A slacks-based Data Envelopment Analysis framework to identify differences in sustainability patterns between four contrasting dairy systems

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Abstract: World food production must increase to meet greater future demand without exacerbating climate change and despite dwindling resources. More efficient dairy farm production is therefore essential if farms are to become- and remain- economically, socially and environmentally sustainable. Data Envelopment Analysis has been increasingly used to measure dairy farm efficiency. However, all studies identified have used radial models that do not account for the farms' slacks, i.e. overused resources for a given production level. This study used a slacks-based measure of efficiency (SBM) in order to identify relationships between the technical, environmental and economic efficiencies of dairy farms by using data from a long-term genetic line × feeding systems experiment comprising of 4 distinct systems. The slacks allowed for the calculation of resource-specific efficiency patterns for each system. Results supported the assumption that technically efficient units were also environmentally efficient. Moreover, there was no clear relationship between economic and environmental efficiency. Notably, technically efficient units did not always manage to reduce their costs to the lowest possible level, compared with their peers. Therefore, there may be economic/environmental trade-offs between dairy farming systems i.e. a 'win-win' may not always be possible. Furthermore, resource-specific efficiency patterns suggested that systems selected for increased milk fat + crude protein yield were better in minimizing their greenhouse gas emissions and nitrogen and phosphorus surpluses, compared to systems selected to remain close to the average UK genetic merit., Systems on high forage required a larger reduction in land use and fertilizer use than systems on low forage. A further step will be to test the hypothesis that the 'best' system is not necessarily the most efficient one, but the least variable one, i.e. further step will be to account for the experiment's temporal nature.

Keywords: farm experiment, contrasting systems, slacks-based DEA, efficiency, sustainability patterns, policy-making indicators

Introduction

Milk is one of the major agricultural commodities produced in the European Union (EU) as it is produced in every single member state and represents 15% of total agricultural output in terms of value (European Commission, 2013). However, milk production is a contributor of greenhouse gas emissions (GHGs) and other pollutants (Toma et al., 2013), while the quality of the management system can also impact on the productivity and welfare of dairy cows (Bowell et al., 2003 ; Kauppinen et al., 2013). Agriculture in the EU (and elsewhere in the developed world) aims for resource-use efficiency with policy increasingly focused on compliance with socio-economic and environmental sustainability standards and less on production controls. Wider definitions of efficient dairy farm production are therefore essential if dairy farms are to be and seen to be sustainable from an economic, social and environmental viewpoint.

In the present study, we adopted an efficiency-based framework to compare four contrasting dairy systems by using data from a long-term genetic line × feeding systems experiment. We calculated the technical, environmental, economic, and resource-specific efficiencies with the use of a novel, slacks-based Data Envelopment Analysis (DEA) model. This model is superior to DEA models used in past dairy farm assessments (e.g.Hansson & Öhlmér, 2008 ; Toma et al., 2013), as the latter do not only ignore the substitutional nature of some of the dairy farms' resources, but also do not account for any potential resource/undesirable output excesses or output shortfalls when evaluating efficiency. Therefore, the slacks-based models allowed for an in-depth examination of the four systems' reasons for inefficiency.

Methods

Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a method for measuring the capacity of Decision Making Units (DMUs) to convert inputs into outputs [see Cooper et al. (2007)]. All DEA dairy studies identified in the literature have used radial models which have two well-known drawbacks. First, any input (output) reduction (improvement) is assumed to be equiproportional, i.e. they assume a given input (output) mix. Second, they do not account for the potential presence of input (output) excesses (shortfalls), i.e. slacks (Tone, 2001).

Tone (2001) proposed a non-radial, slacks-based model; the so-called slacks-based measure of efficiency (SBM). Because SBM accounts for slacks in the calculation of efficiency, it has been mathematically proven that it discriminates better than radial models (Tone, 2001). In this study, SBM variants were used to calculate the technical (TE) and environmental efficiency (EE) of dairy farms. The SBM TE scores were then used for the calculation of the farms' economic (cost) efficiencies (CE). The CE model used here is superior to the widely used Farrell-Debreu model (Hansson & Öhlmér, 2008) in that it does not assume identical input costs for each DMU (Cooper et al., 2007).

Suppose that there are n DMUs each having m inputs and s outputs represented by two vectors $\boldsymbol{x} \in \boldsymbol{R}^m$ and $\boldsymbol{y} \in \boldsymbol{R}^s$ respectively. Let us define the matrices $X = [x_1, \dots, x_n] \in \boldsymbol{R}^{m \times n}$ and $Y = [y_1, \dots, y_n] \in \boldsymbol{R}^{s \times n}$, with $X > 0$ and $Y > 0$. The SBM model is the following fractional programme:

$$\min_{\boldsymbol{s}^-, \boldsymbol{s}^+, \boldsymbol{\lambda}} \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{io}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{ro}}$$

subject to

$$\boldsymbol{x}_o = X\boldsymbol{\lambda} + \boldsymbol{s}^-$$
$$\boldsymbol{y}_o = Y\boldsymbol{\lambda} - \boldsymbol{s}^+$$

$\boldsymbol{s}^- \geq \boldsymbol{0}, \boldsymbol{s}^+ \geq \boldsymbol{0}, \boldsymbol{\lambda} \geq \boldsymbol{0}$,

where the vectors $\boldsymbol{s}^- \in \boldsymbol{R}^m$ and $\boldsymbol{s}^+ \in \boldsymbol{R}^s$ correspond to input excesses and output shortfalls (slacks) respectively, $\boldsymbol{\lambda} \in \boldsymbol{R}^n$ is a nonnegative vector and $\boldsymbol{0} \in \boldsymbol{R}^n$ is a vector of zeros. A linear equivalent of SBM can be found in Tone (2001). Once the SBM has been solved, the optimal slacks $\boldsymbol{s}^{-*}, \boldsymbol{s}^{+*}$ for DMUo can be used to examine variable-specific patterns, e.g. input savings potentials, by calculating the ratio of each slack over its corresponding input. SBM can be modified to an input-oriented model representing TE or to account for the minimization of undesirable outputs, representing EE [see Cooper et al. (2007)]. Unlike radial models, SBM for EE allows for the simultaneous minimization of inputs and undesirable outputs, and for the maximization of desirable outputs. Also, it considers undesirable outputs as such, rather than transforming them into debatable forms, such as considering them as inputs, inverse outputs, etc. (Scheel, 2001 ; Kuosmanen, 2005). In this study, the EE SBM model has been modified so as to consider desirable outputs as fixed in line with current production limited approaches to resource-use efficiency in EU agriculture. Methodologies to modify SBM models in this way, including relaxation of this particular assumption so as to fit them for alternative purposes can be found in Cooper et al. (2007).

After the TE scores have been calculated, the CE of DMUo is calculated by the ratio C/C_o, where $C_o = \sum_{i=1}^{m} c_{io} x_{io}$ $(o = 1, \dots, n)$ is the actual (observed) input cost for DMUo, and C can be calculated by the following linear program:

$$C = \min_{\boldsymbol{x}', \boldsymbol{\mu}} \boldsymbol{e}\boldsymbol{x}'$$

$$\boldsymbol{x}' \geq X'\boldsymbol{\mu}$$

$$\boldsymbol{y}_o \leq Y\boldsymbol{\mu}$$

$\boldsymbol{\mu} \geq \boldsymbol{0}$,

where $X' = (x_1', \dots, x_n') \in \boldsymbol{R}^{m \times n}$, $x_j' = (x_{ij}', \dots, x_{mj}')$, $x_{ij}' = c_{ij} x_{ij}^*$, c_{ij} is the cost of input i for DMUj, $\boldsymbol{x}_j^*$ represents the technically efficient input for producing $\boldsymbol{y}_j$, i.e. $\boldsymbol{x}_j^* = \boldsymbol{x}_j - \boldsymbol{s}_j^{-*}$ and $\boldsymbol{e}$ is a row vector with all elements being equal to 1.

Data

Data were obtained from Scotland's Rural College (SRUC) 7-year genetic line × feeding Holstein-Friesian dairy systems experiment (Pollott & Coffey, 2008). The so-called Langhill herd comprised of a select (S) line: sires selected for the highest fat + protein kg genetic merit at the time of artificial insemination (AI); and of a control (C) line: selected to have the average genetic merit for fat + protein kg at the time of AI. The herd was managed with one group kept indoors on a low forage (LF) diet and the other group on a high forage (HF) diet with summer grazing.

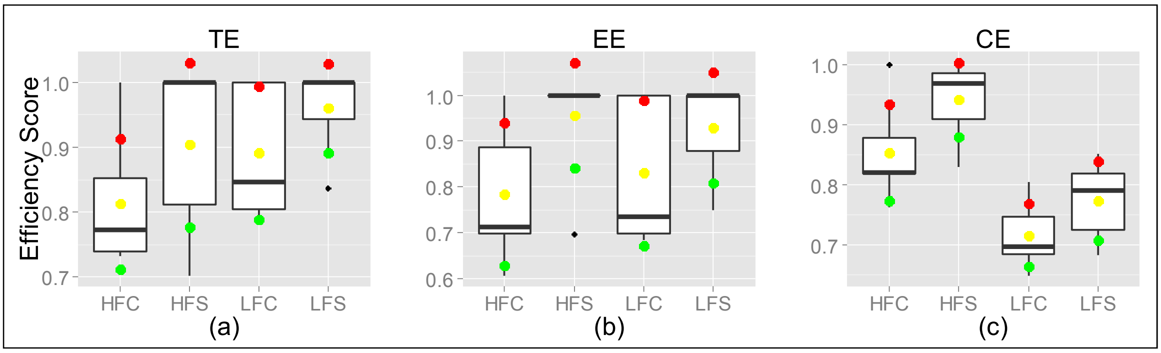
Thus, there were four distinct systems in the experiment, namely High Forage Control (HFC); High Forage Select (HFS); Low Forage Control (LFC); and Low Forage Select (LFS). The number of animals in each system was about 50 per year. In this study, as in Toma et al. (2013), each system was considered as a different DMU for each of the 7 years of the experiment, thus resulting in a total of (7 years) × (4 systems) = 28 DMUs.

For the calculation of TE, EE and CE of the 28 DMUs, the following data were used. Inputs: replacements (numbers), labour (h), land use (ha), nitrogen (N) fertilizer (t N) and dry matter (DM) of feed (t DM); outputs: milk (t energy-corrected milk) and animals sold (numbers); undesirable outputs: greenhouse gas (GHG) emissions (t CO_2 equivalents), N surplus (t) and phosphorous (P) surplus (t). All data except for labour were calculated by Toma et al. (2013) using data from the Langhill database. Regarding labour, data from DairyCo's (2012) Milkbench+ report were used. The report provides labour data for three farm types, namely Cows at Grass, Composite and High-output Cows. In this study, labour data for Cows at Grass corresponded to HFC; Composite to LFC; High-output Cows to LFS; and the average of High-output Cows and Cows at Grass to HFS. Economic data (£/input) were obtained from the following sources: DairyCo's website (http://www.dairyco.org.uk/); the *Milkbench+* report (DairyCo, 2012); SAC Consulting, who publish an annual *Farm Management Handbook* (2010); and, where available, from Langhill's own accounting data. In order to ensure consistency between data sources, data for the financial year 2010/11 (Apr 2010-Mar 2011) were used.

Results

All calculations and visualizations were run in the programming language R (R Development Core Team, 2013). Appropriate statistics for the non-normally distributed efficiency scores TE, EE and CE were summarised in box plots (Figure 1).

Figure 1: Box plots summarizing statistics for efficiency scores per system. TE: technical efficiency; EE: environmental efficiency; CE: cost efficiency; HFC: high-forage control; HFS: high-forage select; LFC: low-forage control; LFS: low-forage select; yellow dot: mean efficiency; red: mean efficiency + 1 standard deviation; green: mean efficiency – 1 standard deviation



More than half the DMUs of systems HFS and LFS were technically and environmentally efficient; while for DMUs of systems HFC and LFC, the number was less than half. The only two cost efficient systems were HF, i.e. no LF DMU or any other HF DMU was cost efficient. Nevertheless, 13 out of the 15 most cost efficient DMUs were HF (i.e. 13 out of 14 HF DMUs), while the eight most cost efficient DMUs all were HF.

The non-parametric Spearman's *rho* rank correlation coefficient was used to test correlation between TE, EE and CE (Table 1). TE and EE were strongly correlated, suggesting the hypothesis that more technically efficient farms were also more efficient in reducing their wastes. CE and EE were modestly correlated, i.e. there was not a clear relationship between cost reduction and reduction of wastes. Notably, correlation between CE with TE was weak. Therefore, DMUs able to best minimize their inputs, given their output production, did not always manage to reduce their costs to the lowest possible levels, in comparison with their peers.

Table 1: Spearman's *rho* correlation coefficient to test for correlations between TE, EE and CE.

Efficiency score	TE	EE	CE
TE	1.000		
EE	0.834	1.000	
CE	0.189	0.415	1.000

The non-parametric Kruskal-Wallis (KW) test was used to test for differences (at 5%) in efficiency scores between the four systems. The test found significant differences between systems for CE (*K* statistic = 17.679) and therefore a post-KW multiple comparison test (Siegel & Castellan, 1988) was run to determine which systems were different. Significant CE differences were identified between the following pairs of systems: HFC-LFC (*K* = 11.786); HFS-LFC (*K* = 17.357); and HFS-LFS (*K* = 11.929). Box plots (Figure 1c) of the CE scores by system provided a way of 'ranking' the aforementioned significant differences: clearly, the HFC system was better than LFC and LFS; and HFS was better than LFS. These results suggested that HF systems were significantly more cost efficient than LF; this could be one reason for the observed weak correlation between TE and CE.

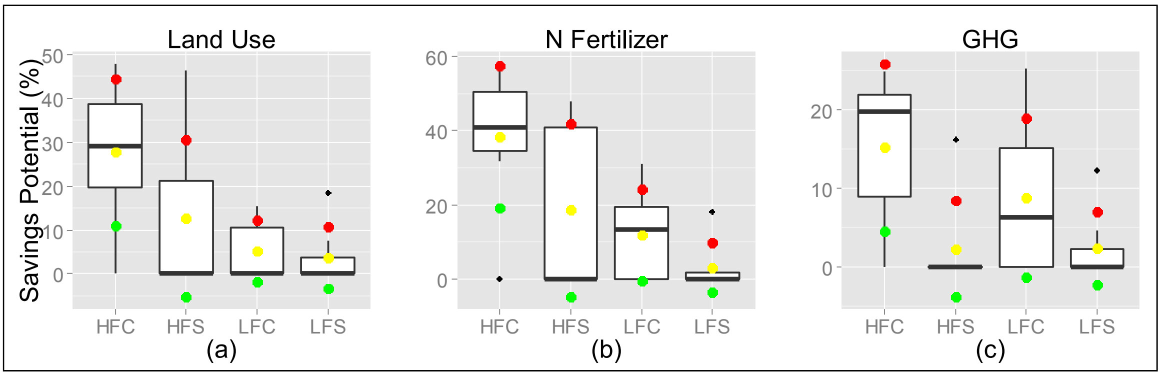
Using the optimal slacks calculated by the SBM models for TE and EE, mean input and undesirable output slacks were expressed as percentages of input and undesirable output levels respectively (Table 2).

Table 2: Mean input/undesirable output slacks expressed as percentages of input/undesirable output levels

	% of input levels					% of undesirable output levels		
System	Replacements	Labour	Land use	N fertilizer	Feed	GHG	N surplus	P surplus
HFC	18.2	5.3	26.8	38.2	3.3	14.8	11.4	13.9
HFS	11.1	7.6	12.7	18.7	0.0	2.4	2.7	0.0
LFC	14.3	12.5	5.9	12.0	10.8	9.1	10.3	7.2
LFS	4.9	2.1	4.1	3.1	5.2	2.2	5.3	5.2

HF had by far the largest ratios regarding land use and N fertilizer. Moreover, the KW test indicated significant differences between HFC and LFS regarding the savings potentials of land use (*K* = 8.480) and N fertilizer (*K* = 9.569), with LFS performing better (Figure 2a-b). HFC and LFC had the largest ratios for GHGs, N surplus and P surplus (Table 2). The KW test found significant differences (*K* = 7.934) between HFC and HFS in terms of GHG savings potentials, with HFS performing better (Figure 2c). Notably, HFS had very small ratios for all three pollutants, with the ratio for P surplus (as well as for feed) being equal to zero. While a savings potential equal to zero may look odd, it should be remembered that DEA is a relative measure and that this result indicates that HFS DMUs performed better than the rest regarding these particular resources.

Figure 2: Box plots summarizing statistics for land use, N fertilizer, and GHG savings potentials per system. Yellow dot: mean efficiency; red: mean efficiency + 1 standard deviation; green: mean efficiency – 1 standard deviation



Discussion

Comments on our findings

This study presented a slacks-based DEA framework based on the SBM models of Tone (2001). The superiority of SBMs to radial DEA models, the latter having been extensively used in dairy farm efficiency assessments, was demonstrated through the measurement of a number of sustainability and resource-use indicators: technical efficiency (TE), environmental efficiency (EE), cost efficiency (CE), and input/undesirable output-specific savings potentials.

This study found that technically efficient farms were also efficient in minimizing their GHG emissions and N and P surpluses. This result extends the assumption of Shortall & Barnes (2013) that Scottish farms which are technically efficient are also efficient in minimizing their GHG emissions. Moreover, an important finding in this study was that technically efficient farms were not always economically efficient. As noted above, the results suggested that HF systems were clearly superior to LF regarding CE, and this might have been the reason for the weak correlation between TE and CE. Nevertheless, the Langhill experimental farm is not a representative sample of commercial herds and the calculation of CE was dependent upon proxy estimates of input costs. Therefore, it is important to test this finding out on commercial herd data. However, it does illustrate that there may be economic/environmental trade-offs between dairy farming systems i.e. a 'win-win' may not always be possible.

Calculating input and undesirable output-specific savings potentials allowed for the identification of specific aspects in which the systems differ. The facts that LFS were significantly better than HFC in terms of land use and N fertilizer saving potentials; and that HF systems had the largest savings potentials for these two inputs were unsurprising, as the HF system required more land and fertilizer than LF (Toma et al., 2013). These results could have been different had land use and fertilizer use for bought-in feed been accounted for. The large pollutant savings potentials of C animals, and the significantly better performance of HFS compared to HFC in terms of GHG savings potentials, indicated that genetic merit could have differential effects on the systems' EE. This was an important finding, as a recent DEA study on the Langhill herd did not identify any genetics × environment interaction regarding EE (Toma et al., 2013). However, Toma et al. (2013) used a radial EE model which does not allow for the decomposition of EE into pollutant-specific efficiencies (i.e. savings potentials). Therefore, this finding also highlighted the usefulness of SBM models in that they are able to provide additional important information about the DMUs under study.

Further steps

The advantages of the SBM framework could be of value to researchers, policy-makers and, ultimately, society. On the one hand, decomposing efficiencies into variable-specific savings potentials offered an in-depth comparison between different dairy farming systems, facilitating dairy research. On the other, aggregating variable-specific saving potentials into a single index (i.e. TE and EE)- or even aggregating efficiencies (i.e. TE, EE and CE) into an overall index (e.g. Despotis, 2005)- can provide important information at the policy-level, as it offers a means of calculating overall sustainability scores for different dairy farm types. Moreover, further steps could also take into account societal issues such as the interactions between efficiency and animal health and welfare (e.g. Barnes et al., 2011 ; Hansson et al., 2011 ; Toma et al., 2013). The latter could be a future step, as could also be the quantification of variability in the long-term performance of different systems: under the assumption that farmers are risk-averse, concluding that the most efficient system is also the 'best' is misleading. It is therefore important to also measure the variability of each system in terms of their efficiency scores and savings potentials. Given the robustness of the SBM framework in combination with an abundance of resource-use, environmental, and animal health data available in SRUC's Langhill database, there exist numerous opportunities for further research. Importantly, while Langhill was a controlled experiment, many of the data capturing technologies that were used to collect information are commercially available and increasingly being used by dairy farmers. Therefore, the suggested framework could soon be used for commercial dairy farm assessments.

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