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Benchmarking Climate Efficiency in UK Cattle Farming: Lessons for Emissions Mitigation in Emerging Agricultural Economies

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Abstract

The livestock sector remains a significant contributor to global greenhouse gas (GHG) emissions, particularly through cattle production. This study evaluates the climate efficiency of the United Kingdom's cattle meat sector between 2016 and 2021 using the Data Envelopment Analysis (DEA) under a Constant Returns to Scale (CRS) model. Key input variables included agricultural land use, emission intensity, methane emissions, and total animal emissions, while cattle meat production served as the output variable. The analysis reveals that, despite fluctuations, average efficiency scores remained below the optimal threshold, indicating that up to 4.33% of land and 7.06% of emissions intensity could potentially be reduced without compromising output. The study identifies 2020 as the only fully efficient year, while the remaining years exhibit varying degrees of inefficiency. These findings underscore opportunities for resource optimization and mitigation within the UK cattle sector. Drawing from the UK's policy experience, this study discusses implications for developing countries, particularly Indonesia, where livestock-related GHG emissions continue to rise. The results support the need for targeted interventions, such as emission-efficient feed strategies and improved land use practices, as part of broader Net-Zero commitments.

Subject Areas

Agronomy, Environmental Economics

Keywords

Climate Efficiency, Data Envelopment Analysis, Cattle Production, Methane Emissions, Agricultural Policy, United Kingdom, Indonesia

1. Introduction

1.1. Agriculture

Agriculture substantially contributes to global greenhouse gas (GHG) emissions. In 2020, emissions of methane (CH_4) and nitrous oxide (N_2O) from agricultural activities constituted over 13% of global greenhouse gas emissions, excluding those from Land Use, Land Use Change, and Forestry (LULUCF) or forestry and other land use (FOLU) (FAO, 2021) [1].

The world Warming Potential over 100 years (GWP-100) has been used in recent studies, and the results imply that the production of cattle is responsible for around 11% to 17% of the world greenhouse gas emissions. However, there is still a significant amount of ambiguity over the veracity of the data that is being used, particularly with regard to the emissions of methane from enteric fermentation, the emissions of carbon dioxide from grazing lands, and the changes in land use that are being caused by animal agriculture (Lauk *et al.*, 2024) [2]. Although the Food and Agriculture Organization (FAO) has just produced a revised estimate that suggests fewer emissions connected to livestock in comparison to past assessments, this does not indicate that there has been a genuine reduction in emissions. According to the Food and Agriculture Organization of the United Nations (FAO), changes in methodology hinder direct comparison with earlier data. A rising trend is indeed revealed by supplementary data from the FAO: between the years 2015 and 2020, enteric methane emissions climbed by 4%, while emissions from manure management increased by 5%. Estimates of the total contribution that livestock makes to global greenhouse gas emissions continue to suffer from significant variation. Currently, the Food and Agriculture Organization (FAO) estimates that this contribution is 11.1%, but studies that have been analyzed by experts in the field show that it might be as high as 19.6% (FAO, 2021) [1]. Considering this diversity, precisely estimating emissions from livestock is a challenging task, and there is an urgent need for standardized procedures and enhanced data gathering.

1.2. Greenhouse Gas Emissions

According to **Figure 1**, which shows that amounting to 46.3 $MtCO_2e$ annually, agriculture is accountable for 10% of the total GHG emissions in the United Kingdom in 2019. Transport (27%), energy supply (21%), business (17%), and residential sectors (15%) had higher emissions than agriculture. The most significant greenhouse gas (GHG) released from agriculture was methane from ruminants (56%), followed by nitrous oxide from fertilizers (31%), and carbon dioxide predominantly from energy and fuel (13%). In the United Kingdom, 47% of methane emissions, 68% of nitrous oxide emissions, and roughly 2% of carbon dioxide emissions are caused by agriculture. All governments are required to report annually on their progress toward internationally agreed-upon GHG reduction targets. The GHG National Inventory serves as the instrument employed for this purpose. Farm enterprises are not categorized within a single inventory; their operations can be divided into four distinct inventories: Agriculture (e.g., farming), Land

Use, Land Use Change, and Forestry (LULUCF) (e.g., tree planting), Energy (e.g., solar panels or wind turbines), and Waste (e.g., slurry management) (AHDB, 2024) [3].

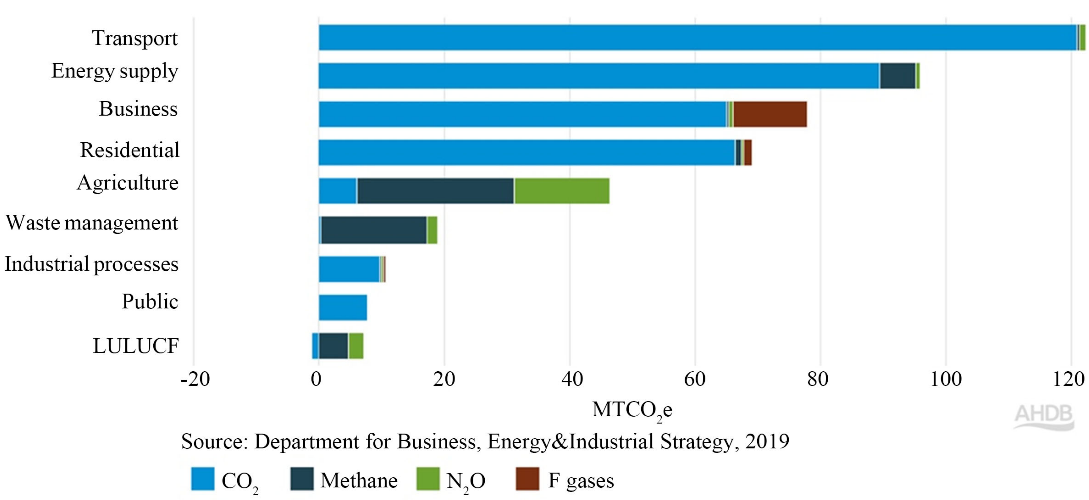

Figure 1. Total UK territorial GHG emission by gas and sector.

The world's population is expected to reach 10 billion people by the middle of the century, and as diets change to include more meat, emissions from livestock production are expected to increase even more. The consumption of meat from ruminant animals, including cattle, is expected to rise by over 90% by the year 2050. (Ivanovich *et al.*, 2023) [4]. Even if all non-food system emissions are promptly eliminated, it is anticipated that emissions from the food system alone will cause global warming to exceed 1.5˚C if current food demand and production patterns persist. The consumption of dairy and beef is anticipated to contribute over fifty percent of future warming associated with the food system, with emissions from meat production alone projected to result in a temperature increase of 0.2˚C - 0.44˚C by the century's end (FAO, 2013) [5].

The primary sources of GHG emissions from European beef and dairy cow production include enteric methane (CH_4) breathed directly by the animals, as well as nitrous oxide (N_2O) and carbon dioxide (CO_2) produced during feed production. The rate of enteric methane excretion is determined by the amount of feed consumed per unit of output, as well as the rate of methanogen digestion. The rate of methanogenesis is influenced by the gut microbiota, which can be genetically altered. Feed emissions are determined by two factors: 1) the feed's emissions intensity (EI) and 2) the feed conversion ratio (FCR), which measures how efficiently the feed is converted into live weight increase or milk (McLeod *et al.*, 2019) [6].

1.3. Data Envelopment Analysis (DEA)

Vlontzos and Pardalos (2017) [7] indicate that many methodologies and data have been employed in studies to substantiate evidence of global warming. They found that surface soil and ocean temperatures have increased, leading to the melting of polar ice caps and elevated sea levels. Consequently, the atmosphere absorbs more water vapor, heightening the probability of unforeseen disasters due to abrupt rainfall. Several researchers have evaluated industrial and agricultural efficiency using the data envelopment analysis (DEA) methodology. Wang (2018) [8] also utilized DEA to evaluate energy and production efficiency in China's industrial sector from 1998 to 2011, while Ray and Ghose (2014) [9] investigated agricultural productivity in India 30 years after the Green Revolution. Bai *et al.* (2019) [10] examined China's agriculture carbon emissions and efficiency from 2000 to 2010.

The main contribution of this study is the application of the Data Envelopment Analysis (DEA) model to evaluate the efficiency of the United Kingdom's greenhouse gas (GHG) emissions, with implications for Indonesia on how to reduce emissions based on the UK's approach. The production of cattle meat, methane emissions, emission intensity, agricultural land usage, and emissions connected to animals are all evaluated using the DEA model. This report offers insights into the UK's greenhouse gas emission efficiency and its advancement towards fulfilling sustainable development objectives, especially in combating climate change. The findings may serve as a benchmark for Indonesia in developing more effective emission-reduction methods.

2. Research Method

The DEA method has been widely used in efficient research in various economic sectors. The optimal combination of each Decision Making unit (DMU) or company can be found using DEA, which does not require a functional definition for the production frontier and eliminates distribution assumptions of inefficiencies (Headey *et al.*, 2010) [11]. The DEA approach allows for a DMU with an efficiency value of one and can identify causes of inefficiency by measuring the potential increase in each input and output (Ramly and Hakim, 2017) [12]. The DEA methodology was evaluated utilising the DEAP Version 2.1 software (Coelli *et al.*, 2005) [13].

Charnes *et al.* (1978) [14] Data Envelopment Analysis (DEA) is a linear programming-based method for estimating the relative technical efficiency of a set of Decision Making Units (DMUs). The DMUs along the frontier are units with a technical efficiency value of one, which is considered best practice.

The output-oriented and input-oriented DEA models will both provide the same efficient DMU according to the results of their respective calculations. The value of efficiency for the model that is oriented toward output will be identical to the value of efficiency for the model that considers input. According to Coelli *et al.* (2008) [15], the input-oriented VRS model will typically have a higher average efficiency value than the input-oriented CRS model at the same level of efficiency. The CRS assumption states that the assumption will be appropriate if all families operate at an optimal scale due to imperfect competition, financial restrictions, and other concerns. This indicates that the assumption will be adequate (Kapsoli *et al.*, 2023) [16].

The efficiency and productivity hypothesis proposed by Banker and Natarajan (2008) [17] serves as a model utilized in nonparametric measurement methods (DEA). DEA is a linear programming application that evaluates the relative efficiency of each production unit in comparison to other units with the same objective. This DEA production unit is known as the Decision Making Unit (DMU), and the focus of this study is on cattle productivity. One of the characteristics of DEA is its ability to measure several inputs and provide multiple outputs. This is DEA's advantage over ratio analysis and multiple regression.

The efficiency score that the DEA generates is between 0 and 1, or 0% and 100%. In comparison to other units, a DMU with a score below one is seen as a particularly inefficient unit. The number of samples used must exceed the number of inputs and outputs in order to distinguish between efficient and inefficient production.

Data Envelopment Analysis, often known as DEA, is a non-parametric technique that is used to evaluate the efficiency of Decision Making Units (DMUs) that have a large number of inputs and outputs. The DMU is allowed to make use of its optimal multiplier weights in standard DEA models, which allows it to improve its efficiency. There are typically multiple effective DMUs that are immune to further discrimination (Qi and Guo, 2014) [18].

Determining suitable weights can be difficult, even when the input and output values for each gas emission can be measured and formulated directly without standardization. Different Decision Making Units (DMUs) may prioritize inputs and outputs differently. To solve this issue, Banker and Natarajan (2008) [17] suggested an optimization strategy based on the Constant Returns to Scale (CRS) model. This strategy allows each DMU to select a set of weights that maximizes its own productivity ratio while ensuring that the productivity ratios of all other DMUs do not exceed a value of one.

c = DMU/production result.

y_{rj} = The value of the r output of the j production.

ij = The value of the i input from the j production.

u_r = The weight chosen for the output r.

v_i = The weight selected for input i.

The assumption of variable returns to scale is not relevant in every efficiency assessment because it is not universally applicable. The Slacks-Based Measure (SBM) model was developed by Tone (2001) [19] in order to address this issue. This approach directly combines input and output slacks into the measurement of efficiency. The SBM model uses a non-radial method, in contrast to conventional radial models, which makes it possible to measure inefficiencies in each input and output separately. The result is a scalar efficiency score that can range from 0 to 1, with a value of 1 indicating that the system is operating at its maximum efficiency. Particularly noteworthy is the fact that the SBM model possesses the characteristics of unit invariance and monotonicity, which guarantees that comparisons made between decision-making units (DMUs) are significant and consistent.

The DEA method identifies inefficiency causes by measuring the possible improvement for each input variable. Before calculating the efficiency scores, the researchers organized the data and set the proper weights for the input and output variables used in this study.

Input and output variables, are too extensive to be presented in this paper; therefore, their statistical descriptions are demonstrated in Table 1. It can be observed from Table 1 that during the period from 2016 to 2021 apart from cattle production in the UK, the means of the other five variables values of emission gases.

Table 1. Input and output variable values of emission gases in the UK 2016-2021.

Variables	Unit	Definitions
Cattle Meat Production (y)	Tons	Total production of cattle meat production
Emissions Intensity (x1)	CO_2e	Total emissions intensity of cattle meat
Agriculture Land Use (x2)	Ha	Total agriculture land use of cattle meat
Methane Emissions (x3)	Kg	Total methane emissions of cattle meat
Animal Emissions (x4)	CO_2e	Total animal emissions of cattle meat

3. Results

The DEA method identifies inefficiency causes by measuring the possible improvement for each input variable. Before calculating the efficiency scores, the researchers organized the data and set the proper weights for the input and output variables used in this study. These weights, which are crucial to the DEA model's evaluation process, are shown in Table 2.

Table 2. Input and output variable values of emission gases in the UK 2016-2021.

DMU	(I) Agriculture Land use (Ha)	(I) Emissions Intensity ($kgCO_2e$/kg meat)	(I) Methane Emissions ($MtCO_2e$)	(I) Animal Emissions ($ktCO_2e$)	(o) Cattle Meat Production (mt)
2016	9,100,000	101.90	60.5	93.12	91.38
2017	9,100,000	101.64	60.9	91.79	90.32
2018	9,060,000	100.03	60.4	89.70	89.67
2019	9,060,000	96.87	60.0	88.43	91.29
2020	8,800,000	93.48	57.5	87.15	93.23
2021	8,800,000	96.22	57.0	87.04	90.46

Furthermore, the input variable data (land use, emission intensity, methane emissions, and animal emission) and output variables (cattle meat production) in Table 3 are calculated using the Frontier Analyst DEA Solver application where the model applied is assumption. Based on the results of the analysis obtained in the form of percentage values or efficiency indexes for each DMU (cattle meat production year) can be seen in Table 3 below.

Table 3. Results of calculation of efficiency level of large emission gas year for the period 2016-2021.

No.	DMU	Score	Index	Information
1	2016	94%	0.94	Inefficient
2	2017	93%	0.93	Inefficient
3	2018	93%	0.93	Inefficient
4	2019	96%	0.96	Inefficient
5	2020	100%	1	Efficient
6	2021	97%	0.97	Inefficient

Based on the analysis results in Table 4, it shows the efficiency value for each DMU (meat production year) where there is the DMU that has an efficiency percentage value of 100%, namely in 2020. While inefficient DMUs <100% occurred in 2016, 2017, 2018, 2019, and 2021. In this model, the optimization is to find the maximum output value based on each input. While the scale model used is with the assumption that each increase in input variables will be accompanied by an increase in output variables as well.

Table 4. Input and output variable values of emission gases in the UK 2016-2021.

Year	Variable	Current	Target	Potential Improvement
2016	Agriculture Land use	9,100,000	8,625,167	−5.22%
	Emissions Intensity	101.90	91.62	−10.09%
	Methane Emissions	60.5	56.4	−6.79%
	Animal Emissions	93.12	85.41	−8.27%
	Cattle Meat Production	91.38	91.38	0.00%
2017	Agriculture Land use	9,100,000	8,524,955	−6.32%
	Emissions Intensity	101.64	90.56	−10.90%
	Methane Emissions	60.9	55.74	−8.45%
	Animal Emissions	91.79	84.42	−8.03%
	Cattle Meat Production	90.32	90.32	0.00%
2018	Agriculture Land use	9,060,000	8,464,152	−6.58%
	Emissions Intensity	100.03	89.91	−10.12%
	Methane Emissions	60.4	55.34	−8.43%
	Animal Emissions	89.70	83.82	−6.55%
	Cattle Meat Production	89.67	89.67	0.00%
2019	Agriculture Land use	9,060,000	8,616,610	−4.89%
	Emissions Intensity	96.87	91.53	−5.52%
	Methane Emissions	60.0	56.33	−6.09%
	Animal Emissions	88.43	85.33	−3.51%
	Cattle Meat Production	91.29	91.29	0.00%

Continued

2020	Agriculture Land use	8,800,000	8,800,000	0.00%
	Emissions Intensity	93.48	93.48	0.00%
	Methane Emissions	57.5	57.5	0.00%
	Animal Emissions	87.15	87.15	0.00%
	Cattle Meat Production	93.23	93.23	0.00%
2021	Agriculture Land use	8,800,000	8,538,929	−2.97%
	Emissions Intensity	96.22	90.70	−5.73%
	Methane Emissions	57.0	55.83	−2.06%
	Animal Emissions	87.04	84.56	−2.84%
	Cattle Meat Production	90.46	90.46	0.00%

Based on Table 4, the percentage value of potential improvement has positive and negative values. A positive value means that the value must be increased by a percentage to achieve 100% efficiency. Likewise, a negative value means that the value must be lowered or reduced by a percentage to achieve 100% efficiency. The largest percentage of potential improvement is in the emissions intensity variable in 2017, which is (−10.90%). This means that the emissions intensity variable that occurred in 2017 experienced an increase in emission intensity where to achieve 100% efficiency, the amount of emission intensity needed is only 90.56 (kgCO_2e/kg meat) from the actual value of 101.64 (kgCO_2e/kg meat).

Based on the data from Table 5 and the DEA (Data Envelopment Analysis) calculation, it can be concluded that none of the input variables meet the efficient criteria. Each of the efficiency levels is below 100%, which indicates that the agricultural land use, emission intensity, methane emissions, and animal emissions are all inefficient in relation to meat production from 2016 to 2021.

That none of these variables are considered efficient suggests that there is potential for improving the use of resources and emissions in meat production. Efficiency improvements in any of these areas could lead to more sustainable production practices. This inefficiency across the board may point to areas where improvements could be made, such as optimizing land use, reducing emissions, or improving animal farming practices to become more sustainable.

The results of this study indicate that the efficiency of large-scale cattle meat production in the UK for the period 2016-2021 fluctuated during the period. From the results of the efficiency analysis using the DEA method, variations in the efficiency of large-scale cattle meat production were caused by the difference between the actual value and the target value (potential improvement). It is known that there are five periods of high-volume cattle meat inefficiency in 2016, 2017, 2018, 2019, and 2021. In agreement with the findings of study carried out by Khunchaikarn *et al.* (2022) [20], these findings imply that the production of beef cattle in Thailand is inefficient on a very large scale. Production of beef cattle in Thailand is suffering diseconomies of scale, and the output does not increase in proportion to changes in the number of inputs used. In the production of beef cattle, significant economic inefficiency can mostly be attributed to the low AE and the poor allocation of resources.

Table 5. Input and output variable values of emission gases in the UK 2016-2021.

Year	Potential Improvement				
	Input				Output
	Agriculture Land use	Emissions Intensity	Methane Emissions	Animal Emissions	Cattle Meat Production
	−5.22%	−10.09%	−6.79%	−8.27%	0.00%
	−6.32%	−10.90%	−8.45%	−8.03%	0.00%
	−6.58%	−10.12%	−8.43%	−6.55%	0.00%
	−4.89%	−5.52%	−6.09%	−3.51%	0.00%
	0.00%	0.00%	0.00%	0.00%	0.00%
	−2.97%	−5.73%	−2.06%	−2.84%	0.00%
Average	**−4.33%**	**−7.06%**	**−5.30%**	**−4.87%**	**0.00%**
Efficient	**95.67%**	**92.94%**	**94.7%**	**95.13%**	**100.00%**

The difference between the actual value and the target value (potential improvement) contained shows a large potential improvement value, namely the Emissions Intensity variable (input) in 2017 of −10.90%. In other words, the large difference in Emissions Intensity of 11.08 kgCO_2e/kg cattle meat production is an increase in emission intensity that occurred in 2017, while on the side of the cattle meat production variable (output), the potential improvement value is 0.00% which means that the amount of production can be increased again to achieve production efficiency in 2017.

The emission intensity in 2017 cannot be considered in isolation from government policy, which has been an essential factor in supporting the efforts of the United Kingdom to reduce emissions of greenhouse gases. To achieve net zero emissions by the year 2050, the United Kingdom is resolutely committed. Consequently, any greenhouse gases that have not yet been removed from the atmosphere must be matched by removals from the atmosphere by that time. This is done with the intention of limiting global warming and mitigating climate change. Emissions of greenhouse gases should be reduced to 43 percent below their levels in 2005 by the year 2030, which is a significant interim aim. This is implemented as a point target for a single year, and it is supplemented with a multi-year emissions budget for the period 2021 to 2030, specifically with an indicative cap of 4,381 million tonnes of CO_2 equivalent. The goal of reducing things by 43 percent is met by this budget.

The climate change act of 2008 serves as the legislative basis for these promises to the environment. This legislation compels adaptation to the hazards posed by climate change and establishes legally enforceable targets for the reduction of emissions.

The agriculture sector is also contributing to the reduction of emissions through the implementation of livestock management practices. The amount of methane produced by feedlot cattle is lower per unit of feed ingested, despite the fact that they consume more feed on a daily basis than pasture-raised cattle will. Methane emissions from cattle can be reduced by the use of grain feeding, which has been demonstrated to be a successful method. As a result, grain feeding is a helpful tool in the larger endeavor to reduce greenhouse gas emissions.

Technological efficiency and greenhouse gas emissions, Ricciardi *et al.* (2021) [21] discovered that there was no discernible difference between small and large farms in their meta-analysis. There is a spatially diverse and country-specific manner in which the relationship between technical efficiency, greenhouse gas emissions, and farm size (measured in hectares) emerges. The utilization of resources is more efficient in nations where large farms are more prevalent, such as the United States of America, yet in countries where small family farms are more prevalent, such as India, those farms are more efficient. Life Cycle Analysis (LCA) data from ten dairy farms in Umbria, Italy, were combined with the SBM–DEA model with unwanted outputs to estimate the farms' potential for emission reduction and environmental efficacy. The effectiveness of crop production systems in Zhejiang Province, China, was investigated by Dong *et al.* (2018) [22] using this methodology. In order to assess the environmental impact of 169 wheat farms located in the northern region of Iran, a combination of environmental life cycle assessment (LCA) and decision analysis (DEA) was utilized (Mohammadi *et al.*, 2022) [23].

DEA method identifies methane emissions as an inefficient input variable, with a possible efficiency increase of −8.45%. This is in addition to the fact that emission intensity is also involved in the model. Methane (CH_4) is a highly potent greenhouse gas, with a global warming potential that is roughly 80 times more than that of carbon dioxide (CO_2) over a period of twenty years, and approximately 30 times greater over a period of one hundred years. Methane, which is the second most important greenhouse gas after carbon dioxide, has been responsible for around twenty percent of the direct radiative forcing that has occurred since the year 1750 (Forster *et al.*, 2021) [24]. Reducing emissions of methane is one of the most effective and cost-efficient measures for limiting the increase in global temperature to 1.5 degrees Celsius. At both the domestic and international levels, the United Kingdom has shown that it is a leader in the fight against methane emissions. The United Kingdom had a significant role in galvanizing global pledges to methane reduction while it was serving as the COP Presidency. Methane emissions in the United Kingdom decreased by 62% between 1990 and 2020, making it the country with the biggest reduction among OECD countries (Brown, 2022) [25]. Approximately thirteen percent of the net greenhouse gas emissions in the United Kingdom are currently accounted for by methane.

The government of the United Kingdom is committed to additional reductions through its Net Zero Strategy and adherence to legally mandated carbon budgets (Pareliussen *et al.*, 2022) [26], with a long-term vision that extends to the year 2050. This commitment represents the government's recognition of the ongoing urgency on the issue.

4. Research Implications

4.1. Greenhouse Gas Emissions Indonesia

The emissions of greenhouse gases (GHG) in Indonesia, excluding land use, land-use change, and forestry (LULUCF), grew by 193% between 1990 and 2019, reaching 933 $MtCO_2e$ yearly. The percentage of total emissions that were attributable to energy-related emissions increased from 59% to 67% during this time period, making it the sector with the highest increase in emissions overall. Notably, emissions from the trash sector increased dramatically, going from just 6 $MtCO_2e$ in 1990 to surpassing emissions from industrial processes by 1998 and then surpassing agriculture by 2013 to become the second-largest source of greenhouse gas emissions (Gütschow *et al.*, 2021) [27].

4.2. Agricultural in Indonesia

Rice cultivation, enteric fermentation, and the management of livestock waste are the key sources of greenhouse gas emissions that are produced by the agricultural sector in Indonesia. The implementation of targeted interventions in these areas is necessary in order to align with a climatic trajectory that is consistent with limiting global warming to 1.5 degrees Celsius. More specifically, the improvement of rice farming techniques and the modification of cow feed in order to reduce methane production are of particular importance. Compared to the levels in 2010, methane emissions from agricultural production need to decrease by ten percent by the year 2030 and by thirty-five percent by the year 2050. Similarly, 10% must be cut by 2030 and 20% by 2050 in nitrous oxide emissions, which are mostly caused by manure and fertilizer use (Rogelj *et al.*, 2018) [28].

Rice cultivation accounts for 43 percent of greenhouse gas (GHG) emissions in Indonesia's agricultural sector, followed by enteric fermentation in cattle at 21 percent, and animal manure management at 20 percent. The use of organic fertilizers, the implementation of improved irrigation techniques (such as alternate wetting and drying), the application of fertilizer in a more effective manner, and the reduction of food waste are all potential ways to drastically cut emissions from this sector. The Food and Agriculture Organization (FAO) has recently altered its classification of emissions from drained organic soils and the cultivation of organic soils. This is a significant development that should be brought to your attention. Indicators that were used in the past may not have taken into consideration the land-use change component that is now regarded to be a part of these emissions. As a consequence of this, these emissions have been omitted from the dataset that is currently being used (FAO, 2022) [29].

4.3. Policy Greenhouse Gas Emissions in the UK

A legally enforceable goal to attain Net Zero greenhouse gas (GHG) emissions by the year 2050 was adopted by the United Kingdom in the first year of 2019. This commitment is reflected in the Sixth Carbon Budget, which establishes the emissions envelope for the years 2033-2037. The Sixth Carbon Budget requires enhanced ambition across all sectors, including agriculture and land use (Eory *et al.*, 2020) [30]. Methane from ruminant cattle is the most common greenhouse gas (GHG) that is released into the atmosphere by the agricultural sector. It is responsible for 56% of all agricultural emissions. Following this are emissions of nitrous oxide, which are caused by the application of fertilizer (31%), and emissions of carbon dioxide, which are principally caused by the use of energy and fuel on the farm (13%). It is estimated that agriculture is responsible for 45 percent of the overall methane emissions in the United Kingdom, as well as 68 percent of the country's nitrous oxide emissions, but just two percent of the nation's carbon dioxide emissions (Mason *et al.*, 2021) [31]. Annual reports that demonstrate compliance with international greenhouse gas reduction targets are required to be submitted by every government. The GHG National Inventory, which works as the official reporting system, is the one responsible for managing this in the United Kingdom. However, agricultural activities are not limited to a single inventory category; rather, they may encompass four distinct sectors: agriculture (for example, crop and livestock production), land use, land use change and forestry (LULUCF) (for example, afforestation), energy (for example, the utilization of solar panels or wind turbines), and waste (for example, the management of slurry or manure) (AHDB, 2024) [3].

4.4. Policy Greenhouse Gas Emissions in Indonesia

Indonesian government policies for reducing greenhouse gas emissions to mitigate the negative impacts of greenhouse gases, the Indonesian government has undertaken various strategic initiatives, including reducing greenhouse gas emissions, enhancing energy efficiency, and developing renewable energy sources. Since 2016, research efforts in the agricultural sector have been carried out to support the achievement of national greenhouse gas emission reduction targets. Key policies implemented by the Indonesian government to reduce greenhouse gas emissions include:

- Utilization of new and renewable energy sources.
- Adoption of energy-efficient equipment.
- Use of non-fossil-based fuels.
- Sustainable waste management and processing.
- Application of environmentally friendly technologies.
- Development of green infrastructure.
- Implementation of carbon tax policies.

These policies aim to accelerate the transition toward more sustainable, low-emission development pathways, while also contributing to global efforts to combat climate change.

This study holds several important implications for efforts to reduce greenhouse gas (GHG) emissions in Indonesia:

1) Policy Support: It highlights the critical role of government policies in supporting the achievement of reduced emission intensity across sectors in Indonesia. Strategic policy interventions are essential to guide and incentivize sustainable practices.

2) Net-Zero Commitment: The findings align with the Indonesian government's commitment to achieving net-zero emissions by 2050. This long-term goal requires coordinated action and continuous progress monitoring.

3) Strengthening Commitments: The study underscores the need for a strong and consistent commitment to reducing GHG emissions, both at national and sub-national levels.

4) Enhancing Reduction Efforts: It encourages the government and stakeholders to intensify efforts to securing further emission reductions through innovation, investment in clean technologies, and improved energy efficiency.

5. Conclusion

Based on the results of the descriptive analysis of the description of cattle meat production in the UK from 2016 to 2021, production (output) continues to increase and decrease, but production factors such as: agricultural land use, emission intensity, methane emissions, and animal emissions (input) have increased and decreased (fluctuation). The results of the efficiency calculation using the DEA model show that the average level of efficiency of agricultural land use for cattle meat production in the UK for the 2016-2021 period is 95.67% (inefficient). This condition is explained by the average value of the potential increase in land area of −4.33%. The results of the efficiency calculation using the DEA model show that the average level of efficiency of emissions intensity for cattle meat production in the UK for the 2016-2021 period is 92.94% (inefficient). This condition is explained by the average value of the potential increase in emissions intensity of -7.06%. The results of the efficiency calculation using the DEA model show that the average level of efficiency of methane emissions on cattle meat production in the UK for the period 2016-2021 is 94.7% (inefficient). This condition is explained by the average value of the potential increase in methane emissions of −5.30%. The results of the efficiency calculation using the DEA model show that the average level of efficiency of animal emissions on cattle meat production in the UK for the period 2016-2021 is 95.13% (inefficient). This condition is explained by the average value of the potential increase in animal emissions of −4.87%.

6. Recommendation

This paper explores the development of animal husbandry in the United Kingdom and examines its potential implications for developing countries. Although various constraints make it difficult to obtain reliable data from developing countries for a direct comparison with the UK, the UK's experience remains a valuable point of reference, particularly for countries such as Indonesia. Future research, contingent upon the availability of more accurate data, is encouraged to conduct more detailed comparative analyses. Such studies could help clarify the specific differences and contextual factors shaping animal husbandry practices in the UK and developing countries.

Conflicts of Interest

The authors declare no conflicts of interest.

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