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Published in:
Agricultural Systems

DOI:
10.1016/j.agsy.2023.103664

Print publication: 01/05/2023

Agricultural Systems 208 (2023) 103664

Contents lists available at ScienceDirect

Agricultural Systems

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

Identifying best practice in Less Favoured Area mixed livestock systems

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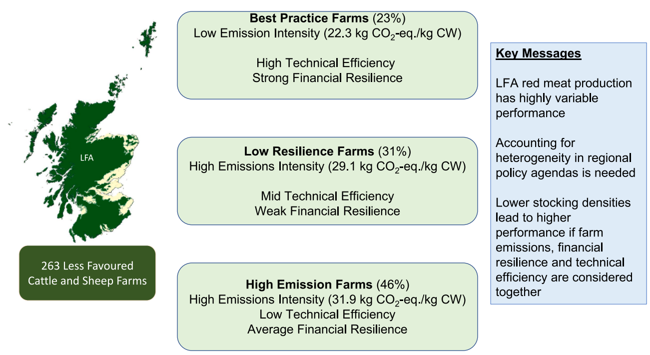
HIGHLIGHTS

- Less Favoured Areas (LFA) provide a significant amount of red meat production globally.
- LFA farms have highly variable impacts on efficiency, financial sustainability, and greenhouse gas emissions.
- Categorising LFA farms based on economic, environmental, and financial indicators reduces heterogeneity.
- Best practice farms have lower emissions intensity, higher financial resilience, and higher technical efficiency.
- More nuance is needed when setting performance targets for heterogenous LFA farming systems.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Guillaume Martin

Keywords:
Greenhouse gas emissions
Latent profile analysis
Mixed ruminant systems
Less Favoured areas

ABSTRACT

CONTEXT: The ruminant livestock sector is under scrutiny for its contribution to greenhouse gas emissions. Less Favoured Areas (LFA) carry a large proportion of Europe's cattle and sheep ruminant population and is also characterised by variable economic and biophysical constraints.
OBJECTIVE: This study aims to assess the heterogeneity in carbon emissions, resource usage and financial performance in a sample of mixed LFA livestock farms in Scotland.
METHODS: Individual farm account data for 263 LFA cattle and sheep producers were augmented with emissions data over the period 2019–2020. Environmental impacts were estimated for each farm using emissions intensity and carbon productivity. Technical efficiency at the farm level (the rate of output to total inputs) was estimated using non-parametric data envelopment analysis. Financial resilience was measured through returns on assets to meet short-term liquidities. To manage the heterogeneity in these indicators Latent Profile Analysis (LPA) was employed. This allocates farms into separate groups, or profiles, representing different levels of environmental, resource efficiency and financial dimensions. To gain understanding of the drivers on membership of profiles we assess the impact of intensity and enterprise mix using multinomial logistic regression (MLN).
RESULTS AND CONCLUSIONS: Three profiles were identified within our sample which reflect different levels of performance; i) a best practice profile (23% of farms) have relatively low mean emissions intensities (22.3 kg CO_2-eq./kg CW), high carbon productivity (£0.17 GVP/ kg CO_2-eq.), high technical efficiencies and strong financial resilience; ii) a low resilience profile (31% of farms) which are the most economically fragile and

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https://doi.org/10.1016/j.agsy.2023.103664
Received 14 December 2022; Received in revised form 14 April 2023; Accepted 17 April 2023
Available online 27 April 2023

susceptible to economic shocks, and iii) a high emissions profile (46% of farms) which have the lowest technical efficiencies and also the highest mean emissions intensities (31.9 kg CO_2-eq./kg CW) and lowest carbon productivity (£0.10 GVP/ / kg CO_2-eq.). The MLN identified that farms within the best practice profile will be more extensive compared to the other profiles.

SIGNIFICANCE: Less Favoured Areas dominate global agricultural systems and they offer a more heterogenous picture compared to more intensive lowland or feedlot cattle systems. Agricultural support payments are changing to reward public goods. Our approach sets realistic thresholds for higher level performance across multiple dimensions that may merit higher payments if an outcomes-based payment scheme were adopted.

1. Introduction

Ruminant livestock production is a fundamental part of most agricultural economies. However, the red meat sector has been under particular scrutiny for its environmental impact, in particular the high methane emissions from enteric fermentation and loss of biodiversity from intensive grazing regimes (Gerber et al., 2013; Herrero et al., 2016; Springmann et al., 2018). Agricultural policies are now attempting to embed ecological and climatic goals within payment regimes, whilst also protecting food production and supporting the resilience of its farming population (European Commission, 2020; DEFRA, 2021).

A tranche of literature argues for investment in efficiency improvements and support for climate smart or 'win-win' solutions as a key route to mitigating greenhouse gas emissions (GHG) in livestock systems (Havlík et al., 2014; Herrero et al., 2016). The bulk of these studies have been conducted at a global level. Whilst valuable these can only offer broad assessments into potential pathways for low environmental impact livestock production (Herrero et al., 2016; Frank et al., 2019). The regional aspect of livestock production and the specific constraints that these systems experience may complicate the requirement to meet globally derived targets, and this is a particularly intractable problem for policy makers (Fellmann et al., 2021; Winterton et al., 2014; Eory et al., 2018). More critically, heterogeneity has been found to bias upscaling of GHG savings for decisions at national or international levels (Dalgaard et al., 2011; Stetter et al., 2022). Accordingly, to progress the debate at national level policy recommendations require more nuance to accommodate local constraints (Manzano and White, 2019; Fellmann et al., 2021).

Within Europe, as elsewhere, large tracts of land are classified as Less Favoured Area (LFA). LFA land covers around 57% of agricultural area across Europe (Eliasson et al., 2010) and is dominated by extensive cattle and sheep farms. The criteria for LFA designation were first established in European legislation in 1975 (Directive 75/268 EEC and accompanying measures). These are usually mountainous or remote regions subject to climatic and topographic pressures. This will lead to more production challenges compared to intensive lowland systems. Consequently, performance is influenced by the heterogeneity of natural and topographic conditions under which livestock is produced. Efficiency levels will be lower than lowland systems, as will farm incomes, but this performance is also variable between farms and over successive years (Barnes, 2023; Vigani and Dwyer, 2020). Conversely, studies of these systems find that low intensity grazing could have benefits for biodiversity (Nunez et al., 2020; Sartorello et al., 2020).

A limited number of studies have explored metrics which infer both the regional environmental and financial performance of livestock systems. Coderoni and Vanino (2022) employed a carbon productivity index, measured as the farm net value added relative to the carbon emitted from individual farms in the Italian Farm Account Data Network (FADN). They found variance between farm type driven, in part, by levels of intensities of inputs. Vogel and Beber (2022) employed cluster analysis on dairy farms within the Parana region of Brazil, finding four distinct groups based on their emissions intensity. Stetter et al. (2022) explored the influence of membership of agri-environmental schemes in South-West Germany in pig, dairy, crop and mixed farming types using machine learning approaches to identify the ranges of environmental impacts. They found a weak but positive association between these schemes and GHG reduction.

A number of studies have focused on the financial aspects of resilience, essentially the ability of a farm to financially survive significant production related shocks (Barnes et al., 2020; Slijper et al., 2022; Loughrey et al., 2022). Again, these studies find much variance between farms that operate similar livestock systems within the same region. A larger tranche of literature has explored the efficiency of grazing livestock systems (Dakpo et al., 2021; Theodoridis et al., 2021) but few have distinguished between LFA and Non-LFA farms (Gaspar et al., 2009; Martinez Cillero et al., 2018; Barnes, 2023). These latter studies also find a large amount of variance in resource use efficiency for farms classified as LFA. However, none of these studies have extended their analysis to understanding financial resilience or the GHG emissions from the challenging situation of LFA livestock farming.

The purpose of this paper is to explore the distribution of farm-level performance on cattle and sheep farms in Less Favoured Areas in Scotland (see supplementary materials). We examine the extent to which these emissions are related to the financial resilience and resource use efficiency. As such this provides some indication of the potential for abatement as well as informing the targeting of policy interventions which address the heterogeneity within LFA ruminant livestock systems (Scottish Government, 2022; DEFRA, 2021; European Commission, 2020). We do this at a micro-level using farm bookkeeping data from the Scottish Farm Business Survey (FBS) augmented by detailed emissions data for each farm. We focus on Scotland as this is a predominantly livestock based agricultural economy with around 88% of agricultural land characterised as Less Favoured Area (see supplementary material). Scotland also has some of the largest numbers of sheep and cattle across Europe (Eurostat, 2020). This is also a pertinent case study as Scotland has the most ambitious net zero pledge in the World, with a commitment to reach net zero by 2045 (Committee on Climate Change, 2019). Finally, as part of post-Brexit planning Scotland is evolving its own support policy which embed climate goals as well as economic sustainability within its farming industry (Scottish Government, 2022).

2. Data and methods

Fig. 1 gives a graphical overview of the approach and methods used within the paper. We firstly use data on outputs and inputs, emissions, and intensification to derive a series of indicators which reflect environmental, economic and resource efficiencies for each farm. As there is much heterogeneity across these indicators, we employ Latent Profile Analysis (LPA) to partition these farms into profiles. This allows us to identify best practice groups and, further, to understand the drivers of these profiles.

2.1. Data collection and greenhouse gas emissions

As part of EU reporting there is an annual requirement to monitor a sample of farms to provide an understanding of their financial, biophysical and structural performance. In Scotland the Farm Business Survey (FBS) is an annual sample of around 400 farms. The main purpose of the FBS is to collect detailed financial data for estimation of average farm income by farm type and size. Whilst this does not

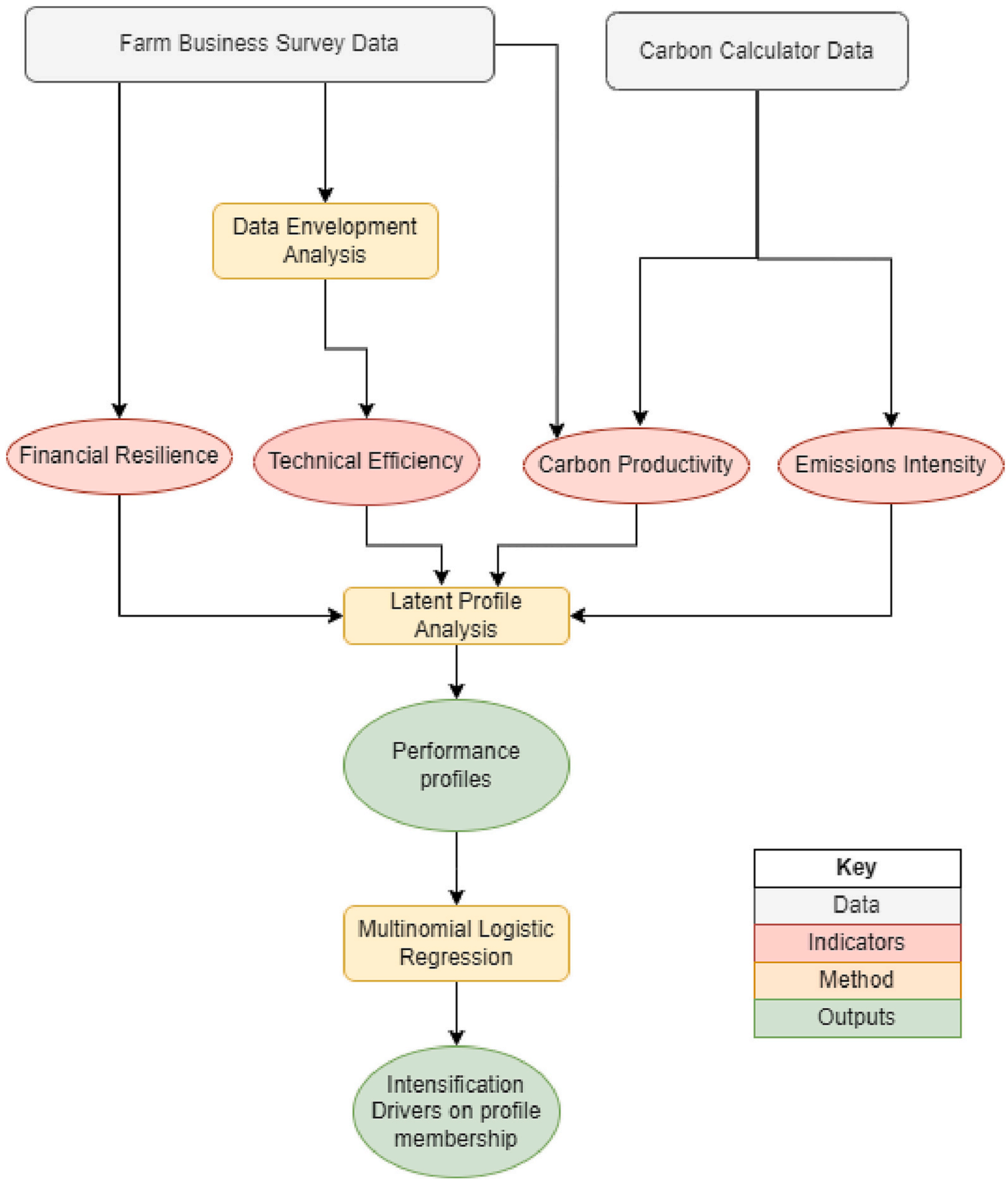

Fig. 1. Overview of data analysis approach. Farm Business Survey data is coupled with carbon calculator estimates to generate indicators of efficiency, emissions, and resilience. These are then categorised using latent profile analysis. Multinomial logistic regression is then used to explain membership of these profiles in terms of key measures of intensification.

necessarily represent all farming systems or management practices, it is intended to represent the majority of economic output from sectors in Scottish farming that are in receipt of Government support payments. Most of the participating farms are retained year-on-year in the FBS sample, allowing identification of long-term trends. Data are collected using a consistent and rigorous methodology that allows for robust comparisons between farms over time[1].

Uniquely, for the period 2019/2020 farmers who had completed the FBS were also asked to carry out a carbon audit. This involved a further detailed interview with each farmer to complete the carbon calculator 'Agrecalc' (Sykes et al., 2017; Kamilaris et al., 2020). 'Agrecalc' is a farm-level tool for measuring resource efficiency to improve profitability and environmental impact. The tool uses Tier 2 calculations and employs information on detailed inputs as well as mixes of outputs at the farm level. For example, it is able to estimate the effects of changes on fertiliser application rates, livestock diets and daily growth rates which reflect areas for best practice adoption. The 'Agrecalc' farmer interview provided valuable data on the provenance of all imported and home-produced inputs and outputs, as well as the underlying biophysical and management aspects of the farm. Another advantage is that using the FBS as the basis to estimate farm-level emissions gives confidence that emission and financial data have been reported in a consistent manner for all farms. As part of quality assurance protocols within the FBS any farms that had significant changes in their breeding herd or flocks were removed from this analysis as they are atypical and would have skewed estimates.

[1] See https://www.sruc.ac.uk/business-services/help-in-your-sector/farm-business-management/scottish-farm-business-survey/ and https://www.gov.scot/collections/scottish-farm-business-income-fbi-annual-estimates/.

Table 1
Descriptive statistics and emissions profile of the LFA ruminant livestock farms in CO_2 equivalent kg, mean and standard deviations, and proportion of contribution.

	Mean	*SD*
Farm output (thousand kg)	57.4	*(73.0)*
Total utilised agricultural area (ha)	188.0	*(189.0)*
Intermediate consumption (£ thousand)	99.7	*(73.0)*
Labour (hours worked thousand)	3.4	*(2.1)*
Grazing livestock units (livestock unit[1])	172.8	*(173.8)*
Capital costs (£ thousands)	224.5	*(186.6)*
Number of cattle (no.)	78.6	*(79.6)*
Number of sheep (no.)	432.1	*(440.4)*
Woodland (ha)	7.5	*(31.1)*
Farm business income (£ thousand)	20.7	*(36.7)*
Gross farm emissions (thousand kg CO_2-eq.)	987.1	*(752.8)*
Of which:		
CO_2 (%)	23%	(26%)
Methane (%)	53%	*(51%)*
Nitrous Oxide (%)	24%	*(27%)*
Emissions intensity (kg CO_2-eq./ kg CW)	28.4	*(15.0)*
Efficiency score (continuous scale from 0 to 1)	0.58	*(0.16)*
Carbon productivity (£ Gross production value / kg CO_2-eq.)	0.13	*(0.06)*
Return on assets (£ Cash income / total assets)	0.04	*(0.06)*

[1] A livestock unit is the conversion of different types of livestock to a consistent unit using a conversion factor.

Farms are typed based on the farm's main enterprise activity.[2] We extracted those farms from the FBS based on the farm types LFA Cattle, LFA Sheep and LFA Cattle and Sheep ($N = 263$).[3] LFA farms will have a mixture of sheep and cattle under similar management and produce a relatively similar output, hence the three farm types were merged.

Table 1 shows the main characteristics of these farms as well as their emissions profile. Methane is clearly the largest emitter but there are large standard deviations attributed to this metric, which is reflective of a range of management factors. The main form of sequestration is farm woodlands, though around half of the sample have no woodland on farm, and only a few have large tracts of woodland area. For most of these farms there is very little uptake of farm woodland grants (Hopkins et al., 2017) and farm woodland infers native and mature woodland which limits the potential for sequestration on these farms. Accordingly, we focus on gross emissions which better reflects the management of farming activity, namely the production of food, rather than net emissions.

2.2. Methods

We calculate key metrics of carbon intensity and resilience. Firstly, emissions intensity (*EI*) is measured as emissions per kg of carcase weight (CW). This represents the amount of carbon equivalent emissions produced from a kilogram of production. Hence it provides a normalised metric to compare across farms and systems:

$$EI_i = \frac{E_i}{P_i} \tag{1}$$

Where E_i represents the emissions for farm i and P_i the amount of physical production – in this case kg of red meat carcase weight – for each farm. These average 28 kg of CO_2 eq. per kg CW. This is slightly higher than those found by McAuliffe et al. (2018) for pasture-based UK cattle (15-23 kg CO_2-eq. / kg. liveweight) and those of Alemu et al. (2017) for the Canadian Beef sector (23.9 CO_2-eq./ kg. liveweight). Though these studies were at a smaller herd level.

To link economic with environmental performance we produce a farm-level carbon productivity index (CP). This links the economic value of output through gross production value (GPV) to each unit of carbon. Hence, much like EI it provides a normalised metric per pound of output value of the carbon emissions across farms. CP is mostly applied at the macro level (OECD, 2014; Xiong et al., 2021) to show relative performance in economic and environmental growth. Only recently Coderoni and Vanino (2022) have applied the metric to individual farms, finding higher carbon productivity to be associated with higher economic performance. The CP for farm i is estimated as

$$CP_i = \frac{GPV_i}{E_i} \tag{2}$$

This provides another dimension to the emissions intensity metric using the value of physical output against emissions in kg CO_2-eq. We find an average CP of £0.13/kg CO_2-eq. which is much lower than those found for 'grazing livestock' of Coderoni and Vanino (2022) though this may reflect their inclusion of intensive lowland and dairy systems which have a higher value.

We also employ a metric of resilience of these farms based on return of assets. Slijper et al. (2022) proposed this as the key resilience metric to show financial resilience to shocks and disturbances. As we have only two years of data, we use cash income which reflects the immediate liquidity of the farm to meet short-term economic shocks. This relates the ability to meet short-term demands, through cash-flow, to the financial asset base of each farm. Hence, this indicator reflects the ability of each farm to survive a financial shock. We calculate a return on assets (RoA) for farm i as:

$$RoA_i = \frac{CI_i}{A_i} \tag{3}$$

Where CI_i is the annual cash income of farm i and A_i is the average of opening and closing valuation of total assets of farm i.

Finally, we apply data envelopment analysis (DEA) to compose our indicator of efficiency. This is a non-parametric approach to identifying relative performance within a sample and has been used extensively within farm management studies (Toma et al., 2017; Gerdessen and Pascucci, 2013). DEA combines multiple inputs and outputs within a framework that optimises individual weights to reflect the best performance of each farm. Its usefulness is as a relative measure of performance within a sample of farms and technically efficient farms are identified based on Farrell (1957). Alternative models are available, but we employ a simple input-orientated model with returns to scale of (Banker et al., 1984). Where a vector of outputs (*Y*) and vector of inputs (*X*) for farm i across a set of farms is solved through the linear programming problem:

$$\begin{aligned} & Min_\theta \\ \text{subject to} \quad & \theta x_i - X\lambda \geq 0 \\ & Y\lambda \geq y_i \end{aligned} \tag{4}$$

$$e\lambda = 1$$

$$\lambda \geq 0$$

The aim of DEA is to maximise the weights for inputs and outputs for each farm. These are constrained within a linear programme to be non-negative but also less than or equal to 1. The estimated value of θ is the efficiency score for each of the N farms, where 1 is a farm that is technically efficient and a value of less 1 represents inefficiency. A further constraint accommodates variable returns to scale (λ) where e is a row

[2] Farms are classified based on the how much of their standard output (the estimated worth of crops and livestock) is from the crop and livestock enterprises on each farm. Farm types contain farms where more than two-thirds of standard output comes from the specified enterprise. Mixed farms are those where no enterprise contributes more than two-thirds of the total.

[3] The Scottish FBS only includes full time farms with economic activity of at least €25,000 (equivalent to around £23,000 in September 2019). Full time farms are considered to be those with a Standard Labour Requirement (SLR) of >0.5. Standard Labour Requirements represent the approximate average labour requirement for a livestock or crop enterprise. The annual hours of a full-time worker is 1900 h.

vector of ones and λ a column vector with all elements non-negative. This imposes a convexity condition which allows the farms to be closely enveloped. The LP is solved for each farm and identifies the most favourable weights for each farm's input and output combination. Our output variable was kg of carcase weight with four input variables, namely intermediate consumption (feed, fuel, livestock expenses and fertiliser), labour inputs (hours worked), grazing livestock units as well as capital costs. All variables were normalised by hectare to scale the inputs and outputs. We use the R Package 'rDEA' (Simm and Besstremyannaya, 2020) to estimate the DEA model above.

2.3. Latent profile analysis

Latent profile analysis (LPA) is part of the suite of latent mixture models (Ferguson et al., 2020; Gibson, 1959; Oberski, 2016). The advantage of LPA is that groupings, referred to as profiles, can be estimated based on the latent structure within populations in a parsimonious manner (Woo et al., 2018; Masyn, 2013). The resultant set of individual profiles offers an insight into how variances are grouped within a set of observations. Hence, these profiles can be characterised by their response to variables which allows a targeted approach towards intervening within the whole population (Barnes et al., 2013).

LPA considers a set of latent profiles (k) across a set of individual farms (i), revealed through a shared pattern of responses to outcomes (j) (Ferguson and Hull, 2018), e.g. efficiency scores, emissions intensity etc. The resulting profiles are identified by examining the joint and marginal probabilities within and between profiles. The within profile model is defined as:

$$y_{ij} = u_j^{(k)} + \varepsilon_{ij} \tag{5}$$

where

$$\varepsilon_{ij} \sim N\left(0, \sigma_j^{2(k)}\right)$$

Where the outcome (y_{ij}) for each individual is determined by the within group mean of each outcome ($u_j^{(k)}$) and the variance of each outcome (ε_{ij}). This will vary both across outcomes ($j = 1 \ldots J$) and by the number of profiles ($k = 1 \ldots .K$). The posterior probability (t) represents the probability of a farm (i) being assigned membership (c_i) to a specific profile (k) given their response to the outcome (y_i) variables. Hence, for each individual farm (i) within profile (k) the posterior probability is defined as:

$$t_{ik} = p(c_i = k|y_i) = \frac{p(c_i = k) f(y_i c_i = k)}{f y_i} \tag{6}$$

The more distinction between the posterior probabilities for an individual, the more certainty there is around their membership assignment (Sterba, 2013).

In order to run the LPA we employed the MCLUST package (Scrucca et al., 2016) within the R software environment. The optimal model and cluster numbers are based on the maximized log likelihood with a penalty on the number of parameters in the model. Overall profile choice in MCLUST is based on maximising the Bayesian Information Criterion (BIC) (Fraley and Raftery, 2003; Wardenaar, 2021).

We profile our farms using four outcomes of economic and environmental impact, namely the technical efficiency, carbon productivity, financial resilience, and emissions intensity metrics derived in Eqs. (1)–(4). These were considered as they offer differing dimensions to understand the economic and environmental heterogeneity of these farms. All variables were scaled by the subtraction of the geometric mean and division by their standard deviation. This is a common step to any pre-clustering as it ensures all variables share a common scale. The LPA estimated from 1 to 9 profiles to identify the optimal profile and across four different variants which reflect progressive levels of complexity in how the LPA treats variances and covariances (Scrucca et al., 2016; Pastor et al., 2007; Wardenaar, 2021). The highest BIC values indicated three profiles and the most complex VVV variant (see Supplementary material). A number of further criteria were used to check the optimal solution. We assessed whether the profile would contain <5% of the sample, and that the likelihood ratio test was significant at 5%. For the latter we used the bootstrap likelihood ratio test (Tein et al., 2013).

2.4. Multinomial regression

The LPA produces a discrete set of profiles based on various economic and environmental outcomes. These profiles are not ordered so a multinomial logistic regression was applied to understand the influence of different management approaches on membership of each profile. In Eq. (7) let J be the number of nominal outcomes, with k the number of profiles. The predicted probability of the i-th farmer belonging to a particular profile (p_i) is:

$$Pr(p_i) = k \vee x_i = \frac{exp(x_i \beta_k)}{\sum_{j=1}^{j} exp(x_i \beta_j)} \tag{7}$$

This estimates the influence of a change in an independent variable for the *ith* farmer (x_i) affecting the members of a particular profile. The multinomial regression produces odds ratios which indicate the influence of a particular variable relative to a reference group. As such it provides an indication of whether a particular driver has a positive impact on membership of a particular profile.

The next section outlines the main results. We firstly present an overview of the emissions, efficiency and resilience of the LFA farms, derived from Eqs. (1)–(4). This has the aim of showing the variance and general trends between these indicators. Then the results of the LPA profiling are presented. These show the characteristics of each farm profile in terms of their emissions and how they relate to financial resilience and efficiency. Finally, we employ the multinomial logistic regression to estimate the impact and significance of key management factors that may predict membership of a particular group.

3. Results

3.1. Technical efficiencies and emissions

The DEA efficiency score had a mean of 0.58 and a standard deviation of 0.16. As a score of 1 is the most technically efficient within the sample then this infers that these farms are mostly technically inefficient, though 10 farms (3.8% of the sample) had a score of 1. This tends to reflect other studies which have explored LFA farming finding similarly lower efficiency scores (Barnes et al., 2010; Vigani and Dwyer, 2020). Moreover, we find most farms have slightly increasing returns to scale. This means that, generally, the farms could increase in size and experience some efficiency gains from expansion. However, capital is constrained within these farming systems and their ability to purchase increased land of quality is limited.

Fig. 2 shows a scatter plot of the standard metric of emissions (emissions intensity) by efficiency score (similar plots of other indicators are provided in the supplementary tables). We remove farms with a score of 1 from the above table to better represent the distribution of efficiency scores. This reveals the high level of variance between efficiency and emissions intensity for the LFA farms. We employ a fractional polynomial trend to best reflect the non-linear nature of the relationship (Royston and Altman, 1994). Though, whilst this shows a general trend downwards, this fall is steeper at lower levels of efficiency. This indicates that modest gains in efficiency from the lowest performers will have a large positive impact on emissions intensity for the sector. However, the relationship is generally weak, with a low R^2 value of 0.17. The next section presents the results of the Latent Profile Analysis to address this variance.

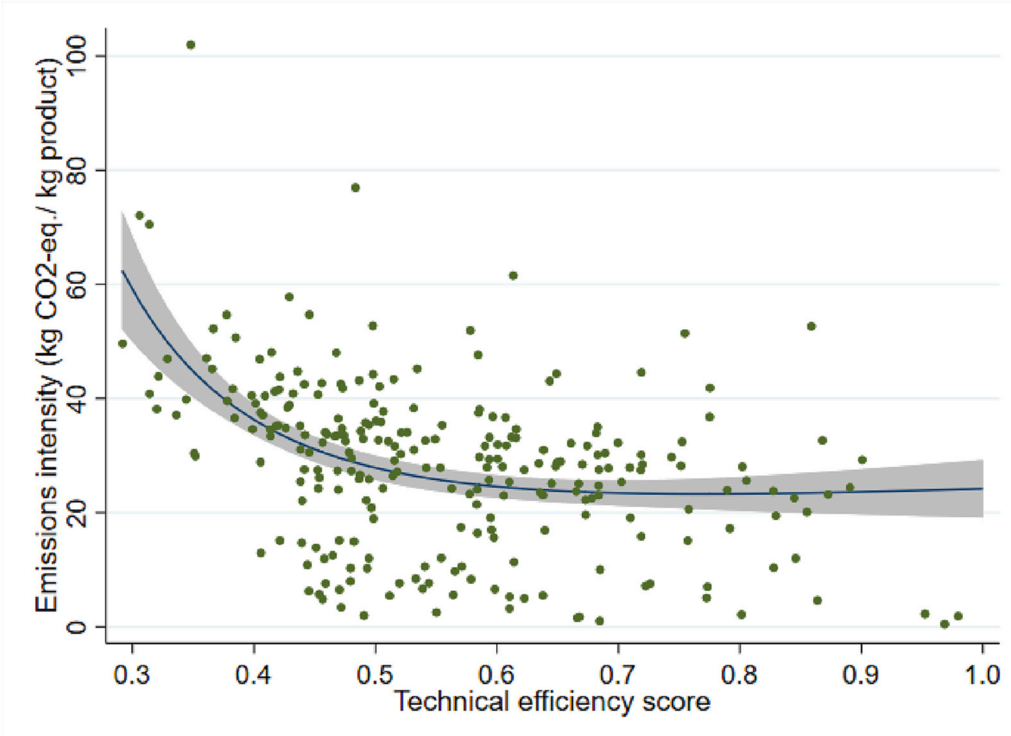

Fig. 2. Emissions intensity by technical efficiency score for LFA ruminant farms, with fractional polynomial trend and confidence intervals. This shows a non-linear trend between improving efficiency and reduction in emissions intensity, with the major gains in emissions achieved from least efficient farms improving their efficiency.

3.2. Characteristics of the profiles

The LPA grouped the farms into three profiles based on distinct characteristics of efficiency, emissions and resilience. These are named to reflect each profile's main characteristics and summarised in Fig. 3. To provide a common metric for the graph we take the deviance from the sample mean of each variable and compare these against each profile. This means a value of 1 indicates that the profile is at the mean for that indicator. On the left-hand side higher values (those above 1) show better performance (Financial resilience, efficiency and carbon productivity), and on the right-hand side lower values (those below 1) show a better than average performance (Farm gross emissions, emissions per kg and emissions per ha).

Table 2 shows the mean and standard deviations of the three profiles. A Bartlett test rejects equal variances for most of the variables, aside from emissions per farm. This indicates that farm level emissions are not significantly different across the three profiles but the per unit metrics tend to have significant differences between the profiles.

Best practice profile (23% of the sample). Farms in this profile have significantly higher technical efficiencies, which indicates they are converting resource inputs into outputs at a more productive rate than farms in the other profiles. Moreover, these farms have the lowest emissions intensities both in terms of kg of production and by area. From an economic perspective the farms in this group also perform better relative to other profiles. They have the highest value of output to carbon produced (carbon productivity) and a much higher return on assets (financial resilience).

Low resilience profile (31% of the sample). These farms tend to have average technical efficiency levels. Hence there is potential to increase resource use efficiency, and this leads to relatively high emissions intensities and low carbon productivities. Whilst not as severe as the 'high emitters' profile there is significant potential to improve these emissions ratios when compared to the best practice farms. More starkly, farms in this profile have the highest exposure to economic shocks as they have low financial resilience relative to other profiles. Hence if there are falling prices or inflationary pressures on costs then this profile, which represents around a third of the sample, will be the worst affected.

High emissions profile (46%). This profile, which represents nearly half of the farms in the sample, is characterised by farms with the lowest technical efficiencies, the highest emissions intensities and lowest carbon productivities across the sample. At the mean, farms in the 'best practice' profile are producing at around 9 kg of CO_2-eq. per kg CW less than those in the highest emissions profile. At the per ha level, this relationship holds but is only weakly significant. This metric accounts for size of the farm and, when normalised per hectare, the 'best practice' profile farms are saving over 1000 kg per ha on kg CO_2-eq. compared to this profile. At an economic level, farms in this profile are returning the lowest output value of £0.10 per kg CO_2-eq. but have a higher level of financial resilience, which will be driven by higher levels of cash income and asset values, compared to the second profile.

3.3. Drivers of membership of profiles

To understand the influence of farm management strategies on profile membership we take a number of management variables from the FBS which indicate enterprise mix and the intensity of activity on efficiency, resilience and emissions.

The results of the multinomial logistic regression are shown below. These are shown as odds ratios (OR) which indicate a variable's influence relative to the best practice group. If a variable has an OR above 1 then an increase in that variable is more likely to influence membership of that profile. For those variables with an odds ratio of below 1 then that variable is more likely to influence membership of the reference group, in this case the 'best practice' profile. Overall, the table shows most of the indicators are significantly affecting membership the 'high emissions' profile, relative to best practice, whereas only around half of these indicators are affecting membership of the 'low resilience' profile relative to best practice (Table 3).

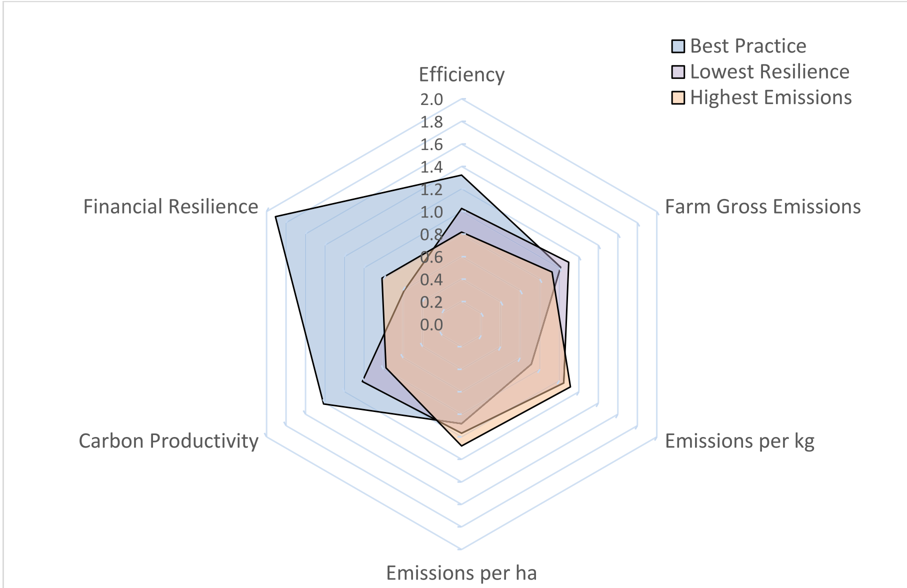

Fig. 3. Radar graph of key variables, measured as the difference from the mean, where 1 is equal to the mean of the sample. This shows the various dimensions on which the three profiles perform. Farms in the Best Practice profile perform at higher levels than other profiles in terms of most metrics, whereas the lowest resilience and highest emissions group tend to perform the least across various dimensions.

Table 2
Summary statistics on emissions profile, descriptive statistics.

		Technical Efficiency	Farm-Gross Emissions	Emissions Intensity per kg CW	Emissions Intensity per ha	Carbon Productivity	Financial Resilience
Profile	*N*		*kg CO_2-eq./farm*	*kg CO_2-eq./kg CW*	*kg CO_2-eq./ha*	*£GVP/kg CO_2-eq.*	*£ cash income/total assets*
Best practice	61	0.755	993,201.3	22.3	4743.5	0.171	0.084
		(0.154)	*(787,285.1)*	*(15.6)*	*(3517.3)*	*(0.084)*	*(0.091)*
Low resilience	82	0.596	1,085,442.7	29.6	5668.4	0.134	0.026
		(0.108)	*(724,300.5)*	*(5.7)*	*(2449.8)*	*(0.026)*	*(0.014)*
High emissions	120	0.469	918,537.7	31.9	6437.8	0.102	0.035
		(0.081)	*(759,492.9)*	*(17.3)*	*(2752.9)*	*(0.023)*	*(0.044)*
Bartlett Test		32.44***	0.46	89.80***	8.82*	165.09***	188.78***

*sig.different at 0.05; **sig.different at 0.01; ***sig.different at 0.001.

There is a significant and positive relationship between the number of cows and membership of the 'high emissions' profile. This means that farms with a greater proportion of activity of cattle compared to sheep will be more likely to have higher carbon emissions intensities, and lower overall efficiency and lower levels of resilience compared to farmers in the 'best practice' profile. This agrees with a range of studies which have explored the benefits of mixed livestock systems (Martin et al., 2020; d'Alexis et al., 2014) and their role in reducing input use for overall financial resilience (Diakité et al., 2019; Dardonville et al., 2020; Mugnier et al., 2021).

The stocking density variable is significant for both profiles and is above 1. This means, relative to the 'best practice' profile, farms in the other profiles will tend to have higher stocking densities and therefore operate more intensive grazing regimes. This correlates with a number of in-field assessments of pasture-based systems which have found a diffuse but positive correlation between increasing stocking rates and increased average GHG emissions (Pinares-Patiño et al., 2007; Chiavegato et al., 2015; Ma et al., 2021). However, these studies have only focused on specialist cattle or sheep systems and not examined the relationships within mixed livestock systems but it seems that the relationship may hold within our sample of farms in LFAs.

Labour intensity is measured as total labour hours per cow and is only significant for the 'high emissions' profile. The OR is above 1 in this

Table 3
Estimates from multinomial logistic regression, presented as odds-ratios (OR).

	OR	SE	Sig.
Low Resilience			
Cow-sheep ratio (Cow LU/Sheep LU)	2.262	(1.31)	
Stocking density (LU/Ha)	1.003	(0.001)	*
Labour intensity (Hours/LU)	1.025	(0.01)	
Revenue to mean $\left(£Rev/\overline{£Rev}\right)$	0.090	(0.08)	**
Fertiliser intensity (£ Fert/Ha)	1.003	(0.001)	*
Feed intensity (£ Feed/LU)	1.118	(0.28)	
High emissions			
Cow-sheep ratio (Cow LU/Sheep LU)	3.777	(2.23)	*
Stocking density (LU/Ha)	1.007	(0.001)	***
Labour intensity (Hours/LU)	1.060	(0.02)	***
Revenue to mean $\left(£Rev/\overline{£Rev}\right)$	0.000	(0.0002)	***
Fertiliser intensity (£Fert/Ha)	1.005	(0.001)	**
Feed intensity (£ Feed/LU)	2.837	(0.72)	***
LR chi^2		142.45	***
Pseudo R^2		0.27	
Log likelihood		−190.92	
% correctly classified		89.7	

* sig. at 0.05, ** sig. at 0.01, *** sig. at 0.001.

profile indicating that these farms have more intense labour activity per animal relative to the best performer farms. Access to off-farm labour is limited on these farms and family labour tends to dominate, which means farms in this profile are using more paid labour which will also impact financial resilience and resource use efficiencies (Vigani and Dwyer, 2020; Barnes, 2023).

The revenue to mean indicator is used to infer the relative economic returns across the sample population. This measures the farm revenue, either positive or negative, from the mean. These are significant for both profiles but also below 1. This reflects the better financial performance of the 'best practice' profile, which had the highest return on assets of the three profiles.

The additional intensification markers, fertiliser and feed intensities, reveal various differences in the management of livestock and grassland. For the two profiles, fertiliser intensities are above 1 and significant, reflecting more intensive grassland regimes compared to farms in the 'best practice' profile. Moreover, for the 'high emissions' profile, feed intensities are also significant. As both these profiles have lower farm efficiencies, this tends to infer the potential mismanagement of inputs from more intensive activity on upland mixed systems (Gaspar et al., 2009).

4. Discussion

The desire to reduce greenhouse gas emissions from red meat production is prominent in global climate debates (Mayberry et al., 2019; Mazzetto et al., 2015). Farms in Less Favoured Areas produce a significant amount of red meat but are also constrained by low incomes, variable production conditions and limited access to capital. This limits their ability to adapt by adoption of new practices and techniques. We find a range of performance amongst LFA farms and argue that we should not focus on assessments of emissions alone but on the relationships between emissions, efficiency, and financial resilience. This relationship is more diffuse when compared to specialized intensive red meat production systems. Hence, this paper offers an approach that allows some partitioning of this farm level variance.

4.1. Patterns within greenhouse gas emissions, efficiency, and resilience

We find three groups operating within our sample based on our chosen metrics. The main characteristic of farms in the 'best practice' profile is that they operate more extensive systems, and this adds to calls for nuance around the future management of grazing land in high income agriculture (Soussana et al., 2010; Schulte et al., 2014). These farms operate above the sector average both financially and environmentally and provide exemplars for other farms within the region. Moreover, whilst we do not consider biodiversity within our metrics, extensive grazing systems have been found to support biodiversity (Marriott et al., 2009; Olén et al., 2021). This is important as policy solutions for meeting net zero commitments should also consider the social and ecological impacts of changing payment regimes (Westhoek et al., 2014; Modernel et al., 2019).

A major concern for policy targeting in Scotland will be the two lesser performing profiles. The 'low resilience' profile will be especially susceptible to financial perturbations. LFA farms are characterised by a high reliance on government support payments and payment agendas are changing within the UK, where agricultural support policies now embed the incentivization of sustainable approaches (Scottish Government, 2022; DEFRA, 2021). These payments may offer a potential trajectory for LFA family farms who are economically unviable without their current subsidy.

The 'high emitters' profile represents nearly half of the sample. Whilst not as economically fragile as the 'low resilience' profile, farms in this profile have significant potential to improve their resource efficiency as well as their emissions per unit of product. When measured against output metrics, e.g., per kilogram of produce, these farms are overusing material inputs. A more direct form of support for farms in this profile would therefore be the promotion of decision-making tools, such as nutrient management software, for these farms. This would address both the input use inefficiencies of these farms and their emissions intensities. Moreover, these have an over-utilisation of labour which is a common finding on inefficient LFA farms (Martinez Cillero et al., 2018; Betts, 2020; Vigani and Dwyer, 2020). This infers there may be structural aspects to these farms that define their profile, for instance due to the farm family life cycle. Barnes (2023) found that planning for succession had a significant positive effect on addressing structural inefficiencies, as those farmers without succession plans had no incentive to invest in more efficient approaches. Whilst we do not accommodate for these factors in this paper further analysis of the family life-cycle dynamics behind financial resilience and lower emissions intensities would be valuable.

4.2. Trajectories towards net zero targets

Setting targets for net zero will require increased adoption of climate smart practices. Recognising that overall emissions are composed of discrete sets of emitters who experience a range of biophysical and economic barriers allows some understanding of why farmers do not adopt cost-effective mitigation measures (Moran et al., 2013; Vogel and Beber, 2022; Stetter et al., 2022). Our approach identifies a pragmatic win-win solution, namely if we accept red meat production as part of a climate-smart agricultural economy we have identified a set of farms that would inform government aims for this sector. If the 'best practice' profile reflected the LFA livestock sector as a whole then a large economic and environmental burden would be lifted from red meat production in Scotland's LFAs and this would support stated ambitions towards net zero farming for 2045.

For future payment regimes our analysis provides farm targets for best practice across a range of dimensions. As we identify these farms based on current industry data, they could provide parameters for releasing higher tier support payments. This firstly would reflect a more outcomes driven payment system but also potential targeting of payments to reward better practice. This may provide an incentive to encourage those farms currently in other profiles to engage in these practices. This means targeted intervention within the LFA sector may be more effective than blanket approaches for these farms. The cost of employing mitigating technology will vary across these farms as will the socio-economic and biophysical characteristics which constrain the opportunities for adaptation (Doole, 2014; Eory et al., 2018). This suggests that support payments and other interventions, such as training or advisory services, would also benefit from a targeted approach.

The specific challenge of engaging communities of farmers within a climate mission requires discussion on what can feasibly be adopted. The farms within the 'best practice' profile provide exemplars for an engagement strategy which may align with the 'living lab' concept. This aims to support better practice adoption by encouraging a community of farming interest to share and support learning around social and economic goals (European Commission, 2021). Our approach identifies characteristics of the range of farms that could be recruited for regional LFA living labs. This would help demonstrate practices or discuss constraints to achieve lower per unit emissions, as well as higher efficiencies and financial resilience. The Scottish Government have developed dialogues within its sectors, known as Farmer Led Groups.[4] These groups have identified practices, such as improved storage and handling of manure, and the potential for innovation, e.g., towards hydrogen power vehicles and accelerated breeding selection. Accordingly, our approach offers the opportunity for peer group promotion of better practice as well as farmer validation of what is feasible for adoption on these farms

[4] See for example https://www.gov.scot/groups/suckler-beef-climate-group/.

(Kernecker et al., 2020).

A more radical solution is to raise the thresholds of regulatory compliance for support payments to achieve net zero targets. Currently compliance towards 'good agricultural and environmental practice' (GAEC) is the baseline expectation for basic payments in Europe. This requires farmers to actively manage the land but also to an agreed environmental standard. If payments were based on raising these standards, then net zero targets may become more achievable. Increasing regulation however would incur increased monitoring costs and an compulsory element to payment support needs to accommodate the constraints faced by these farms.

4.3. Benefits and limitations to our work

We have only considered gross emissions from farm production as these are emissions which directly result from farming activity. These farms may also have some native woodland within their farm boundary which would further sequester carbon. Traditionally this is not actively managed by the farmer and there are definitional issues around what constitutes woodland in the recording of farm accounts. If land were freed up there are also challenges to establishing new woodland on upland systems (Iversen, 2019; Holt and Morris, 2022). The Scottish Government recently promoted a 'sheep and trees' initiative, but uptake was low for a variety of attitudinal and institutional, e.g., tenancy restrictions, reasons (Weston and Philip, 2020).

Our estimates of emissions do not account for changes in soil carbon storage as we assume land under long-term grass tends to have soil carbon in equilibrium. There will be limited management of this land given the poor potential of LFA grazing. The challenge for producers is maintenance through, for example, rotational grazing, but options are limited given constraints on resources within this sector. The Scottish FBS does not currently collect information on practices adopted, but the desire for extending the current European FADN to develop farm sustainability indicators (Kelly et al., 2018) may include questions on management approaches to grazing land.

Extensive livestock grazing has been found to sustain efficiency of production (Michalk et al., 2019) and has been found to support the link between ecosystem health and food production when compared to more intensive stocking regimes (Huang et al., 2016). However, a low stocking density regime may run counter to a food security agenda. We must also recognize that reduced stocking rates could raise the threat of off-shoring environmental impacts through imports. Nevertheless, UK red meat consumption is declining, and the UK is mostly self-sufficient in beef and lamb meat which reduces the need for imports (Stewart et al., 2021).

Finally, this work relies on access to farm business level data and these data are collected annually for a number of sectors and countries. Replicating this approach by coupling these large-scale data sets with carbon emissions would offer a comparative assessment of the different emissions, efficiency and resilience clusters that are operating within and between countries. As such this would support a more regional approach for net zero targets within agricultural systems.

5. Conclusions

This study shows that we should not ignore regional variance in greenhouse gas emissions if we want to include red meat in a carbon neutral future. Moreover, we must consider the constraints faced by livestock farms in Less Favoured Areas which may limit trajectories towards net zero agriculture. Nearly a quarter of our sample show best performance and the remainder are poor performers which confirms previous findings in other regions (Ang, 2019; Dakpo et al., 2021).

To raise performance levels for reaching best practice will require significant investment to support a trajectory which mitigates the emissions from red meat production. Government support systems are now changing in the UK and offer the chance to reward climatic and resilience positive outcomes within incentive structures. If successfully implemented these could go a long way to achieving a financial and environmentally sustainable cattle and sheep sector.[1]

Declaration of Competing Interest

The authors declare no Conflict of Interest.

Data availability

The data that has been used is confidential.

Acknowledgments

This work was supported by the Scottish Government as part of the Rural Affairs, Food and the Environment (RAFE) Strategic Research Programme 2022-2027 SRUC-B3-1—Ensuring positive behavioural change for farmers towards best practice for clean growth: economic and behavioural investigations. We also thank Jay Gilliam and David French from the agricultural analysis division of RESAS for receipt of data. We also thank the Scottish Government funded ClimatexChange (CXC) for initial funding towards this work. Thanks, are also due to anonymous reviewers for their constructive comments on an earlier draft.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2023.103664.

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