How does extended grassland-based dairy production affect energy productivity and GHG emission intensity? Trade-offs in milk-specialised farms

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Abstract:

This study examines how the share of grassland shapes the relationship between energy productivity and greenhouse gas (GHG) emission intensity in Polish milk-specialised farms operating under mixed-forage systems. The analysis uses a balanced panel of dairy farms observed from 2014 to 2022 in the Polish FADN database. In the first stage, farm-level GHG estimates are used together with FADN input and output data to construct Hicks-Moorsteen indices of energy productivity change and GHG emission-intensity change. In the second stage, the causal effect of grassland share is identified using the Generalised Propensity Score combined with Generalised Additive Models. The results indicate that energy productivity generally increases with the grassland share, although the effect is non-linear and strongest at very low and very high levels. GHG emission intensity follows a U-shaped pattern: it declines as grassland share rises to around 50%, then increases at higher shares. The findings suggest a synergy zone at moderate grassland shares and a trade-off when pasture-based production becomes too dominant.

Keywords: dairy farming, grassland share, energy productivity, GHG emission intensity, generalised propensity score

JEL Codes: Q12, D24, Q56

1. Introduction

From a biodiversity perspective, preserving pastureland within grassland ecosystems is of critical importance. Grazing livestock exert a level of grazing pressure that fosters favourable habitat conditions for numerous rare and red-listed species (Nilsson, 2009). Systems characterised by lower grazing intensity can sustain and enhance ecological diversity (Resare Sahlin et al., 2024). However, fully grassland-based milk production requires special geographical conditions, which are rarely found in Central and Eastern European countries such as Poland, where the rural landscape is dominated by plains and field crops. Moreover, Meunier et al. (2025) argue that the growing separation between crop and livestock production can lead to significant environmental issues in Europe, and integrating livestock into crop farming can contribute positively to agri-environmental sustainability. Therefore, there is limited evidence as to what proportion of grassland-based production and arable forage crops is most favourable in terms of environmental performance. Moreover, the relationship between grassland share and environmental performance indicators may be non-linear. A literature review about the benefits and trade-offs in the expansion of grassland-based systems is presented in Table A1 in Appendix.

In Poland, the vast majority of dairy farms operate under a specific mixed-forage system, combining grassland-based production with roughage forage crops on arable land. There is a lack of evidence regarding what proportion of grassland-based production would be optimal in terms of agricultural sustainability. As mentioned above, extensive grassland-based production enhances biodiversity and carbon storage. However, the interplay between grassland share, emissions intensity and energy productivity is more nuanced and has not yet been sufficiently investigated. Recent studies have focused on the environmental impacts and economic efficiency of different forage systems (Gislon et al., 2020; Hou et al., 2022; Cashman et al., 2024), while largely overlooking the potential trade-offs associated with expanding grassland-based milk production, such as lower energy productivity or higher GHG emissions intensity. This study addresses this gap by examining how grassland share jointly affects energy productivity and GHG emission intensity and whether these relationships are non-linear. Its contribution is primarily empirical rather than methodological: it evaluates both outcomes jointly, identifies potential synergies and trade-offs, and provides evidence from Polish mixed-forage dairy farms, a context that remains underrepresented in the literature.

Energy productivity in agriculture is one of the key issues in today's sustainability debate. This is because the agricultural sector, like other industries, is a significant energy consumer and thus shares responsibility for greenhouse gas emissions. In practice, increasing energy productivity means using energy resources more efficiently in agricultural production processes. This translates into reduced fossil fuel consumption, an improved energy mix and reduced farm operating costs (Schneider & Smith, 2008).

Alongside the discussion of energy consumption, the issue of greenhouse gas emission intensity, defined as emissions per unit of agricultural product, is becoming increasingly important (Mrówczyńska-Kamińska et al., 2021). The European Green Deal aims to achieve climate neutrality by 2050 by reducing both direct and indirect emissions (Boix-Fayos & de Vente, 2023). Therefore, both dimensions of energy productivity and emissions intensity must be considered together to capture potential trade-offs and synergies between economic and environmental efficiency (Moutinho et al., 2018).

The main goal of this article is therefore to assess how the share of grassland in utilised agricultural area affects energy productivity and GHG emission intensity in highly specialised dairy farms in Poland operating in mixed-forage systems. To achieve this goal, we evaluate 1530 observations from a balanced panel of 170 dairy farms observed from 2014 to 2022 as part of the Polish Farm Accountancy Data Network (FADN).

Methodologically, the key challenge is that grassland share is a continuous and non-randomly assigned farm characteristic. Farms with low, moderate and high grassland shares may differ systematically in soil quality, natural constraints, location, farm-manager characteristics and other factors that can also affect energy productivity and GHG emission intensity. A simple regression of the outcome indices on grassland share would therefore risk confounding structural differences between farms with the effect attributed to grassland share. For this reason, we treat the share of grassland in utilised agricultural area (GRASS_SHR) as a continuous treatment and apply the generalised propensity score to balance observed covariates across different treatment levels. We then combine GPS-based weighting with generalised additive models to estimate a flexible dose-response relationship, allowing the effect of grassland share to vary non-linearly rather than imposing a linear association.

Empirically, the study combines Hicks–Moorsteen productivity indices with a GPS-GAM dose-response strategy, which is appropriate for analysing a continuous, non-random treatment and for capturing non-linear relationships between grassland share and environmental-energy performance. Although the methods applied are well established, their combined use enables us to examine energy productivity and GHG emission intensity jointly, while accounting for observed differences between farms and the non-linear nature of the relationships.

The choice of dairy production as the subject of analysis is deliberate. Dairy farms are one of the most energy-intensive types of agricultural production, consuming significant amounts of fuel and electricity for processes such as milking, cooling milk and preparing and delivering feed (Upton et al., 2013; Shine et al., 2020). At the same time, they emit large quantities of greenhouse gases, primarily in the form of methane and nitrous oxide, although this depends on the farming practices employed (Gerber et al., 2011). Dairy production therefore provides an ideal "research model": its technological processes are relatively homogeneous, facilitating comparisons between farms and countries, while the sector also generates significant environmental challenges.

Most studies to date have focused on Western European countries with high production intensity, such as the Netherlands, Denmark and Germany (Guerci et al., 2013; Kraatz, 2012; Ang, Kerstens & Sadeghi, 2023), while evidence from the Polish context remains limited. Farms in these countries have already undergone profound structural changes, including a significant reduction in the area of permanent grassland, resulting in specific emission and energy profiles. Unlike these Western European countries, Poland is at a different stage of agricultural development. Dairy production is less intensive, and pasture and grassland still account for a relatively high proportion of agricultural land (Taube et al., 2014). Therefore, the results of the study for Poland have the potential to inform not only national but also international conclusions. Aggregated FADN data for 2023 show that specialist milk farms in the EU generally combine permanent grassland with other utilised agricultural area. At the EU27 level, permanent grassland accounts for 44.7% of total UAA in specialist milk farms, while the corresponding share in Poland is 35.1%. Across Member States with available data, the share ranges from 0.8% in Finland to 97.7% in Ireland, and 20 out of 24 countries fall between 20% and 75%. This indicates substantial heterogeneity in the role of grassland within specialist milk production and suggests that the trade-offs analysed in the Polish mixed-forage context may also be relevant for other European dairy systems. However, these aggregated data are used only to motivate the broader relevance of the research question; they do not provide a basis for cross-country causal inference.

The remainder of the article is organised as follows. Section 2 describes the data, sample selection and variables. Section 3 presents the construction of the Hicks-Moorsteen-based indices, the DEA VRS/FDH frontiers and the GPS-GAM strategy used to estimate dose-response relationships while addressing observed confounding. Section 4 presents the results. Section 5 includes discussion of the results. Section 6 concludes.

2. Data

2.1. Data source and sample selection

This study uses farm-level data from the Farm Accountancy Data Network (FADN), covering the period from 2014 to 2022. Because FADN is not inherently a balanced panel, we first restricted the dataset to farms observed continuously in each year from 2014 to 2022. The resulting analytical dataset contains 170 farms observed over nine years, yielding a balanced panel of 1530 farm-year observations. The dataset was supplemented with additional socio-economic information gathered by the Institute of Agricultural and Food Economics - National Research Institute in Poland. These supplementary data, which are not available in the publicly accessible FADN database, provide additional information for the analysis. The analysis focuses on dairy cattle specialisation, specifically farms classified as type TF-45 according to the TF14 FADN typology. This category encompasses holdings where at least two-thirds of the standard output (SO) is derived from milk production. Before, FADN data have also been used to examine how dairy farms adjust land use and resource management in response to environmental pressures (Buttinelli et al. 2026). For a summary of the data-processing procedure, see Table 1.

Table 1. Data sources, variable construction and use in the empirical analysis

Data block / step	Source	Constructed variables	Role in the analysis	Data processing
Farm accounting data	Polish FADN, 2014-2022	Output, input and cost variables: milk output, meat output, livestock units, land, labour, depreciation, energy costs, other costs	Inputs and outputs in Hicks-Moorsteen / DEA estimation	Balanced panel of milk-specialised TF-45 farms observed over the full 2014-2022 period; restricted to mixed-forage holdings selling only milk and cattle meat, using other agricultural output internally for forage, and excluding fully external-feed and fully grassland-based systems.
Additional farm characteristics	IERiGŻ PIB / additional socio-economic FADN-linked data	LFA, education, agricultural education, soil quality, off-farm income, Natura 2000, age	Covariates/confounders in GPS estimation	Recoded as binary/categorical controls where necessary
GHG emissions	IERiGŻ PIB estimates based on FADN, IPCC methodology and national indicators	GHG emissions in CO2 equivalent	Polluting input / emission variable in GHG intensity index	Farm-level estimates constructed from accounting and technical data
Outlier treatment	Constructed from DEA scores	Cleaned analytical sample	Main estimation sample	DEA VRS output-oriented model estimated by year; undefined and extreme efficiency observations below p5 and above p95 removed
Treatment variable	FADN land-use data	GRASS_SHR: share of grassland in utilised agricultural area	Continuous treatment in GPS/GAM dose-response models	Expressed as a share from 0 to 1
Outcome construction	Hicks-Moorsteen framework estimated with DEA	EPRODC: energy productivity change; GHGIC: GHG emission intensity change	Dependent variables in second-stage models	Estimated under VRS and FDH assumptions

Data block / step	Source	Constructed variables	Role in the analysis	Data processing
GPS weighting	Treatment and covariates	Generalised propensity score weights	Balancing observed confounders across grassland-share levels	GBM grid search; model selected by minimum mean weighted correlation
Dose-response estimation	Weighted analytical sample	Smooth treatment-outcome functions	Final effect estimation	GAM with REML; linear model used as robustness check

Note: FADN - Farm Accountancy Data Network; IERiGŻ PIB - Institute of Agricultural and Food Economics - National Research Institute; TF-45 - FADN type of farming for specialist dairying; SO - standard output; UAA - utilised agricultural area; GHG - greenhouse gas emissions; IPCC - Intergovernmental Panel on Climate Change; DEA - data envelopment analysis; VRS - variable returns to scale; FDH - free disposal hull; GPS - generalised propensity score; GBM - gradient boosting machine; GAM - generalised additive model; REML - restricted maximum likelihood.

To refine the scope of the analysis, the sample was restricted to farms exhibiting the highest degree of specialisation in dairy production within a mixed-forage system. We define such system as a combination of grassland-based feeding and the cultivation of forage crops on arable land for on-farm use. The selected farms generate agricultural income solely from the sale of milk and cattle for meat, utilising all other agricultural outputs internally for forage purposes. Furthermore, each farm uses both grassland and arable land. The sample excludes operations that rely entirely on externally purchased feed, as well as those that meet all their feed requirements through grassland-based production alone.

As the data envelopment analysis (DEA) method is not robust to outliers (Daraio & Simar, 2007), we applied the following procedure to exclude outliers, following Ang, Kerstens & Sadeghi (2023). First, technical efficiency was calculated separately for each year using an output-oriented VRS DEA model. We then removed observations with undefined efficiency scores and those falling below the 5th or above the 95th percentile of the annual efficiency distribution. As a robustness check, we also report models estimated using the full sample in the Appendix. These results are similar to those presented in the main text .

2.2. Variable construction and GHG emission estimates

Set of variables used as inputs and outputs, together with their detailed definitions, is presented in Table A2 in the Appendix. In the Figure 1 a summary of used inputs and outputs is presented.

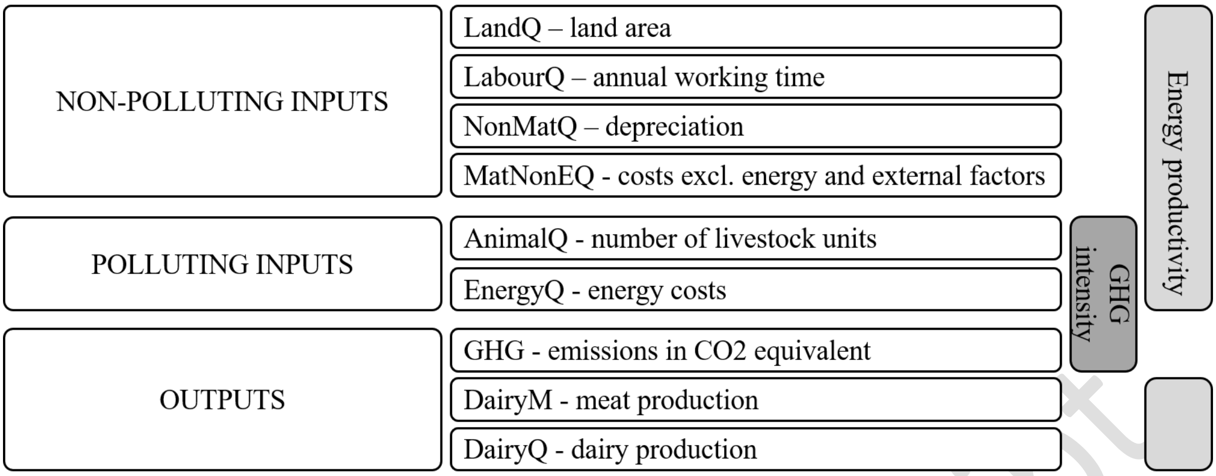

Figure 1. Inputs and outputs in the study

In contrast to standard approach where economic inputs are represented by animals, land, labour and capital (Madau, Furesi & Pulina, 2017; Latruffe et al., 2023) we we disaggregate capital-related inputs into depreciation, energy costs and other current costs, to estimate energy productivity (Ang, Kerstens & Sadeghi, 2023). To calculate emission intensity, we used farm-level greenhouse gases emission estimates prepared according to the IPCC methodology, which is described in details in the Appendix.

Table A2, in the Appendix, presents also descriptive statistics for the full sample and separately for the extreme case of farms without grassland. This distinction was introduced to explain why farms without grassland were included in the sample of milk-specialised farms operating under mixed-forage systems. The descriptive statistics show that all farms without grassland nevertheless utilise agricultural land. Because the sample includes only farms that do not sell crop output, the agricultural land used by these farms can be assumed to serve forage-production purposes. Therefore, these farms can also be classified as mixed.

2.3 Confounders selection

Furthermore, we include the following covariates, which previous studies have identified as external factors affecting efficiency measures:

- LFA: This variable identifies areas subject to natural constraints, encompassing both mountainous and highland regions characterised by shorter vegetation periods, as well as non-mountainous areas facing limitations (Baráth, Fertő & Bojnec 2018; Czyżewski et al. 2025; Staniszewski et al. 2025);
- EDUCATION LEVEL (EDU1): A categorical variable representing the general level of formal education attained by the farm manager, classified as basic, secondary, or higher education (Gadanakis et al. 2015; Kuhn et al. 2020; Stępień et al. 2021; Maietta et al., 2019);
- AGRICULTURAL EDUCATION (EDU2): A binary categorical variable indicating whether the farm manager has received formal education in agriculture (Gadanakis et al. 2015; Kuhn et al. 2020; Stępień et al. 2021; Maietta et al., 2019);
- SOIL QUALITY INDEX (SOIL): This index reflects soil quality, calculated as the ratio between the area converted into "reference hectares" and the total area of agricultural land measured in "physical" hectares. A reference hectare corresponds to one hectare of land classified under bonitation class IV, which includes medium to low-quality arable soils (IVa and IVb). These soils typically comprise brown and flat soils with well-developed humus layers, selected chernozems and muds, shallow chalky soils, chernozemic soils, brown soils, deluvial till soils, gypsum till soils, and soils with suboptimal physiographic conditions prone to erosion or waterlogging (Skevas & Serra 2016; Czyżewski et al. 2025; Staniszewski et al. 2025);
- OFF-FARM INCOME (OGA): A binary indicator denoting the presence of income derived from non-agricultural activities (Baráth, Fertő & Bojnec 2018; ; Dono, Buttinelli & Cortignani 2022);

- NATURA2000: A binary variable coded as 1 if the most of the utilised agricultural area (UAA) falls within designated NATURA 2000 conservation zones; otherwise coded as 0. (Czyżewski et al. 2025; Staniszewski et al. 2025);
- AGE_U50: A binary categorical variable indicating whether the farm manager is aged under or over fifty years (Gadanakis et al. 2015; Kuhn et al. 2020; Stępień et al. 2021; Czyżewski et al. 2025; Staniszewski et al. 2025).

3. Methods

3.1. Hicks–Moorsteen productivity and emission-intensity indices

The first step of the analysis is to estimate changes in energy productivity and emission intensity. This study uses a production economics framework to jointly evaluate changes in energy efficiency and greenhouse gas (GHG) intensity on dairy farms. The approach applies the Hicks-Moorsteen formulation within a non-parametric data envelopment analysis (DEA) framework, following the method described in details by Ang, Kerstens and Sadeghi (2023). Further methodological details are provided in the Appendix.

To ensure the robustness of the results, efficiency was measured under both the variable returns to scale (VRS) and free disposal hull (FDH) assumptions. The VRS specification is widely applied in non-parametric efficiency analysis (Zarrin & Brunner, 2023), because it accomodates heterogeneity in farm size and scale without imposing constant returns. It assumes a convex production possibility set, an assumption supported by economic theory (Guillen, Charles & Aparicio, 2025). However, the convexity assumption has been questioned in the literature, as it “assumes away indivisible inputs and outputs, economies of scale, and economies of specialization” (Van Puyenbroeck, 2002, p. 3). The FDH approach relaxes this assumption and relies only on the principle of free disposability, providing a more flexible frontier that can capture non-convexities typical of agricultural systems, such as stepwise changes in herd size or mixed feeding regimes (Briec, Kerstens & Van de Woestyne, 2020).

Following these arguments, both VRS and FDH estimations were employed to test the stability of the findings against alternative assumptions about the shape of the production frontier.

3.2. Generalised Propensity Score and covariate balancing

In the next step of the study, to address potential confounding in the estimation of the causal effect of the share of permanent grassland in the farm's utilised agricultural area (GRASS_SHR), we applied the generalised propensity score (GPS) approach for continuous treatments.

The productivity indices used in this study are composite indicators rather than outcomes generated by an underlying stochastic data-generating process (DGP). Consequently, formal statistical inference based on regressing such indicators on external determinants may be considered problematic (Simar & Wilson, 2007). In agricultural and ecological economics research one way to address the critique raised by Simar and Wilson is to apply a two-stage procedure in which treatment effects are estimated using composite indicators, such as efficiency or productivity indices, after accounting for potential confounders. This approach has been adopted, for example, by Ait Sidhoum et al. (2023), Ait Sidhoum et al. (2024), Bartolini et al. (2021), Czyżewski et al. (2026), and Gatti et al. (2026). Moreover, Banker et al. (2019), using simulation evidence, show that a two-stage approach performs even better than the more complex Simar-Wilson model.

The propensity score framework was originally developed for binary treatments, where it represents the conditional probability of receiving the treatment given pre-treatment covariates. Extending this idea to continuous exposures, the generalised propensity score (GPS) is defined as the conditional density of the treatment variable given observed covariates (Hirano & Imbens, 2004). Intuitively, the GPS summarises the multi-dimensional set of covariates into a single balancing score that captures the probability of being exposed to a given treatment intensity.

The central property of the GPS is covariate balancing. Within strata of the GPS, the distribution of covariates should be independent of the treatment. This allows for the construction of weights or adjustment strategies that reduce confounding in observational studies with non-random treatment assignment (Imai & van Dyk, 2004)

In practice, the GPS can be estimated using either parametric models (e.g., normal linear regression of treatment on covariates) or flexible machine learning methods. In this study, we used gradient boosted regression (GBM) trees (Friedman, 2001) which are well-suited for capturing non-linearities and higher-order interactions between covariates and treatment.

To verify robustness and optimise model specification, we conducted a grid search across a range of hyperparameters:

- number of trees (20000-50000),
- interaction depth (2-4),
- shrinkage parameter (0.0001-0.001),
- bag fraction (1.0).

For each configuration, the mean weighted correlation across covariates was computed, and the model achieving the lowest imbalance (minimum mean.wcor) was selected as the best specification. The full grid-search results are reported in Table A3 in the Appendix, while Figure A1 shows the evolution of the balance measure across boosting iterations.

Table 2. Covariate balance before and after generalised propensity score weighting

Specification	N	ESS	Max. weighted correlation	Mean weighted correlation	RMS weighted correlation	Iterations
Unweighted	1530	1530.00	0.346	0.159	0.194	-
Weighted	1530	802.02	0.082	0.018	0.031	16 415

Note: ESS - effective sample size after weighting

After selecting the GBM model, we evaluated the covariate balance before and after weighting. The corresponding diagnostics are presented in Table 2. In the unweighted sample, the treatment variable (GRASS_SHR) exhibited substantial correlations with farm characteristics (mean weighted correlation = 0.159; maximum = 0.346), indicating the presence of confounding. After applying the weights from the selected boosting model, covariate balance improved markedly: the mean weighted correlation decreased to 0.018 and the maximum weighted correlation to 0.082. The root-mean-square correlation likewise dropped from 0.194 to 0.031, suggesting that the treatment is approximately independent of observed covariates after weighting. The effective sample size was reduced from 1530 to 802, reflecting some loss of precision due to weighting, but remaining sufficiently large for inference.

3.3. Dose–response estimation using Generalised Additive Models

In the final step, the estimated GPS was used to construct weights that reweighted the sample such that, after weighting, the treatment became approximately independent of the covariates. We then estimated a flexible dose-response relationships between the treatment variable (GRASS_SHR) and the outcomes. We employed Generalised Additive Models (GAM) (Hastie & Tibshirani, 1990; Wood, 2017) – see Appendix for more technical details.

3.4. Robustness and sensitivity checks

In summary, the following robustness and sensitivity checks were implemented to assess the stability of the empirical results. First, the Hicks-Moorsteen indices were estimated under both VRS and FDH assumptions, allowing us to verify whether the findings depend on the convexity assumption imposed on the production frontier. In the main text we present only findings from the VRS models. Estimates of DEA under FDH assumption can be found in the appendix. Second, the dose-response relationship was estimated using both flexible GAM specifications and linear regression models, providing a check on functional-form dependence. Third, the GPS model was selected through a grid search over alternative GBM hyperparameter combinations; this procedure serves as a specification-sensitivity check for the weighting model and reduces dependence on an arbitrary choice of tuning parameters. Finally, the main estimates are based on the cleaned sample after outlier treatment, while corresponding full-sample estimates are reported in the Appendix to assess the sensitivity of the results to sample filtering.

4. Results

4.1 Energy productivity and emission intensity estimates

We first examine the estimates of energy productivity change and GHG emission-intensity change. The density distributions of the two indices are shown below in Figure 2.

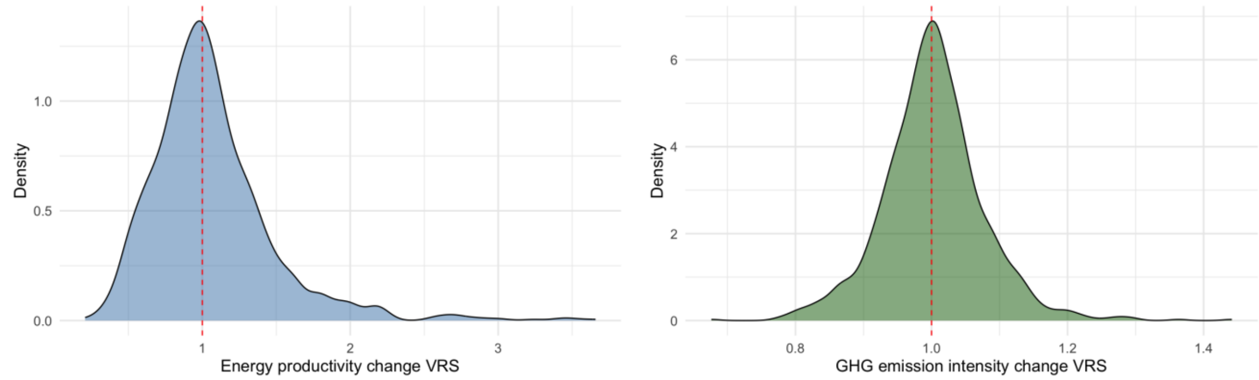

Figure 2. Density of results of the study (DEA VRS) on changes in energy productivity and GHG emission intensity

The estimated energy productivity-change index (EPRODC_DEA) has a mean of 1.06 (median 0.997), with large differences between farms (0.21-3.66, SD 0.42), indicating that while some farms achieve significant improvements, more than half do not. In contrast, the change in GHG intensity (GHGIC_DEA) remains very stable, averaging 1.002 (median 1.001) with a narrower range (0.68-1.44, SD 0.075). These results indicate substantial heterogeneity in energy productivity growth, whereas the growth of GHG emissions remains approximately proportional to the growth of polluting inputs. This underscores the potential trade-off between energy productivity and emission reduction.

Table 3. Correlation of energy productivity and emission intensity

Year	Spearman correlation	p-value	N
2015	-0.0353	0.6657	152

Year	Spearman correlation	p-value	N
2016	0.0939	0.2529	150
2017	0.1418	0.0868	147
2018	0.1146	0.1666	147
2019	0.2334	0.0045	147
2020	0.2250	0.0061	148
2021	0.2535	0.0020	147
2022	-0.0268	0.7459	148
2014-2022	0.1382	0.0000	1186

We also observe a positive correlation between energy productivity and emission intensity; however, this relationship is weak (0.14-0.25) and statistically insignificant in some years (see Table 3). It suggests that the relationship between the two indicators may vary across different forage systems in milk production. Because grassland share is a key feature distinguishing forage systems, we focus on its role in shaping this relationship.

4.2 Energy productivity and grassland share

In this study, we examine how energy productivity and emission intensity depend on the extent of grassland-based dairy production. Results for energy productivity are summarised in Figure 3.

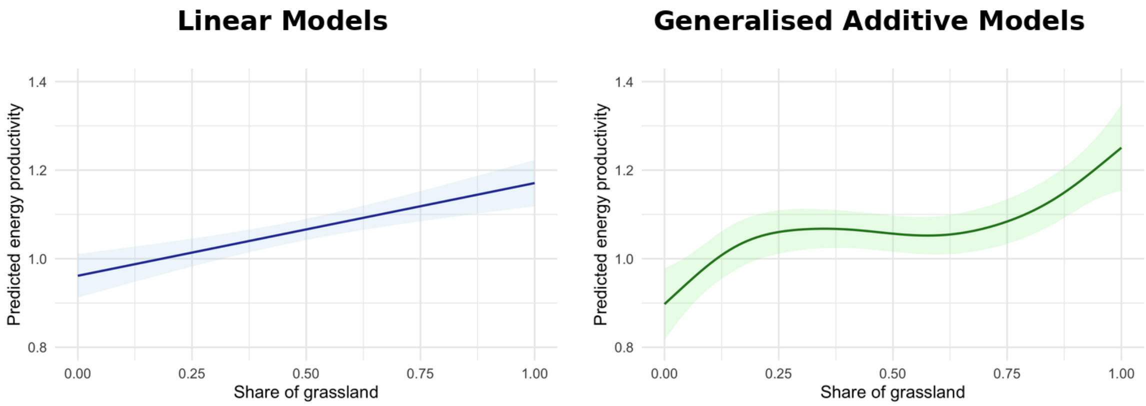

Figure 3. Estimated dose-response for energy productivity in the DEA VRS model

The initial evidence from the linear models suggests that increasing the grassland share improves energy productivity. . However, the GAM specification provides deeper insight by identifying non-linearities in this relationship. The model indicates particularly strong response of energy productivity at grassland shares of 0–20% and 80–100%. Model statistics are reported in Table 4.

Table 4. Goodness-of-fit statistics for energy productivity models without outliers

Outcome	Model	edf	F	p.value	Adj. R2
DEA_vrs	GAM (without weights)	1.000	2.211	0.137283	0.001021
DEA_vrs	GAM weighted (GPS)	3.895	6.686	0.000009	0.025591

Outcome	Model	estimate	std.error	statistic	p.value	R2
DEA_vrs	OLS (without weights)	0.073	0.0491	1.487	0.137283	0.001864
DEA_vrs	OLS weighted (GPS)	0.209	0.0457	4.577	0.000005	0.017384

Note: DEA_vrs denote the Hicks–Moorsteen outcome index estimated using data envelopment analysis under the variable returns to scale (VRS) assumption. GAM – generalised additive model; OLS – ordinary least squares; GPS – generalised propensity score; edf – effective degrees of freedom of the smooth term; F – F-statistic for the smooth term in the GAM specification; estimate – estimated coefficient of grassland share in the OLS specification; std.error – standard error; statistic – t-statistic; p-value – significance level; Adj. R^2 – adjusted coefficient of determination; R^2 – coefficient of determination.

Under the VRS assumption, the relationship between the share of permanent grassland and energy productivity change is not statistically significant in the unweighted specifications ($p = 0.137$ in both the linear and GAM models). After applying GPS weights, however, both model types reveal a highly significant positive association. The weighted GAM model indicates a significant non-linear relationship ($p < 0.001$; edf = 3.895), while the weighted OLS model shows a positive and statistically significant effect (estimate = 0.209; $p < 0.001$). Although the explanatory power of the weighted GAM model remains low (adjusted $R^2 = 0.026$), the results indicate greater improvements in energy productivity among farms with higher proportions of permanent grassland after balancing the observed covariates. The FDH results presented in the Appendix support those findings.

4.3 Emission intensity and grassland share

When it comes to emission intensity, evidence of the impact of grassland share is weaker and the results are rather inconclusive. In the VRS-based emission intensity model, the results differ between the unweighted and GPS-weighted specifications, as well as between the linear and GAM approaches (see Figure 4). In the unweighted models, neither the linear specification nor the GAM specification indicates a statistically significant relationship between grassland share and emission intensity ($p = 0.956$ and $p = 0.915$, respectively). After applying GPS weights, the linear model still shows no statistically significant relationship (estimate = -0.010; $p = 0.237$), whereas the weighted GAM specification indicates a significant non-linear effect (edf = 2.665; $F = 4.744$; $p = 0.002$). This suggests that the effect of the proportion of permanent grassland on emission intensity is not linear and may follow a threshold or curve pattern, although the overall explanatory power remains very limited (Adj. $R^2 = 0.013$).

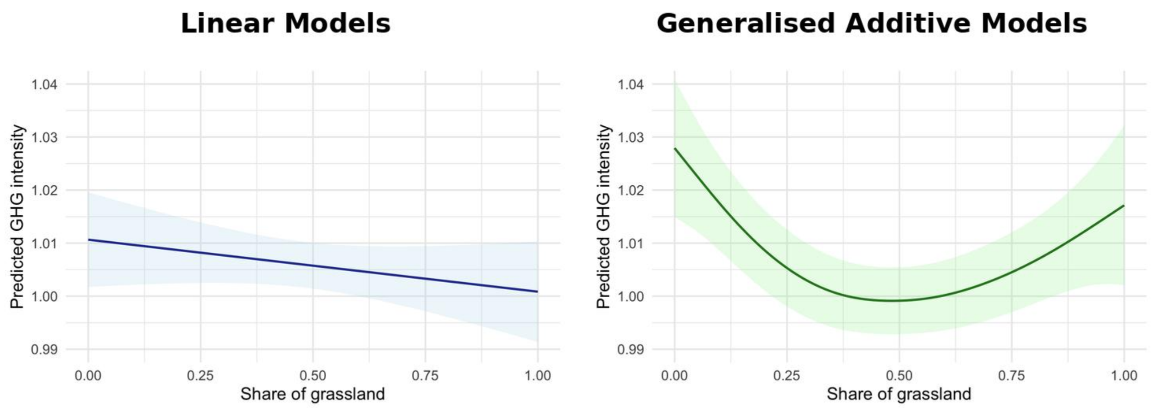

Figure 4. Estimated dose-response for emission intensity in the DEA VRS model

The full set of statistics is presented in Table 5.

Table 5. Goodness-of-fit statistics for emission intensity DEA VRS models without outliers

Outcome	Model	edf	F	p.value	Adj. R2	
DEA_vrs	GAM (without weights)	1.199	0.080	0.914827	-0.000633	
DEA_vrs	GAM weighted (GPS)	2.665	4.744	0.001852	0.012582	
Outcome	Model	estimate	std.error	statistic	p.value	R2
DEA_vrs	OLS (without weights)	4.88e-04	0.0088	0.056	0.955625	0.000003
DEA_vrs	OLS weighted (GPS)	-0.010	0.0083	-1.184	0.236802	0.001182

Note: DEA_vrs denote the Hicks–Moorsteen outcome index estimated using data envelopment analysis under the variable returns to scale (VRS) assumption. GAM – generalised additive model; OLS – ordinary least squares; GPS – generalised propensity score; edf – effective degrees of freedom of the smooth term; F – F-statistic for the smooth term in the GAM specification; estimate – estimated coefficient of grassland share in the OLS specification; std.error – standard error; statistic – t-statistic; p-value – significance level; Adj. R^2 – adjusted coefficient of determination; R^2 – coefficient of determination.

The only statistically significant result considered further is obtained from the VRS–GAM model. This model indicates a U-shaped relationship between grassland share and GHG emission intensity, with higher intensity at both low and high grassland shares. At grassland shares between 0% and 50%, the mechanisms underlying this effect may be similar to those affecting energy productivity. Similarly weak relation is reported in FDH models presented in the Appendix.

4.4 Combined effect across different grassland shares

Finally, it is important to evaluate the joint effects of grassland share on energy productivity and GHG emission intensity. These joint effects are summarised in Table 6. The above findings reveal a synergistic relationship between reduced greenhouse gas (GHG) emission intensity and enhanced energy productivity up to a grassland share of around 20-25%. On the other hand, when grassland-based production exceeds 75%, a trade-off emerges: energy productivity continues to rise, but at the cost of increased GHG emission intensity.

Table 6. The overall effect of changes in the grassland share

Grassland share	0-25%	25-50%	50-75%	75-100%
Energy productivity	↗ 0.9-1.05	↔ 1.05		↗ 1.05-1.25
Emission intensity	↘ 1.027-1.005	↘ 1.005-1	↗ 1-1.005	↗1.005-1.017

Importantly, the most beneficial synergy effect is obtained above 10-12% share of grassland as below this point energy productivity remained lower than one, which indicates a decline. Further, the highest productivity gains without an increase in emission intensity (i.e. with an indicator value close to 1) were observed at a grassland share of around 50%. Farms with this grassland share benefited from the lower energy use associated with pasture-based dairy production systems, while avoiding an increase in emission intensity associated with changes in the use of polluting inputs.

When it comes to trade-offs, according to our results, they appear when grassland share exceeds 50%, and are the most severe in the range of 50-75%. This is when we do not record increase in energy productivity, but emission intensity increases. Above 75% intensity is still increasing, but in line with increase in productivity

5. Discussion

5.1 Energy productivity and emission intensity in context

Two findings are central to the interpretation of the results. First, the long-term improvement in energy productivity observed in Polish dairy farms is consistent with evidence from other European countries (Ang, Kerstens & Sadeghi, 2023). Second, improvements in energy productivity do not necessarily coincide with lower GHG emission intensity (Baležentis, Butkus & Štreimikienė, 2023). This relationship may depend on farm equipment and, more importantly, on the production system, particularly the balance between pasture-based feeding and purchased or conserved feed (Moerkerken et al., 2021). Mixed-forage systems may therefore reduce energy use while maintaining productivity (Llanos et al., 2018).

5.2 Energy productivity and grassland share

The positive association between grassland share and energy productivity may reflect lower reliance on energy-intensive field operations, including ploughing, reseeding and fertiliser application (European Commission, 2014). The initial conversion of less productive arable land could therefore generate energy savings without a corresponding reduction in output. A higher grassland share may also be associated with greater use of grazing and lower housing-related energy consumption (Mohsenimanesh et al., 2021). These mechanisms cannot be tested directly because the dataset does not contain detailed information on land-conversion sequences, grazing practices or housing systems.

At grassland shares of 80–100%, the stronger response of energy productivity may indicate a technological threshold. Farms may shift from semi-intensive systems that depend on mechanised feeding and arable forage production towards predominantly grazing-based systems. Such a transition could reduce energy use related to housing, feed production and fertiliser application, producing a disproportionate improvement in energy productivity.

5.3 Emission intensity and grassland share

The decline in GHG emission intensity likely reflects a partial shift from intensive, crop-based systems toward more forage- and grass-based production. As the proportion of grasslands increases, farms rely less on emission-intensive practices such as ploughing, fertiliser application, and the use of purchased feed concentrates. This reduces emissions from fuel combustion and nitrogen fertilisation, while methane emissions from livestock remain relatively stable. Consequently, the growth rate of total GHG emissions becomes lower than that of polluting inputs, resulting in a gradual decline in emission intensity.

On the other hand, farms with more than 50% grassland in the farm structure also have higher emissions intensity. This effect may indicate a transition toward highly extensive, pasture-based systems. In such systems, the use of external inputs like fertilisers and purchased feed becomes very limited, meaning that the growth rate of polluting inputs slows down or even turns negative. At the same time, biological emissions, particularly methane from enteric fermentation, remain relatively stable or may increase slightly as animals spend more time grazing. As a result, total GHG emissions begin to rise faster than polluting inputs, causing the emission intensity ratio to increase. This pattern does not necessarily imply higher absolute emissions but rather a less favourable relationship between emission change and input change in fully grass-based production systems.

A comparable denominator effect has been observed in studies measuring emissions per unit of milk: lower absolute emissions may coexist with higher emission intensity when milk productivity declines (Kankanamge et al., 2025; García-Souto et al., 2022). In the present study, an analogous mechanism operates through changes in polluting inputs rather than milk output.

5.4 Combined effect across a different grassland share

The synergy identified at moderate grassland shares is consistent with evidence that well-managed grassland-based systems can combine environmental and economic benefits

(Oenema & Oenema, 2021; Cashman et al., 2024). These studies also indicate that environmental outcomes depend on management practices rather than on grassland share alone. The importance of combining grassland with arable forage production is supported by Gislon et al. (2020), who associate mixed-forage systems with relatively low carbon dioxide and fossil-fuel emissions, and by Hou et al. (2022), who show that mixed dairy-cropping systems can improve nutrient use. This evidence is consistent with our finding that GHG emission intensity is lowest at approximately equal shares of grassland and arable land.

The trade-off identified at higher grassland shares is consistent with the positive association between energy productivity and emission intensity reported for Dutch dairy farms by Ang, Kerstens and Sadeghi (2023). However, evidence differs across production contexts: Le, Jeffrey and An (2020) find no comparable trade-off in Canadian dairy farming. This contrast suggests that the relationship depends on the structure and management of the production system rather than on grassland share alone.

6. Conclusions

This paper examined how grassland share affects energy productivity and GHG emission intensity in Polish milk-specialised farms operating under mixed-forage systems. The results show that grassland share is linked to both dimensions of environmental-energy performance, but in a non-linear way. Energy productivity tends to improve as the grassland share increases, whereas GHG emission intensity follows a U-shaped pattern, with the most favourable joint performance observed at intermediate grassland shares. This suggests that moderate integration of grassland into mixed-forage systems can create a synergy between energy productivity and emission performance, while very high grassland shares may involve a trade-off.

These findings are consistent with the broader literature showing that dairy systems differ substantially in their energy use, emission intensity and environmental performance depending on forage structure, production intensity and management practices (Gislon et al., 2020;

Oenema & Oenema, 2021; Ang et al., 2023; Cashman et al., 2024). The contribution of this study is to show that the grassland–performance relationship should not be interpreted as simply linear or uniformly beneficial. In the Polish mixed-forage context, grassland appears most favourable when it complements arable forage production rather than almost entirely replacing it.

However, the generalisability of the findings is limited by the focus on Polish milk-specialised mixed-forage farms, and the estimated thresholds should therefore be treated as context-specific. Cross-country validation would require comparable farm-level data combining accounting variables, detailed land-use information and farm-level GHG estimates. In addition, although the GPS approach improves the balance of observed covariates, unobserved factors such as grazing duration, housing systems, feed-purchasing strategies, manure management, investment history or regional feed-market conditions may still affect both grassland share and environmental-energy performance. The results should therefore be interpreted as conditional on the observed control set and on the assumptions underlying the model-based farm-level GHG estimates. Finally, the overall goodness of fit of the estimated models is weak, which limits the strength of the empirical conclusions and suggests that grassland share explains only part of the variation in environmental-energy performance.

From a policy perspective, the findings suggest that grassland-related support should be more strongly differentiated according to the initial grassland share of the farm. In Poland, CAP instruments related to permanent grassland are primarily designed to protect existing grassland and regulate its management intensity. GAEC 1 maintains the national ratio of permanent grassland to agricultural land, while GAEC 9 prohibits the conversion or ploughing of environmentally sensitive permanent grassland in Natura 2000 areas.Eco-schemes additionally support the extensive use of permanent grassland with livestock or water retention on permanent grassland (ARiMR, 2025a, 2025b, 2025c). This issue extends beyond Poland because all EU Member States pursue common CAP environmental and climate objectives, while the 2023–2027 CAP Strategic Plans allow them to tailor intervention strategies and policy instruments to national production structures and policy priorities (European Commission, n.d.). The design of grassland-related instruments is therefore part of a broader EU policy debate on how to balance permanent grassland protection, climate mitigation, biodiversity and farm performance. Our results suggest that increasing grassland shares from very low to moderate levels may generate a "double dividend", improving energy productivity while reducing or stabilising GHG emission intensity. At the same time, farms already characterised by high grassland shares may face a trade-off, as further reliance on grassland-based production can improve energy productivity but increase GHG emission intensity. As an example of how policy instruments addressing livestock emissions may combine regulatory measures with farm-level incentives, see the work of Dell'Unto, Coderoni and Cortignani (2026), who examine a tax-and-subsidy mechanism designed to achieve methane-reduction targets in livestock farms. According to our results, a more targeted approach would support farms with low grassland shares in moving towards moderate, agronomically feasible levels, while focusing support for high-grassland farms on management quality, grazing practices, nutrient balance and methane mitigation rather than on further grassland expansion.

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Appendix

Contents

Additional literature on grassland-based systems

Table A1. Environmental benefits and trade-offs in the expansion of grassland-based systems – a literature review

Citation(s)	Summary of the claim, thesis or conclusion attributed to the cited text
Smolková et al. (2025)	Grassland ecosystems provide a broad range of ecosystem services that benefit both agricultural producers and the wider public. In the reviewed text, these services are linked especially to biodiversity conservation and the potential reduction of net greenhouse-gas emissions.
Jordon et al. (2024)	The carbon-sequestration potential of grasslands remains scientifically contested. Therefore, claims about the climate-mitigation role of grassland systems should be treated as context-dependent rather than automatic.
Myrgiotis et al. (2022)	Permanent-grassland soils can contain approximately 1.2 gigatonnes of carbon in the upper one metre of soil. This large existing stock implies that even relatively small increases in soil organic carbon may make a meaningful contribution to lowering net greenhouse-gas emissions.
Liu et al. (2023)	Although forests hold a larger total carbon stock, grasslands account for an estimated 25–34% of the global carbon reservoir. Grasslands are therefore an important component of the global carbon cycle and climate-mitigation strategies.
Pol-van Dasselaar et al. (2019)	Many grassland systems have not yet reached their maximum carbon-storage capacity. This indicates scope for additional sequestration of atmospheric carbon under appropriate management.
Huber et al. (2022)	Extensively managed grasslands generally produce less forage, but tend to support greater biodiversity and may offer stronger carbon-

	sequestration potential. The evidence therefore points to a trade-off between ecosystem-service provision and physical or energy productivity.
Fenger et al. (2023); Hanrahan et al. (2018)	Traditional grassland-based dairy systems typically use limited external concentrate feed, maintain long grazing periods and require relatively short winter housing. These features are central to cost-effective pasture-based milk production and may reduce reliance on externally produced feed.
Gislon et al. (2020)	The study is cited as evidence that feed efficiency differs across forage systems used on dairy farms. It contributes to the assessment of how alternative forage strategies affect the technical performance of milk production.
Hou et al. (2022)	The study is cited for its analysis of the environmental impacts of different forage systems on dairy farms. It provides evidence relevant to evaluating whether a greater reliance on grassland improves whole-farm environmental performance.
Cashman et al. (2024)	The study is cited for comparing the economic efficiency of different dairy-farm forage systems. It shows that environmental assessment of grassland-based production should be considered alongside its economic consequences.
Bos, Smit and Schröder (2013)	Evidence from intensive dairy production in the Netherlands shows that high energy productivity does not necessarily correspond to low carbon intensity. Energy efficiency and emissions performance must therefore be assessed as distinct, although related, dimensions.
Paris et al. (2022)	At the macroeconomic level, higher energy productivity reduces dependence on imported energy, strengthens energy security and supports the achievement of EU climate and energy-policy objectives.
Urak et al. (2024)	At farm level, higher energy productivity can strengthen resilience to energy-price shocks. This became particularly important during the energy crisis associated with the war in Ukraine and the price increases that followed the pandemic.

Variable construction and GHG emission estimates

The IPCC methodology (IPCC, 2006) serves as the standard framework for greenhouse gas (GHG) accounting and was also applied in this study. In Poland, certain estimates are refined using more detailed national indicators, reflecting the application of more complex sector-level calculation methods. These indicators are published annually by the National Centre for Emissions Management (e.g., KOBiZE, 2024). For this study, GHG estimates were provided by the Institute of Agricultural and Food Economics - National Research Institute (IERiGŻ PIB).

Long-term data essential for GHG estimation are drawn from the Farm Accountancy Data Network (FADN), a system operating across all EU countries that collects production, organisational, and economic information at the farm level. FADN data encompass a broad range of details, including classifications of livestock groups, crop species, and mineral fertilisers such as nitrogen and lime, enabling detailed GHG emission calculations. However, as noted by Wrzaszcz (2014) and Prandecki & Wrzaszcz (2025) , FADN accounting data are not directly designed for estimating environmental and climate-related variables. Consequently, additional assumptions and supplementary indicators were required to meet the study's objectives. For example, estimating CO_2 emissions from urea and liming necessitated market data, while other calculations relied on specific indicators that, in some cases, such as organic nitrogen fertilisers from animal manure, varied by year.

Table A2. Descriptive statistics of variables used in the study

Variable	Groups according to the share of grassland in the land structure			
	Non-grassland farms		All	
Number of observations (N)	48		1530	
Statistics	mean (SD)	min-max	mean (SD)	min-max
NON-POLLUTING INPUTS				
LandQ - Land area (ha)	33.82 (15.33)	12.13-70	34.8 (19.95)	5.31-135.87
LabourQ - annual working time (hours)	5184 (1199)	2522-7130	5049 (1375)	2200-18960
NonMatQ* - Depreciation ('000 PLN)	407.8 (206.2)	73.4-1022.9	321.7 (276.1)	31.6-2315.4
POLLUTING INPUT				
AnimalQ - number of livestock units	72.49 (26.29)	24.99-116.36	58.54 (40.43)	6.89-422.7
EnergyQ* - Energy costs ('000 PLN)	34.4 (17.3)	9.3-79.8	31.0 (29.1)	2.1-335.3
MatNonEQ* - Costs excl. energy and external factors ('000 PLN)	50.4 (26.2)	7.5-106.5	54.7 (46.9)	2.6-450.5
OUTPUTS				
GHG - emissions in CO2 equivalent ('000 kg)	320.8 (120.3)	99.5-541.0	258.8 (179.2)	29.6-1800.5
DairyM - Meat production (kg)	113.31 (78.14)	11-301.11	68.66 (63.87)	0.5-602.5
DairyQ - Dairy production ('00 kg)	3112 (1465)	689-6409	2495 (2282)	162-20968
SOCIO-ECONOMIC FACTORS				

Variable	Groups according to the share of grassland in the land structure			
	Non-grassland farms		All	
GRASS_SHR - Share of grassland in utilised agricultural area	28.14 (13.6)	10.43-62.9	12.78 (13.59)	0-88.53
LFA - majority of UAA in less-favoured areas no/yes (0/1)	0.6 (0.49)	x	0.18 (0.38)	x
EDU1 - Education basic/secondary/high (1/2/3)	1.69 (0.62)	x	1.6 (0.64)	x
EDU2 - Education agri or non-agri (0/1)	0.67 (0.48)	x	0.56 (0.5)	x
SOIL - Soil quality index	0.94 (0.36)	0.34-1.65	0.57 (0.26)	0.08-1.65
OGA - Non-farm income of the family (0/1)	0.25 (0.44)	x	0.33 (0.47)	x
NATURA2000 - Farm in NATURA2000 zone? (0/1)	0 (0)	x	0.11 (0.32)	x
AGE_U50 - under/over 50 years old (0/1)	0.46 (0.5)	x	0.48 (0.5)	x

Note: mean(std. dev.) min-max; * - values deflated

Hicks–Moorsteen productivity and emission-intensity indices

Energy productivity change (EPRODC) is the ratio of total production change (YC) to energy consumption change (EC). Values above one indicate a decoupling of production from energy consumption. It is calculated using the formula:

$$EPRODC_{t,t+1} = \frac{YC_{t,t+1}}{EC_{t,t+1}} = \frac{\sqrt{\frac{D^{y}_{t+1}(E_{t+1},z_{t+1},v_{t+1},y_{t+1})}{D^{y}_{t+1}(E_{t+1},z_{t+1},v_{t+1},y_{t})} \times \frac{D^{y}_{t}(E_{t},z_{t},v_{t},y_{t+1})}{D^{y}_{t}(E_{t},z_{t},v_{t},y_{t})}}}{\sqrt{\frac{D^{E}_{t+1}(E_{t+1},z_{t+1},v_{t+1},y_{t+1})}{D^{E}_{t+1}(E_{t+1},z_{t+1},v_{t+1},y_{t})} \times \frac{D^{E}_{t}(E_{t},z_{t},v_{t},y_{t+1})}{D^{E}_{t}(E_{t},z_{t},v_{t},y_{t})}}} \quad (1)$$

where,

$\boldsymbol{D^{y}_{t}}$ - as an output distance function

$\boldsymbol{D^{E}_{t}}$ - is a sub-vector energy distance function

$\boldsymbol{E}$ - is an energy input

$\boldsymbol{z}$ - is other polluting input

$\boldsymbol{v}$ - is a non-polluting input

$\boldsymbol{y}$ - is an output vector

The change in GHG emission intensity is defined as the ratio of the change in greenhouse gas emissions (GHGC) to the change in polluting inputs (XPC). Values above one indicate intensification, meaning that emissions are increasing faster than polluting inputs. It is calculated according to the formula:

$$GHGIC_{t,t+1} = \frac{GHGC_{t,t+1}}{XPC_{t,t+1}} = \frac{\sqrt{\frac{D_{t+1}^{u}(u_{t+1},ghg_{t+1})}{D_{t+1}^{u}(u_t,ghg_{t+1})} \times \frac{D_{t+1}^{u}(u_{t+1},ghg_t)}{D_t^{u}(u_t,ghg_t)}}}{\sqrt{\frac{D_{t+1}^{ghg}(u_{t+1},ghg_{t+1})}{D_{t+1}^{ghg}(u_{t+1},ghg_{t+1})} \times \frac{D_t^{ghg}(u_t,ghg_t)}{D_t^{ghg}(u_t,ghg_t)}}} \tag{2}$$

where,

$\boldsymbol{D_t^{ghg}}$ - GHG emission distance function

$\boldsymbol{D_t^{u}}$ - polluting input distance function

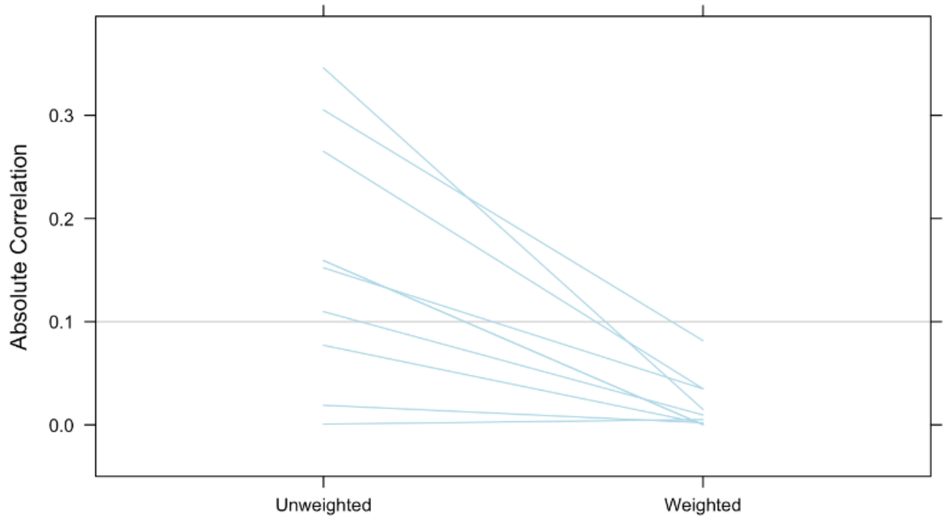
$\boldsymbol{u}$ - is a polluting input

$\boldsymbol{ghg}$ - is greenhouse gas emissions

For each farm and year, DEA models are solved to obtain the required distance functions. Co-temporal indicators reflect results in a given period, while inter-temporal indicators combine successive years. Multiplicative decomposition allows for separate analysis of the dynamics of production, inputs, and emissions.

Generalised Propensity Score and covariate balancing

Overall, the diagnostics confirm that the GPS estimation achieved satisfactory covariate balance. Figure A1 shows in detail how the weighting procedure reduced the correlations between the treatment and each confounding variable.



Note: unw - unweighted correlation; wcor - weighted correlation; EDU2 - agri education, SOIL - soil quality index, EDU12 - secondary education, EDU13 - higher education, OGA - non-farm income, NATURA2000 - farm in Natura 2000 area, AGE_U50 - age under 50, LFA2 - majority of UAA in less-favoured areas, LFA3 - majority of UAA in mountain areas

Figure A1. Absolute correlations between treatment and covariates before and after weighting with the generalised propensity score.

Figure A1 illustrates the reduction in absolute correlations between the treatment (GRASS_SHR) and covariates after applying generalised propensity score weights. In the unweighted data, several covariates show moderate correlations with the treatment (up to 0.35 in absolute value), indicating confounding. After weighting, all correlations are substantially reduced, most approaching zero, which reflects improved covariate balance. The horizontal reference line at 0.1 marks a commonly used heuristic threshold for acceptable balance: absolute correlations below 0.1 are typically interpreted as negligible association between treatment and covariates (Zhu, Coffman & Ghosh, 2015). The figure shows that all weighted correlations fall below this benchmark, supporting the conclusion that the weighting procedure successfully eliminated systematic differences in covariates across levels of treatment.

Table A3. Grid search results

model_id	n.trees	depth	shrinkage	bag.fraction	best.iter	mean.wcor
8	50000	2	1.00E-03	1	16415	0.01841536
2	20000	2	1.00E-03	1	16417	0.01841734

model_id	n.trees	depth	shrinkage	bag.fraction	best.iter	mean.wcor
11	50000	4	1.00E-04	1	34453	0.02869821
12	50000	4	1.00E-03	1	3437	0.02885436
6	20000	4	1.00E-03	1	3454	0.02889491
4	20000	3	1.00E-03	1	11052	0.04495845
10	50000	3	1.00E-03	1	11052	0.04495845
9	50000	3	1.00E-04	1	38258	0.0456022
5	20000	4	1.00E-04	1	19996	0.05565953
3	20000	3	1.00E-04	1	19503	0.06231771
7	50000	2	1.00E-04	1	23246	0.06418541
1	20000	2	1.00E-04	1	19983	0.06473867

Note:**:** *model_id* - internal identifier assigned to each candidate model in the grid search; *n.trees* - number of boosting iterations (trees) used in the gradient boosting machine; *depth* - maximum depth of each tree (controls model complexity); shrinkage - learning rate (step size reduction applied at each iteration); *bag.fraction* - fraction of the training data randomly sampled (without replacement) for each iteration (subsampling rate); *best.iter* - optimal number of boosting iterations selected based on the mean.wcor; *mean.wcor* - average weighted correlation between predicted and observed values across resamples; the performance metric used to evaluate models.

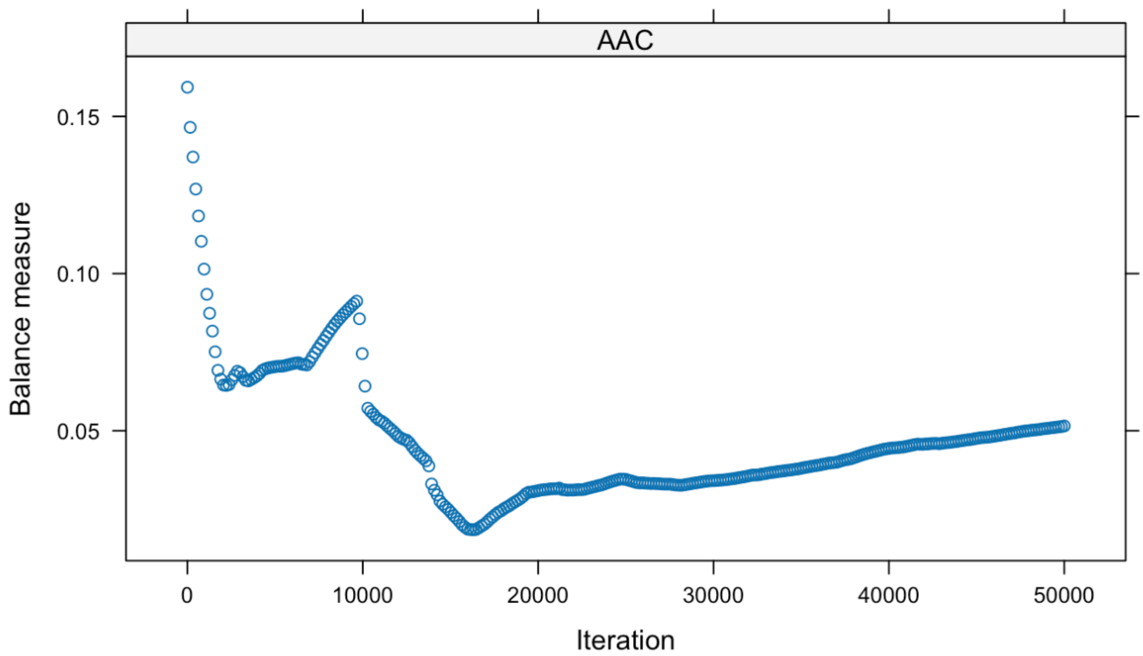


Figure A2. Evolution of the balance measure across boosting iterations

Dose–response estimation using Generalised Additive Models

GAMs extend the framework of generalised linear models by allowing the effect of covariates to be modelled as smooth, non-parametric functions rather than imposing linearity. The general form of a GAM can be written as:

$$E(Yi) = \beta_0 + f_1(X_{i1}) + f_2(X_{i2}) + \cdots + f_p(X_{ip}) \quad (3)$$

where $f_j(\cdot)$ are smooth functions (typically regression splines) estimated from the data. This structure retains additivity across covariates but relaxes the linearity assumption, enabling the model to capture potential non-linear relationships between treatment intensity and outcomes. In practice, we specified models of the form:

$$Y \sim s(GRASS\_SHR) \quad (4)$$

where $s(\cdot)$ denotes a penalised spline function. The degree of smoothness was estimated using Restricted Maximum Likelihood (REML). In this framework, the smoothing penalty is treated as a variance component in a mixed model representation of the GAM. REML estimation proceeds by maximizing the restricted likelihood of the residuals, integrating out the fixed effects and focusing on the variance parameters that control the wiggliness of the smooth functions. This ensures that the spline is penalised according to how much additional complexity it adds to the model, with higher penalties shrinking the curve towards linearity and lower penalties allowing more flexibility. The GAM estimation was supplemented with standard linear regression, which was added for robustness check.

Results for DEA FDH models without outliers

The FDH results (Figure A3 and Table A4) for energy productivity are broadly consistent with the VRS findings. In the unweighted specifications, the relationship between permanent grassland share and energy productivity change is not statistically significant ($p = 0.644$ in both the linear and GAM models). After GPS weighting, the GAM model captures a significant non-linear pattern ($p < 0.001$; edf = 5.252), and the weighted OLS model confirms a positive association of a comparable magnitude (estimate = 0.173; $p < 0.001$). The explanatory power of the weighted GAM model also remains low (adjusted $R^2 = 0.026$). Overall, the FDH estimates support the robustness of the main VRS results.

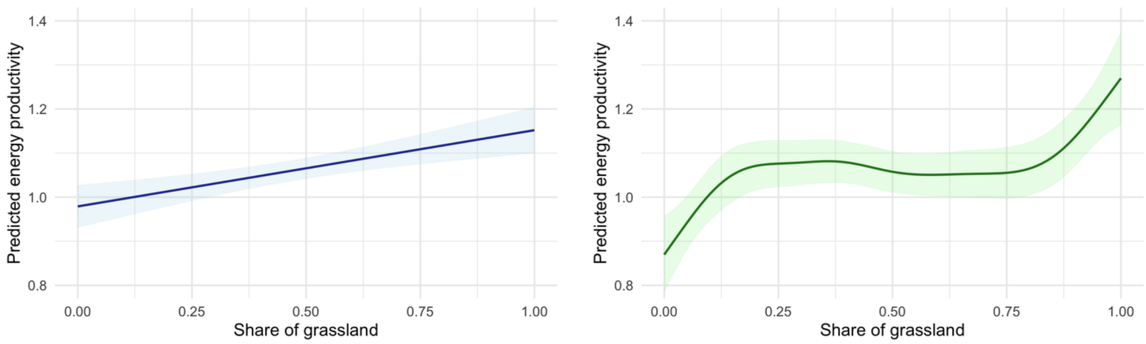


Figure A3. Estimated dose-response for energy productivity in the DEA FDH model

Table A4. Goodness-of-fit statistics for energy productivity DEA FDH models without outliers

Outcome	Model	edf	F	p.value	Adj. R2
DEA_fdh	GAM (without weights)	1.000	0.213	0.644248	-0.000673
DEA_fdh	GAM weighted (GPS)	5.252	5.271	0.000018	0.026444

Outcome	Model	estimate	std.error	statistic	p.value	R2
DEA_fdh	OLS (without weights)	0.023	0.0495	0.462	0.644249	0.000183
DEA_fdh	OLS weighted (GPS)	0.173	0.0455	3.803	0.000150	0.012232

Note: DEA_fdh denote the Hicks–Moorsteen outcome index estimated using data envelopment analysis under the free disposal hull (FDH) assumption. GAM – generalised additive model; OLS – ordinary least squares; GPS – generalised propensity score; edf – effective degrees of freedom of the smooth term; F – F-statistic for the smooth term in the GAM specification; estimate – estimated coefficient of grassland share in the OLS specification; std.error – standard error; statistic – t-statistic; p-value – significance level; Adj. R^2 – adjusted coefficient of determination; R^2 – coefficient of determination.

For the FDH-based emission intensity model (Figure A4 and Table A5), neither the linear regression nor the GAM specification produces significant results for grassland share. This applies to both the unweighted models ($p = 0.890$) and the GPS-weighted models, although the p-values differ between the weighted linear and GAM specifications ($p = 0.814$ and $p = 0.479$, respectively). The effective degrees of freedom equal 1 in the unweighted GAM specification and 1.656 in the weighted GAM specification, indicating no statistically confirmed evidence of a non-linear relationship under the FDH assumption. This suggests that, within the FDH framework, the share of permanent grassland has no detectable systematic effect on GHG emission intensity.

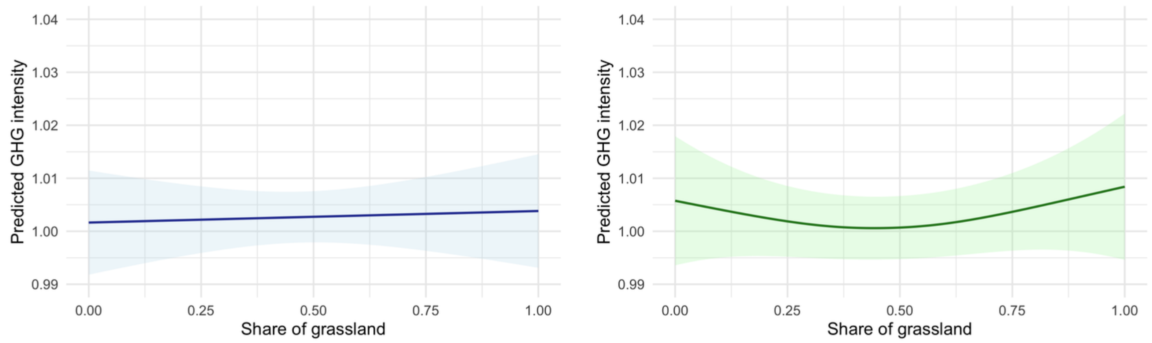


Figure A4. Estimated dose-response for emission intensity in the DEA FDH model

Table A5. Goodness-of-fit statistics for emission intensity DEA FDH models without outliers

Outcome	Model	edf	F	p.value	Adj. R2
DEA_fdh	GAM (without weights)	1.000	0.019	0.890269	-0.000840
DEA_fdh	GAM weighted (GPS)	1.656	0.757	0.478507	0.000408

Outcome	Model	estimate	std.error	statistic	p.value	R2
DEA_fdh	OLS (without weights)	0.001	0.0100	0.138	0.890268	0.000016
DEA_fdh	OLS weighted (GPS)	0.002	0.0093	0.236	0.813656	0.000048

Note: DEA_fdh denote the Hicks–Moorsteen outcome index estimated using data envelopment analysis under the free disposal hull (FDH) assumption. GAM – generalised additive model; OLS – ordinary least squares; GPS – generalised propensity score; edf – effective degrees of freedom of the smooth term; F – F-statistic for the smooth term in the GAM specification; estimate – estimated coefficient of grassland share in the OLS specification; std.error – standard error; statistic – t-statistic; p-value – significance level; Adj. R^2 – adjusted coefficient of determination; R^2 – coefficient of determination.

Results for models with outliers

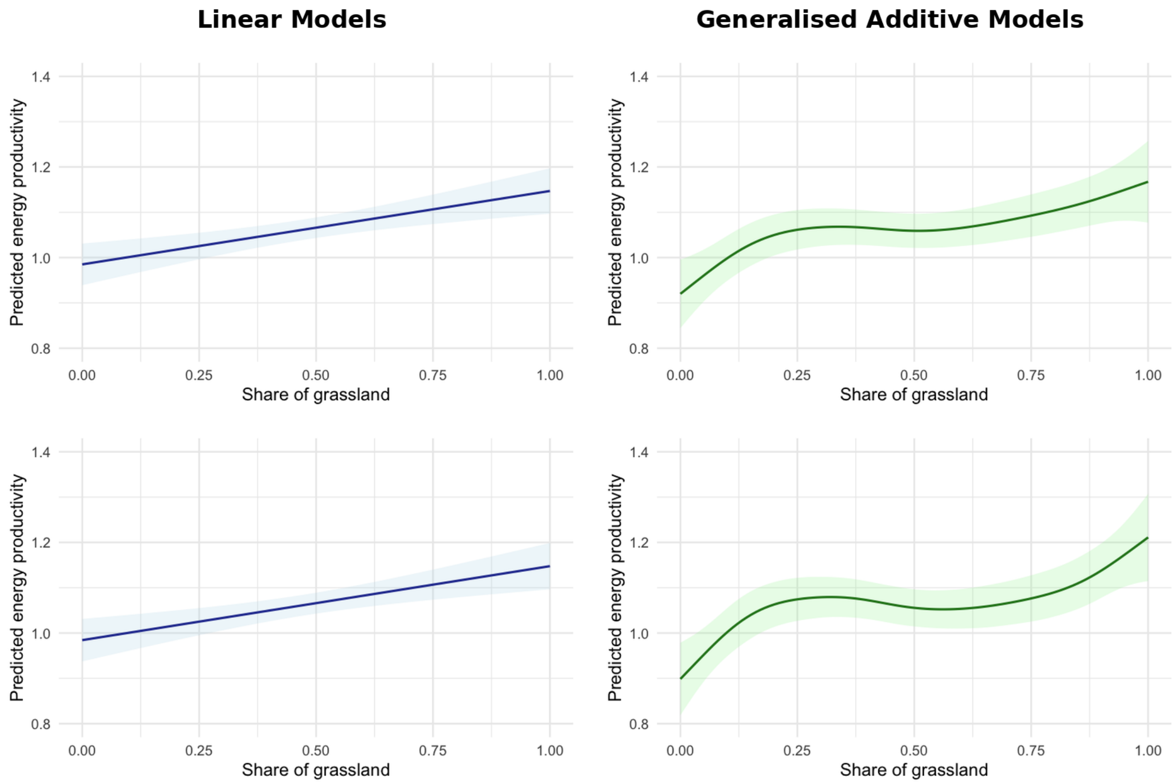


Figure A5. Estimated dose-response for energy productivity, sample with outliers

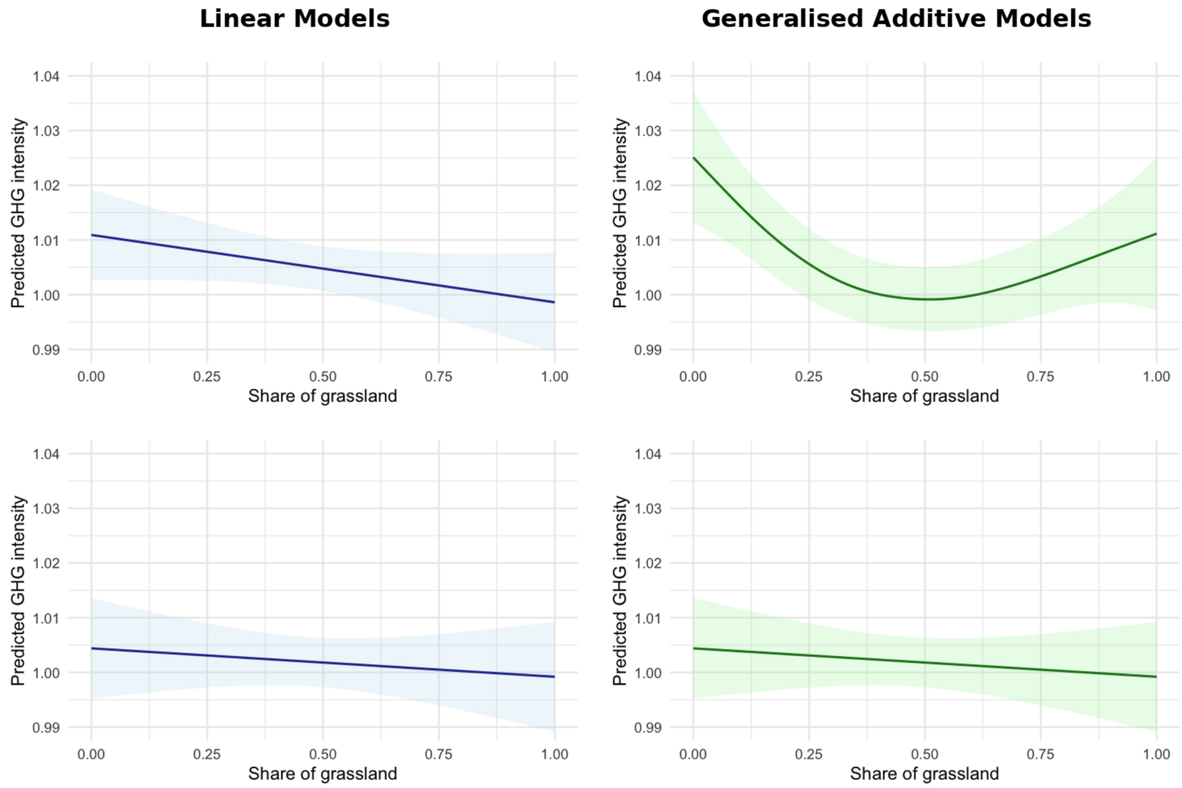


Figure A6. Estimated dose-response for emission intensity, sample with outliers

Table A6. Goodness-of-fit statistics for linear models with outliers

Outcome	Model	estimate	std.error	statistic	p.value	R2
EPRODC_DEA_fdh	OLS (without weights)	-0,003	0,0091	-0,287	0,774219	0,000061
EPRODC_DEA_fdh	OLS weighted (GPS)	-0,005	0,0087	-0,600	0,548812	0,000265
EPRODC_DEA_vrs	OLS (without weights)	0,047	0,0469	1,007	0,313942	0,000747
EPRODC_DEA_vrs	OLS weighted (GPS)	0,163	0,0441	3,700	0,000225	0,009978
GHGIC_DEA_fdh	OLS (without weights)	-0,002	0,0081	-0,192	0,847983	0,000027
GHGIC_DEA_fdh	OLS weighted (GPS)	-0,012	0,0078	-1,574	0,115807	0,001820
GHGIC_DEA_vrs	OLS (without weights)	0,063	0,0462	1,364	0,172743	0,001368
GHGIC_DEA_vrs	OLS weighted (GPS)	0,162	0,0432	3,748	0,000185	0,010240

Table A7. Goodness-of-fit statistics for GAM models with outliers

Outcome	Model	edf	F	p.value	Adj. R2
EPRODC_DEA_fdh	GAM (without weights)	1,000	0,082	0,774219	-0,000676
EPRODC_DEA_fdh	GAM weighted (GPS)	1,000	0,360	0,548812	-0,000463
EPRODC_DEA_vrs	GAM (without weights)	1,000	1,015	0,313942	0,000011
EPRODC_DEA_vrs	GAM weighted (GPS)	4,221	4,978	0,000139	0,017818
GHGIC_DEA_fdh	GAM (without weights)	1,000	0,037	0,847984	-0,000709
GHGIC_DEA_fdh	GAM weighted (GPS)	2,504	4,439	0,003575	0,009603
GHGIC_DEA_vrs	GAM (without weights)	1,000	1,861	0,172743	0,000633
GHGIC_DEA_vrs	GAM weighted (GPS)	3,679	4,568	0,000872	0,013827

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