Journal of Environmental Management 370 (2024) 122521

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

A framework for cost-effectiveness analysis of greenhouse gas mitigation measures in dairy industry with an application to dairy farms in China

Saiwei Li [a,b], Mingxue Zhang [a], Lingling Hou [a], Binlei Gong [c], Kevin Chen [c,d,*]

[a] China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, No. 5 Yiheyuan Road, Haidian District, 100080, Beijing, PR China
[b] Digital Business and Capital Development Innovation Center, Beijing Technology and Business University, No. 33 Fucheng Road, Haidian District, 100048, Beijing, PR China
[c] China Academy for Rural Development, School of Public Affairs, Zhejiang University, No. 866 Yuhangtang Road, Xihu District, 310058, Hangzhou, PR China
[d] International Food Policy Research Institute, East and Central Asia Office, No. 12 Zhongguancun South Street, Haidian District, 100081, Beijing, PR China

ARTICLE INFO

Keywords:
Climate change
Cost-effectiveness analysis
dairy industry
mitigation measures

ABSTRACT

The dairy industry is a significant contributor to global greenhouse gas emissions (GHG). Although much effort has been directed to explore the cost-effective measures for many sectors such as electricity, building infrastructure, transportation, research on mitigation measures within dairy industry remains limited. A notable obstacle is the absence of a cost-effectiveness analysis (CEA) framework to guide decision-makers and practitioners in this sector. In response, we propose a comprehensive CEA framework tailored to mitigate GHG emissions in the dairy industry. Our conceptual framework consists of six steps: defining the system boundary to determine the activities generating GHG emissions; identifying GHG emission sources within the system boundary; identifying potential mitigation measures; determining methods to quantify GHG emissions; collecting data to estimate both GHG emissions and mitigation costs; and applying general econometric methodologies to analyze the cost-effectiveness of mitigation measures. We further conducted a case study focusing on dairy farms in China, analyzing three categories of mitigation measures: feed, energy, and manure management. The results indicate that implementing effective feed and energy measures is a cost-saving strategy, reducing the cost per unit of milk production. Conversely, adopting effective manure management measures may lead to increased costs for dairy farms. The findings offer strategic recommendations for reducing GHG emissions from dairy production in China and provide analytical insights and strategic references applicable to other developing countries.

1. Introduction

Achieving the goal of limiting global temperature rise to well below 2 °C is quite challenging and requires substantial efforts from all sectors. To date, primary attention has been directed toward mitigating greenhouse gas (GHG) emissions from fossil fuel combustion in electricity generation, transportation, and industrial processes (Clark et al., 2020). However, it is crucial to recognize that the global food system is a major source of GHG emissions, contributing approximately 30% of annual anthropogenic emissions during the 2007 and 2016 (IPCC, 2019). Unfortunately, this sector has been relatively overlooked. Clark et al. (2020) highlighted that even if fossil fuel emissions were immediately halted, the current trends in global food systems would prevent achieving the 1.5 °C target and would threaten the achievement of the 2 °C target by the end of the century. Encouragingly, in the latest submissions to the Paris Agreement in 2021, encompassing 165 nationally determined contributions (NDCs) from all 192 participating parties, 81% of these NDCs incorporate mitigation measures in the agricultural sector (Crumpler et al., 2021).

The dairy sector is a main contributor to GHG emissions within the livestock domain. Livestock supply chains account for 14.5% of anthropogenic GHG emissions in the broader context of the global food system (FAO, 2017). Of these emissions, cattle, including both beef and milk production, contributed approximately two-thirds for the total emissions in 2010 (FAO, 2017). Dairy production systems are complex sources of GHG emissions, primarily releasing methane (CH_4), nitrous

* Corresponding author. China Academy for Rural Development, School of Public Affairs, Zhejiang University, No. 866 Yuhangtang Road, Xihu District, 310058, Hangzhou, PR China.
E-mail address: kzchen@zju.edu.cn (K. Chen).

https://doi.org/10.1016/j.jenvman.2024.122521
Received 13 June 2024; Received in revised form 9 September 2024; Accepted 12 September 2024
Available online 26 September 2024

oxide (N_2O), and carbon dioxide (CO_2) (FAO and GDP, 2018). Notably, GHG emissions from the dairy sector are expected to increase due to the anticipated growth in meat and milk consumption, driven by projections of global population expansion and increased income (FAO and GDP, 2018).

Previous studies have demonstrated the significant potential for reducing GHG emissions within the dairy industry (Gerber et al., 2013). Various measures have been identified as effective in reducing GHG emissions across all stages of the dairy industry, from feed production and dairy farming to dairy processing and consumption. In feed production, optimizing fertilizer inputs, increasing fertilization efficiency, using chemical inputs, and implementing land conservation measures such as cover cropping are considered effective in reducing GHG emissions (Gryze et al., 2010; Jian et al., 2020). Mitigation measures targeting dairy farming has garnered significant attention. These strategies are categorized into four main areas: diminishing emissions from enteric fermentation, enhancing manure management, increasing animal fertility and productivity, and improving energy management (Beldman et al., 2021; Gerber et al., 2013; Lovarelli et al., 2022; Tullo et al., 2019; Warner et al., 2017). Furthermore, implementing diversification strategies at the production system level has also been shown to effectively reduce GHG emissions (O'Brien et al., 2023). During the processing stage, improving energy management has been recognized as an important measure (Xu and Flapper, 2011), such as continuous assessment of energy use and the application of energy-efficient equipment. In the dairy consumption phase, changing consumers' dietary structures, advocating for low-carbon consumption concepts, and incentivizing the purchase of low-carbon products have shown potential in reducing GHG emissions (Burke et al., 2023; Edjabou and Smed, 2013; Herrero et al., 2016).

It is worth noting that reducing GHG emissions can often be costly and may threaten both food security and farm profitability (Havlík et al., 2014). Dairy products are a rich and essential source of nutrients, playing a crucial role in maintaining a healthy and nutritious diet. With the rising global demand for animal-sourced protein, the dairy industry is critical to ensuring food security and alleviating poverty (FAO and GDP, 2018). Therefore, mitigation measures in the dairy sector should ideally minimize socioeconomic and environmental trade-offs.

Determining the economically optimal mitigation strategies requires understanding the costs associated with GHG emissions reduction. Cost-effectiveness analysis (CEA) is a valuable decision-making tool that aids in identifying the most economically efficient means to achieve specific objectives or estimate the costs involved in attaining particular outcomes (Tietenberg and Lewis, 2001). In the context of climate change mitigation, CEA is employed to evaluate and rank the performance of various mitigation measures based on their cost-effectiveness in reducing GHG emissions and limiting global temperature rise. Measures with lower abatement costs (or costs below the carbon price) are considered cost-effective and economically efficient for society to implement (Eory et al., 2015). Currently, CEA has been extensively applied to assess the expenses associated with GHG mitigation across various sectors, including electricity (Jiang et al., 2020; Sims et al., 2003; Sotiriou et al., 2019), building infrastructure (Hoogwijk et al., 2010; Teamah et al., 2022; Zhang et al., 2020), agricultural practices (Fellmann et al., 2021; Macleod et al., 2015; Moran et al., 2011; Sapkota et al., 2019) and transportation systems (Kok et al., 2011; Wu et al., 2024). By applying CEA to GHG mitigation measures, governments and relevant stakeholders can optimize resource allocation by prioritizing the implementation of more cost-effective measures within climate-related policies and programs.

However, CEA studies focused on assessing the economic feasibility of mitigation measures in the dairy industry remains limited. Existing CEA research primarily addresses GHG mitigation in dairy production. These studies typically establish a unified baseline farms using national or regional statistics or average farm data collected through field surveys. Some of studies directly estimate changes in GHG emissions and associated costs resulting from the adoption of mitigation measures by making stringent assumptions on specific actions, input prices, and changes within the production system under these measures (Cantillon et al., 2024; Doreau et al., 2014; Duffy et al., 2021). Other researchers have utilized bio-economic models, setting empirical parameters to simulate farm production and operational activities (Adler et al., 2013; Cecchini et al., 2018; Dutreuil et al., 2014; Huber et al., 2023; Mosnier et al., 2019; Van Middelaar et al., 2014). By simulating farm activities under targeted mitigation measures within specific agronomic and economic constraints, the models aim to maximize profitability while providing insights into GHG emissions and farm profitability, thereby assessing the cost-effectiveness of these mitigation measures.

While existing CEA studies have endeavored to assess the economic viability of mitigation measures in the dairy industry, a comprehensive CEA framework tailored to this sector is notably absent. Current research provides relatively approximate estimates and relies heavily on broad assumptions regarding specific measures and changes within the dairy production system. Additionally, these studies often overlook the significant heterogeneity among dairy farms. Furthermore, much of the existing research focuses on developed countries, requiring highly detailed empirical and statistical data. Therefore, establishing a comprehensive CEA framework is critical to support further studies that offer more robust empirical evidence on the economic feasibility of various mitigation measures in the dairy industry.

The contribution of this study is the development of a general econometric framework for the CEA of GHG mitigation measures in the dairy industry. We highlight the importance of analyzing the cost-effectiveness of mitigation measures using micro-level data and actual adoption behaviors. The framework facilitates a more realistic estimation on cost-effectiveness of mitigation measures by accounting for the heterogenous characteristics and diverse production activities of individual implementers under real market conditions. Utilizing such an analytical framework helps ensure that the substantial expenditure involved in public and private mitigation programs deliver value for money. Based on this framework, we conducted a case study of Chinese dairy farms, providing valuable quantitative evidence on the mitigation costs associated with feed, manure, and energy management measures. The findings offer practical insights for the dairy industry in China and other developing countries to achieve emission reduction targets economically and efficiently.

2. A framework for CEA of GHG mitigation measures in dairy industry

We propose a CEA framework for GHG emission mitigation measures in the dairy industry based on existing literature (e.g. CC-ME, 2019; Defra, 2004; IPCC, 2007). This framework employs a generalized econometric methodology and relies heavily on micro-level data collected through field surveys (see Fig. 1).

2.1. Step 1: defining the system boundary

The definition of the system boundary is largely contingent on the study's overarching objectives and should adhere to the principles of the Life Cycle Assessment (LCA) approach. LCA is a widely utilized method in previous studies to assess the environmental impacts of production processes and identify resource-intensive and emission-intensive stages within a product's life cycle (FAO, 2010). To conduct a CEA for the whole dairy industry, four main subsystems below collectively form the comprehensive system boundary for evaluating the environmental and economic implications of GHG mitigation measures (see Fig. 2) (Duffy et al., 2021; FAO, 2010; Feng and Kebreab, 2020):

1) Feed production. This subsystem involves the primary production activities of crop and feed additive production. The main inputs for these activities are water, energy, fertilizer, and pesticide, with the outputs primarily being used as feed and transported to the milk production

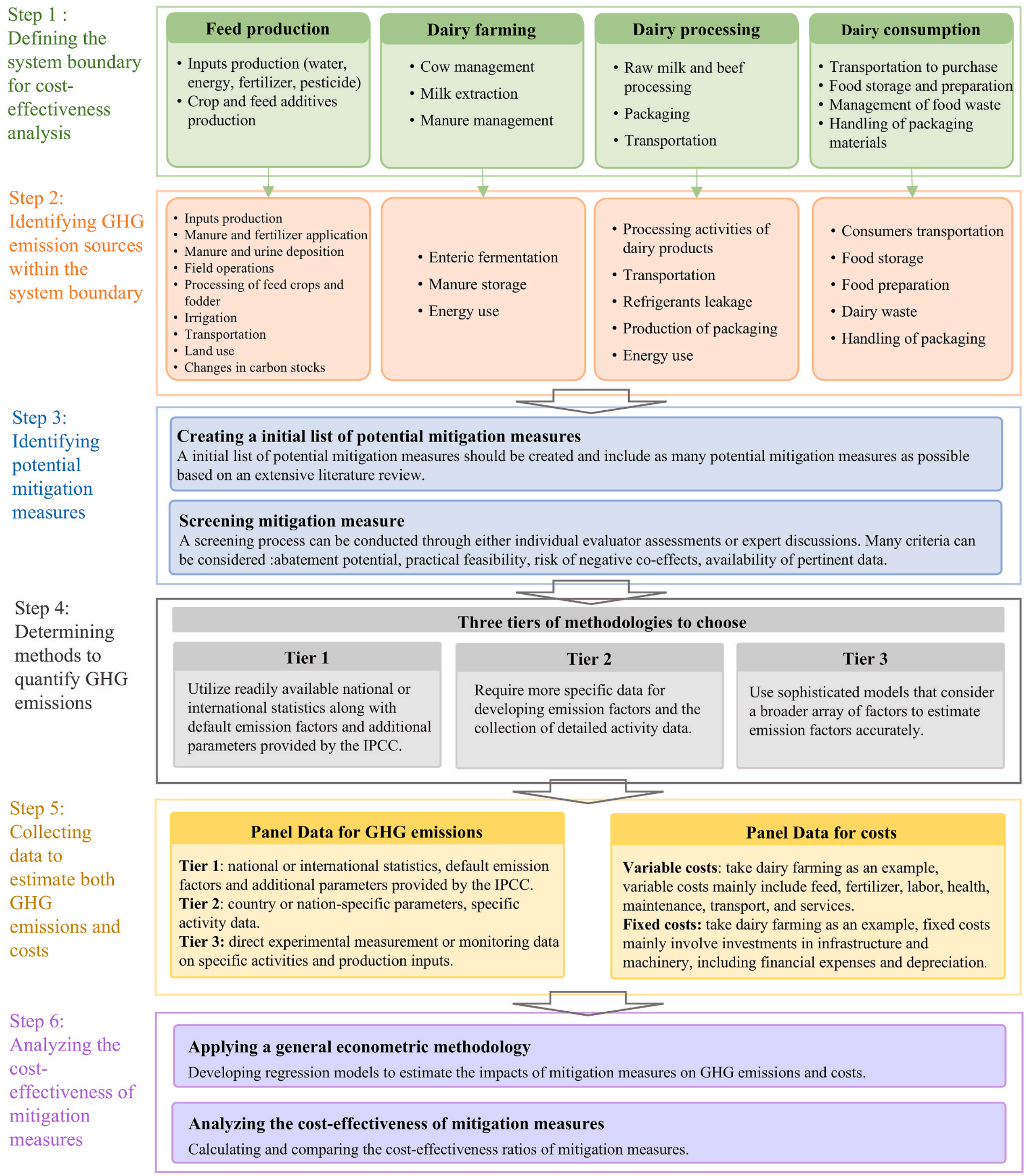

Fig. 1. Cost-effectiveness Analysis framework for mitigation measures in the dairy industry.

stage. 2) Dairy farming. Cow management, milk extraction, and manure management are the main production activities in this subsystem, requiring fuel, electricity, and refrigerants. The main outputs are raw milk and beef, which proceed to the processing stage. Additionally, manure can be used as fertilizer for crop production. 3) Dairy processing. This stage involves activities such as processing, packaging, and transportation of dairy products, which require various types of energy, including fuel and electricity. 4) Dairy consumption. This sub-system encompasses consumer activities such as transportation to purchase the product, food storage and preparation, management of food waste, and handling of packaging materials. These activities require the use of fuel, electricity and natural gas.

2.2. Step 2: identifying GHG emission sources

In accordance with the system boundary, the subsequent step involves identifying the sources of GHG emissions arising from the production activities within the boundary. This foundational step is crucial for pinpointing mitigation measures and conducting the subsequent CEA. According to the FAO report titled “Greenhouse Gas Emissions from the Dairy Sector” (FAO, 2010), the main GHG emissions and related sources in the major production stages are as follows:

During feed production and transportation to dairy farms, nitrogen fertilizer production is a major source of CO_2 emissions. The production and manufacturing of pesticides are energy-intensive process that emit CO_2, CH_4, and N_2O. The application of manure and chemical fertilizers

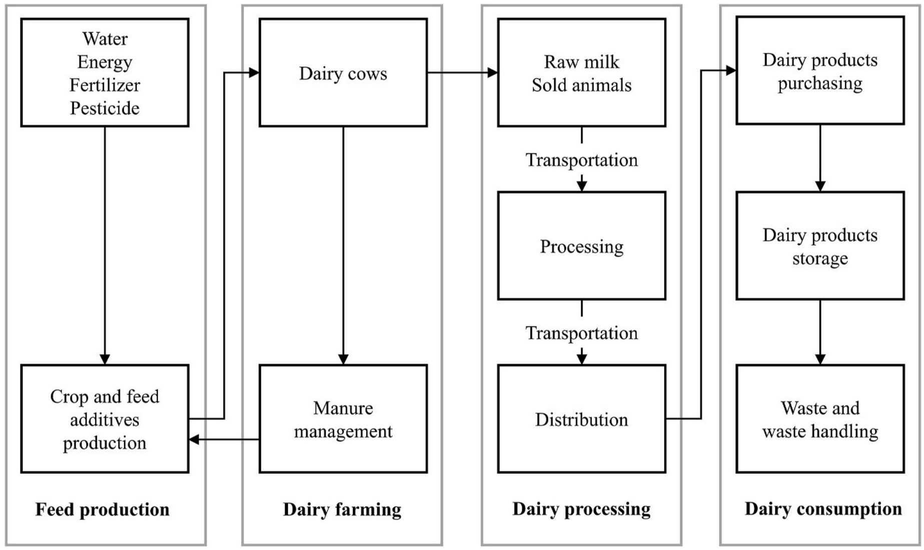

Fig. 2. A system boundary for the whole dairy value chain.

to crops, as well as the deposition of manure and urine, can generate both direct and indirect N_2O emissions. Field operations, the drying and processing of feed crops and fodder, and irrigation (including water pumping and conveyance) are significant sources of CO_2 emissions due to their energy use. Additionally, the transportation of feed from production sites to dairy farms generates substantial GHG emissions. Land use changes, particularly deforestation over the past 20 years, have resulted in changes in carbon stocks of the land, contributing further to emissions (IPCC, 2006). These changes in carbon stocks can also lead to nitrogen losses.

Dairy farms are the most significant contributors to global warming within the dairy sector, accounting for approximately 80% of the total carbon footprint (CF) associated with dairy products (Guzmán-Luna et al., 2022). During dairy farming, enteric fermentation by dairy cows is the primary source of CH_4 emissions. Secondly, manure storage and management generate N_2O and CH_4 emissions. The third major source of emissions is the energy used throughout the entire operation of dairy farms.

In dairy processing, the main GHG emissions arise from the processing activities of dairy products, transportation, and energy use. Transportation activities include the movement of milk and animals to dairies and slaughterhouses, as well as the distribution of processed products to retail points. Additionally, the production of packaging, energy use, and refrigerants leakage contribute significantly to GHG emissions.

Lastly, during dairy consumption, GHG emissions are primarily generated from consumers activities such as transportation, food storage, and preparation. Dairy waste and the handling of packaging also contribute to GHG emissions.

Among the diverse sources of GHG emissions in the dairy industry, the major contributions come from dairy farming and feed production. These include enteric fermentation during cattle digestion, urine deposition on pasture, manure storage, and the application of nitrogen fertilizer and manure to crops and pastures (Eckard et al., 2010).

2.3. *Step 3: identifying potential mitigation measures*

In this phase, it is essential to identify feasible mitigation measures tailored to the specific GHG-emitting activities and sources. Based on an extensive literature review, an initial list of potential mitigation measures should be created, including as many options as possible. For the dairy industry, existing literature has investigated GHG emissions across various stages, including feed production, dairy farming, processing, and consumption. Numerous mitigation measures have been studied and shown potential in mitigating GHG emissions (a comprehensive literature review of these measures and their effectiveness is provided in Supplementary Materials A). The conclusions of these studies are based on specific regional environments and rigorous experimental conditions. Therefore, whether potential mitigation measures can be incorporated into CEA requires further discussion and screening.

A screening process can be conducted through either individual evaluator assessments or expert discussions. The ultimate objective is to develop a comprehensive inventory of mitigation measures to support a subsequent formal CEA. Many criteria can be considered for screening these measures, including abatement potential, practical feasibility, risk of negative co-effects, and availability of pertinent data (Eory et al., 2013; Moran et al., 2011).

2.4. *Step 4: determining methods to quantify GHG emissions*

Identifying the estimation method for GHG emissions is a prerequisite for subsequent data collection and CEA of mitigation measures. The 2006 IPCC Guideline for National Greenhouse Gas Inventories (IPCC, 2006) are widely recognized as a reliable reference for estimating GHG emissions. These guidelines provide general methodologies for estimating GHG emissions and specific references for calculating emissions in five areas: energy, industrial processes and product use (IPPU), agriculture, forestry and other land use (AFOLU), and waste. The GHG emissions of main sources in the dairy industry can be estimated using the methods outlined in the IPCC 2006 guidelines. For example, energy use in the production, processing, and transportation phases of the dairy industry can be estimated using the IPCC's energy section. Additionally, the IPCC's AFOLU section provides methods for estimating GHG emissions from feed production, enteric fermentation in dairy farming, and manure management.

The IPCC (2006) delineates three tiers of methodologies for estimating GHG emissions, each representing a different level of methodological complexity. Tier 1 serves as the fundamental method, utilizing readily available national or international statistics along with default emission factors and additional parameters provided by the IPCC. Tier 2 methods are of intermediate complexity, requiring more specific data for developing emission factors and the collection of detailed activity data. In contrast, Tier 3 methods are the most intricate and demanding, involving the use of sophisticated models that consider a broader array of factors to estimate emission factors accurately.

The selection of suitable methods primarily hinges on the importance of GHG emission sources and the availability of data. The importance of a GHG emission source is determined by its impact on a country's overall inventory of GHG, both in terms of the absolute level of emissions and removals. As the importance of the emission source increases, it is advisable to employ higher-tier methods for estimation. Regarding data availability, when more detailed data can be obtained, Tier 2 or Tier 3 are typically selected. The IPCC 2006 guidelines offer recommendations regarding the selection of estimation methods. For instance, GHG estimation related to enteric fermentation typically utilizes Tier 2 or Tier 3 methods.

According to the IPCC 2006 guidelines, taking dairy farming as an example, we introduce the main inputs that affect the calculation of GHG emissions from enteric fermentation and manure management. Regarding enteric fermentation, in Tier1 methods, methane emissions are determined by the cattle population and a default emission factor. In Tier 2 methods, the emission factors for each category of dairy cattle are estimated based on their gross energy intake and methane conversion factor for the category. Regarding manure management, in Tier 1 methods, methane emissions are estimated based on the cattle population and a default emission factor influenced by the average annual temperature. In Tier 2 methods, the calculation of methane emission factors is affected by manure characteristics and manure management system characteristics. Manure characteristics include the amount of volatile solids produced and the maximum methane production potential of the manure. Manure management system characteristics encompass the types of systems used to manage manure and a system-specific methane conversion factor.

2.5. Step 5: collecting data

A panel dataset consisting of time-series data for a large cross-sectional sample is required before analyzing the cost-effectiveness of mitigation measures. The repeated observations for each sample allow the researcher to estimate distinct intercepts for each cross-sectional sample, thereby capturing unobserved heterogeneity through these intercepts. To assess the impact of mitigation measures on GHG emissions and costs, the panel data should span time points both before and after the implementation of the measures.

Data collection should aim to estimate GHG emissions and costs. The estimation methods for GHG emissions specify the data required. In Tier 1, the data consist of emission factors and activity data. In Tier 2, the data include country or nation-specific parameters and specific activity data. These parameters could be commissioned by a qualified professional organization for testing or derived from data published by national or local competent authorities. The activity data can be obtained from national or international statistics or field surveys. For instance, in the case of enteric fermentation in dairy farming, the activity data for Tier 1 would be the total cattle population, while for Tier 2, it would include the population, feed formula and intake levels for every cattle category. In Tier 3, sophisticated models are developed, incorporating additional country-specific information. For enteric fermentation, this includes detailed diet composition, concentration of products arising from ruminant fermentation, seasonal variation in animal population or feed quality and availability, and possible mitigation strategies. Many of these estimates would be derived from direct experimental measurements or monitoring data.

The cost calculation encompasses the net additional variable and fixed costs. Variable costs include inputs like feed, fertilizer, labor, health, maintenance, transport, and services. Additionally, any supplementary returns resulting from the implementation of mitigation measures should be taken into account, such as the benefits derived from biogas power generation. Fixed costs involve investments in infrastructure and machinery, including financial expenses and depreciation. These costs are incorporated into the financial calculations and assumed as the amortization of initial expenses. It is important to establish a base year for costs and adjust prior costs based on inflation rates.

2.6. Step 6: analyzing cost-effectiveness

In this step, we propose a general econometric methodology to conduct a CEA. Given the available cross-section data over time, regression methods are appropriate methodologies for evaluating the cost-effectiveness of mitigation measures. To calculate the cost-effectiveness of mitigation measures, the following regressions need to be estimated:

$$Cost_{irt} = \alpha_0 + \alpha_1 T_{irt} + \lambda X_{irt} + \sigma_{ir} + \gamma_{rt} + \epsilon_{irt}$$

$$GHG\_emission_{irt} = \beta_0 + \beta_1 T_{irt} + \omega X_{irt} + \theta_{ir} + \eta_{rt} + \delta_{irt}$$

Where $Cost_{irt}$ is the cost per ton of milk production for sample i in region r during year t, $GHG\_emission_{irt}$ is the GHG emissions per ton of milk production from sample i in region r during year t. T_{irt}, are vectors of t mitigation measures variables. If the sample i implemented the mitigation measures, then $T_{irt} = 1$, otherwise as opposed to $T_{irt} = 0$. The same applies to other mitigation measures. X_{irt} is a set of characteristics of sample i. Taking dairy farms as examples, the characteristics to be included in the analysis comprise types of farm organization, farm milk production, farm herd size, methods of farming husbandry. The parameters α_1 and β_1 measure the impacts of mitigation measures on GHG emissions and costs. σ_{ir} and θ_{ir} are region fixed effects; γ_{rt} and η_{rt} are state-by-year fixed effects; ϵ_{irt} and δ_{irt} are error terms.

Then, for a mitigation measure T_{irt}, the cost-effectiveness ratio can be estimated as:

$$CER = \frac{\Delta Cost}{\Delta GHG\_emissions} = \frac{\alpha_1}{\beta_1}$$

3. A case study of dairy farms in China

Applying the aforementioned analytical framework, this section embarks on a case study of dairy farms in China to identify cost-effective mitigation measures.

3.1. Data and method

3.1.1. Data collection and description

The empirical analysis is based on farm-level data from a cross-sectional survey conducted in May 2023 in three prominent provinces in China: Inner Mongolia, Yunnan, and Heilongjiang. These provinces collectively represent major milk production hubs, contributing to 33.7% of the nation's total milk output in 2021(National Bureau of Statistics, 2023). A stratified random sampling technique was employed to selected dairy farm samples. In Inner Mongolia, the study focused on four cities with significant pastoral regions, namely Hohhot, Baotou, Bayannur, and Ulanqab, and 20 dairy farms were randomly selected in each city. In Yunnan province, Dali Prefecture was prioritized as the survey site due to its prominence as one of the most vital milk production hubs, with a random selection of 10 dairy farm samples. The Heilongjiang province presented a unique scenario, with dairy farms dispersed across various locations. Consequently, we initially identified four cities—Qiqihar, Heihe, Suihua, and Harbin—and then judiciously employed a random sampling approach to select 1–2 samples from each city. Through this meticulous process, we successfully accumulated a comprehensive collection of 97 samples spanning three provinces.

A structured survey questionnaires was developed to facilitate data collection. For each selected dairy farm, face-to-face interviews were conducted with managerial representatives. In the case study of Chinese dairy farms, we followed the principles of LCA and defined the boundary of the analysis system as the dairy farm gate. Within this system, the main sources of GHG emissions are enteric fermentation, manure management, and energy use. To calculate the emissions of these three types of GHG emissions, we investigated the production activity data of dairy farms for 2022 as follows: For enteric fermentation, the data collected includes the number, weight, purchase and sale, feed formula, feed usage, and conventional nutrient content of feed for cattle of each type raised; For manure management and energy use, the treatment methods and time of manure, effluent, mixtures, and the types and amounts of energy used are included. To calculate the operational costs of dairy farms and analyze the cost-effectiveness of mitigation measures, the questionnaire survey further collected data including the type of dairy farm, milk production, implementation of mitigation measures, feed purchase price, annual feed usage, investment in manure treatment facility construction and related maintenance costs, energy equipment investment and related maintenance costs, and energy prices. Before the formal investigation, a pilot study was executed in Beijing, which yielded improvements in the questionnaire design.

The detailed description of the selected dairy farms is shown in Table 1. The total sample comprises 97 dairy farms, encompassing 76 enterprises and 21 smallholders. Overall, the sampled dairy farms exhibit a relatively large scale of operation, resulting in a high level of milk production. The average number of cattle and lactating cows stand at 1722.5 heads, 599.2 heads, respectively. The total milk production for all dairy farms was 6309.6 tons, with an average yield of 8.7 tons per lactating cow. In comparison, the breeding scale and production capacity of dairy enterprises are notably higher than those of smallholders. This discrepancy suggests that dairy enterprises may possess superior cow breeds, breeding techniques, and management practices compared to smallholders. From the perspective of production inputs on the dairy farms, it is evident that enterprises have significantly higher labor and energy inputs compared to smallholders, while their feed inputs are lower. The larger scale of production in enterprises implies a greater need for infrastructure, equipment, and a higher labor force involvement in production management activities. Meanwhile, the lower feed input indicates superior feed utilization efficiency within these enterprises.

3.1.2. Method

In accordance with the developed CEA framework, the initial step involved delineating the system boundary of this study, which was established at the dairy farm gate. Drawing insights from a comprehensive literature review and expert consultations, three primary sources of GHG emissions were identified for Chinese dairy farms: enteric fermentation, manure management, and energy use. Consequently, integrating insights from the aforementioned review and consultations with Chinese experts, tailored lists of potential mitigation measures were formulated for each source. These measures were specifically categorized as feed management measures, manure management measures, and energy management measures (more detail definition of mitigation measures are provided in Supplementary Materials B).

Feed management measures. Four measures are included: forage quality, concentrate inclusion, adding inhibitors and oilseeds. Forage quality is measured by the proportion of whole plant corn silage in the forage of lactating cows, categorized into three levels (diet dry matter basis): low level (less than 50%), medium level (50% to 70%), and high level (more than 70%). Concentrate inclusion is measured by the proportion of concentrate in the feed diet of lactating cows, categorized into three levels (diet dry matter basis): low level (less than 35%), medium level (35% to 50%), and high level (more than 50%). Both adding inhibitors and oilseeds are assessed by determining whether the dairy farms have added inhibitors and oilseeds in feed diet.

Energy management measures. Two measures are included in the CEA analysis: energy intensity and energy structure. Energy intensity is measured by the amount of energy used per unit of milk production. Three levels of energy intensity (low, medium, high) are generated by dividing the distribution of energy intensity into three groups, each containing a third of the population. Energy structure is measured by the proportion of energy provided by diesel oil in the total energy per unit of milk production. Similarly, three levels of energy structure (low, medium, high) are generated by dividing the distribution of the percentage of energy use from diesel oil in the total energy use per unit of milk production.

Manure management measures. Six manure management measures are analyzed: returning to farmland directly, storage with cover, storage with no covers, composting only, composting after/and storage, and recycling for cow bedding. These measures are assessed by inquiring which of the above measures the dairy farms have implemented in their manure management.

GHG emissions and costs were derived from survey data collected from dairy farms. For GHG emissions, the calculation encompassed CH_4 emissions from enteric fermentation and manure management, direct and indirect N_2O emissions from manure management, and CO_2 emissions from energy use on dairy farms. The methodology aligns with guidelines from IPCC (2006) and Wei et al. (2024). The diverse GHG emissions are consolidated using equivalence factors in terms of CO_2-e over a 100-year time horizon: 1 for CO_2, 27 for CH_4, and 273 for N_2O, as stipulated by IPCC (2021). Concerning costs, three categories were estimated—feed inputs, manure management, and energy use. Feed input costs were computed based on feed formulas and related prices for all cow types. Manure management costs were calculated based on the method of manure treatment, fixed investments in facilities and equipment, estimated service life, annual maintenance fees, annual labor costs, and material investment. Energy costs were estimated considering the types, usage, and prices of all energy used on dairy farms. Following LCA principles, the GHG emission intensity and management costs of a dairy farm are expressed per functional unit—1 ton of fat- and protein-corrected milk (FPCM). Specifically, the calculated sum of GHG emissions is presented in tons of CO_2-e per ton of FPCM, and the management costs are expressed as the cost per ton of FPCM.

Finally, we estimate the economic regression models as below:

$$Cost_{ir,m} = \alpha_0 + \sum\nolimits_n \alpha_{nm} \boldsymbol{T}_{\boldsymbol{irn,m}} + \lambda_m X_{ir} + \sigma_r + \epsilon_{ir,m} \tag{1}$$

$$GHG\_emission_{ir,m} = \beta_0 + \sum\nolimits_n \beta_{nm} \boldsymbol{T}_{\boldsymbol{irn,m}} + \omega_m X_{ir} + \eta_r + \delta_{ir,m} \tag{2}$$

Where $Cost_{ir,m}$, $GHG\_emission_{ir,m}$ represent the costs and GHG emissions per ton of FPCM for each dairy farm *i* in region *r*, and $\boldsymbol{T}_{\boldsymbol{irn,m}}$ are vectors of mitigation measures variables applied by each dairy farm *i* in region r. The indicator *m* refers to the three management stages, namely feed management ($m = 1$), manure management ($m = 2$) and energy management($m = 3$), and the indicator *n* refers to each mitigation measure *n* of *m* management stages. When *m* indicates feed management, $Cost_{ir,m}$ and $GHG\_emission_{ir,m}$ refers to feed costs and GHG emissions from enteric fermentation for each dairy farm *i*, and $\boldsymbol{T}_{\boldsymbol{irn,m}}$ are vectors of four feed management measures variables, including forage quality, concentrate inclusion, adding oilseeds, and adding inhibitors. When *m* indicates manure management, $Cost_{ir,m}$ and $GHG\_emission_{ir,m}$ refers to costs and GHG emissions from manure management for each dairy farm *i*, and $\boldsymbol{T}_{\boldsymbol{irn,m}}$ contain six dummy variables of manure management measures, including returning to farmland directly, storage with covers,

Table 1
Description of the characteristics of dairy farms

<!—Col Count:4—>Variables	All sample	Enterprises	Smallholders
Number	97	76	21
Total stock of cattle (per farm)	1,722.5	2,184.7	49.7
Stock of lactating cows (per farm)	599.2	761.4	12.1
Total milk yield (ton/farm)	6,309.6	8,063.7	44.6
Milk yield per lactating cow(ton/cow)	8.7	9.5	5.7
Number of workers in farm (per farm)	35.7	44.5	2.5
Feed input (ton/ton milk)	5.7	5.1	7.8
Feeding expenditure (USD/ton milk)	1092.6	1074.1	1158.0
Energy input (kW·h/ton milk)	784.2	854.5	536.5
Energy expenditure (USD/ton milk)	46.6	49.3	37.5

Note: 1 USD = 7.27 RMB (accessed on July 23, 2024), the same below.

storage without covers, composting only, composting after/and storage, and recycling for cow bedding. The benchmark group is defined as those who recycle manure for bow bedding. When m indicates energy management, $Cost_{ir,m}$ and $GHG\_emission_{ir,m}$ refers to costs and GHG emissions from energy management for each dairy farm i, and $\boldsymbol{T}_{irn,m}$ are vectors of two energy management measure variables: energy intensity and energy structure, respectively. α_{nm} and β_{nm} are the coefficients of the interest to be estimated, capturing the impact of each mitigation measure n on costs and GHG emissions, respectively.

X_{irt} is a set of characteristics of dairy farms, including type of dairy farms, province, total cattle stock, the proportion of lactating cows, total milk production in logarithmic form, lactating cow yield, forage to concentrate ratio of dairy farms, the proportion of corn silage in forage of dairy farms, and number of used energy type. σ_r and η_r are region fixed effects to control for fixed differences between provinces. ϵ_{ir} and δ_{ir} are error terms. Table 2 shows the statistics description of all variables in model estimations.

Therefore, in m management stage, the cost-effectiveness ratio (CER) of a mitigation measure $\boldsymbol{T}_{irn,m}$ can be estimated as:

$$\boldsymbol{CER\_T}_{irn,m} = \frac{\Delta Cost}{\Delta GHG\_emissions} = \frac{\alpha_{nm}}{\beta_{nm}}$$

3.2. Results

Table 3 presents the Ordinary Least Squares (OLS) results on the impact of feed management measures on GHG emissions from enteric fermentation and feed management costs.[1] Column 1 indicates that improving concentrate inclusion and enhancing forage quality in the feed diet of lactating cows are significantly associated with GHG emissions from enteric fermentation, with the latter having a more substantial mitigation effect. Dairy farms with high forage quality emit 0.289 tons less CO_2-e per ton of FPCM compared to those with low forage quality. It suggests that increasing the proportion of corn silage in forage from less than 50% to more than 70% can notably reduce GHG emissions. Additionally, farms with medium concentrate inclusion (35% to 50%) reduce GHG emissions by 0.179 tons of CO_2-e per ton of FPCM compared to those with low concentrate inclusion (less than 35%). The impact of adding feed supplements like inhibitors or oilseeds on GHG emissions is not significant. The possible explanation is that the mitigation effect of adding supplements might be linked to the quantity used, which warrants further investigation in future studies.

Column (2) and Column (3) illustrate the impact of feed management measures on feed costs and the abatement cost for effective measures. The results demonstrate that improving forage quality and increasing concentrate inclusion can not only effectively reduce GHG emissions from enteric fermentation but also yielding cost savings in feed management for dairy farming. Specifically, farms with high forage quality incur feed costs that are 156 USD lower per ton of FPCM compared to those with low forage quality. This implies that improving forage quality from a low level (less than 50%) to a high level (more than 70%) can result in a savings of 540 USD per ton of CO_2-e reduction. Similarly, for concentrate inclusion, dairy farms with a medium level of concentrate inclusion have feed management costs that are 58 USD lower per ton of FPCM compared to those with a low level. Consequently, improving concentrate inclusion from a low level (less than 35%) to a medium level (35% to 50%) can save 325 USD per ton of CO_2-e reduction.

The modelling results of energy management measures are shown in Table 4. The results indicate that reducing the energy intensity of dairy farms and the use of diesel oil can significantly decrease GHG emissions from energy use. Specifically, compared to farms with the highest energy intensity, those with low and medium energy intensity emit 0.600 tons and 0.515 tons of CO_2-e less per ton of FPCM, respectively. These findings highlight that improving the energy efficiency of dairy farms and reducing energy use per unit of product can serve as effective mitigation measures. Regarding energy structure, decreasing the proportion of diesel oil use is associated with a reduction in GHG emissions. Farms with a medium level of diesel oil use emit 0.192 tons of CO_2-e per ton of FPCM more than farms with a low level of diesel oil use. This underscores the importance of carefully considering adjustments to the energy use structure of dairy farms as a potentially effective mitigation measure.

From the perspective of abatement costs, both reducing energy intensity and altering energy structure are cost-effective measures. Compared to farms with high energy intensity, those with low and medium energy intensity can save 143 USD and 132 USD in energy costs

Table 2
Statistics description of variables in models.

Variable	Obs	Mean	Std. dev.	Min	Max
Response variable:					
Enteric fermentation (ton CO_2-e/ton FPCM)	75	0.610	0.352	0.117	2.204
Manure management (ton CO_2-e/ton FPCM)	92	0.351	0.773	0.002	5.567
Energy use (ton CO_2-e/ton FPCM)	94	0.257	0.417	0.002	2.779
Feed input cost (1000 USD/ ton FPCM)	89	0.771	0.616	0.101	3.402
Manure management cost (1000 USD/ton FPCM)	86	0.015	0.056	0.000	0.518
Energy use cost (1000 USD/ ton FPCM)	89	0.046	0.104	0.001	0.825
Explanatory Variable:					
Concentrate inclusion					
Low level (<35%)	93	0.204	0.405	0	1
Medium level (35%–50%)	93	0.430	0.498	0	1
High level (>50%)	93	0.366	0.484	0	1
Forage quality (proportion of corn silage)					
Low level (<50%)	89	0.281	0.452	0	1
Medium level (50%–70%)	89	0.506	0.503	0	1
High level (>70%)	89	0.202	0.404	0	1
Add inhibitors	97	0.216	0.414	0	1
Add oilseeds	97	0.175	0.382	0	1
Returning to farmland directly	97	0.124	0.331	0	1
Storage with covers	97	0.124	0.331	0	1
Storage with no covers	97	0.289	0.455	0	1
Composting only	97	0.124	0.331	0	1
Composting after/and storage	97	0.216	0.414	0	1
Recycling for cow bedding	97	0.124	0.331	0	1
Energy intensity					
Low level	94	0.330	0.473	0	1
Medium level	94	0.330	0.473	0	1
High level	94	0.334	0.476	0	1
Energy structure					
Low level of diesel oil use	94	0.330	0.473	0	1
Medium level of diesel oil use	94	0.330	0.473	0	1
High level of diesel oil use	94	0.340	0.476	0	1
Control variables:					
Enterprise	97	0.784	0.414	0	1
Province					
Inner Mongolia	97	0.845	0.363	0	1
Yunnan	97	0.103	0.306	0	1
Heilongjiang	97	0.052	0.222	0	1
Total stock	97	1722.464	2442.839	3	15,500
Proportion of lactating cows (%)	97	0.333	0.156	0	1
Ln (milk production)	95	6.953	2.489	1.609	10.840
Lactating cow yield (ton/ cow)	97	8.687	3.678	0	27
Forage to concentrate ratio of dairy farms	97	0.334	0.483	0	4.667
Proportion of corn silage in forage of dairy farms	92	0.574	0.222	0.065	1
Numbers of used energy type	97	2.536	0.737	1	4

[1] GHG emissions and the adoption of mitigation measures for dairy farms are analyzed and provided in Supplementary Materials C.

Table 3
GHG abatement costs for feed management measures

<!—Col Count:4—>Variables	Per unit carbon emission (ton CO_2–e/ton FPCM)<!—Para Run–on—>	Per unit cost (1000 USD/ ton FPCM)	Unit carbon reduction cost (USD/ton CO_2–e)
	(1)	(2)	(3)
Concentrate inclusion			
Medium level (35%–50%)	–0.179*	–0.058	–325
	(0.095)	(0.190)	
high level (>50%)	–0.073	–0.004	
	(0.113)	(0.238)	
Forage quality			
Medium level (50–70%)	–0.146	–0.280	
	(0.110)	(0.174)	
High level (>70%)	–0.289**	–0.156	–540
	(0.130)	(0.213)	
Add inhibitors	–0.058	–0.078	
	(0.087)	(0.157)	
Add oilseeds	–0.012	–0.318**	
	(0.089)	(0.152)	
Control variables	Yes	Yes	
Observations	69	83	
Mean variance inflation factor (VIF)	1.84	1.84	
R–squared	0.492	0.278	

Note: Concentrate inclusion refers to the proportion of concentrate to feed diet of lactating cows (diet dry matter basis). Forage quality refers to the proportion of corn silage to the forage of lactating cows (diet dry matter basis). The VIF measures multicollinearity in a multiple regression model, and values below 10 indicate the model does not suffer from severe multicollinearity issues. In this table, the VIF value of each variable and the mean VIF for all variables in regressions are below 10. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

Table 4
GHG abatement costs for energy management measures

Variables	Per unit carbon emission (ton CO_2-e/ton FPCM)	Per unit cost (1000 USD/ton FPCM)	Unit carbon reduction cost (USD/ton CO_2-e)
	(1)	(2)	(3)
Energy intensity			
Low level	−0.600***	−0.143***	−238
	(0.168)	(0.054)	
Medium level	−0.515***	−0.132**	−256
	(0.165)	(0.052)	
Energy structure			
Medium level of diesel oil use	0.192**	0.029	149
	(0.079)	(0.018)	
High level of diesel oil use	0.122	0.040*	
	(0.087)	(0.023)	
Control variables	Yes	Yes	
Observations	94	89	
Mean variance inflation factor (VIF)	1.56	1.56	
R-squared	0.404	0.348	

Note: Energy intensity is measured by the usage of energy by one unit of FPCM. Energy structure is measured by proportion of energy provided by diesel oil in energy use per unit of FPCM. The VIF measures multicollinearity in a multiple regression model, and values below 10 indicate the model does not suffer from severe multicollinearity issues. In this table, the VIF value of each variable and the mean VIF for all variables in regressions are below 10. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

per ton of FPCM, respectively. Correspondingly, reducing energy intensity from a high to a low or medium level can yield emission reduction benefits of 238 USD and 256 USD per ton of CO_2-e, respectively. Additionally, dairy farms employing a medium level of diesel oil incur energy costs that are 29 USD per ton FPCM higher than those utilizing a low level. Thus, reducing diesel oil usage from a medium to a low level can yield emission reduction benefits of 149 USD per ton of CO_2-e emissions reductions.

As shown in Table 5, in the context of manure management measures, compared to dairy farms that recycle manure for cow bedding, four management measures result in significant GHG emissions reductions: returning to farmland directly, storage with covers, composting only, and composting after/and storage. Among these, composting only can achieve the most substantial reduction, lowering emissions by 0.838 tons of CO_2-e per ton of FPCM, and yielding a benefit of 1 USD per ton of CO_2-e emission reduction. In comparison, composting after/and storage significantly reduce emissions by 0.700 tons of CO_2-e per ton of FPCM, with a unit reduction cost of 1 USD per ton of CO_2-e. Composting only can save dairy farms the cost of investing in storage equipment while allowing the sale of composted manure for additional income. Therefore, composting only is a mitigation measure that can achieve both environmental and economic benefits for Chinese dairy farms.

Returning to farmland directly is also a cost-effective mitigation measure. Compared to dairy farms that recycle manure into cow bedding, direct returning to the field can reduce GHG emissions by 0.733 tons of CO_2-e per ton of FPCM. Not only that, adopting this measure can also save costs by 11 USD per ton of CO_2-e emissions reduction for dairy farms.

Lastly, the results confirm that covering manure during storage significantly reduces GHG emissions by 0.688 tons of CO_2-e per ton of FPCM. However, it is important to note that this measure, while effective, is also the most expensive mitigation measure, with a carbon reduction cost of 63 USD per ton of CO_2-e for dairy farms.

Overall, measures from all three categories can effectively reduce GHG emissions from dairy farms (see Fig. 3). Among these effective measures, feed and energy measures are cost-saving, whereas implementing effective manure management measures may result in increased costs for dairy farms. Upon comparison, it is evident that effective feed management measures offer substantial cost savings and should be prioritized as the primary mitigation options. Although implementing two effective manure management measures may incur emission reduction costs, the incurred expenses are considered acceptable, particularly for enterprises.

Table 5
GHG abatement costs for manure management measures

Variables	Per unit carbon emission (ton CO_2-e/ton FPCM)	Per unit cost (1000 USD/ ton FPCM)	Unit carbon reduction cost (USD/ton CO_2-e)
	(1)	(2)	(3)
Returning to farmland directly	−0.733*	−0.008	−11
	(0.404)	(0.009)	
Storage with covers	−0.688*	0.044	63
	(0.402)	(0.046)	
Storage with no covers	−0.693	−0.005	
	(0.422)	(0.005)	
Composting only	−0.838*	−0.001	−1
	(0.488)	(0.010)	
Composting after/ and storage	−0.700*	0.001	1
	(0.354)	(0.005)	
Control variables	Yes	Yes	
Observations	85	85	
Mean variance inflation factor (VIF)	2.54	2.54	
R-squared	0.300	0.124	

Note: The VIF measures multicollinearity in a multiple regression model, and values below 10 indicate the model does not suffer from severe multicollinearity issues. In this table, the VIF value of each variable and the mean VIF for all variables in regressions are below 10. * denotes $p < 0.1$, ** denotes $p < 0.05$, *** denotes $p < 0.01$.

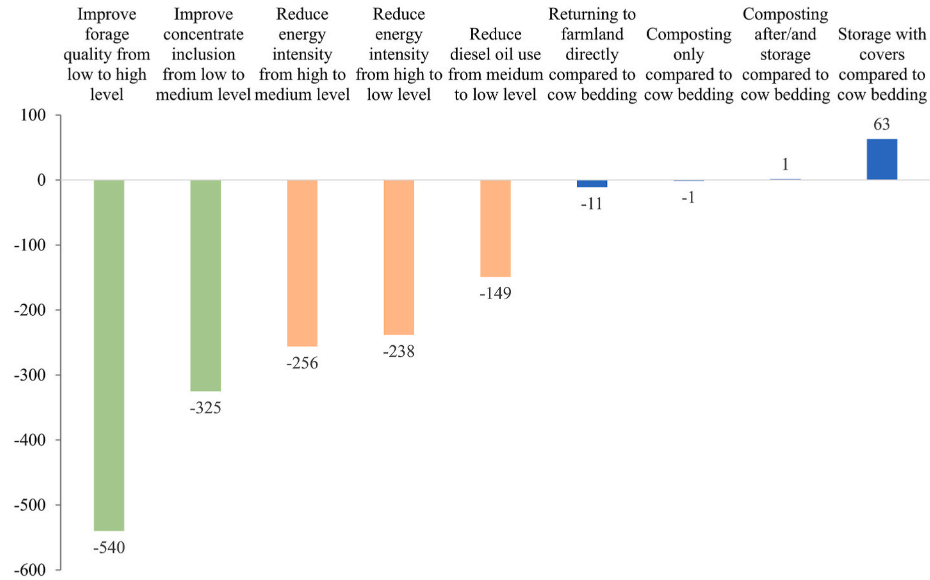

Fig. 3. The marginal mitigation costs for all effective mitigation measures (USD/ton CO_2-e reduction).

4. Discussion

This analytical framework provides a feasible step for analyzing the cost-effectiveness of GHG mitigation measures in the dairy industry. It is based on micro-level data to estimate the cost-effectiveness of mitigation measures. Most existing CEA studies in the dairy industry typically define an average farm based on statistical data, simulating changes in GHG emissions and costs by setting unified parameters and utilizing empirical data from the literature (Cecchini et al., 2018; Dutreuil et al., 2014; Huber et al., 2023; Mosnier et al., 2019; Van Middelaar et al., 2014). The bioeconomic models applied in these studies are relatively complex and require specific, quantitative definitions of each mitigation measure to determine simulated mitigation costs. Meanwhile, the effective measures identified by these studies are often context-specific, tailored to particular regions or countries, and may lack universality. In contrast, the economic analysis framework developed in this study accounts for the heterogeneity of dairy actors. By collecting micro data on actual adoption behavior, this framework can provide more realistic estimates of the effects of mitigation measures, accounting for real market prices and scenarios where multiple measures are implemented simultaneously. Furthermore, the evaluation results by this framework indicate broad applicability, offering actionable suggestions for dairy industry stakeholders to adjust their production and consumption behaviors.

In the case study, enhancing forage quality and increasing concentrate inclusion for lactating cows were identified as the two most cost-effective mitigation measures. They can effectively reduce GHG emissions and lower feed costs. As strategies for modifying feed diet composition, improving forage quality and increasing concentrate content have been widely shown to offer the dual benefits of reducing enteric CH_4 production (Benchaar et al., 2014; Knapp et al., 2014) while improving production efficiency (Gerber et al., 2013; Hristov et al., 2013). Our results indicate that the increased costs of improving forage quality and increasing concentrate inclusion are offset by increased cow productivity. Therefore, these two feed management measures both can decrease feed costs per unit of milk production by increased yields per cow. Duffy et al. (2021) also found that increasing concentrate feed can reduce enteric CH_4 production while decreasing feed costs per unit of milk production for dairy farms in Costa Rica. Similarly, Dutreuil et al. (2014) reported that decreasing the forage-to-concentrate ratio in the diet is cost-effective for grazing and organic farms in Wisconsin. The positive impact on the environment and the potential for economic gains position feed management as a promising avenue for reducing GHG emissions in the dairy industry. In contrast to Doreau et al. (2014), our study did not identify the effectiveness of adding supplements in reducing GHG emissions from enteric fermentation. This lack of conclusive findings could be attributed to the absence of quantitative data on supplement usage. Additionally, our examination focused solely on oilseeds and inhibitors as supplements, leaving the effects of other supplements unexplored. Further research is warranted to comprehensively quantify supplement usage and investigate the impact of additional supplements on GHG emissions.

In the realm of energy management measures, reducing energy intensity and adjusting energy structure to decrease diesel oil use emerged as two economically viable mitigation strategies that can effectively lower energy costs for dairy farms. The reduction of energy intensity can be achieved through various targeted measures, including the adoption of intelligent management software to enhance operational efficiency, as well as the incorporation of energy-saving equipment and technologies. Notably, our survey revealed minimal utilization of clean energy sources, such as solar energy, among the sampled dairy farms. Given the environmental benefits, we recommend emphasizing the optimization of the energy structure by integrating green electricity into dairy farm operations. This shift towards renewable energy aligns with broader strategies for reducing GHG emissions (Djekic et al., 2014).

The differences in mitigation costs are pronounced among various effective manure management measures. Notably, returning manure to farmland directly and composting only stand out as measures that not only effectively reduce GHG emissions but also lead to cost savings for manure management. While composting after/and storage and storage with covers are also effective, they introduce additional costs for dairy farms. Dutreuil et al. (2014) similarly highlighted the cost-effectiveness of adding a 12-month covered storage unit for manure management in conventional farms. This insight empowers dairy producers to make informed decisions, selecting strategies that are both effective in GHG emission reduction and economically viable. It's crucial to recognize that effective manure treatments often involve significant investments in equipment, infrastructure, and labor, potentially straining the financial resources of dairy farms. Moreover, these measures may necessitate adjustments to farm operations, encountering resistance or operational challenges. Achieving the right balance between GHG emission reductions, cost-effectiveness, and practicality is essential for successful manure management in dairy production. Despite potential challenges, the substantial positive environmental impact and long-term sustainability benefits underscore the value and importance of pursuing mitigation measures in manure management for dairy farms.

It is important to note that several sources of uncertainty may cause the estimated cost-effectiveness of the mitigation measures in this case study to differ from the true values. First, our case study relies on random sampling for data collection. Although our survey collected a sufficient number of samples in Inner Mongolia, the samples from Yunnan and Heilongjiang provinces were selected using a simple random sampling method with a limited sample size. Consequently, these samples may lack representativeness to some extent and could introduce statistical random sampling errors. Second, measurement error is another potential source of uncertainty. The data collected were based on the dairy farms' measurements, records, or recalls of production activities and finances. Variations in measurement methods, recording standards, and recall accuracy among dairy farms may lead to discrepancies in the data on GHG emissions and costs. Third, models simplify the real dairy farm production system and, as such, is inherently limited in accuracy. For instance, the methods used to estimate GHG emissions apply uniform parameters, assuming all dairy farms have the same emission activity intensity. This approach overlooks variations in emission activities between farmers and enterprises. Additionally, the regression model we constructed cannot account for all possible influencing factors, such as the organizational management of dairy farms and the skill levels of employees.

The case study is subject to certain limitations. Firstly, utilizing a cross-sectional dataset, the analysis controls for several observed variables; however, the presence of omitted unobserved variables could potentially introduce bias to the results. Future studies are recommended to gather panel data, allowing for the consideration of fixed effects to mitigate bias from time-invariant unobserved variables. An even more robust approach would involve conducting randomized controlled trials, offering a more definitive identification of the cost-effectiveness of mitigation measures. Secondly, expanding the dataset to encompass a more extensive range of dairy farms from diverse milk production regions in China is advisable. This expansion would contribute to incorporating greater heterogeneity in the CEA of mitigation measures. For instance, identifying effective mitigation measures tailored to dairy farms in different regions and production scales would yield more targeted strategies. Lastly, in this case study, the system boundary for the CEA is defined as the dairy farm gate. While dairy farming is a crucial source of GHG emissions within the dairy farm, it is also important to consider the emissions from feed production and the transportation of products to retail locations. Therefore, future research is recommended to follow our analytical framework and LCA principles to provide a more comprehensive estimation of GHG emissions from feed production to retail for dairy farms and to incorporate a broader range of mitigation measures. Moreover, other stages, such as retail and consumption, warrant attention to achieve emission reduction targets within the dairy industry. Therefore, applying our analytical framework to estimate the cost-effectiveness of mitigation measures in other dairy sectors is essential, providing economically feasible and effective strategies for all dairy stakeholders.

5. Conclusion

This study developed a comprehensive framework for conducting a CEA of GHG emission mitigation measures within the dairy industry. This framework provides stakeholders and policymakers with a systematic approach to identify cost-effective GHG mitigation strategies. The analysis process is delineated six essential steps: defining the system boundary, identifying GHG emission sources, identifying potential mitigation measures, determining methods to quantify GHG emissions, collecting data, and analyzing the cost-effectiveness of mitigation measures. Additionally, we applied this analytical framework and utilized field survey data to identify cost-effective mitigation measures for Chinese dairy farms. The findings of the case study reveal highly cost-effective opportunities for GHG mitigation in the Chinese dairy production. The results highlight potential measures to reduce GHG emissions across feed, manure, and energy management. Furthermore, many of these effective mitigation measures offer both environmental and economic benefits.

CRediT authorship contribution statement

Saiwei Li: Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **Mingxue Zhang:** Writing – original draft, Formal analysis, Data curation. **Lingling Hou:** Writing – review & editing, Supervision, Investigation, Conceptualization. **Binlei Gong:** Investigation, Conceptualization. **Kevin Chen:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgement

This research was supported by Consortium of International Agricultural Research Centers (CGIAR) Trust Fund for Mitigate+: Research for Low Emissions Food Systems, and National Nature Science Foundation of China (NSFC 72322008 and NSFC 72348003). We thank Sha Wei for the professional consultation provided on the greenhouse gas calculations and all survey enumerators for data collection.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.122521.

References

Adler, A.A., Doole, G.J., Romera, A.J., Beukes, P.C., 2013. Cost-effective mitigation of greenhouse gas emissions from different dairy systems in the Waikato region of New Zealand. J. Environ. Manag. 131, 33–43. https://doi.org/10.1016/j.jenvman.2013.09.038.

Beldman, A., Pishgar-Komleh, S.H., Termeer, E., 2021. Mitigation Options to Reduce GHG Emissions at Dairy and Beef Farms: Results from a Literature Review and Survey on Mitigation Options Currently Being Used within the Network of the Sustainable Agriculture Initiative Platform (SAI Platform). Wageningen Economic Research. https://doi.org/10.18174/554786.

Benchaar, C., Hassanat, F., Gervais, R., Chouinard, P.Y., Petit, H.V., Massé, D.I., 2014. Methane production, digestion, ruminal fermentation, nitrogen balance, and milk production of cows fed corn silage- or barley silage-based diets. J. Dairy Sci. 97 (2), 961–974. https://doi.org/10.3168/jds.2013-7122.

Burke, D.T., Hynds, P., Priyadarshini, A., 2023. Quantifying farm-to-fork greenhouse gas emissions for five dietary patterns across Europe and North America: a pooled analysis from 2009 to 2020. Resour. Environ. Sust. 12, 100108. https://doi.org/10.1016/j.resenv.2023.100108.

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. J. Environ. Manag. 352, 119904. https://doi.org/10.1016/j.jenvman.2023.119904.

CC-ME (Competence Centre on Microeconomic Impact Evaluation), 2019. Cost Effectiveness Analysis: Methodology for the Food Chain Area, EUR 29659 EN. Publications Office of the European Union, Luxembourg. https://doi.org/10.2760/270802.

Cecchini, L., Venanzi, S., Pierri, A., Chiorri, M., 2018. Environmental efficiency analysis and estimation of CO_2 abatement costs in dairy cattle farms in Umbria (Italy): a SBM-DEA model with undesirable output. J. Clean. Prod. 197, 895–907. https://doi.org/10.1016/j.jclepro.2018.06.165.

Clark, M.A., Domingo, N.G., Colgan, K., Thakrar, S.K., Tilman, D., Lynch, J., Azevedo, I. L., Hill, J.D., 2020. Global food system emissions could preclude achieving the 1.5

and 2 C climate change targets. Science 370 (6517), 705–708. https://doi.org/10.1126/science.aba7357.

Crumpler, K., Abi Khalil, R., Tanganelli, E., Rai, N., Roffredi, L., Meybeck, A., Umulisa, V., Wolf, J., Bernoux, M., 2021. 2021 (Interim) Global update report – agriculture, forestry and fisheries in the nationally determined contributions. Environment and Natural Resources Management. Working Paper No. 91. Rome. FAO. https://doi.org/10.4060/cb7442e.

Defra, 2004. Cost curve of nitrate mitigation options. Defra Report No. NT2511. Institute of Grassland and Environmental Research (IGER), Devon, UK.

Djekic, I., Miocinovic, J., Tomasevic, I., Smigic, N., Tomic, N., 2014. Environmental life-cycle assessment of various dairy products. J. Clean. Prod. 68, 64–72. https://doi.org/10.1016/j.jclepro.2013.12.054.

Doreau, M., Bamière, L., Pellerin, S., Lherm, M., Benoit, M., 2014. Mitigation of enteric methane for French cattle: potential extent and cost of selected actions. Anim. Prod. Sci. 54 (9), 1417–1422. https://doi.org/10.1071/AN14207.

Duffy, C., Apdini, T., Styles, D., Gibbons, J., Peguero, F., Arndt, C., Mazzetto, A., Vega, A., Chavarro-Lobo, J.A., Brook, R., Chadwick, D., 2021. Marginal abatement cost curves for Latin American dairy production: a Costa Rica case study. J. Clean. Prod. 311, 127556. https://doi.org/10.1016/j.jclepro.2021.127556.

Dutreuil, M., Wattiaux, M., Hardie, C.A., Cabrera, V.E., 2014. Feeding strategies and manure management for cost-effective mitigation of greenhouse gas emissions from dairy farms in Wisconsin. J. Dairy Sci. 97 (9), 5904–5917. https://doi.org/10.3168/jds.2014-8082.

Eckard, R.J., Grainger, C., de Klein, C.A.M., 2010. Options for the abatement of methane and nitrous oxide from ruminant production: a review. Livest. Sci. 130 (1), 47–56. https://doi.org/10.1016/j.livsci.2010.02.010.

Edjabou, L.D., Smed, S., 2013. The effect of using consumption taxes on foods to promote climate friendly diets—the case of Denmark. Food Pol. 39, 84–96. https://doi.org/10.1016/j.foodpol.2012.12.004.

Eory, V., Topp, C.F.E., Moran, D., 2013. Multiple-pollutant cost-effectiveness of greenhouse gas mitigation measures in the UK agriculture. Environ. Sci. Pol. 27, 55–67. https://doi.org/10.1016/j.envsci.2012.11.003.

Eory, V., MacLeod, M., Topp, C.F.E., Rees, R.M., Webb, J., McVittie, A., Wall, E., Borthwick, F., Watson, C.A., Waterhouse, A., Wiltshire, J., Bell, H., Moran, D., Dewhurst, R.J., 2015. Review and update the UK agriculture MACC to assess the abatement potential for the 5th carbon budget period and to 2050: Final report submitted for the project contract "Provision of services to review and update the UK agriculture MACC and to assess abatement potential for the 5th carbon budget period and to 2050". Prepared for the Climate Change Committee. https://www.theccc.org.uk/publication/scotlands-rural-collage-sruc-ricardo-energy-and-environment-2015-review-and-update-of-the-uk-agriculture-macc-to-assess-abatement-potential-for-the-fifth-carbon-budget-period-and-to-2050/. (Accessed 13 May 2024).

FAO (Food and Agriculture Organization), 2010. Greenhouse gas emissions from the dairy sector: a life cycle assessment. Rome, Italy. https://www.uncclearn.org/wp-content/uploads/library/fao149.pdf. (Accessed 13 May 2024).

FAO (Food and Agriculture Organization), 2017. Livestock Solutions for Climate Change. Rome, Italy. https://www.fao.org/3/i8098e/i8098e.pdf.

FAO (Food and Agriculture Organization) and GDP (Global Dairy Platform), 2018. Climate change and the global dairy cattle sector – the role of the dairy sector in a low-carbon future. Licence: CC BY-NC-SA- 3.0 IGO. https://openknowledge.fao.org/server/api/core/bitstreams/8749a956-0725-414f-8c35-58a5db0c2b5c/content. (Accessed 13 May 2024).

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.

Feng, X., Kebreab, E., 2020. Net reductions in greenhouse gas emissions from feed additive use in California dairy cattle. PLoS One 15 (9), e0234289. https://doi.org/10.1371/journal.pone.0234289.

Gerber, P.J., Henderson, B., Makkar, H.P.S., 2013. Mitigation of Greenhouse Gas Emissions in Livestock Production: A Review of Technical Options for non-CO_2 Emissions. FAO. https://openknowledge.fao.org/server/api/core/bitstreams/c655a3d2-7d4b-49d6-8362-2752c0a28ae7/content. (Accessed 13 May 2024).

Gryze, S.D., Wolf, A., Kaffka, S.R., Mitchell, J., Rolston, D.E., Temple, S.R., Lee, J., Six, J., 2010. Simulating greenhouse gas budgets of four California cropping systems under conventional and alternative management. Ecol. Appl. 20 (7), 1805–1819. https://doi.org/10.1890/09-0772.1.

Guzmán-Luna, P., Mauricio-Iglesias, M., Flysjö, A., Hospido, A., 2022. Analysing the interaction between the dairy sector and climate change from a life cycle perspective: a review. Trends Food Sci. Technol. 126, 168–179. https://doi.org/10.1016/j.tifs.2021.09.001.

Havlík, P., Valin, H., Herrero, M., Obersteiner, M., Schmid, E., Rufino, M.C., Mosnier, A., Thornton, P.K., Bottcher, H., Conant, R.T., Frank, S., Fritz, Steffen, Fuss, S., Kraxner, F., Notenbaert, A., 2014. Climate change mitigation through livestock system transitions. Proc. Natl. Acad. Sci. USA 111 (10), 3709–3714. https://doi.org/10.1073/pnas.1308044111.

Herrero, M., Henderson, B., Havlík, P., Thornton, P.K., Conant, R.T., Smith, P., Wirsenius, S., Hristov, A.N., Gerber, P., Gill, M., Butterbach-Bahl, K., Valin, H., Garnett, T., Stehfest, E., 2016. Greenhouse gas mitigation potentials in the livestock sector. Nat. Clim. Change 6, 452–461. https://doi.org/10.1038/nclimate2925.

Hoogwijk, M., du Can, S.D.L.R., Novikova, A., Urge-Vorsatz, D., Blomen, E., Blok, K., 2010. Assessment of bottom-up sectoral and regional mitigation potentials. Energy Pol. 38 (6), 3044–3057. https://doi.org/10.1016/j.enpol.2010.01.045.

Hristov, A.N., Ott, T., Tricarico, J., Rotz, A., Waghorn, G., Adesogan, A., Dijkstra, J., Montes, F., Oh, J., Kebreab, E., Oosting, S.J., Gerber, P.J., Henderson, B., Makkar, H.P.S., Firkins, J.L., 2013. Special topics—mitigation of methane and nitrous oxide emissions from animal operations: III. A review of animal management mitigation options. J. Anim. Sci. 91 (11), 5095–5113. https://doi.org/10.2527/jas.2013-6585.

Huber, R., Tarruella, M., Schäfer, D., Finger, R., 2023. Marginal climate change abatement costs in Swiss dairy production considering farm heterogeneity and interaction effects. Agric. Syst. 207, 103639. https://doi.org/10.1016/j.agsy.2023.103639.

IPCC (Intergovernmental Panel on Climate Change), 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Intergovernmental Panel on Climate Change, Cambridge, UK. https://www.ipcc-nggip.iges.or.jp/public/2006gl/. (Accessed 13 May 2024).

IPCC (Intergovernmental Panel on Climate Change), 2007. Climate Change 2007: the Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK. https://home.iscte-iul.pt/~apad/risco01/textos/ONUClima.pdf. (Accessed 13 May 2024).

IPCC (Intergovernmental Panel on Climate Change), 2019. Summary for policymakers. In: Climate Change and Land: an IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems. https://doi.org/10.1017/9781009157988.001.

IPCC (Intergovernmental Panel on Climate Change), 2021. Climate Change 2021: the Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, p. 2391. https://doi.org/10.1017/9781009157896.

Jian, J., Du, X., Reiter, M.S., Stewart, R.D., 2020. A meta-analysis of global cropland soil carbon changes due to cover cropping. Soil Biol. Biochem. 143, 107735. https://doi.org/10.1016/j.soilbio.2020.107735.

Jiang, P., Khishgee, S., Alimujiang, A., Dong, H., 2020. Cost-effective approaches for reducing carbon and air pollution emissions in the power industry in China. J. Environ. Manag. 264, 110452. https://doi.org/10.1016/j.jenvman.2020.110452.

Knapp, J.R., Laur, G.L., Vadas, P.A., Weiss, W.P., Tricarico, J.M., 2014. Invited review: enteric methane in dairy cattle production: quantifying the opportunities and impact of reducing emissions. J. Dairy Sci. https://doi.org/10.3168/jds.2013-7234.

Kok, R., Annema, J.A., van Wee, B., 2011. Cost-effectiveness of greenhouse gas mitigation in transport: a review of methodological approaches and their impact. Energy Pol. 39 (12), 7776–7793. https://doi.org/10.1016/j.enpol.2011.09.023.

Lovarelli, D., Tamburini, A., Garimberti, S., D'Imporzano, G., Adani, F., 2022. Life cycle assessment of Parmigiano Reggiano PDO cheese with product environmental footprint method: a case study implementing improved slurry management strategies. Sci. Total Environ. 842, 156856. https://doi.org/10.1016/j.scitotenv.2022.156856.

MacLeod, M., Eory, V., Gruère, G., Lankoski, J., 2015. Cost-effectiveness of greenhouse gas mitigation measures for agriculture: a literature review. OECD Food, Agriculture and Fisheries Papers. OECD Publishing, Paris. https://doi.org/10.1787/5jrvvkq900vj-en.

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: UK agricultural greenhouse gas emissions. J. Agric. Econ. 62 (1), 93–118. https://doi.org/10.1111/j.1477-9552.2010.00268.x.

Mosnier, C., Britz, W., Julliere, T., De Cara, S., Jayet, P.A., Havlík, P., Frank, S., Mosnier, A., 2019. Greenhouse gas abatement strategies and costs in French dairy production. J. Clean. Prod. 236, 117589.

National Bureau of Statistics, 2023. 2022 China Rural Statistical Yearbook (Chinese).

O'Brien, D., Markiewicz-Keszycka, M., Herron, J., 2023. Environmental impact of grass-based cattle farms: a life cycle assessment of nature-based diversification scenarios. Resour. Environ. Sust. 14, 100126. https://doi.org/10.1016/j.resenv.2023.100126.

Sapkota, T.B., Vetter, S.H., Jat, M.L., Sirohi, S., Shirsath, P.B., Singh, R., Jat, H.S., Smith, P., Hillier, J., Stirling, C.M., 2019. Cost-effective opportunities for climate change mitigation in Indian agriculture. Sci. Total Environ. 655, 1342–1354. https://doi.org/10.1016/j.scitotenv.2018.11.225.

Sims, R.E., Rogner, H.H., Gregory, K., 2003. Carbon emission and mitigation cost comparisons between fossil fuel, nuclear and renewable energy resources for electricity generation. Energy Pol. 31 (13), 1315–1326. https://doi.org/10.1016/S0301-4215(02)00192-1.

Sotiriou, C., Michopoulos, A., Zachariadis, T., 2019. On the cost-effectiveness of national economy-wide greenhouse gas emissions abatement measures. Energy Pol. 128, 519–529. https://doi.org/10.1016/j.enpol.2019.01.028.

Teamah, H.M., Kabeel, A.E., Teamah, M., 2022. Potential retrofits in office buildings located in harsh Northern climate for better energy efficiency, cost effectiveness, and environmental impact. Process Saf. Environ. Protect. 162, 124–133. https://doi.org/10.1016/j.psep.2022.03.067.

Tietenberg, T., Lewis, L., 2001. Environmental and Natural Resource Economics. Routledge.

Tullo, E., Finzi, A., Guarino, M., 2019. Review: environmental impact of livestock farming and Precision Livestock Farming as a mitigation strategy. Sci. Total Environ. 650, 2751–2760. https://doi.org/10.1016/j.scitotenv.2018.10.018.

Van Middelaar, C.E., Dijkstra, J., Berentsen, P.B.M., De Boer, I.J.M., 2014. Cost-effectiveness of feeding strategies to reduce greenhouse gas emissions from dairy farming. J. Dairy Sci. 97 (4), 2427–2439. https://doi.org/10.3168/jds.2013-7648.

Warner, D., Bannink, A., Hatew, B., Van Laar, H., Dijkstra, J., 2017. Effects of grass silage quality and level of feed intake on enteric methane production in lactating dairy cows. J. Anim. Sci. 95 (8), 3687–3699. https://doi.org/10.2527/jas.2017.1459.

Wei, S., Ledgard, S., Fan, J., Tian, Y., Dong, H., 2024. Carbon footprints, mitigation effects and economic performance of dairy farm systems in Inner Mongolia. Agric. Syst. 214, 103835. https://doi.org/10.1016/j.agsy.2023.103835.

Wu, X., Harrison, R.M., Chen, M., Wang, T., Lyu, R., Peng, S., Liu, R., Chen, Y., Fang, Y. R., Yang, P., 2024. Assessing climate/air quality synergies and cost-effectiveness for Beijing transportation: insights into sustainable development. Sustain. Cities Soc. 104, 105296. https://doi.org/10.1016/j.scs.2024.105296.

Xu, T., Flapper, J., 2011. Reduce energy use and greenhouse gas emissions from global dairy processing facilities. Energy Pol. 39 (1), 234–247. https://doi.org/10.1016/j.enpol.2010.09.037.

Zhang, C., Hu, M., Yang, X., Amati, A., Tukker, A., 2020. Life cycle greenhouse gas emission and cost analysis of prefabricated concrete building façade elements. J. Ind. Ecol. 24 (5), 1016–1030. https://doi.org/10.1111/jiec.12991.