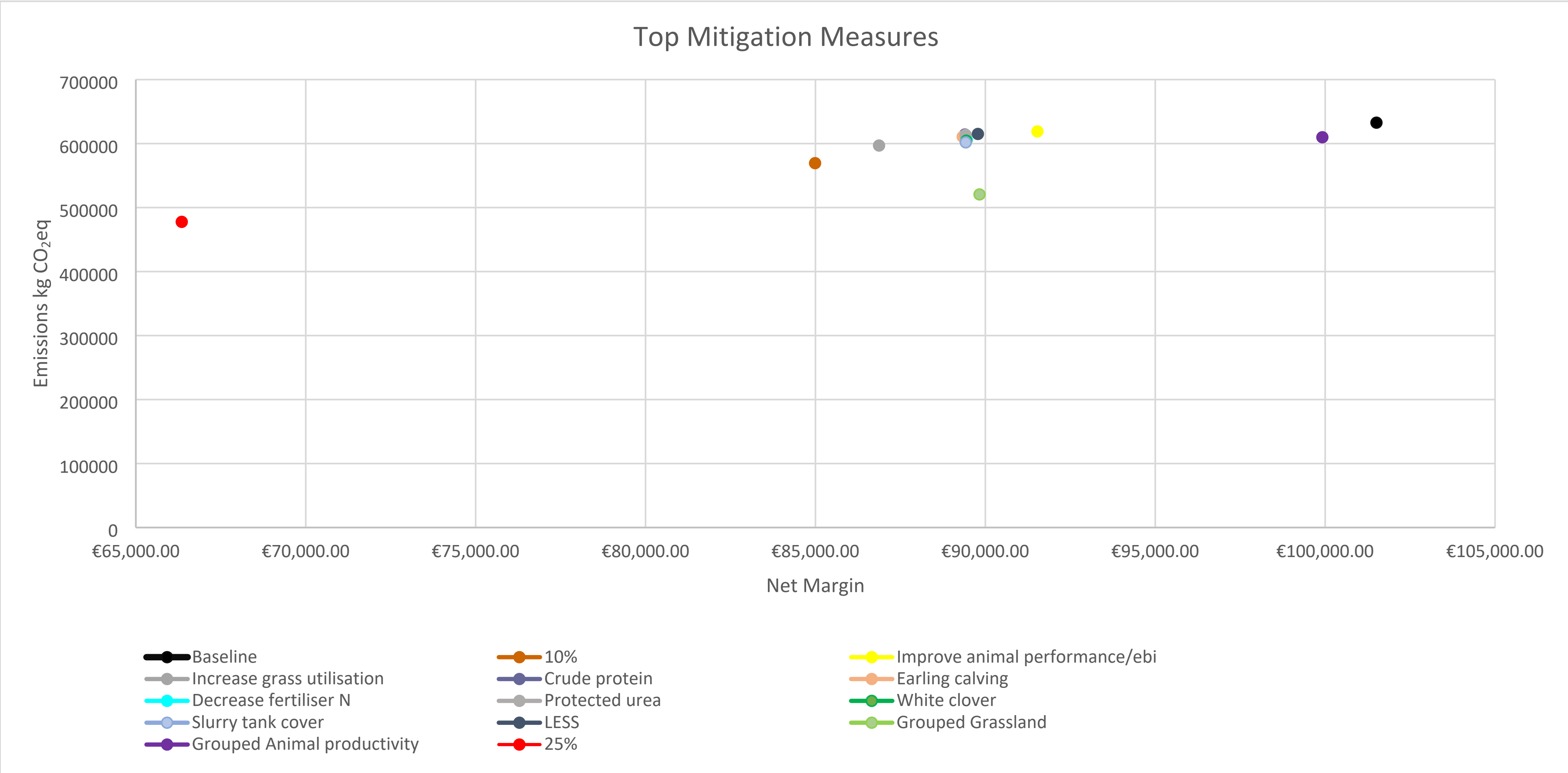

Figure 10.15 Top Mitigation Measures.

J.4 Herd Dynamics and Milk Yield

Herd dynamics indicate the annual average of dairy cattle characteristics on the farm. Figures 10.16-10.18 outlines the milk yields for the representative baseline farm for each group (Top, Middle and Bottom). The herd is categorised into six distinct groups: calves, dairy heifers (aged 12 to 24 months), and milking cows aged three to six years.

To analyse the results of herd dynamics across the mitigation measures, an average of 10 years is calculated and then highlighted for the years with the highest and lowest stocking rates.

J.5 Top Representative Farm

The baseline scenario consistently outperforms the other measures for the Top representative of farms, averaging around 607,777 litres. The two emission ceiling scenarios (S1, S2) exhibit significant reductions in milk yield compared to the baseline, with average yields of 556,876 litres and 459,636 litres, respectively. In Figure 10.6, crude protein, age at first calving, decreased fertiliser N, protected urea, white clover and slurry tank cover all record average milk yield of around 573,000 litres, similar to the baseline with slight variation throughout the years. Although the model indicates a small decrease in average milk yield with the slurry cover scenario, this is due to indirect system adjustments rather than a biological impact of the measure itself. Improved animal performance peaks in year 1 with 687,760 litres but averages closer to 573,267 litres over the ten years. At the same time, the emission ceiling of 25% (S2) resulted in the lowest yield overall, indicating that an emission ceiling is not a suitable approach for this group.

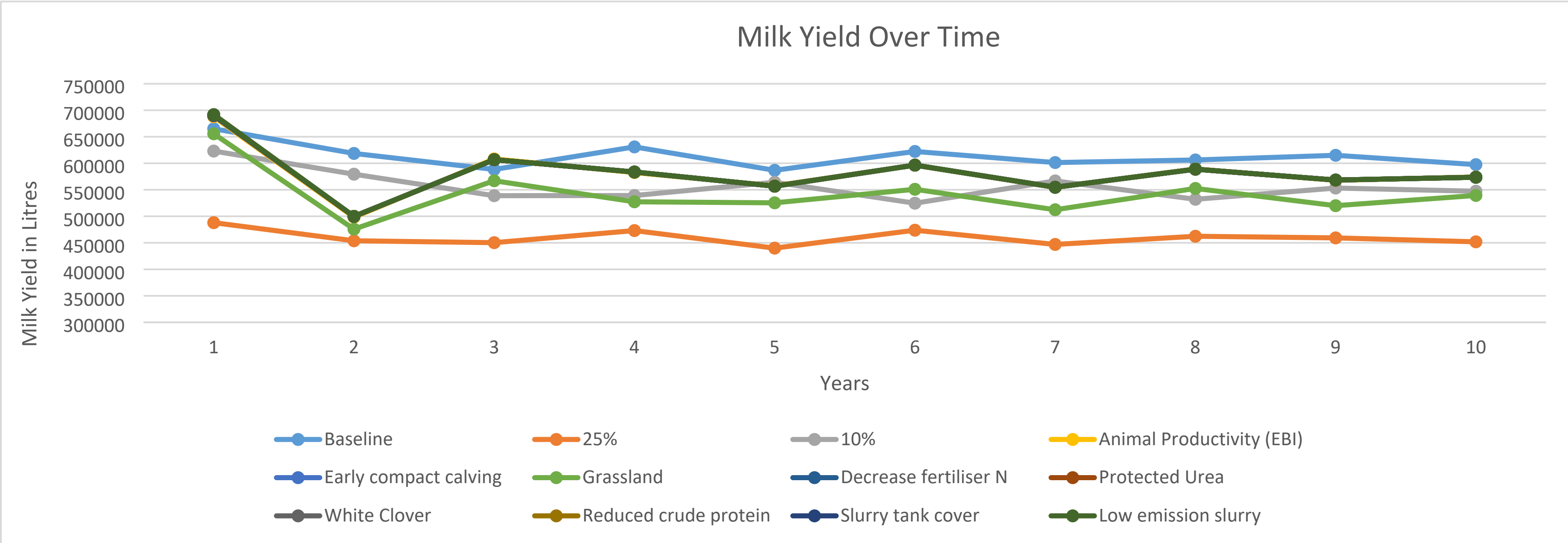

Figure 10.16 Top Milk Yield over time.

J.6 Middle Representative Farm

In Figure 10.17, the MBL yielded approximately 558,503 litres over the ten years for the middle representative of farms. Increased grass utilisation outperformed the baseline, averaging 567,663 litres, reinforcing the notion that this is a suitable strategy for this farm group. Lowering fertiliser N also yielded good results, with an average of 562,120 litres, while early compact calving achieved a modest 555,878 litres. Protected urea and white clover had similar averages at 557,715 litres. Reducing crude protein and enhancing reproduction (EBI) produced moderate results at 545,745 litres and 540,703 litres, respectively. The grouped measures showed mixed outcomes, with grouped animal productivity averaging 555,993 litres but grouped grassland lagging behind at 518,104 litres. Both emission ceilings led to decreased yields, with the 10% ceiling averaging 504,778 litres and the 25% ceiling, the strictest, dropping to 413,479 litres.

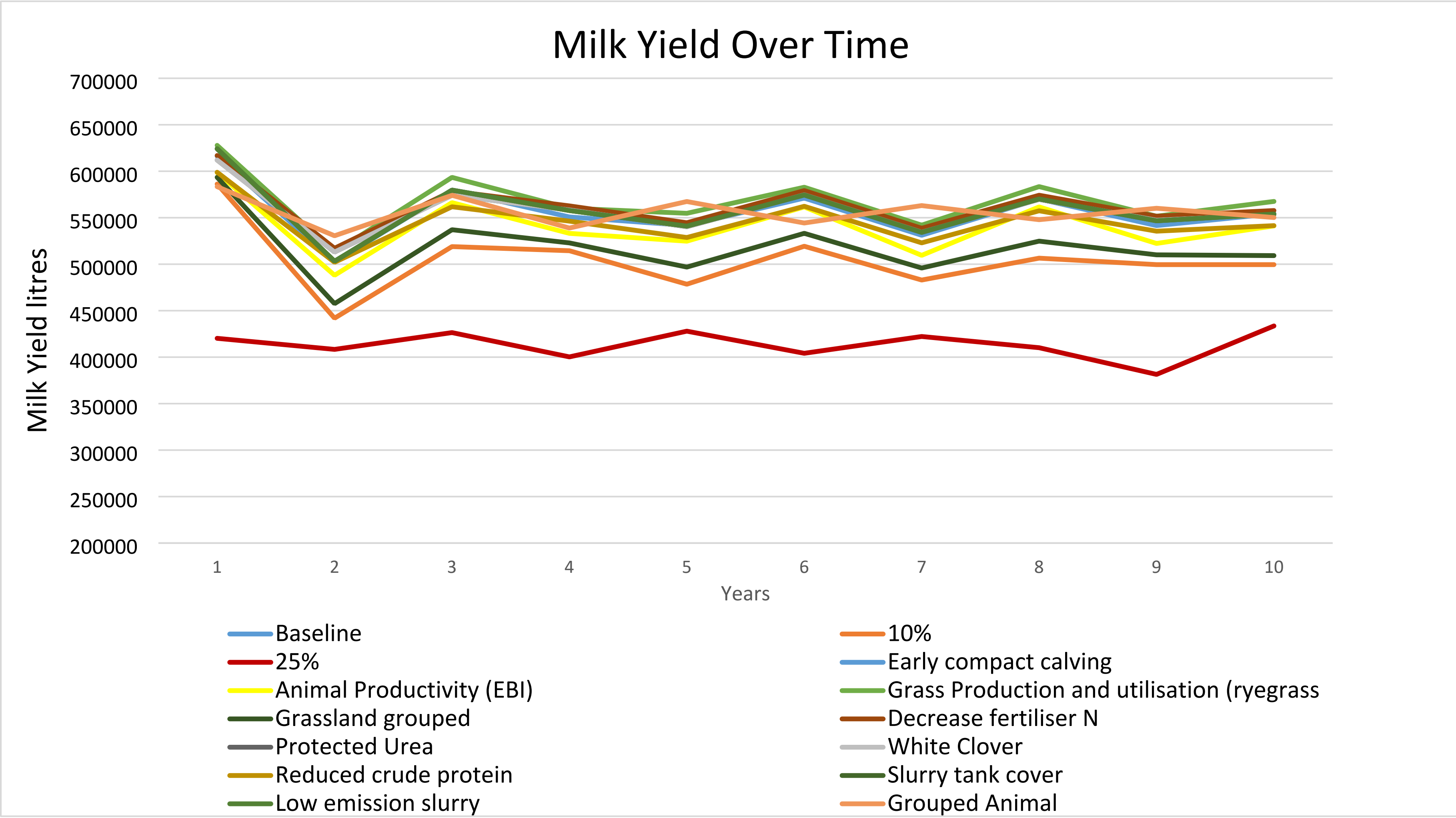

Figure 10.17 Middle Milk Yield over time.

J.7 Bottom Representative Farm

In Figure 10.18, the baseline for the Bottom farm group consistently yields a high of 378,067 litres on average. Low emission slurry was the top performer, averaging 392,853 litres, followed by protected urea at 384,000 litres and decreased fertiliser N at 379,000 litres. The slurry tank cover also showed strong results, with an average of 372,000 litres, while crude protein and white clover yielded very similar amounts, around 371,000 litres. Early calving resulted in slightly lower outputs at 365,000 litres, with age at first calving decreasing further to 348,000 litres. Among the grouped measures, grassland averaged 348,200 litres, while overall animal productivity was lower at 299,300 litres. Both emission ceilings notably reduced yields, with the 10% ceiling at an average of 341,000 litres and the 25% ceiling, which performed the worst overall, at 220,280 litres.

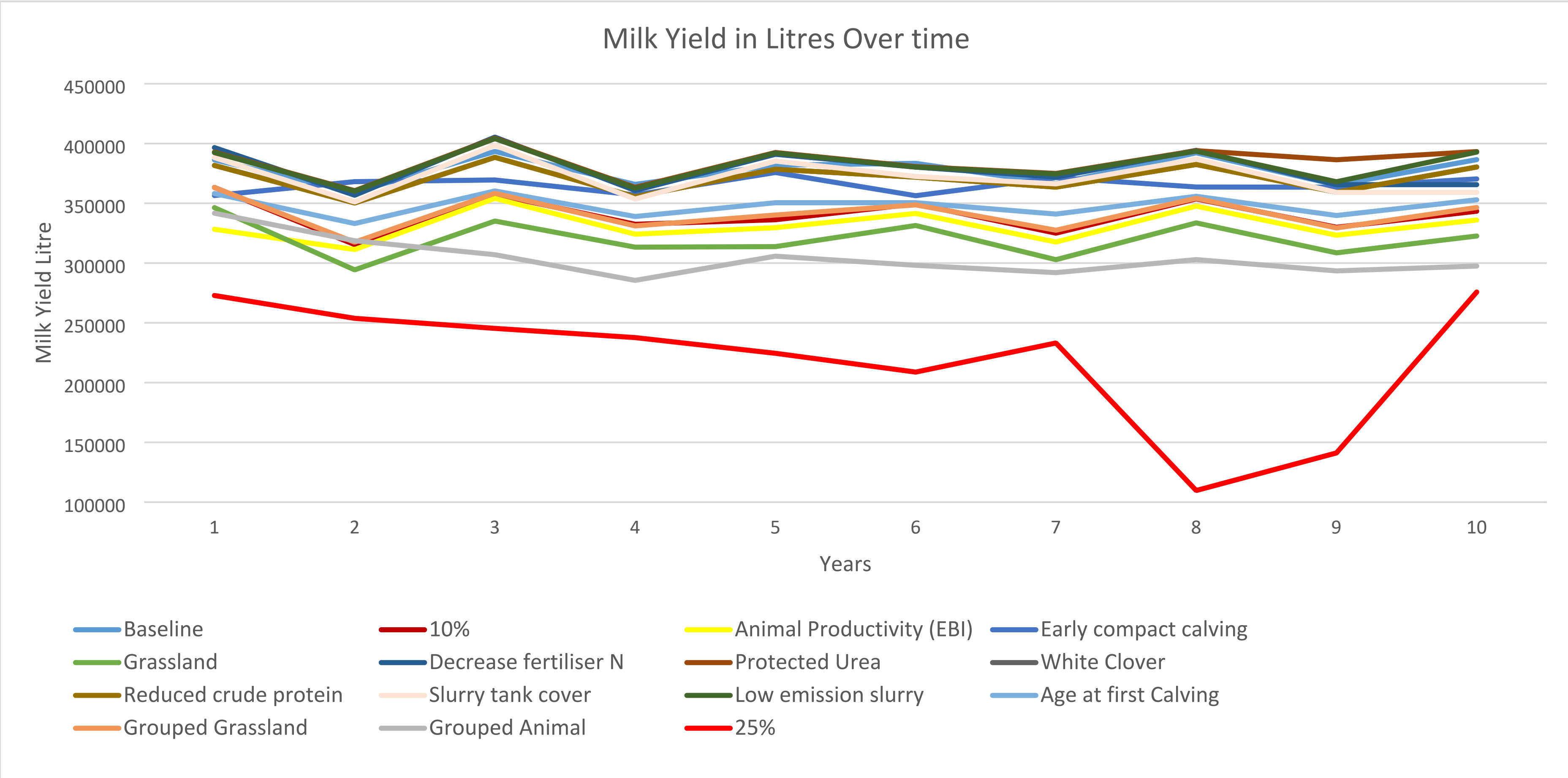

Figure 10.18 Bottom Milk Yield Over time.

The system operates with one breeding bull that changes every two years; all male calves are sold. Therefore, for this paper, the herd dynamics represent the distribution of cows. As the LP model is an optimisation model with the primary objective of maximising net margin, it is worth noting that the yearlings and 2-year-old groups were not populated in any runs of the model due to these age groups not contributing to the milk pool.In the section the ages contributing to the milk pool (3yrs-5yrs) are combined into one average figure across the planning horizon.