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Farm-level greenhouse gas mitigation: Understanding the effect of interactions and heterogeneity

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ABSTRACT

Mitigation of climate change remains a central focus of the European Union (EU). Under its 2030 Climate Target Plan, the European Commission proposes to raise the EU's ambition in this area, targeting a reduction in greenhouse gas emissions (GHG) of at least 55 % below 1990 levels by 2030. In Ireland, the proportion of GHG emissions from the agricultural sector is high compared to other developed countries, contributing 38.1 % of total economy-wide GHG emissions. The extent to which mitigation measures reduce GHG emissions at the farm level has received limited attention, especially the implications of farm-level heterogeneity on the optimal policy design for emission reduction. Using EU Farm Accountancy Data Network data for the Republic of Ireland in 2020, this study uses Marginal Abatement Cost Curve (MACC) analysis to assess a suite of GHG mitigation measures and accounts for interaction and heterogeneous effects across five different farm system types. The result of the study shows that reducing crude protein in animal diets is the most cost-effective measure for all farm systems. Liming and substitution to protected urea fertilisers are also cost-effective measures for all farm systems. However, some measures fluctuate between cost-intensive and cost-saving depending on the farm system type. The findings show that no two farm-level MACC curves are the same, thus farm heterogeneity needs to be accounted for efficient policy design.

1. Introduction

Globally, climatic change continues at pace because of GHG emissions into the atmosphere. These changes manifest in the form of increased temperature, alterations in rainfall durations and intensities, and increased heat and sunshine duration, as well as other climate parameter alterations. The changes in these climate parameters may lead to reduced crop and livestock production while also affecting both animal and human health (Darwin, 2004; El-Sayed and Kamel, 2020). In the Republic of Ireland (henceforth called Ireland), these alterations in climate are expected to reduce forage and grass production and changes in grazing patterns with associated impacts on livestock production (Holden and Brereton, 2002; Ljungqvist et al., 2021). Climate change impacts in Ireland have also led to more weather shocks in the form of droughts, floods and extreme snowfall events (DCCAE., 2019).

The agricultural sector is a significant contributor to GHG emissions globally. Moreover, the proportion of agriculture's contribution to global GHG emissions has continued to increase from about 12 % of global emissions in 2012 (Hosonuma et al., 2012; Tubiello et al., 2015) to 17 % in 2018 (FAO., 2020) and 20 % in 2019 and 2020 (Ahmed et al., 2020; FAO., 2021, 2022). In the European Union (EU), agriculture accounts for approximately 10 % of the total GHG emissions (EEA, 2019). However, in 2022, the agricultural sector accounted for over 38 % of national GHG emissions in Ireland, and this sector was the single largest contributor to GHG emissions economy-wide (EPA, 2022; 2023).

Under the Paris Agreement, the agricultural sector is required to reduce its GHG emissions in line with national level targets for Ireland. The agreement posits that the EU has a 55 % reduction target for GHG emissions in 2030 relative to a 1990 baseline (DCCAE, 2023). Individual EU Member State targets have also been established as part of the Plan. For Ireland, this implies a 51 % reduction level in GHG emissions compared to 2018 to be achieved by 2030 (EPA, 2022; DCCAE, 2023). The Climate Action and Low Carbon Development Act set down a 25 % emissions sectoral reduction target for agriculture, which implies a reduction in emissions from 22 mega tonnes of carbon dioxide equivalence (Mt CO_2e) in 2018 to 17.25 Mt CO_2e by 2030 (DCCAE, 2021,

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2023).

Reducing GHG emissions would also contribute to achieving sustainable food production, which is the central aim of many national and global communities. This is also a central aim of the EU Farm to Fork Strategy, which seeks to ensure sustainable food production and consumption, food security, avoid food losses and wastage and to ensure the efficient movement of food along the value chain system (EU., 2020). Thus, to ensure sustainable food production across the different farm systems, there is a need to critically assess the optimal abatement of these GHG emissions across different farm types while trying to minimise any adverse impacts on food production.

The literature on the cost-effectiveness of GHG mitigation options in agriculture focuses on both methodological approaches and the evaluation of specific measures. One study by Moran et al. (2011) addressed the challenges of constructing a "bottom-up" marginal abatement cost curve (MACC) for GHG emissions from UK agriculture. Their findings suggested that a substantial amount of GHG emissions (5.38 Mt CO2e) could be mitigated by implementing cost-beneficial, cost-neutral, and cost-effective measures.

Building on this, Eory et al. (2018a) emphasised the importance of addressing interactions between mitigation measures, which could affect their cost-effectiveness. In a related study, Eory et al. (2018b) examined the significance of incorporating uncertainties when constructing bottom-up GHG MACCs for individual and combined measures. Their results highlighted that while many measures are cost-effective under certain scenarios, others may become too costly under different circumstances. This attention to interaction effects and uncertainty in MACCs has influenced the design of subsequent studies, including the present study, which adopts a similar bottom-up approach while considering the interactions between mitigation measures.

Pexas et al. (2020) applied a bottom-up approach to assess the marginal abatement costs of mitigation measures in European pig production systems. Their findings identified slurry removal as a key mitigation measure and showed that the cost-effectiveness of abatement measures varied significantly depending on whether measures were assessed individually or in combination. Their analysis also reinforced the importance of considering interaction effects between measures under different scenarios, further contributing to understanding cost-benefit variability in agricultural GHG mitigation.

In the context of Irish agriculture, Schulte and Donnellan (2012); O'Brien et al. (2014); Lanigan et al. (2018), and Lanigan et al. (2023) produced MACCs that evaluated GHG emissions and mitigation measures at a national level using a top-down approach. For example, Schulte and Donnellan (2012) employed both the Life Cycle Assessment (LCA) and the Intergovernmental Panel on Climate Change for National Inventories (IPCC—NI) methodologies to assess the abatement potential of Irish agriculture. Their results demonstrated a 0.7 Mt CO2e difference in abatement potential between the two methods, with significant variation in the rankings of mitigation measures depending on the methodology used.

O'Brien et al. (2014) further explored these differences, highlighting the challenges of recommending mitigation measures to farmers when the LCA and IPCC—NI methodologies offer contradictory cost-effectiveness assessments. Lanigan et al. (2018) extended this work by using the FAPRI-IRELAND model to project future agricultural activity and assess 27 abatement measures across various sectors, including agriculture, land-use, and energy. This progression of research demonstrates the increasing complexity and importance of understanding interactions, uncertainties, and methodological differences in evaluating GHG mitigation options in agriculture. This body of literature emphasises the value of bottom-up approaches to GHG MACC construction while accounting for interactions between mitigation measures and uncertainties.

While several studies exist on the abatement of GHG emissions in Ireland and the global community at an aggregate scale, very few studies (Jones et al., 2015) have considered assessing the importance of farm heterogeneity and interactions amongst abatement measures. This study hypothesises that a "one type fits all" approach to assessing MACC is not optimal for policy design.

Thus, this study contributes to the research gap by assessing the abatement potential and cost-effectiveness of a suite of GHG mitigation measures using the Marginal Abatement Cost Curve (MACC) based methodology at a farm scale across a sample of 812 farms. The effect of mitigation measures across the sample will be assessed for heterogeneity of impact. Finally, the effect of interactions between the mitigation measures will also be assessed.

The structure of this article is as follows: Section 2 outlines the methodology used in the analysis. Section 3 presents the results, followed by a discussion of the findings in Section 4. Finally some conclusions and policy recommendations are provided in Section 5.

2. Methodology

The Intergovernmental Panel on Climate Change (IPCC) methodology is the standard approach used to estimate GHG emissions at a national scale. The approach calculates the GHG emissions as those emanating from the production, consumption and exportation of goods from the geographical location of a country but does not account for those emissions that occur during the production of imported inputs (O'Brien et al., 2014).[1] Based on the nature and availability of data, this study adopts the IPCC approach in calculating the total GHG emissions from each Irish farm in the EU Farm Accountancy Data Network (FADN) sample.

The IPCC framework identifies ten categories of activity that contribute to agricultural GHG emissions. These include enteric fermentation, manure management, rice cultivation, agricultural soils, prescribed burning of savannahs, field burning of agricultural residues, liming, urea application, other carbon-containing fertilisers and others (EPA., 2021). This study focused on mitigation measures which impact four major categories applicable to Irish agriculture at the farm scale. These include manure management, agricultural soils, liming and urea application.

2.1. Data

Emissions are estimated from farm-level data using the IPCC-based national inventory accounting methodology (as implemented by the Environmental Protection Agency in Ireland) (Duffy et al., 2022). Results across the relevant categories (i.e. manure management, agricultural soils, liming and urea application) are estimated by multiplying the farm's activity data with the relevant emission factor for each activity shown in Eq. (1) below.

$$Total\ GHG = \sum_{i=1}^{n} (A_i E) \tag{1}$$

where A is a vector of activities for farm i and E is the corresponding vector of emission factors.

Data on emission factors were obtained from the Irish National Inventory Report (EPA, 2020) and farm-level activity data were obtained from the Teagasc (Irish Agricultural and Food Development Authority) National Farm Survey (NFS) 2020 dataset. The NFS is part of the EU FADN and collects data on a randomly selected nationally representative sample of farms ($N = 812$), which are population-weighted to represent 93,244 farms in the national population for 2020. Data is collected by a team of trained farm recorders who collect data on a range of farm and

[1] An alternative to the IPCC approach is the Lifecycle Approach (LCA), this approach considers all of the GHG emissions from the raw materials, through the value chain to final disposal (ISO, 2006). The study restricted to using IPCC due to data availability.

economic activities (Teagasc, 2017). In this study, farms are categorised as dairy, cattle, sheep, tillage and mixed livestock based on EU FADN typologies. However, it is noteworthy that the farm types only represent the dominant enterprise and that these farms can have multiple enterprises. Table A1 in the appendix presents the farm system classification details and profile of farms that fall within these typologies.

2.2. Bottom-up marginal abatement cost curve (MACC) methodology

The MACC methodology involves estimating the cost and abatement potential of a mitigation measure relative to a baseline (business as usual). The cost of the measure is divided by the abatement potential (AP) to obtain the cost-effectiveness (CE) of implementing a mitigation measure (Moran et al., 2011; Schwarz et al., 2013; Dequiedt and Moran, 2015; Lanigan et al., 2015; Lanigan et al., 2018). Following Moran et al. (2008) and Bockel et al. (2012), the following methodological steps are followed to develop a bottom-up MACC for the assessment of mitigation measures at the farm scale:

i. Select the abatement options to appraise.
The abatement options used in this study were based on those proven to be effective in Ireland. These measures were selected and adopted from the previous work of Lanigan et al. (2018) and Buckley et al. (2020). However, unlike the aforementioned studies, this study focused on measures that can be assessed at the farm level.

ii. Identify the baseline level of emissions on a farm.
Using the IPCC framework and NFS 2020 data, the total baseline GHG emissions for individual farms were calculated as shown in Eq. (1).

iii. Assess the abatement potential (AP) from the implementation of a mitigation measure, taking account of the adoption rate.
The abatement potential was estimated based on the assumptions and adoption rate, as explained in Table A2 in the appendix. The equation for estimating the abatement potential is also presented in Eq. (2)

iv. Identify and quantify the costs and benefits.
The general equation for estimating the costs and benefits of the abatement measures is presented in Eq. (3). Specifically, the formulas for estimating each measure's costs and benefits are detailed in the supplementary material.

v. Calculate the 'stand-alone' Cost-effectiveness (CE) of each measure (i.e. if measures do not interact) to generate 'stand-alone' MACCS;

Estimation of the abatement potential (Eq. (2)), cost (Eq. (3)) and cost-effectiveness (Eq. (4)) are detailed below:

$$AP = AR * \rho * E \tag{2}$$

where AP is the abatement potential, AR is the adoption rate (percentage of farms adopting the measure), E is the emission factor, ρ is the land area or the number of livestock units (over and above the baseline land area or animal numbers) that the measure could be applied to in the given time period. The cost of abatement (versus the baseline) (CA) at a given discount factor (D) is defined as:

$$CA = \left(Cost_{with\ mitigation} - Cost_{baseline}\right) * D \tag{3}$$

The stand-alone cost-effectiveness (CE) measured as € per tCO_2e abated is:

$$CE = \frac{CA\ (€)}{AP\ (tC0_2e\ avoided)} \tag{4}$$

Firstly, the estimation of abatement potential, cost, and cost-effectiveness of each mitigation measure is made on a stand-alone basis. However, some measures may interact; hence, the quantity of mitigation may be less than the abatement from each individual measure added together (Webb et al., 2005). This analysis examines the effect of these interactions and generates estimates for the total abatement, cost and cost-effectiveness in a holistic interactive scenario where all measures are enacted simultaneously, in addition to considering each measure in isolation. Mitigation measures are assumed to be implemented in sequence where the first measure to be implemented is not affected by any of the other mitigation measures. The first mitigation measure reduces the baseline level of emissions; this reduced level of emissions is then the subject of the second mitigation measure, and so on. For each stage of measure implementation, the baseline level of emissions is reduced based on the previous stage. Since emissions are based on multiplicative factors, this avoids double counting of impacts. This combined abatement potential is represented as follows:

$$CAP = Baseline - baseline * (1 - \%reduction_1) * (1 - \%reduction_2) * \ldots\ldots * ((1 - \%reduction_k)) \tag{5}$$

Where $CAP = combined\ abatement\ potential$

$Baseline = GHG\ emissions\ at\ baseline$

baseline=new baseline level at each stage of the manure management framework to which each of the abatement measures is applied to.

$\%reduction_k = Emission\ reduction\ from\ the\ kth\ mitigation\ measures.$

2.2.1. Rationale for the selection of abatement measures

Following Lanigan et al. (2018), the abatement measures considered in this study include:

1. **Protected Urea:** The use of nitrogen fertilisers to achieve increased crop and livestock production is quite popular in Europe. Calcium ammonium nitrate (CAN) fertiliser dominates all other nitrogen fertilisers in Western Europe (Tzemi and Breen, 2019). However, the use of CAN fertiliser contributes higher levels of atmospheric N_2O compared to urea fertiliser. The replacement of CAN-based fertilisers with protected urea has been reported to reduce N_2O emissions and also reduce cost (Harty et al., 2016). The rationale behind using protected urea, which is in the form of urea fertiliser treated with N-(n-butyl) thiophosphoric triamide (NBPT) is evidenced by past studies that found that protected urea resulted in lower GHG emissions (Abalos et al., 2012; Nkwonta et al., 2021; Bobrowski et al., 2021; Krol et al., 2020) and increased nitrogen uptake by plants.
2. **Liming:** The application of lime on acidic soils (characteristics of most of the Irish soils) increases soil pH and contributes to the plant's absorption of nutrients, minimises the spread of plant diseases, forms better soil moisture, soil structure and aeration for plants (Nadeem et al., 2020). Controversies exist on the implication of liming on GHG emissions. Some studies have indicated that liming reduces the need for inorganic fertilisers and consequently N_2O emissions (García-Marco et al., 2016; Lanigan et al., 2018; Barton et al., 2013). However, liming increases the direct emissions of CO_2 (Kunhikrishnan et al., 2016). The net effect of the measure, hence, needs to be assessed. The application of lime was ranked as one of the most effective abatement measures for both Irish (Lanigan et al., 2018) and Scottish agriculture (Eory et al., 2021) at an aggregate level.
3. **Clover:** Extensive literature (Spink et al., 2019; Eory et al., 2021) exists on using clover as a mitigation strategy for GHG emissions. The importance of using clover as an abatement practice can be attributed to its natural fixation of nitrogen, which reduces the need for chemical fertilisation, thus reducing emissions from chemical fertiliser (Yan et al., 2013; Buckley et al., 2020; Harris and Ratnieks, 2021). Spink et al. (2019) affirmed that an inverse relationship exists between GHG emissions and biologically fixed nitrogen from the use

of white clover. On the other hand, Yan et al. (2013) reported that the use of white clover reduces N_2O and CO_2 but has no effect on CH_4 emissions.

4. **Low Emission Slurry Spreading (LESS):** Historically, the most common method of applying liquid-based animal manure (slurry) across Ireland is a splash plate at the back of a slurry spreader. This method broadcasts the slurry over a wide area. Alternative application methods exist under the broad label of Low Emission Slurry Spreading techniques (LESS). LESS consists of the use of slurry injection, trailing hose and trailing shoe equipment. These techniques reduce ammonia (NH_3) emissions (an indirect greenhouse gas) compared to the use of a splash plate. Thus, the reduction in NH_3 leads to an indirect reduction in N_2O emissions during slurry spreading (Lanigan et al., 2018). The use of the LESS method as a mitigation option is an accepted mitigation practice across developed countries (Wagner et al., 2017).
5. **Covering of Slurry Stores:** Some studies have applied the use of slurry covers to abate ammonia emissions; they reported that the covering of slurry led to a significant reduction of NH_3 emissions (Zhang et al., 2019; Buckley et al., 2020) and GHG emissions (Amon et al., 2006; Eory et al., 2021). NH_3 reduction at the slurry storage stage leads to higher nitrogen retention in the farm system, thereby reducing the need for chemical nitrogen fertilizer to maintain a given level of agricultural production. The use of covered stores will also reduce the emission of CH_4 emissions (Amon et al., 2006; Kupper et al., 2020)
6. **Slurry Amendments:** GHG emissions during slurry storage can potentially be mitigated by adding slurry amendments (Kavanagh et al., 2019). These amendments may include alum, ferric acid, sulphuric acid or other acids. Kupper et al. (2020) argued that previous works of slurry amendment led to a reduction of CH_4 during storage and an increase in N_2O emissions, while Lanigan et al. (2018) posited that the use of slurry amendment led to a reduction in both CH_4 and N_2O emissions.
7. **Crude protein in diets:** The effect of optimisation of crude protein in dairy and pig diets is evidenced by Sajeev et al. (2018a) and Buckley et al. (2020). Reducing excess crude protein (or actual demand) in diets works by lowering the proportion of N in urine and that excreted thus leading to a reduction in NH_3 and N_2O emissions among other nitrogen emissions (Chadwick et al., 2011; Külling et al., 2002; Abbasi et al., 2018).

2.3. *Cluster analysis*

This was used to identify and understand the inherent heterogeneity between and within farm systems based on abatement potential and cost-effectiveness of measures. First, hierarchical cluster analysis based on Ward and squared Euclidean method was used to select the optimal number of clusters. Ward's method was chosen to allow for minimum variance within clusters (Köbrich et al., 2003; Gelasakis et al., 2012; Gelasakis et al., 2017). The optimal number of clusters was selected based on the elbow rule of the agglomeration schedule (Ward Jr, 1963). The number of clusters derived from the agglomeration schedule of the hierarchical cluster was then used in the K-means cluster to group farms into different clusters (Gelasakis et al., 2017; Gelasakis et al., 2012). Following this, the cost-effectiveness and abatement potential within specific clusters will be presented, and descriptive statistics for each cluster will be provided.

3. Results

This section presents the result with a focus on the farm-level GHG abatement potential of mitigation measures as well as costs, cost-effectiveness and MACC across the different farm systems.

3.1. *Baseline scenario of farm-level GHG emissions*

Table A3 in the appendix describes the baseline scenario of total farm-level GHG emissions across the 5 farm system types in the baseline year (2020). Table A3 shows that enteric fermentation accounts for the majority (65 %) of GHG emissions across all farms, followed by agricultural soils (23 %) and manure management (10 %).

Dairy farms tend to have higher GHG emissions compared to other farm systems, about 4 times higher than the cattle, specialist sheep and tillage farms and about 2 times higher than the mixed livestock farm. Table 1 shows the baseline level of adoption across the measures examined. Results indicate that most of the farmers are already adopting covered stores with varying levels of uptake of the other abatement measures. The use of LESS and protected urea measures appear to be more popular amongst dairy farms compared to other farm systems.

According to NFS 2020 data, no farmers are currently using slurry amendments. Also, based on the DAFM survey conducted in 2019 and the report by Buckley et al. (2020); Shalloo et al. (2018); O`Brien et al. (2018), crude protein is being fed to livestock at a sub-optimal level of about 17 % among farmers on average.

3.2. *Farm-level GHG abatement potential*

Table 2 reports the GHG mitigation potential of each individual measure examined across the 5 different farm systems. It is important to understand the abatement potential of each measure in order to assess their respective contributions to GHG emissions reductions within various farm systems. On an average all-farm basis, implementation of a grass-clover sward has the highest abatement potential of 12 tCO_2e followed by the slurry amendments (11 tCO_2e) and then substitution to protected urea (8 tCO_2e). The abatement potential for clover is about 12 times that of the LESS measure (1 tCO_2e). For 'all farms', clover and slurry amendments account for about 65 % of the total abatement potential.

The ranking of abatement measures differs by farm system. For example, the highest level of mitigation on specialist dairy farms was associated with slurry amendments, clover and protected urea (28, 26 and 20 tonnes of CO_2e respectively). For mixed livestock farms, the same measures ranked in the top three but in a different order namely clover, slurry amendments and protected urea. This was a similar result for livestock farms (cattle and sheep) but with a different order of magnitude compared to specialist dairy and mixed livestock farms. For specialist tillage farms the fertiliser measures and slurry amendments had by far the most mitigation potential of between 3 and 6 tonnes of CO_2e.

When accounting for the interaction effects the total combined GHG abatement potential is lower than the sum of the individual measures as seen in Table 2.

3.3. *Cost of farm-level abatement*

Table 3 outlines the average net cost of implementing the different mitigation measures across the different farm systems. As outlined in Appendix 1 some mitigation measures lead to more nitrogen recovery / higher use efficiency, where this is the case a reduction in chemical N is assumed on foot of this efficiency gain. Hence, as seen in Table 3 a significant number of the mitigation measures are cost-saving (negative sign) on average across each farm system e.g. protected urea, liming, and reduction in crude protein. Others are cost-intensive across all farm systems e.g. LESS, slurry amendments, and covering of slurry stores. Clover on average can be either cost intensive or saving depending on the farm system. However, the order of magnitude of the cost varies substantially across the different systems as seen in Table 3.

Table 1
Baseline Adoption of Abatement Measures by Farm Type.

Abatement measures	Specialist Dairy	Cattle	Specialist sheep	Specialist Tillage	Mixed Livestock	All farms
1. % of fertiliser applied as Protected Urea	16 %	3 %	8 %	2 %	3 %	6 %
2. % of soils at optimum pH	54 %	50 %	50 %	78 %	66 %	53 %
3. Grass clover swards	0 %[a]	0 %[a]	0 %[a]	0 %[a]	0 %[a]	0 %[a]
4. % of slurry applied by Low emissions slurry spreading (LESS) equipment	50 %	15 %	9 %	17 %	25 %	20 %
5. Use of Slurry amendments	0 %	0 %	0 %	0 %	0 %	0 %
6. % of farmers at the optimum level of crude protein in dairy cow diet	0 %	0 %	0 %	0 %	0 %	0 %
7. % of slurry stores that are covered	85 %	93 %	95 %	91 %	98 %	92 %

Source: Authors Computation of 2020 NFS and assumptions data. [a] Own assumption.

Table 2
Farm-level GHG Abatement Potentials

Abatement potential (tonnes CO2 equivalent) per farm	Specialist Dairy	Cattle	Specialist sheep	Specialist Tillage	Mixed Livestock	All farms
1. Protected Urea	20	4	4	3	11	8
2. Liming	8	2	1	4	5	3
3. Clover	26	10	9	5	20	12
4. Low emissions slurry spreading (LESS)	2	1	0	0	2	1
5. Slurry amendments	28	8	6	6	18	11
6. Reduction in crude protein	1	0	0	0	1	0
7. Covering of slurry stores	0	0	0	0	0	0
Sum (1 to 7)	**86**	**25**	**20**	**33**	**57**	**35**
*** Combined Measure – when accounting for interactions**	**78**	**17**	**12**	**32**	**46**	**28**

Table 3
Cost of Implementing Abatement Measures per Farm.

Cost per farm (€)	Specialist Dairy	Cattle	Specialist sheep	Specialist Tillage	Mixed Livestock	All farms
1. Protected Urea	-€538	-€51	-€58	-€156	-€170	-€142
2. Liming	-€1337	-€399	-€337	-€517	-€687	-€558
3. Clover	-€1550	-€102	€137	€166	-€466	-€291
4. LESS	€127	€102	€68	€33	€202	€98
5. Slurry amendments	€1410	€767	€460	€394	€1527	€813
6.Reduction in crude protein	-€745	-€106	-€60	-€68	-€386	-€207
7. Covering of slurry stores	€8	€1	€0	€0	€2	€2
Combined cost	**-€6255**	**-€758**	**-€1074**	**-€1956**	**-€2633**	**-€1840**

3.4. *Cost effectiveness of mitigation measures*

Table 4 presents average cost-effectiveness results (measured in euros per tonne of carbon dioxide equivalence € $t^{-1}CO_2e$ abated) for each measure across each farm system type. A negative sign (-) implies a win-win scenario for the farmer, that is, the mitigation option reduces GHG emissions and saves money for the farmers, while a positive sign (+) implies a win-lose scenario where an option despite reducing GHG emissions has some net costs attached to its implementation.

Table 4
GHG Farm-level Cost-effectiveness across Different Farm Typologies.

Cost-effectiveness GHG (€ per tonne CO_2e abated)	Dairy (€)	Cattle (€)	Sheep (€)	Tillage (€)	Mixed (€)	All (€)
1. Protected Urea	- 69	-13	-21	229	-15	-15
2. Liming	-200	-119	-140	-120	-77	-135
3. Clover	-77	-9	162	61	5	12
4. Low emissions slurry spreading (LESS)	56	113	112	39	114	98
5. Slurry amendments	52	98	64	40	115	81
6. Reduction in crude protein	-750	-332	-298	-173	-447	-386
7. Covering of slurry stores	62	48	32	13	4	45
***Combined Measure – when accounting for interactions**	**-53**	**72**	**78**	**-37**	**73**	**44**

Source: Authors' Computation of 2020 NFS and NIR data.

The cost-effectiveness across the all-farm average ranges from -€386 $t^{-1}CO_2e$ to €98 $t^{-1}CO_2e$ with the reduction in crude protein indicated as the most cost-effective measure (-€386 $t^{-1}CO_2e$), followed by the liming measure (-€135 $t^{-1}CO_2e$) and protected urea (-€15 $t^{-1}CO_2e$). Additionally, on an all-farm basis, all fertiliser measures (that is, liming, clover and protected urea) are cost-savings, whereas all of the bovine measures (except the reduction in crude protein) are cost-intensive.

The cost-effective ranking order is similar across the different farm system types, namely, reduction in crude protein, liming and substitution to protected urea fertiliser (except specialist tillage farms). LESS and slurry amendments (except for specialist dairying) indicate the lowest cost-effectiveness for GHG mitigation across the different farm systems. Clover is the only measure where the sign differs by farm system, it is cost-saving for Specialist Dairy and Cattle farms but cost-intensive for the rest.

The result of the CE analysis in Table 4 showed that the combination of abatement measures in reducing GHG emissions doesn't necessarily lead to lower costs. Combining all the abatement measures leads to a cost-beneficial scenario for only the dairy and tillage farms.

3.5. *Marginal abatement cost curve*

Table 4 above outlined the cost-effectiveness of mitigation per tonne of CO_2e abated. However, whether it is cost-effective to adopt a mitigation measure depends on the shadow price of carbon. The price of carbon was set at €48.50 $t^{-1}CO_2e$ following the information provided by the Ireland Revenue Services (IRS., 2022). Fig. 1 (a-f) below present results by farm system in MACC diagrammatical form, where the width of the bar represents the abatement potential of a mitigation measure and the height of the bar represents the cost of the measure (where anything below 0 is cost-saving and anything above this is cost intensive).

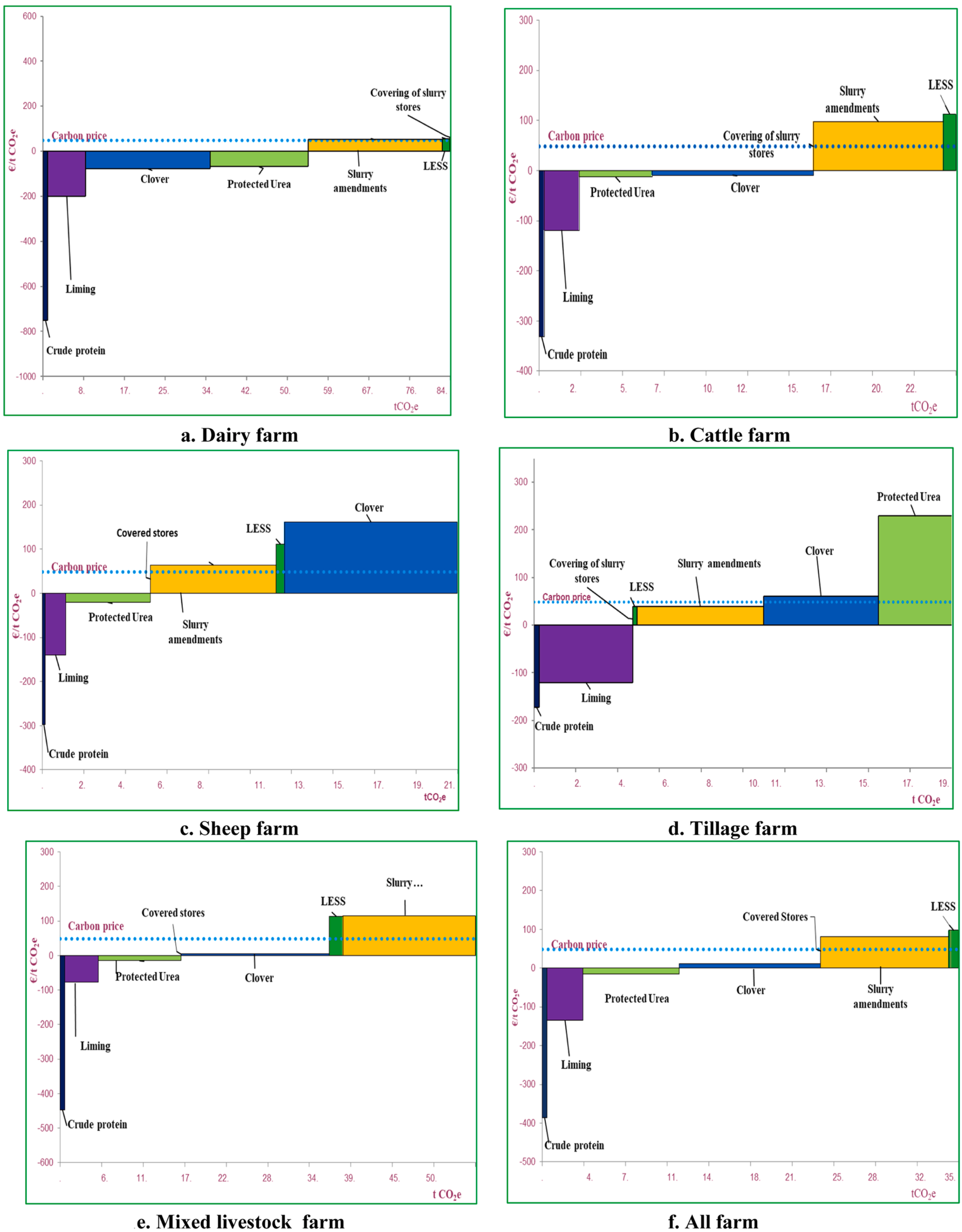

Fig. 1. Diagram showing the MACC Curves for Different Farm Systems.

It is clear that some mitigation measures are very cost-effective (e.g. crude protein) but do not deliver a lot of GHG mitigation, while other measures such as slurry amendments or clover have the potential to deliver more significant quantities of GHG mitigation but depending on the farm system they can be cost-saving or cost-intensive. On an average farm systems basis (that is, presenting the result across the different farm systems), no two systems have the same ranking of the measures. While some measures are cost-saving (crude protein, liming and protected urea) or cost-intensive (slurry amendments and LESS) across all farm systems, the relative abatement potential and costs differ. Clover is the one measure that moves from cost-saving (Specialist dairying, Cattle and mixed livestock) to cost-intensive (sheep and tillage). At a shadow carbon price of €48.50 $t^{-1}CO_2e$, the majority of measures are cost-effective on an average farm systems basis except for slurry amendments, clover and LESS depending on the farm system.

Results indicate that depending on the farm system, some measures have lower abatement potentials but may be cost saving. For instance, for the dairy and cattle farms, the GHG abatement potentials for liming is 8 tCO_2e and 2 tCO_2e per farm, while for slurry amendments it is 28 tCO_2e and 8 tCO_2e per farm respectively. However, liming has a benefit (negative cost) compared to slurry amendments, which have a net total farm cost of €1410 and €767. This is because liming leads to higher chemical nitrogen savings, significantly reducing the need for fertiliser application and resulting in overall net benefits, unlike slurry amendments. This explanation also applies to the clover measure which is cost-intensive in the sheep farm despite having a large abatement potential for GHG emissions.

For tillage farms, protected urea is cost-intensive as against the other farm types mainly because the benefits of protected urea on arable land is not as great as on grassland. and as such the replacement of CAN for protected urea on the arable land is cost-intensive. It is noteworthy that the results of the analysis were obtained as a farm average and not an aggregate average. That is, the figure indicated in Table 4 was obtained as an average of the ratio of individuals farm cost of abatement and abatement potential and not a ratio of the average cost of abatement and average abatement potential.

Results presented in Fig. 1 (a-f) present results on an average farm system basis. In contrast, Fig. 2 (a-e) presents the distribution of results within each farm system type. Results in Fig. 2 clearly illustrate the heterogeneous effect within a farm system. Across nearly all farm systems, there are farms that are cost-intensive (above the origin) or cost-saving (below the origin) for an individual measure. This clearly demonstrates that different mitigation measures are more cost-effective across some individual farms within the same farm system types as well as across farm systems.

3.6. Sensitivity analysis and uncertainties

Systematic sensitivity analysis was conducted to assess the cost of abatement and the cost-effectiveness of various measures based on a 50 % fluctuation in chemical fertiliser prices. As shown in Table B3 of the supplementary material, for most abatement measures (excluding crude protein and protected urea), a 50 % increase in fertiliser prices, assuming constant abatement potential, resulted in lower costs (>30 % for most of the measures in the all farm). In comparison, a 50 % decrease in fertiliser prices (Table B4) led to higher costs (>29 % for most of the measures in the all farm).

The cost-effectiveness of the measures responded differently to changes in fertiliser prices across various farm systems. For most measures, an increase in fertiliser price led to reduced cost-effectiveness (Table B5), while a price decrease (Table B6) improved cost-effectiveness. However, the degree of this response varied across the different farm systems.

A sensitivity analysis of the adoption rates of mitigation measures was also undertaken. This sensitivity analysis was based on assuming adoption rates at 50 % and 75 % (as opposed to 100 %). Results (presented in Table B7) indicate that at a 50 % adoption rate, the proportionate decrease in the abatement potential varies from as low as 0 % for covered stores to as high as 75 % for the white clover. Similarly, at a 75 % (Tables B10) adoption rate, the abatement potentials were reduced by approximately 0 % for covered stores to as high as 44 % for the white clover option.

The ranking of measures remains generally consistent regarding cost-effectiveness across different adoption rates, with one notable exception: the white clover measure. At 50 % and 75 % adoption rates (see Tables B9 and B12), this measure is cost-effective for dairy farms but remains cost-prohibitive for other farm types.

The absence of specific emission factors for varying soils across different locations limits the ability to assess regional heterogeneity accurately. Nonetheless, this study addresses uncertainties around costs and abatement potential across different locations, based on NFS region identifiers. As shown in Table B13 in the supplementary material, farms in the Mid-East region demonstrate a higher reduction in GHG emissions through the use of protected urea (12 tCO_2e), clover (13 tCO_2e), and slurry amendments (12 tCO_2e). While cost-effectiveness remains fairly consistent across regions, notable heterogeneity emerges in the application of clover and liming. In Table B15, liming shows a positive cost effect in the Mid-East, whereas clover is cost-positive in the South-West and West regions.

3.7. Cluster analysis

To explore the within and across farm system heterogeneity a cluster analysis was employed to investigate if more homogeneous groups of farms can be identified which may assist in targeting mitigation measures. Following a hierarchical cluster approach revealed an ideal cluster number of 5 (see Table A2 in the appendix) based on the cost-effectiveness and abatement potential. The K-mean cluster analysis was then used to allocate farms into the 5 clusters based on abatement potentials and cost-effectiveness, this is required to identify the cluster of farms that has higher abatement potentials and thus contribute more to GHG emissions.

Table 5 presents the result of the cluster analysis. The farms in clusters 3, 4 and 2 are responsible for the majority of the abatement potential respectively on an average farm basis. Conversely, clusters 1 and 5 indicate lower mitigation potential on an average farm basis but each of these clusters has a significant number of farms within so on an aggregate basis their collective abatement potential is the highest and third highest of all the clusters. Clusters 1 and 5 tend to be associated more with livestock systems (cattle and sheep rearing). Cluster 2 has the second-highest average farm and aggregate abatement potential of all the clusters and tends to comprise of dairy-orientated farms.

Cluster 1 has a low abatement potential of 15 tCO_2e compared to other categories, with a total cost-effectiveness of -€109 and an average cost of €10. For cluster 1 the result indicate that although low in mitigation potential the use of protected measures is cost-saving, conversely, the use of clover and slurry amendments can significantly reduce GHG emissions in this cluster, they are very cost-intensive to implement.

Cluster 3, consisting mostly of dairy farms and has the highest average abatement potential of 196 tCO_2e. Fertiliser measures, including slurry amendments, contribute significantly to this high potential. Similar to Cluster 2, all fertiliser measures in Cluster 3 are cost-saving to implement.

Cluster 4, comprising mainly of tillage farms and some dairy farms, has the second highest average abatement potential of 110 tCO_2e. Fertiliser measures, including slurry amendments and LESS, significantly contribute to this high potential, with the fertiliser measures being at cost-effective to implement.

The cost of implementing the abatement measure is shown in Table 5, with significant disparities evident across the different clusters. As indicated, an overall benefit is accrued with the use of abatement measures with values ranging from as low as €10 in cluster 1 to €4815 in

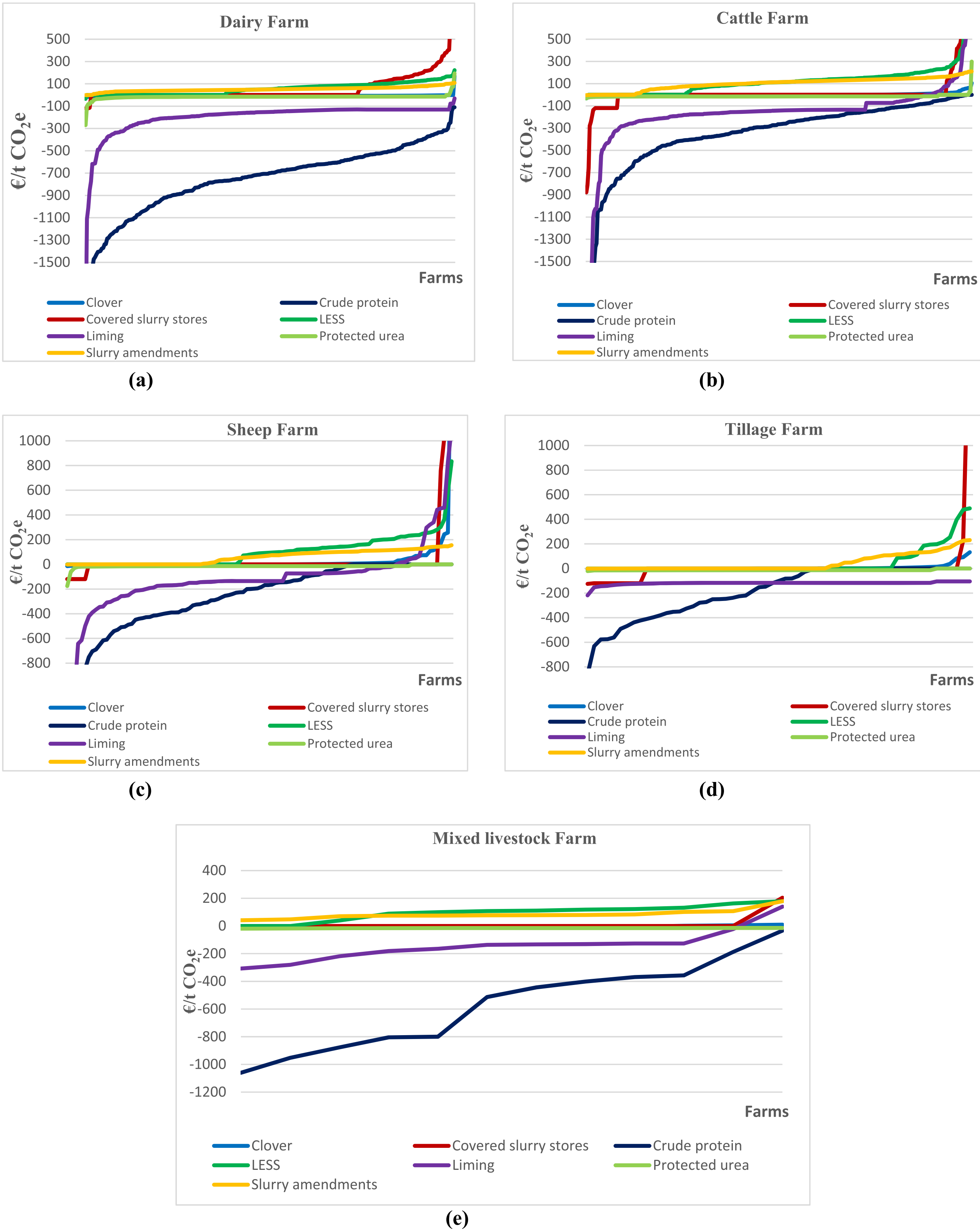

Fig. 2. Diagram showing Farm-level MAC distribution across different farm systemIn Cluster 2, the average farm level abatement potential is 98 tCO_2e, primarily due to fertiliser measures and the use of slurry amendments. These fertiliser measures are well-suited for farms in Cluster 2, as they not only contribute significantly to GHG reduction but are also cost-effective to implement within this cluster of farms.

Table 5
Result of the K-means Cluster Analysis.

Cluster Number of Case	1	2	3	4	5	Total
Abatement potentials of each Cluster (tCO_2e)						
Protected Urea	3	23	51	65	9	8
Liming	0	10	19	14	5	3
Clover	5	32	58	11	16	12
LESS	0	2	3	1	1	1
Slurry amendments	5	30	63	19	12	11
Crude protein	0	1	2	1	0	0
Covered	0	0	0	0	0	0
Average potential abatement (tCO2e)	13	98	196	110	44	35
Aggregate of Cluster ('000 tCO_2e)	713	992	352	108	1077	3229
Cost & Cost-effectiveness of measures for each Cluster						
Average cost (€)	-10	-2649	-4815	-2380	-1227	-741
Protected Urea	-15	-17	-16	-15	-14	-15
Liming	-105	-182	-163	-131	-180	-135
Clover	62	-76	-77	36	-58	12
LESS	108	75	43	50	91	98
Slurry amendments	86	66	58	51	80	81
Crude protein	-301	-649	-844	-488	-430	-386
Covered	56	25	59	-7	28	45
Total C.E (€ $t^{-1}CO_2e$)	-109	-759	-940	-503	-484	-300
Distribution of Farms in each cluster						
Unweighted Frequency	325	167	50	14	239	795
Weighted Frequency	54,880	10,120	1798	981	24,486	92,264
Percent	59.5	11	1.9	1.1	26.5	100
Farm size (ha)	30	78	131	137	46	43
Total livestock unit (LU)	28	148	285	101	67	57
Stocking rate (LU/ha)	1	2	2	1	2	1
Area of Grassland	24.50	72.13	122.77	40.54	40.59	36.08
Area of Arable	1.67	3.74	4.86	92.13	2.90	3.25
The composition of Farm systems in each Cluster (%)						
Specialist Dairying	6	44	11	2	37	100
Cattle Farms	71	4	0	0	25	100
Specialist Sheep	73	5	0	0	22	100
Specialist Tillage	64	4	0	9	23	100
Mixed Livestock	40	20	4	2	34	100
All farm	59	11	2	1	27	100

cluster 3. The higher the average farm abatement potential the higher the average cost and cost-effectiveness. It is cost-beneficial to implement the abatement measures across the clusters as shown in Table 5; however, the order of magnitude of the cost-effectiveness varies significantly.

4. Discussions

This study set out to test the hypothesises that a 'one-size-fits-all' approach to the proposition of GHG mitigation measures across farms is sub-optimal due to farm-level heterogeneity as well as the effect of mitigation measure interactions and to explore this heterogeneity. Results here indicate that efficient policy design dictates that ideally, mitigation measures should be farm specific or at least farm typology orientated. A one-size fits all approach could overestimate or underestimate the abatement potentials and cost-effectiveness for some farm systems and could in turn lead to a fallacious recommendation for these farm systems.

4.1. Findings related to mitigation measures

The study revealed that dairy farm systems has higher baseline emissions compared to the other farm systems. This is due to the higher stocking rate on dairy farms compared to the other farm systems which results in higher enteric fermentation (CH_4) and chemical nitrogen based emissions (N_2O) from this system (EPA, 2022).

This study also finds that reducing crude protein in diets is the most cost-beneficial option for reducing GHG emissions, this argument is supported by Sajeev et al. (2018b); Sajeev et al. (2018a) and Huhtanen and Huuskonen (2020). The findings of this study are in line with other studies (Chojnacka et al., 2021; Abbasi et al., 2018; Kidane et al., 2018) which found that the reduction of crude protein in diets reduces GHG emissions by reducing direct emissions of N_2O from managed soils. This is manifest through the reduction in organic nitrogen generated via urine and animal dung deposited at grazing and through reduced N_2O directly and indirectly from manure management.

While the crude protein in diets is the most cost-effective measure in this study as it actually saves farmers money while simultaneously reducing GHG emissions, the measure does not deliver the same level of GHG reduction compared to other measures, which are less cost-effective.

Results here support that of other research on the importance of substitution of CAN fertiliser for protected urea fertiliser in reducing GHG emissions which is in line with previous works (e.g. (Krol et al., 2020) Martins et al. (2017) and Tzemi and Breen (2019)). Across the five farm systems, the use of protected urea serves as a cost-beneficial measure and thus may be attractive to the farmers as it saves cost, similarly, the measure has a moderate to high abatement potential across the different farm systems and thus can act as an important strategy for absolute GHG reduction.

In Lanigan et al. (2018), the use of protected urea was ranked as a cost-effective (win-lose) measure as against our study where it is mainly a cost-beneficial measure (win-win) measure, the difference in our results is attributable to the baseline assumptions. In addition, this study also used more recent farm level activity data as well as updated data on emission factors compared to Lanigan et al. (2018).

The use of clover as an abatement strategy lowers N_2O emissions through the reduction of inorganic fertilisers which is consistent with the findings of previous studies (Yan et al., 2013; Herron et al., 2021; Schils et al., 2005). It is an important GHG abatement strategy for dairy, cattle and mixed livestock farms as it is cost-beneficial to implement.

In addition, the clover measure has a high abatement potential unlike the reduction of crude protein in diets thus a conscious policy design towards emission reduction could focus on the clover measure while putting the heterogeneity around farm systems into perspective. Similar to the protected urea measure, the difference in the abatement potential of clover in this study compared to Lanigan et al. (2018) is attributed to the difference in the underlying baseline assumption in that all grassland areas are reseeded with clover farms as against 15–25 % of grassland area.

In line with other studies, liming was found to reduce GHG emissions (Hénault et al., 2019; García-Marco et al., 2016; Lanigan et al., 2018) by lowering both direct and indirect N_2O emissions. It may however also increase GHG emissions through CO_2 emissions associated with carbon mineralisation (Goulding, 2016; Kunhikrishnan et al., 2016; Wang et al., 2021; Lanigan et al., 2018). As with clover, it is important to note that GHG reduction here is mainly associated with reduced requirement for chemical N-based fertilisers.

Thus, a balance between the reduction in N_2O emissions and an increase in CO_2 emissions on the farm will determine whether liming leads to the abatement of GHG emissions. In the case of this study, the reduction of N_2O emissions far outweighs that of the increased CO_2 emissions across the different farm systems. In addition, the adoption of this strategy leads to a win-win situation where it not only reduces the overall GHG emissions but also saves the farmer some money, hence this is an important strategy in the abatement of GHG emissions (Eory et al., 2021).

The LESS measure reduces GHG emissions by lowering the N_2O emissions from atmospheric depositions and runoff. The result obtained from this study showed that the LESS measure reduces GHG emissions across most farm systems. However, the impact of LESS in reducing GHG emissions is not as profound as for NH_3 emissions (Ogunpaimo et al., 2024). The finding of this study on LESS supports the result of Wagner et al. (2015) Lanigan et al. (2018), and Eory et al. (2021) but disagrees with some studies (et al., 2011; Bourdin et al., 2014). The latter studies argued that the implementation of LESS measures leads to increased N_2O emissions. The findings of this study also disagree with the result of Wagner et al. (2015), that reported that the use of covered stores led to increases in N_2O emissions, the difference in the result may be attributed to the type of manure storage techniques used in the study. The use of covered stores resulted in low abatement potentials across the different farm systems and this may be attributed to the already high adoption rate at the baseline.

The use of slurry amendments is an important strategy for reducing GHG emissions (Kavanagh et al., 2019). In this study, the use of slurry amendments indicated the highest level of GHG mitigation of all the manure management options (that is vs LESS, covered stores and slurry amendments) and records the highest abatement potential for the dairy farm system. The use of slurry amendments reduces GHG emissions by reducing CH_4 emissions and indirect emissions of N_2O. This result follows closely the report of Lanigan et al. (2018) on the ranking of the abatement measure, however, in our study, slurry amendments are cost-ineffective as opposed to Kavanagh et al. (2019). A difference in the baseline assumption and the type of slurry amendments used, carbon price and scale of analysis could be responsible for the divergent results obtained from the studies. The use of slurry amendments may be a very attractive option for the few farms with high abatement potential.

Consistent with other studies (Chojnacka et al., 2021; Krol et al., 2020) results here indicate that some mitigation measures are shown to be cost-saving on average across all farm systems (protected urea, liming, and reduction in crude protein) while others are on average cost intensive (LESS, slurry amendments, covering of slurry stores). Clover was the only mitigation measure that moved from cost intensive to cost-saving depending on farm system type (on average). Cost-effectiveness criteria are important for efficient policy design and all except a few of the measures (slurry amendments, LESS and clover) across some farm systems (cattle, sheep and mixed livestock) are below the shadow price of carbon (on average).

However, in a MACC framework, absolute cost-effectiveness is not the only criterion that must be assessed. Results indicate that some mitigation measures are highly cost-effective (e.g. crude protein) but do not deliver a lot of absolute GHG mitigation. While other measures such as slurry amendments or clover have the potential to deliver more significant quantities of GHG mitigation but depending on the farm system, they can be cost-intensive or cost-saving.

Based on the result of the baseline adoption of abatement measures, increased farmers' awareness of the use of these measures in reducing GHG emissions is necessary. Farmers need to be educated and involved in the implementation of these measures especially clover, liming and protected urea in reducing emissions especially when the implementation of these measures may result in a monetary benefit to the farmer.

4.2. Farm heterogeneity

While some consistent trends were observed at a farm systems level, significant within-system heterogeneity was found to exist. Within each farm system type the distribution of results for each mitigation measure ranged from cost intensive to cost saving for each individual measure. Indicating that some mitigation measures are more cost-effective on individual farms within the same farm system. Customising policies for individual farms could pose significant challenges due to potential cost constraints, making farm system analysis a practical compromise between broader aggregate or national-level assessments and detailed individual-level analyses. Albeit the literature on GHG MACC is vast, those investigating the presence of heterogeneity across similar farm types are limited. One such study conducted by Jones et al. (2015) on sheep farms buttressed the importance of assessing the presence of heterogeneity across farms.

Similarly, Krimly et al. (2016) support the finding that different farm biophysical conditions affect the optimality of GHG emission reduction. Tang et al. (2021) also highlighted the importance of considering farm heterogeneity when assessing and recommending GHG measures. De Cara and Jayet (2000) pointed out that the effectiveness of measures across farm types differ, in their study, with arable farms better-off due to reduced abatement cost as against the livestock farmers. In Ireland, although the study worked on NH_3 abatement Ogunpaimo et al. (2024) argued in favour of assessing farm heterogeneity, the study concluded that the absence of farm-heterogeneity in MACC construction could lead to sub-optimal levels of emission reductions.

Due to the presence of heterogeneity, variations exist in the abatement potential, cost-effectiveness and MACC across and within different farm systems. For instance, the impact of protected urea in reducing GHG emissions was evident more on the dairy, tillage and mixed livestock farms compared to the other farm systems. Similarly, the ranking of the protected urea measure changed across the different farm system MACCs which typically supports the presence of farm-system heterogeneity. As a farmer or policy maker, it is important to take farm heterogeneity into consideration as it ensures the optimal level of emission reduction and or cost saving.

The application of lime is another cost-beneficial measure across the five farm system types and has a relatively moderate level of abatement potential. However, the level of abatement potential varies across the different farm systems due to farm-level heterogeneity. Also, the ranking of the clover measure varies between cost-beneficial to a cost-effective measure depend on the farm system. The abatement potential of crude protein reduction in diets is highest on dairy and mixed livestock but almost negligible for cattle, sheep and tillage farms. The difference in the results across the farm systems is attributable to the presence of farm system heterogeneity.

Similar to the heterogeneity issue addressed in this study, the disparities in the result revealed by the different studies (For instance Bourdin et al., 2014 and Lanigan et al. 2018) may be due to the presence of heterogeneity (farm system, location, economic) or other reasons such as differences in underlying assumptions. In this study, farm system heterogeneity for the clover measure is more evident in the ranking of the measure, the clover measure fluctuated from being a cost-beneficial measure (Lanigan et al. 2018; Eory et al., 2021) to being a cost-prohibited measure depending on the farm system mainly due to their varying activity levels on farms.

It is evident that across the different farm system types there exist variations in the mitigation measures' abatement potential, abatement cost and cost-effectiveness. This reflects the presence of heterogeneity across the different farm systems. To further support the inherent heterogeneity present amongst farms a cluster analysis was undertaken to try and account for across and within farm system heterogeneity to explore if more homogenous groups of farmers exist which in the absence of individual farm level assessment could aid policy design.

Results indicate five cluster types, two clusters indicated smaller average farm level mitigation potential but each contained a large number of farmers so aggregate potential was significant. Two other clusters indicated higher levels of average farm level mitigation potential but each had a smaller number of farms within the cluster. Given the scale of the challenge facing the agricultural sector, cost-effective measures will have to be promoted for adoption across all farm system types starting with the most cost-effective that will deliver the most abatement.

In the case of combining measures to account for interactions, various studies (Kesicki and Ekins, 2012; Eory et al., 2018a, 2018b; Kesicki and Strachan, 2011; Fellmann et al., 2021) have shown the importance of interactions in MACC analysis. This may be evident in the form of complementary and conflicting measures in reducing GHG emissions. If all measures were implemented across all farm systems simultaneously, results indicate that the combination of impacts is only cost-beneficial for two farm systems (Dairy and Mixed Livestock). This motivates taking a more tailored policy approach. It should also be noted that interaction effects between the measures indicate a lower level of overall abatement compared to the sum of the impacts of each individual measure.

It is noteworthy that certain limitations are inherent in this study. One of which is that farmer behavioural change in response to measures was not considered. Secondly, spatial heterogeneity was not accounted for since different biophysical conditions of farms may influence the measures' effectiveness of GHG mitigation. In addition, the total GHG abatement potential realisable across the different locations may vary (Cui et al., 2022). It is also noteworthy that other abatement measures that have been proven to reduce GHG emissions such as improved genetics were not considered in this study due to lack of available data at a farm scale. It should also be noted that the measures examined here just explored impacts on GHG emissions, some of the measures could also have synergistic or antagonist implications for other environmental dimensions such as ammonia or water quality.

5. Conclusion

This study affirmed that the suite of mitigation measures assessed in this study are effective in reducing GHG emissions at the farm level. Nevertheless, the cost-effectiveness of these measures varies, ranging from being cost-saving to being cost-intensive contingent on the specific farm system or individual farm under consideration. The results reveal a clear interdependence among the mitigation measures in reducing GHG emissions. However, it's important to note that the combination of these measures in terms of interactions doesn't automatically guarantee a cost-effective resolution, as farms exhibited distinct behaviours in response. As such, policy design should be tailored towards the specific characteristics of each farm system and farmers should be encouraged to adopt those measure that are at least cost-effective in their implementation.

Although it is the rule of thumb to implement the measures that ranked first in the MACC curve (most cost-effective), this may not yield a desirable result from the perspective of the policy maker concerned with the absolute level of GHG reduction. For these policy makers, measures that are cost-effective but with high abatement potential such as liming, clover, protected urea and slurry amendments are important. Also where policy makers have difficulty in implementing individual farm-level policies for emission reduction which may be expensive, adopting a farm-system approach offers a more targeted method for MACC analysis compared to broader national or sectoral approaches.

The study's cost-effectiveness analysis is also just based on a single time point. An analysis of cost-effectiveness trends over time could help policymakers develop more sustainable, long-term emission reduction strategies and is an avenue for future research.

CRediT authorship contribution statement

Oyinlola Rafiat Ogunpaimo: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Cathal Buckley:** Writing – review & editing, Validation, Supervision, Software, Methodology, Funding acquisition, Conceptualization. **Stephen Hynes:** Writing – review & editing, Supervision. **Stephen O'Neill:** Writing – review & editing, Supervision.

Declaration of competing interest

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

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envc.2024.101070.

Data availability

The data that has been used is confidential.

References

Abalos, D., Sanz-Cobena, A., Misselbrook, T., Vallejo, A., 2012. Effectiveness of urease inhibition on the abatement of ammonia, nitrous oxide and nitric oxide emissions in a non-irrigated Mediterranean barley field. Chemosphere 89 (3), 310–318. https://doi.org/10.1016/j.chemosphere.2012.04.043.

Abbasi, I.H.R., Abbasi, F., El-Hack, A., Mohamed, E., Abdel-Latif, M.A., Soomro, R.N., Hayat, K., Mohamed, M.A., Bodinga, B.M., Yao, J., 2018. Critical analysis of excessive utilisation of crude protein in ruminants ration: impact on environmental ecosystem and opportunities of supplementation of limiting amino acids—a review. Environmental Science and Pollution Research 25 (1), 181–190. https://doi.org/10.1007/s11356-017-0555-4.

Ahmed, J., Almeida, E., Aminetzah, D., Denis, N., Henderson, K., Katz, J., Kitchel, H., & Mannion, P. (2020). Agriculture and climate change. Reducing emissions through improved farming practices. https://www.mckinsey.com/~/media/mckinsey/industries/agriculture/our%20insights/reducing%20agriculture%20emissions%20through%20improved%20farming%20practices/agriculture-and-climate-change.pdf.

Amon, B., Kryvoruchko, V., Amon, T., 2006. Influence of different methods of covering slurry stores on greenhouse gas and ammonia emissions. Int. Congr. Ser. 1293, 315–318. https://doi.org/10.1016/j.ics.2006.03.001.

Barton, L., Murphy, D.V., Butterbach-Bahl, K., 2013. Influence of crop rotation and liming on greenhouse gas emissions from a semi-arid soil. Agric. Ecosyst. Environ. 167, 23–32. https://doi.org/10.1016/j.agee.2013.01.003.

Bobrowski, A.B., Van Dooren, H.J., Ogink, N., Hagenkamp-Korth, F., Hasler, M., Hartung, E., 2021. Reduction of ammonia emissions by using a urease inhibitor in a mechanically ventilated dairy housing system. Biosyst. Eng. 204, 115–129. https://doi.org/10.1016/j.biosystemseng.2021.01.006.

Bourdin, F., Sakrabani, R., Kibblewhite, M., Lanigan, G., 2014. Effect of slurry dry matter content, application technique and timing on emissions of ammonia and greenhouse gas from cattle slurry applied to grassland soils in Ireland. Agric. Ecosyst. Environ. 188, 122–133. https://doi.org/10.1016/j.agee.2014.02.025.

Buckley, C., Krol, D., Lanigan, G.J., Donnellan, T., Spink, J., Hanrahan, K., Boland, A., Forrestal, P., Humphreys, J., Murphy, P., NiFhlatharta, N., O'Brien, D., O'Dwyer, T., O'Mara, F., Richards, K., Shalloo, L., Wall, D., & Waters, S. (2020). An Analysis of the Cost of the Abatement of Ammonia Emissions in Irish Agriculture to 2030. https://t-stor.teagasc.ie/handle/11019/2678.

Chadwick, D., Sommer, S., Thorman, R., Fangueiro, D., Cardenas, L., Amon, B., Misselbrook, T., 2011. Manure management: Implications for greenhouse gas emissions. Animal Feed Science and Technology, 166-167 514–531. https://doi.org/10.1016/j.anifeedsci.2011.04.036.

Chojnacka, K., Mikula, K., Izydorczyk, G., Skrzypczak, D., Witek-Krowiak, A., Gersz, A., Moustakas, K., Iwaniuk, J., Grzędzicki, M., Korczyński, M., 2021. Innovative high digestibility protein feed materials reducing environmental impact through improved nitrogen-use efficiency in sustainable agriculture. J. Environ. Manage 291, 112693. https://doi.org/10.1016/j.jenvman.2021.112693.

Cui, Y., Khan, S.U., Deng, Y., Zhao, M., 2022. Spatiotemporal heterogeneity, convergence and its impact factors: Perspective of carbon emission intensity and carbon emission per capita considering carbon sink effect. Environ. Impact. Assess. Rev. 92, 106699. https://doi.org/10.1016/j.eiar.2021.106699.

Darwin, R., 2004. Effects of greenhouse gas emissions on world agriculture, food consumption, and economic welfare. Clim. Change 66 (1), 191–238. https://doi.org/10.1023/B:CLIM.0000043138.67784.27.

DCCAE. (2021). Department of Environment, Climate and Communication:Climate Action Plan 2021 Securing our future. https://www.gov.ie/en/publication/6223e-climate-action-plan-2021/.

DCCAE. (2023). Department of Environment, Climate and Communication: Climate Action Plan 2023 (CAP23) Changing Ireland for the Better. https://www.gov.ie/pdf/?file=https://assets.gov.ie/243585/9942d689-2490-4ccf-9dc8-f50166bab0e7.pdf#page=null.

DCCAE. (2019). Department of Communications, Climate Action and Environment Climate Action Plan. https://assets.gov.ie/10206/d042e174c1654c6ca14f39242fb07d22.pdf.

Dequiedt, B., Moran, D., 2015. The cost of emission mitigation by legume crops in French agriculture [Article]. Ecological Economics 110, 51–60. https://doi.org/10.1016/j.ecolecon.2014.12.006.

Duffy, P., Black, K., Fahey, D., Hyde, B., Kehoe, A., Monaghan, S., Murphy, J., Ryan, A.M. a., & Ponzi, J. (2022). Ireland National Inventory Report 2022 Greenhouse Gas

Emissions 1990 - 2020. Reported to the United Nations Framework Convention on Climate Change. https://www.epa.ie/publications/monitoring–assessment/climate-change/air-emissions/Ireland-NIR-2022_Merge_v2.pdf.
EEA. (2019). Air Quality in Europe-2019 Report. (10/2019), 99pp. doi:10.2800/822355.
El-Sayed, A., Kamel, M., 2020. Climatic changes and their role in emergence and re-emergence of diseases. Environmental Science and Pollution Research 27, 22336–22352. https://doi.org/10.1007/s11356-020-08896-w.
Eory, V., Pellerin, S., Carmona Garcia, G., Lehtonen, H., Licite, I., Mattila, H., Lund-Sørensen, T., Muldowney, J., Popluga, D., Strandmark, L., Schulte, R., 2018a. Marginal abatement cost curves for agricultural climate policy: State-of-the art, lessons learnt and future potential [Review]. J. Clean. Prod. 182, 705–716. https://doi.org/10.1016/j.jclepro.2018.01.252.
Eory, V., Topp, C., Rees, R., Leinonen, I., Maire, J., MacLeod, M., Sykes, A., & Wall, E. (2021). Marginal abatement cost curve for Scottish agriculture. https://pure.sruc.ac.uk/en/publications/marginal-abatement-cost-curve-for-scottish-agriculture.
EPA. (2022). Ireland's Greenhouse Gas Emissions Projections 2021-2040. https://www.epa.ie/publications/monitoring–assessment/climate-change/air-emissions/EPA-Ireland's-GHG-Projections-Report-2021-2040v4.pdf.
EPA. (2023). Ireland's Final Greenhouse Gas Emissions 1990-2021. https://www.epa.ie/publications/monitoring–assessment/climate-change/air-emissions/Ireland's-Final-Greenhouse-gas-report-1990-2021_April-2023.pdf.
EPA. (2021). Greenhouse Gas Emissions share by sector in 2019. Retrieved 22/01/2021 from http://www.epa.ie/ghg/currentsituation/.
EU. (2020). Farm to Fork Strategy. For a fair, healthy and environmentally-friendly food system. https://food.ec.europa.eu/system/files/2020-05/f2f_action-plan_2020_strategy-info_en.pdf.
Eory, V., Topp, C.F.E., Butler, A., Moran, D., 2018b. Addressing Uncertainty in Efficient Mitigation of Agricultural Greenhouse Gas Emissions [Article]. J. Agric. Econ. 69 (3), 627–645. https://doi.org/10.1111/1477-9552.12269.
FAO, 2020. Emissions due to agriculture. Global, regional and country trends 2000–2018. FAOSTAT Analytical Brief Series, No 18. Rome 14. https://www.fao.org/3/cb3808en/cb3808en.pdf.
FAO, 2021. Emissions from agriculture and forest land. Global, regional and country trends 1990–2019. FAOSTAT Analytical Brief Series No 25. Rome 17. https://www.fao.org/documents/card/en/c/cb5293en.
FAO, 2022. Greenhouse gas emissions from agrifood systems. Global, regional and country trends, 2000–2020. FAOSTAT Analytical Brief Series, No 50. Rome 12. https://www.fao.org/3/cc2672en/cc2672en.pdf.
Fellmann, T., Domínguez, I.P., Witzke, P., Weiss, F., Hristov, J., Barreiro-Hurle, J., Leip, A., Himics, M., 2021. Greenhouse gas mitigation technologies in agriculture: regional circumstances and interactions determine cost-effectiveness. J. Clean. Prod. 317, 128406. https://doi.org/10.1016/j.jclepro.2021.128406.
García-Marco, S., Abalos, D., Espejo, R., Vallejo, A., Mariscal-Sancho, I., 2016. No tillage and liming reduce greenhouse gas emissions from poorly drained agricultural soils in Mediterranean regions. Science of the Total Environment, 566-567 512–520. https://doi.org/10.1016/j.scitotenv.2016.05.117.
Gelasakis, A., Rose, G., Giannakou, R., Valergakis, G., Theodoridis, A., Fortomaris, P., Arsenos, G., 2017. Typology and characteristics of dairy goat production systems in Greece. Livest. Sci. 197, 22–29. https://doi.org/10.1016/j.livsci.2017.01.003.
Gelasakis, A.I., Valergakis, G., Arsenos, G., Banos, G., 2012. Description and typology of intensive Chios dairy sheep farms in Greece. J. Dairy. Sci. 95 (6), 3070–3079. https://doi.org/10.3168/jds.2011-4975.
Goulding, K., 2016. Soil acidification and the importance of liming agricultural soils with particular reference to the United Kingdom. Soil. Use Manage 32 (3), 390–399. https://bsssjournals.onlinelibrary.wiley.com/doi/full/10.1111/sum.12270.
Harris, C., Ratnieks, F.L., 2021. Clover in agriculture: combined benefits for bees, environment, and farmer. J. Insect Conserv. 1–19.
Harty, M.A., Forrestal, P.J., Watson, C.J., McGeough, K.L., Carolan, R., Elliot, C., Krol, D., Laughlin, R.J., Richards, K.G., Lanigan, G.J., 2016. Reducing nitrous oxide emissions by changing N fertiliser use from calcium ammonium nitrate (CAN) to urea based formulations. Science of the Total Environment, 563-564 576–586. https://doi.org/10.1016/j.scitotenv.2016.04.120.
Hénault, C., Bourennane, H., Ayzac, A., Ratié, C., Saby, N.P.A., Cohan, J.P., Eglin, T., Gall, C.L., 2019. Management of soil pH promotes nitrous oxide reduction and thus mitigates soil emissions of this greenhouse gas. Sci. Rep. 9 (1), 20182, 10.1038/s41598-019-56694-3.
Herron, J., Hennessy, D., Curran, T., Moloney, A., O'Brien, D., 2021. The simulated environmental impact of incorporating white clover into pasture-based dairy production systems. J. Dairy. Sci. https://doi.org/10.3168/jds.2020-19077.
Holden, N., Brereton, A., 2002. An assessment of the potential impact of climate change on grass yield in Ireland over the next 100 years. Irish Journal of Agricultural and Food Research 213–226. https://www.jstor.org/stable/25562465.
Hosonuma, N., Herold, M., De Sy, V., De Fries, R.S., Brockhaus, M., Verchot, L., Angelsen, A., Romijn, E., 2012. An assessment of deforestation and forest degradation drivers in developing countries. Environmental Research Letters 7 (4), 044009. https://doi.org/10.1088/1748-9326/7/4/044009.
Huhtanen, P., Huuskonen, A., 2020. Modelling effects of carcass weight, dietary concentrate and protein levels on the CH4 emission, N and P excretion of dairy bulls. Livest. Sci. 232, 103896. https://doi.org/10.1016/j.livsci.2019.103896.
International Organisation for Standardisation (ISO), 2006. Environmental Management—Life Cycle Assessment: Principles and Framework (ISO 14040:2006). European Committee for Standardisation, Brussels, Belgium.
IRS. (2022). Budget Excise Duty Rates: Tax Duty Manual. https://www.revenue.ie/en/tax-professionals/tdm/excise/excise-duty-rates/budget-excise-duty-rates.pdf.
Jones, A.K., Jones, D., Cross, P., 2015. Developing farm-specific marginal abatement cost curves: Cost-effective greenhouse gas mitigation opportunities in sheep farming systems. Land. use policy. 49, 394–403. https://doi.org/10.1016/j.landusepol.2015.08.006.
Kavanagh, I., Burchill, W., Healy, M.G., Fenton, O., Krol, D., Lanigan, G., 2019. Mitigation of ammonia and greenhouse gas emissions from stored cattle slurry using acidifiers and chemical amendments. J. Clean. Prod. 237, 117822. https://doi.org/10.1016/j.jclepro.2019.117822.
Kesicki, F., Ekins, P., 2012. Marginal abatement cost curves: A call for caution [Article]. Clim. Policy. 12 (2), 219–236. https://doi.org/10.1080/14693062.2011.582347.
Kesicki, F., Strachan, N., 2011. Marginal abatement cost (MAC) curves: Confronting theory and practice [Article]. Environmental Science and Policy 14 (8), 1195–1204. https://doi.org/10.1016/j.envsci.2011.08.004.
Kidane, A., Øverland, M., Mydland, L.T., Prestløkken, E., 2018. Interaction between feed use efficiency and level of dietary crude protein on enteric methane emission and apparent nitrogen use efficiency with Norwegian Red dairy cows. J. Anim. Sci. 96 (9), 3967–3982. https://doi.org/10.1093/jas/sky256.
Köbrich, C., Rehman, T., Khan, M., 2003. Typification of farming systems for constructing representative farm models: two illustrations of the application of multi-variate analyses in Chile and Pakistan. Agricultural Systems 76 (1), 141–157. https://doi.org/10.1016/S0308-521X(02)00013-6.
Krimly, T., Angenendt, E., Bahrs, E., Dabbert, S., 2016. Global warming potential and abatement costs of different peatland management options: A case study for the Pre-alpine Hill and Moorland in Germany. Agricultural Systems 145, 1–12. https://doi.org/10.1016/j.agsy.2016.02.009.
Krol, D., Forrestal, P., Wall, D., Lanigan, G., Sanz-Gomez, J., Richards, K., 2020. Nitrogen fertilisers with urease inhibitors reduce nitrous oxide and ammonia losses, while retaining yield in temperate grassland. Science of the Total Environment 725, 138329. https://doi.org/10.1016/j.scitotenv.2020.138329.
Külling, D., Dohme, F., Menzi, H., Sutter, F., Lischer, P., Kreuzer, M., 2002. Methane emissions of differently fed dairy cows and corresponding methane and nitrogen emissions from their manure during storage. Environ. Monit. Assess. 79 (2), 129–150. https://doi.org/10.1023/A:1020248700255.
Kunhikrishnan, A., Thangarajan, R., Bolan, N., Xu, Y., Mandal, S., Gleeson, D., Seshadri, B., Zaman, M., Barton, L., Tang, C., 2016. Functional relationships of soil acidification, liming, and greenhouse gas flux. Advances in agronomy 139, 1–71. https://doi.org/10.1016/bs.agron.2016.05.001.
Kupper, T., Häni, C., Neftel, A., Kincaid, C., Bühler, M., Amon, B., VanderZaag, A., 2020. Ammonia and greenhouse gas emissions from slurry storage-A review. Agric. Ecosyst. Environ. 300, 106963. https://doi.org/10.1016/j.agee.2020.106963.
Lanigan, G., Black, K., Donnellan, T., Crosson, P., Beausang, C., Hanrahan, K., , Buckley, C., Lahart, B., Herron, J., Redmond, J., Shalloo, L., Krol, D., Forrestal, P., Farrelly, N., O'Brien, D., Lenehan, J.J., Hennessy, M., O'Donovan M., , Wall, D., O'Sullivan, L., O'Dwyer, T., . . . Richards, K. (2023). MACC 2023: An Updated Analysis of the Greenhouse Gas, Abatement Potential of the Irish Agriculture and Land-Use Sectors between 2021 and 2030. https://www.teagasc.ie/media/website/environment/climate-action/climate-centre/MACC-2023.pdf.
Lanigan, G., Donnellan, T., Hanrahan, K., Carsten, P., Shalloo, L., Krol, D., Forrestal, P.J., Farrelly, N., O'Brien, D., & Ryan, M. (2018). An analysis of abatement potential of Greenhouse Gas emissions in Irish agriculture 2021-2030. http://hdl.handle.net/11019/2092.
Lanigan, G.J., Donnellan, T., Hanrahan, K., Burchill, W., Forrestal, P., McCutcheon, G., Crosson, P., Murphy, P., Schulte, R., Richards, K., 2015. An Analysis of the Cost of the Abatement of Ammonia Emissions in Irish Agriculture to 2030. Teagasc Oak Park, Carlow. https://www.teagasc.ie/media/website/publications/2015/An-Analysis-of-the-Cost-of-the-Abatement-of-Ammonia-Emissions-in-Irish-Agriculture-to-2030.pdf.
Ljungqvist, F.C., Seim, A., Huhtamaa, H., 2021. Climate and society in European history. Wiley Interdisciplinary Reviews: Climate Change 12 (2), e691. https://doi.org/10.1002/wcc.691.
Martins, M.R., Sant'Anna, S.A.C., Zaman, M., Santos, R.C., Monteiro, R.C., Alves, B.J.R., Jantalia, C.P., Boddey, R.M., Urquiaga, S., 2017. Strategies for the use of urease and nitrification inhibitors with urea: Impact on N2O and NH3 emissions, fertilizer-15N recovery and maise yield in a tropical soil. Agric. Ecosyst. Environ. 247, 54–62. https://doi.org/10.1016/j.agee.2017.06.021.
Moran, D., Macleod, M., Wall, E., Eory, V., McVittie, A., Barnes, A., Rees, R., Topp, C.F.E., Moxey, A., 2011. Marginal Abatement Cost Curves for UK Agricultural Greenhouse Gas Emissions [Article]. J. Agric. Econ. 62 (1), 93–118. https://doi.org/10.1111/j.1477-9552.2010.00268.x.
Nadeem, S., Bakken, L.R., Frostegård, Å., Gaby, J.C., Dörsch, P., 2020. Contingent Effects of Liming on N2O-Emissions Driven by Autotrophic Nitrification. Front. Environ. Sci. https://doi.org/10.3389/fenvs.2020.598513.
Nkwonta, C.G., O'Neill, M., Rahman, N., Moloney, M., Forrestal, P.J., Hogan, S.A., Richards, K.G., Cummins, E., Danaher, M., 2021. Development of One-Step Non-Solvent Extraction and Sensitive UHPLC-MS/MS Method for Assessment of N-(n-Butyl) Thiophosphoric Triamide (NBPT) and N-(n-Butyl) Phosphoric Triamide (NBPTo) in Milk. Molecules. 26 (10), 2890. https://doi.org/10.3390/molecules26102890.
O'Brien, D., Shalloo, L., Crosson, P., Donnellan, T., Farrelly, N., Finnan, J., Hanrahan, K., Lalor, S., Lanigan, G., Thorne, F., Schulte, R., 2014. An evaluation of the effect of greenhouse gas accounting methods on a marginal abatement cost curve for Irish agricultural greenhouse gas emissions [Article]. Environmental Science and Policy 39, 107–118. https://doi.org/10.1016/j.envsci.2013.09.001.
O'Brien, D., Moran, B., Shalloo, L., 2018. A national methodology to quantify the diet of grazing dairy cows. J. Dairy. Sci. 101 (9), 8595–8604. https://doi.org/10.3168/jds.2017-13604.
Ogunpaimo, O.R., Buckley, C., Hynes, S., O'Neill, S., 2024. Analysis of Marginal Abatement Cost Curve for Ammonia Emissions: Addressing Farm-System

Heterogeneity. Irish J. Agric. and Food Res. 63 (1), 76–100. https://doi.org/10.15212/ijafr-2023-0113.

Pexas, G., Mackenzie, S.G., Wallace, M., Kyriazakis, I., 2020. Cost-effectiveness of environmental impact abatement measures in a European pig production system. Agricultural Systems 182, 102843.

Sajeev, E.P.M., Amon, B., Ammon, C., Zollitsch, W., Winiwarter, W., 2018a. Evaluating the potential of dietary crude protein manipulation in reducing ammonia emissions from cattle and pig manure: A meta-analysis. Nutr. Cycl. Agroecosyst. 110 (1), 161–175. https://doi.org/10.1007/s10705-017-9893-3.

Sajeev, E.P.M., Winiwarter, W., Amon, B., 2018b. Greenhouse gas and ammonia emissions from different stages of liquid manure management chains: abatement options and emission interactions. J. Environ. Qual. 47 (1), 30–41. https://doi.org/10.2134/jeq2017.05.0199.

Schils, R., Verhagen, A., Aarts, H., Šebek, L., 2005. A farm level approach to define successful mitigation strategies for GHG emissions from ruminant livestock systems. Nutr. Cycl. Agroecosyst. 71 (2), 163–175. https://doi.org/10.1007/s10705-004-2212-9.

Schwarz, M., Goers, S., Schmidthaler, M., Tichler, R., 2013. Measuring greenhouse gas abatement costs in Upper Austria [Article]. Int. J. Clim. Chang. Strateg. Manage 5 (3), 246–266. https://doi.org/10.1108/IJCCSM-06-2012-0030.

Schulte, R., Donnellan, T., 2012. A Marginal Abatement Cost Curve For Irish agriculture. Teagasc submission to the National Climate Policy Development Consultation. Teagasc, Oakpark, Carlow, Ireland.

Shalloo, L., Moran, B., O'Brien, D, 2018. Define and verify pasture base – how does Irish "pasture fed" compare to the world. In: Proceedings of the Grass-Fed Dairy Conference. Naas, Co., Kildare, Ireland.

Spink, J., Buckley, C., Burgess, E., Daly, K.M., Dillon, P., Fenton, O., Horan, B., Humphreys, J., Hyde, T., McCarthy, B., Meehan, N., Mellander, P.E., Murphy, P., O'hUallacháin, D., O'Dwyer, T., O'Donovan, M., Plunkett, M., Richards, K.G., Shalloo, L., & Wall, D. (2019). Teagasc submission made in response to the Consultation Paper on Interim Review of Ireland's Nitrates Derogation 2019. http://hdl.handle.net/11019/1944.

Tang, K., Wang, M., Zhou, D., 2021. Abatement potential and cost of agricultural greenhouse gases in Australian dryland farming system. Environmental Science and Pollution Research 28 (17), 21862–21873. https://doi.org/10.1007/s11356-020-11867-w.

Teagasc. (2017). National Farm Survey. https://www.teagasc.ie/rural-economy/rural-economy/national-farm-survey/.

Tubiello, F.N., Salvatore, M., Ferrara, A.F., House, J., Federici, S., Rossi, S., Biancalani, R., Condor Golec, R.D., Jacobs, H., Flammini, A., 2015. The contribution of agriculture, forestry and other land use activities to global warming, 1990–2012. Glob. Chang. Biol. 21 (7), 2655–2660. https://doi.org/10.1111/gcb.12865.

Tzemi, D., Breen, J., 2019. Reducing greenhouse gas emissions through the use of urease inhibitors: A farm level analysis. Ecol. Modell. 394, 18–26. https://doi.org/10.1016/j.ecolmodel.2018.12.023.

Wagner, S., Angenendt, E., Beletskaya, O., Zeddies, J., 2015. Costs and benefits of ammonia and particulate matter abatement in German agriculture including interactions with greenhouse gas emissions. Agricultural Systems 141, 58–68. https://doi.org/10.1016/j.agsy.2015.09.003.

Wagner, S., Angenendt, E., Beletskaya, O., Zeddies, J., 2017. Assessing ammonia emission abatement measures in agriculture: Farmers' costs and society's benefits–A case study for Lower Saxony, Germany. Agricultural Systems 157, 70–80. https://doi.org/10.1016/j.agsy.2017.06.008.

Wang, Y., Yao, Z., Zhan, Y., Zheng, X., Zhou, M., Yan, G., Wang, L., Werner, C., Butterbach-Bahl, K., 2021. Potential benefits of liming to acid soils on climate change mitigation and food security. Glob. Chang. Biol. 27 (12), 2807–2821. https://doi.org/10.1111/gcb.15607.

Ward Jr, J.H., 1963. Hierarchical grouping to optimise an objective function. J. Am. Stat. Assoc. 58 (301), 236–244. https://doi.org/10.1080/01621459.1963.10500845.

Webb, J., Menzi, H., Pain, B., Misselbrook, T., Dämmgen, U., Hendriks, H., Döhler, H., 2005. Managing ammonia emissions from livestock production in Europe. Environmental pollution 135 (3), 399–406. https://doi.org/10.1016/j.envpol.2004.11.013.

Yan, M.J., Humphreys, J., Holden, N.M., 2013. The carbon footprint of pasture-based milk production: Can white clover make a difference? J. Dairy. Sci. 96 (2), 857–865. https://doi.org/10.3168/jds.2012-5904.

Zhang, N., Bai, Z., Winiwarter, W., Ledgard, S., Luo, J., Liu, J., Guo, Y., Ma, L., 2019. Reducing ammonia emissions from dairy cattle production via cost-effective manure management techniques in China. Environ. Sci. Technol. 53 (20), 11840–11848. https://doi.org/10.1021/acs.est.9b04284.