

Scotland's Rural College

An approach to holistically assess (dairy) farm eco-efficiency by combining Life Cycle Analysis with Data Envelopment Analysis models and methodologies

Soteriades, AD; Faverdin, P; Moreau, S; Charroin, T; Blanchard, M; Stott, AW

Published in:
Animal

DOI:
[10.1017/S1751731116000707](https://doi.org/10.1017/S1751731116000707)

First published: 29/04/2016

Document Version
Peer reviewed version

[Link to publication](#)

Citation for published version (APA):

Soteriades, AD., Faverdin, P., Moreau, S., Charroin, T., Blanchard, M., & Stott, AW. (2016). An approach to holistically assess (dairy) farm eco-efficiency by combining Life Cycle Analysis with Data Envelopment Analysis models and methodologies. *Animal*, 10(11), 1899 - 1910. <https://doi.org/10.1017/S1751731116000707>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal ?

Take down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

1 **An approach to holistically assess (dairy) farm eco-efficiency by combining**
2 **Life Cycle Analysis with Data Envelopment Analysis models and**
3 **methodologies**

4 A. D. Soteriades ¹, P. Faverdin ^{2,3}, S. Moreau ⁴, T. Charroin ⁴, M. Blanchard ⁵ and A.
5 W. Stott ¹

6
7 ¹ *Scotland's Rural College, Future Farming Systems Group, Edinburgh, United*
8 *Kingdom*

9 ² *INRA, UMR 1348 PEGASE, F-35590 St-Gilles, France*

10 ³ *Agrocampus-Ouest, UMR 1348 PEGASE, F-35000 Rennes, France*

11 ⁴ *Institut de l'Elevage, F-75000 Paris, France*

12 ⁵ *CIRAD, UMR 0868 SELMET, Bobo-Dioulasso, Burkina Faso*

13

14 Corresponding author: Andreas Diomedes Soteriades. Email:

15 andreas.soteriades@sruc.ac.uk

16

17 Short title: Measuring eco-efficiency with LCA and DEA

18

19 **Abstract**

20 Eco-efficiency is a useful guide to dairy farm sustainability analysis aimed at
21 increasing output (physical or value added) and minimizing environmental impacts
22 (EIs). Widely-used partial eco-efficiency ratios (EIs per some functional unit, e.g. kg
23 milk) can be problematic because (i) substitution possibilities between EIs are
24 ignored, (ii) multiple ratios can complicate decision-making and (iii) EIs are not
25 usually associated with just the functional unit in the ratio's denominator. The

26 objective of this study was to demonstrate a 'global' eco-efficiency modelling
27 framework dealing with issues (i)-(iii) by combining Life Cycle Analysis (LCA) data
28 and the multiple-input, multiple-output production efficiency method Data
29 Envelopment Analysis (DEA). With DEA each dairy farm's outputs and LCA-derived
30 EIs are aggregated into a single, relative, bounded, dimensionless eco-efficiency
31 score, thus overcoming issues (i)-(iii). A novelty of this study is that a model providing
32 a number of additional desirable properties was employed, known as the Range
33 Adjusted Measure (RAM) of inefficiency. These properties altogether make RAM
34 advantageous over other DEA models and are as follows. First, RAM is able to
35 simultaneously minimize EIs and maximize outputs. Second, it indicates which EIs
36 and/or outputs contribute the most to a farm's eco-inefficiency. Third it can be used to
37 rank farms in terms of eco-efficiency scores. Thus, non-parametric rank tests can be
38 employed to test for significant differences in terms of eco-efficiency score ranks
39 between different farm groups. An additional DEA methodology was employed to
40 'correct' the farms' eco-efficiency scores for inefficiencies attributed to managerial
41 factors. By removing managerial inefficiencies it was possible to detect differences in
42 eco-efficiency between farms solely attributed to uncontrollable factors such as
43 region. Such analysis is lacking in previous dairy studies combining LCA with DEA.
44 RAM and the 'corrective' methodology were demonstrated with LCA data from
45 French specialized dairy farms grouped by region (West France, Continental France)
46 and feeding strategy (regardless of region). Mean eco-efficiency score ranks were
47 significantly higher for farms with <10% and 10-30% maize than farms with >30%
48 maize in the total forage area before correcting for managerial inefficiencies. Mean
49 eco-efficiency score ranks were higher for West than Continental farms, but
50 significantly higher only after correcting for managerial inefficiencies. These results

51 helped identify the eco-efficiency potential of each region and feeding strategy and
52 could therefore aid advisors and policy makers at farm or region/sector level. The
53 proposed framework helped better measure and understand (dairy) farm eco-
54 efficiency, both within and between different farm groups.

55

56 **Keywords:** eco-efficiency, composite indicators, managerial inefficiency,
57 uncontrollable factors, French dairy farm data

58

59 **Implications**

60 Dairying contributes significantly to society (employment, economy, nutritional value
61 of dairy products etc.) at the cost of several environmental impacts. Therefore,
62 improvements in dairy farm 'eco-efficiency' are essential to ensure more output with
63 fewer impacts. This study introduced a modelling framework to measure, analyse
64 and understand dairy farm eco-efficiency in much more depth than previously
65 published assessments. The framework was demonstrated with data from French
66 specialized dairy farms. This framework can be a powerful tool for improving the
67 sustainability of dairy farming systems, especially when multiple, conflicting
68 objectives (multiple-output maximization *versus* multiple-impact minimization) are
69 involved.

70

71 **Introduction**

72 Facing the environmental impacts of agriculture, the challenge to satisfy the
73 demands of a growing and more affluent global population, the scarcity of natural
74 resources and the consequences of climate change, agricultural policies are
75 increasingly directed towards 'sustainable intensification' of agriculture (Foresight,

76 2011). Consequently, the dairy industry (along with other sectors) is required to
77 comply with several policies promoting environmentally sustainable and resource
78 use-efficient production (Casey and Holden, 2005). This necessitates the application
79 of tools to measure dairy farm performance in terms of resource use efficiency and
80 productivity, increased product quantity and value and minimization of EIs. Such a
81 tool is 'eco-efficiency', originally developed for the business sector; it is expressed as
82 a ratio of product or service value to EI (Economic and Social Commission for Asia
83 and the Pacific [ESCAP], 2009).

84 In dairy studies, eco-efficiency is usually expressed as the ratio of an EI per
85 some functional unit such as kg milk or ha land (e.g. Basset-Mens *et al.*, 2009, Bava
86 *et al.*, 2014, Casey and Holden, 2005, Guerci *et al.*, 2013, van Calker *et al.*, 2008).
87 To calculate the EIs dairy studies (including the aforementioned) are increasingly
88 using Life Cycle Analysis (LCA), an internationally standardized method for
89 estimating the EIs of agricultural products from a global perspective (Bava *et al.*,
90 2014). Using LCA, some studies have been confined to comparing different dairy
91 systems in terms of several eco-efficiency indicators defined by two or more
92 functional units (e.g. Basset-Mens *et al.*, 2009). Others have examined the
93 relationships between eco-efficiency ratios and related factors (e.g. farming intensity,
94 farm self-sufficiency) by employing multivariate methods such as regression (Casey
95 and Holden, 2005) and principal component analysis (Bava *et al.*, 2014). Other
96 studies have focused on expressing the relative importance of several eco-efficiency
97 indicators based on different stakeholder weighting schemes (see van Calker *et al.*,
98 2008).

99 There are six main comments to be made on the approaches to dairy farm
100 eco-efficiency in the aforementioned studies. First, analyses involving multiple partial

101 eco-efficiency ratios ignore the substitution possibilities that might exist between
102 different EIs. That is, farms performing moderately for several EIs tend to be
103 overlooked in favour of farms performing exceptionally well for one EI (Kuosmanen
104 and Kortelainen, 2005). Second, with these ratios the allocation of EIs to products is
105 challenging as dairy farms generally produce other products too, such as meat.
106 Third, incommensurability between several criteria expressed by multiple eco-
107 efficiency ratios rather than a single performance index can complicate decision
108 making (Kuosmanen and Kortelainen, 2005). Fourth, analyses with methods such as
109 regression and principal component analysis are subject to the method chosen to
110 normalize/standardize eco-efficiency ratios expressed in different units. Fifth,
111 assigning subjective weights to indicators (e.g. the eco-efficiency ratios) has been
112 debated in the literature (Kuosmanen and Kortelainen, 2005). Sixth, allowance
113 should be made for the fact that there exist factors affecting eco-efficiency that are
114 beyond managerial control, such as the different bio-physical conditions under which
115 farms operate (see Bogetoft and Otto, 2011, Jan *et al.*, 2012).

116 All six aforementioned limitations can be overcome with the productive
117 efficiency method of Data Envelopment Analysis (DEA; see Cooper *et al.*, 2007),
118 employed in this study. DEA is a relative, multiple-input, multiple-output efficiency
119 measurement method calculating single aggregated efficiency indices for each dairy
120 farm by assessing the whole production system, including EIs. Importantly, with DEA
121 no allocation of EIs to specific products is required because the farm is assessed as
122 a whole, multiple-input, multiple-output entity. Most DEA models are not affected by
123 the different measurement units of the data and their weighting schemes are
124 endogenous, that is, 'data-driven' (e.g. the model of Cooper *et al.*, 1999 employed in
125 this study). DEA methodologies correcting for managerial inefficiencies and

126 accounting for uncontrollable factors are available, such as that of Brockett and
127 Golany (1996) adopted in this study.

128 DEA has been applied in several dairy studies for the calculation of eco-
129 efficiency. For example, Jan *et al.* (2012) and subsequently Pérez Urdiales *et al.*
130 (2015) used the DEA eco-efficiency model of Kuosmanen and Kortelainen (2005) to
131 define a dairy farm eco-efficiency ratio. This ratio equalled the amount of (physical or
132 monetary) dairy farm output to an aggregate EI index calculated as a weighted
133 summation of all EIs considered in their study. This ratio was then maximized by
134 minimizing the aggregate EIs for the given production levels. Importantly, the EIs in
135 Jan *et al.* (2012) were LCA-derived. In fact, efficiency studies are increasingly
136 recognizing the advantages of combining LCA with DEA as the former can capture
137 EIs using detailed, cradle-to-grave data (e.g. land use required for the production of
138 feed imported in the dairy farm plus on-farm land use), while the latter has the
139 aforementioned advantages (Vázquez-Rowe and Iribarren, 2015).

140 The objective of this study was to propose a framework combining LCA with
141 DEA that not only overcomes the six aforementioned issues, but also improves the
142 measurement and understanding of farm eco-efficiency using dairying as exemplar.
143 This will guide farming practice to greater yet sustainable production (sustainable
144 intensification) as advocated for example by the UK Foresight report (2011). The
145 DEA model employed, known as the range adjusted measure (RAM) of inefficiency
146 (Cooper *et al.*, 1999), has several desirable properties, for example it allows for the
147 ranking of farms in terms of eco-efficiency performance. Moreover, it seeks to
148 maximize eco-efficiency by simultaneously minimizing EIs and maximizing
149 production. Furthermore, it can identify the factors contributing the most to
150 inefficiency, such as excess EIs and/or under-produced outputs. A method to isolate

151 managerial inefficiency from uncontrollable factors was also demonstrated. That way,
152 it was possible to compare different dairy systems in terms of eco-efficiency solely
153 under the influence of uncontrollable, rather than managerial, factors. The exercise
154 was run using detailed LCA data for French specialized dairy farms. Region was
155 considered as the uncontrollable factor in this study due to the remarkable
156 differences between West and Continental France in terms of farm structure and bio-
157 physical conditions (Gac *et al.*, 2010b). The results helped identify the eco-efficiency
158 potential of each region and feeding strategy and could therefore aid advisors and
159 policy makers at farm or region/sector level.

160

161 **Material and methods**

162 *Data*

163 LCA was used to estimate several important midpoint impacts of dairy farming
164 systems. It was conducted using the DIAPASON database resulting from a
165 partnership involving voluntary participation of farmers, the Chambers of Agriculture
166 (France) and the French Livestock Institute. This database contains detailed
167 information on technical and economic operations of nearly 500 farms each year
168 throughout France (Charroin *et al.*, 2005).

169 Environmental performance was assessed by indicators of pressure from
170 agricultural activity on the environment considering midpoint impact indicators of
171 LCA. The frontier of the farm system was limited to the farm, considered as a system
172 dedicated to agricultural products (crops, milk, meat) at farm gate. Impacts
173 associated with these products beyond the farm gate were not considered in this
174 study. The limits of the system included the whole farm and all the inputs of the
175 farming system. The system and its main processes are described in Figure 1.

176

177 Figure 1: about here

178

179 The different EIs considered in this study were midpoint impacts consistent
180 with the CML 2001 methodology (Guinée *et al.*, 2002) with some specific equations
181 to estimate the emissions. They concern global warming potential and non-
182 renewable energy according to the greenhouse gas emissions GES'TIM
183 methodology (Gac *et al.*, 2010a) and non-renewable energy use (Béguin *et al.*, 2008)
184 and based on the Fourth Assessment Report of the Intergovernmental Panel on
185 Climate Change (IPCC, 2007). Eutrophication was calculated as a unique impact
186 according to the CML 2001 methodology (Guinée *et al.*, 2002) and acidification using
187 equations from the European Monitoring and Evaluation Programme/Core Inventory
188 of Air Emissions in Europe (EMEP/CORINAIR, 2002). Table 1 summarizes the
189 inventory of all the emissions considered to calculate the different impacts.

190

191 Table 1: about here

192

193 The factors applied to the nitrogen (N), phosphorus and carbon fluxes
194 (calculated with the DIAPASON database), generated estimates of EIs. Dry matter
195 intake and mineral excretion in the faeces and urine of animals were calculated
196 according to physiological needs (milk production, weight after calving) using
197 equations proposed by CORPEN (Comité d'orientation pour de pratiques agricoles
198 respectueuses de l'environnement, 1999) taking into account the farmers' feeding
199 practices (types of forages and concentrates). The carbon (C) storage of permanent
200 grassland that was taken into account was up to 500 kg C/ha per year (Gac *et al.*,

201 2010b). On-farm N leaching was estimated using the N farm surplus, including
202 symbiotic fixation (based on a fixed proportion of legumes for permanent grassland),
203 but after removing losses of ammonia and organic N storage in soils assumed as
204 10% of C storage (with C:N ratio of 10), which represents 50 kg N/ha per year in
205 permanent pasture. The impact values of inputs were derived from the LCA database
206 'ecoinvent' (Nemecek and Kägi, 2007) and Gac *et al.* (2010a). Because the whole
207 farm was chosen as the functional unit, all farm products were considered
208 simultaneously in this analysis, therefore no allocation of emissions to the different
209 products was applied.

210 Finally, 185 dairy farms [specialized dairy farms according to the widely
211 recognised Farm Accounts Data Network (FADN) typology] located in different
212 French lowland regions in 2007 and 2008 were kept in this study. The different farms
213 were classified into two main groups according to climate zone and specialisation:
214 Oceanic Specialized Systems (OSS; West France, consisting of the following
215 regions: Basse-Normandie, Bretagne, Haute-Normandie, Pays de la Loire, Poitou-
216 Charente) and Continental Specialized Systems (CSS; Continental France,
217 consisting of the following regions: Alsace, Centre, Champagne-Ardenne, Franche-
218 Comté, Lorraine, Rhône-Alpes). The second dimension of the typology, crossed with
219 the first dimension, concerned the type of feeding strategies, based on the area of
220 maize silage in the total forage area of the farm: <10%, 10-30%, >30% maize. Other
221 farm classes were not considered due to insufficient number of farms in the class.
222 Table 2 summarizes the five EIs and three outputs used in this study per system for
223 the years 2007 and 2008.

224

225 Table 2: about here

226

227 *Data envelopment analysis*

228 DEA is a non-stochastic, non-parametric technique that benchmarks different
229 decision-making units (DMUs) performing the same task in terms of their capacity to
230 convert inputs into outputs. DEA calculates dimensionless and aggregated efficiency
231 indices without requiring *a priori* assumptions on the importance of each variable for
232 the DMUs' performance, making it a particularly attractive multiple-criteria tool. DEA
233 constructs an efficient frontier, that is, a convex, piece-wise linear surface over
234 observed data points against which all DMUs are benchmarked (or 'enveloped').

235 Figure 2 represents an efficient frontier ABC for the single-EI, single-output case. The
236 efficient frontier comprises of the best performers (DMUs A, B and C in Figure 2) and
237 the performance of all other DMUs (e.g. DMU D in Figure 2) is evaluated by
238 deviations from the frontier line (Cooper *et al.*, 2007). This is a fundamental
239 difference between DEA and methods such as regression as the latter reflects
240 'average' or 'central tendency' behaviour (Cooper *et al.*, 2007) and is unable to
241 provide a holistic characterization of DMUs within a multiple-objective assessment.

242 Convexity in DEA allows for the interpolation from observed DMUs to 'virtual' DMUs
243 with input- output profiles between the observations, allowing us to rely on fewer
244 actual observations. These 'virtual' DMUs are derived as convex combinations of
245 inputs and outputs of observed DMUs. Convexity can be illustrated in Figure 2 as
246 follows. Any line connecting any two points belonging to, or being placed below, the
247 frontier would also be placed on or below the frontier, and never outside this space
248 (i.e. above the frontier). The points these lines comprise of can represent both
249 observed and 'virtual' DMUs. See Bogetoft and Otto (2011) for a theoretical
250 background on convexity in DEA.

251

252 Figure 2: about here

253

254 *Data envelopment analysis in the eco-efficiency context*

255 As mentioned in the introduction, eco-efficiency measurement with DEA is

256 advantageous for three main reasons: (i) several EIs are aggregated into a single

257 index, (ii) substitution possibilities between EIs are not left unaccounted for and (iii)

258 no allocation of EIs to specific outputs is required. Points (i)-(iii) can be expressed in

259 the DEA context by minimizing the denominator of the following ratio:

260
$$\text{Eco - efficiency} = \max \left\{ \frac{\text{Output}}{\text{Weighted sum of EIs}} \right\}, \quad (1)$$

261 subject to a number of constraints (see Kuosmanen and Kortelainen, 2005). In ratio 1

262 the output can be expressed in monetary or physical terms. The weights summing

263 the various EIs are calculated by the DEA model itself so one need not rely on

264 subjective, pre-defined weight choices for the importance of each EI. Specifically, the

265 DEA model maximizing ratio 1, selects the most self-favourable weights for each

266 DMU so that its eco-efficiency is maximized. These weights cancel out the (often)

267 different measurement units of the EIs, making the DEA model 'units invariant'

268 (Cooper *et al.*, 2007).

269 Despite its usefulness, there are two main limitations with the eco-efficiency

270 DEA model of Kuosmanen and Kortelainen (2005). First, ratio 1 can only be

271 maximized by minimizing the EIs for the *given* output levels. In other words,

272 simultaneous minimization of EIs and maximization of output is not possible. For

273 example, DMU D in Figure 2 would have to move horizontally towards the frontier to

274 become efficient, ignoring any potential increases in its output. Because eco-

275 efficiency expresses the idea of firms (e.g. dairy farms) providing 'more' to society
276 with less EIs, it is desirable to use a DEA model allowing for simultaneous
277 adjustments in EIs and output. Second, full eco-efficiency can only be achieved by
278 minimizing all EIs by the *same* proportion. A DEA model should be able to identify
279 those EIs generating the most detrimental excess (or 'slack' in the DEA terminology)
280 to a DMU's eco-'inefficiency'.

281 Both aforementioned limitations can be overcome with the use of so-called
282 'additive' DEA models (see Cooper *et al.*, 2007). These models are able to
283 simultaneously, and non-proportionally, minimize EIs and maximize output for a
284 given DMU. In such a case, DMU D in Figure 2 would move towards point B. The
285 term 'additive' is attributed to the fact that these models' objective functions involve
286 summations of all input and output slacks in order to identify all potential sources of
287 inefficiency. In Figure 2 this summation is represented by the vector heading from
288 point D towards point B and equals the maximal sum of the EI slack and the Output
289 slack. As will be shown below, this summation of all slacks in the objective function
290 departs from the ratio form of ratio 1. However, it is consistent with the idea of
291 maximizing output while minimizing EIs and thus has been adopted in past eco-
292 efficiency studies (see Ramli and Munisamy, 2015 and the related studies they cite).
293 This study employed the RAM additive model (Cooper *et al.*, 1999), presented below.
294 RAM and its variants have been used in several eco-efficiency studies of industries
295 other than dairy, see Ramli and Munisamy (2015).

296

297 *Range adjusted measure of inefficiency.* Suppose that there are n DMUs (e.g. dairy
298 farms) each using m inputs (or EIs in the case of this study) to produce s outputs,
299 denoted as x_i ($i = 1, \dots, m$) and y_r ($r = 1, \dots, s$) respectively. The RAM inefficiency score

300 of the j th DMU, denoted as DMU_o, is given by the following linear program (Cooper *et*
 301 *al.*, 1999):

$$302 \quad \rho^* = \max_{\lambda_j, s_{io}, s_{ro}} \frac{1}{m + s} \left(\sum_{i=1}^m \frac{s_{io}}{R_i} + \sum_{r=1}^s \frac{s_{ro}}{R_r} \right) \quad (2)$$

303 subject to

$$x_{io} = \sum_{j=1}^n x_{ij} \lambda_j + s_{io} \quad (i = 1, \dots, m)$$

$$304 \quad y_{ro} = \sum_{j=1}^n y_{rj} \lambda_j - s_{ro} \quad (r = 1, \dots, s)$$

$$\sum_{j=1}^n \lambda_j = 1$$

$$\lambda_j, s_{io}, s_{ro} \geq 0,$$

305 where x_{io} and y_{ro} are the inputs and outputs of DMU_o respectively; s_{io} and s_{ro} are the

306 input and output slacks respectively (Note: input slacks represent overused inputs,

307 i.e. DMU_o could have produced the same amount of output using less input. Output

308 slacks represent output shortfalls, i.e. DMU_o could have produced more output given

309 its current input use.); λ_j is a scalar which, when positive, indicates that DMU_j has

310 been used as a reference (i.e. benchmark) by DMU_o; and $R_i = \max_j \{x_{ij}\} - \min_j \{x_{ij}\}$,

311 $R_r = \max_j \{y_{rj}\} - \min_j \{y_{rj}\}$ represent the ranges in inputs and outputs, respectively,

312 common across *all* DMUs. The ranges act as a 'data-driven' weighting scheme, a

313 more objective one compared to methods where the weights are (subjectively) pre-

314 defined by the user. These weights normalize the slacks and make RAM units

315 invariant. The objective function represents the average proportion of the

316 inefficiencies that the ranges show to be possible in each input and output (Cooper *et*

317 *al.*, 1999). The constraint $\sum_{j=1}^n \lambda_j = 1$ is the 'variable returns-to-scale' specification (see

318 Cooper *et al.*, 2007) which ensures that a farm is only compared to farms of similar

319 size. This specification was desirable in this study as DEA works with absolute
 320 values rather than ratios.

321 Model 2 is run n times, once for each DMU. When DMU_o is efficient all its
 322 slacks equal zero as this means that it does not need to further reduce its inputs and
 323 increase its outputs to become efficient (e.g. DMUs A, B and C in Figure 2). In this
 324 case RAM inefficiency ρ^* in model 2 equals 0, indicating that DMU_o is 100%
 325 efficient. If DMU_o is inefficient, one can identify through the slack values (which in this
 326 case are non-proportional) the inputs and desirable outputs contributing the most to
 327 its inefficiency. For an inefficient DMU (e.g. DMU D in Figure 2) any choice of input

328 resulting in $x_{io} > \sum_{j=1}^n x_{ij} \lambda_j$ means that with some combination of inputs *other* DMUs
 329 (identified by the non-zero λ_j values) could have improved this input in amount by

330 $s_{io} = x_{io} - \sum_{j=1}^n x_{ij} \lambda_j$ without worsening any other input or output (Brockett *et al.*, 2004).

331 Consider, for example a DMU on ABC with coordinates (2.7, 3) as opposed to DMU
 332 D with coordinates (7, 3) in Figure 2. The same applies for the desirable outputs and

333 their shortfalls $s_{ro} = \sum_{j=1}^n y_{rj} \lambda_j - y_{ro}$. In this case consider a DMU with coordinates (7,

334 5.7) as opposed to DMU D in Figure 2. In either case RAM inefficiency ρ^* is greater
 335 than 0, indicating that DMU_o is inefficient.

336 Because $\sum_{j=1}^n \lambda_j = 1$ in model 2 it follows that $s_{io} = \sum_{j=1}^n (x_{io} - x_{ij}) \lambda_j \leq \sum_{j=1}^n R_i \lambda_j = R_i$

337 and similarly $s_{ro} \leq R_r$ and thus $0 \leq \rho^* \leq 1$. Hence, the measure of *inefficiency* ρ^* in

338 model 2 can be easily converted to a measure of *efficiency* as follows:

339 $RAM \text{ efficiency} = 1 - \rho^*$. (3)

340 RAM efficiency score is bounded by 0 and 1. Unity indicates that the DMU under
341 evaluation is efficient while values less than 1 imply that it is inefficient.

342 Two very attractive properties of RAM are the following: (i) RAM uses the
343 ranges as a common weighting scheme across *all* DMUs; and (ii) RAM is strongly
344 monotone in the slacks, that is, holding any other inputs and outputs constant, an
345 increase (decrease) in any of its inputs (outputs) will increase the inefficiency score
346 for an inefficient DMU. Model 1 does not carry properties (i-ii).

347 Properties (i)-(ii) allow for a full ranking of inefficient DMUs in terms of their
348 RAM efficiency score (Cooper *et al.*, 1999). (Not all DEA models carry this
349 property. For example, with ratio 1 one cannot say that a DMU with a score of 0.8 is
350 more eco-efficient than a DMU with a score of 0.7 because the EI weights are DMU-
351 specific and will generally differ between DMUs.) This was strongly desirable in the
352 current study so as to determine whether farms ranked higher in terms of eco-
353 efficiency in a specific region or under a certain feeding strategy.

354

355 *DEA variables.* This study used the five EIs and three outputs in Table 2 for the
356 calculation of eco-efficiency with RAM, namely non-renewable energy use, land use,
357 eutrophication, acidification, global warming potential and milk, meat and crop
358 production. With DEA, increasing the number of variables also increases the number
359 of efficient DMUs which can be quite problematic with small sample sizes. A rough
360 rule of thumb is to choose $n \geq \max \{m \times s, 3 \times (m + s)\}$ (Cooper *et al.*, 2007, p.116). The
361 rule of thumb was satisfied in this study: $n = 185 \geq \max \{m \times s, 3 \times (m + s)\} = 24$.

362

363 *Testing for differences in eco-efficiency between regions and feeding strategies*

364 Differences in dairy farm eco-efficiency scores between regions and feeding
365 strategies were tested for using the non-parametric Kruskal-Wallis test (see Conover,
366 1999), also known as ‘non-parametric Kruskal-Wallis one-way ANOVA by ranks’
367 (Sheskin, 1997). The Kruskal-Wallis test is employed with ordinal (rank-order) data in
368 hypothesis testing involving a design with two or more independent samples
369 (Sheskin, 1997). That is, dairy farms were ranked in terms of their eco-efficiency
370 scores and differences between groups were tested based on each group’s average
371 rank. The null hypothesis is that all of the populations are identical against the
372 alternative that at least one of the populations tends to yield larger observations than
373 at least one of the other observations (Conover, 1999). When at least three groups
374 are compared the Kruskal-Wallis test cannot indicate which pairs of groups
375 significantly differ (provided that significant differences occur). The *post*-Kruskal-
376 Wallis non-parametric rank test known as Dunn’s test (see Sheskin, 1997) was
377 therefore employed to identify specific differences between the three feeding
378 strategies.

379 Choosing non-parametric tests over the parametric one-way ANOVA and its
380 *post-hoc* tests was done for two reasons. First, the theoretical distribution of
381 efficiency scores in DEA is generally unknown so a convention in the DEA literature
382 is to use non-parametric tests (Bogetoft and Otto, 2011, Brockett and Golany, 1996,
383 Cooper *et al.*, 2007). Second, because RAM can be used to rank DMUs, it lends
384 itself to the rankings that underlie non-parametric rank statistics (Brockett *et al.*,
385 2004). Both tests employed in this study operate based on the rank transformation
386 approach; that is, the data are replaced by their ranks and then the usual parametric
387 tests (e.g. *t* test, *F* test, etc.) are applied on the ranks. (Tied observations [e.g. when
388 at least two DMUs are eco-efficient] are given the average rank of the tied scores.)

389 Therefore, these tests are not affected by outliers or skewed data. See Conover
390 (1999).

391

392 *Examining the effect of region on eco-efficiency*

393 The bio-physical conditions under which dairy farms operate largely differ between
394 West and Continental France. Regional differences in eco-efficiency were therefore
395 tested. It would seem appropriate to pool farms from both regions in one dataset, run
396 the RAM model and then test for differences between regions with the Kruskal-Wallis
397 test. Such practice, however, would reveal any differences between regions under
398 the *observed* levels of EIs and output (i.e. the EI and output values outlined in Table
399 2). This means that inefficiencies attributed to both managerial and regional factors
400 would not allow inefficient farms to operate under their full potential. Indeed, the risk
401 of amalgamating both sources of inefficiency (managerial and regional) is to grant
402 inadvertently some bad managers (farmers) good eco-efficiency scores when they
403 are only benefitting from operating under particularly favourable bio-physical
404 conditions (see Brockett and Golany, 1996). Removing EI and output managerial
405 inefficiencies (i.e. slacks) was therefore essential before comparing the two regions
406 in terms of eco-efficiency. This was done by adopting the methodology of Brockett
407 and Golany (1996) which involved the following four steps:

- 408 1. Run two separate DEA exercises, one for CSS only and one for OSS only with
409 model 2.
- 410 2. Using the optimal EI and output slacks obtained from the previous step make the
411 necessary reductions in EIs and outputs so that inefficient DMUs in each group
412 become efficient. This is done using the following formulas:

413
$$\hat{x}_{io} = x_{io} - s_{io}^* (i = 1, \dots, m)$$

414
$$\hat{y}_{ro} = y_{ro} + s_{ro}^* (r = 1, \dots, s),$$
 (4)

414 where the asterisks (*) denote optimality. (For example, let us assume that Figure
 415 2 represents OSS farms. With formulas 4 the OSS farm D would have been
 416 projected onto the OSS efficient frontier at point B.) Now managerial inefficiency
 417 has been eliminated within OSS and CSS and both are operating ‘up to the
 418 boundary of the capabilities which the evidence showed was possible for [OSS
 419 and CSS]’ (Cooper *et al.*, 2007, p.238).

- 420 3. Pool all DMUs deriving from the previous step and run a new DEA exercise with
 421 model 2.
- 422 4. Test for significant differences between the systems’ efficiency scores using non-
 423 parametric rank statistics, i.e. the Kruskal-Wallis test.

424 Following the steps above it was possible to compare the two regions in terms of
 425 eco-efficiency. It should be noted, however, that the DMUs were then evaluated not
 426 based on their *actual* levels of EIs and output, but on their *efficient* ones. Because
 427 this methodology corrects for any managerial inefficiencies present in DMUs, from
 428 this point it is referred to as the ‘corrective’ methodology.

429

430 *Putting all methods together*

431 Figure 3 summarizes the methodology employed in this study. Phase 1 did not apply
 432 the ‘corrective’ methodology and involved two steps. In Step 1.1 the EIs and outputs
 433 for each farm were fed into RAM and the eco-efficiency scores were obtained. Note
 434 that in this step DMUs from *both* CSS and OSS were pooled before the RAM was
 435 run. Step 1.2a tested for differences in eco-efficiency scores between the two
 436 systems and between the three feeding strategies with non-parametric rank tests.

437 Moreover, the EI and output slacks were compared between systems in Step 1.2b.
438 Phase 2 applied the 'corrective' methodology and involved four steps. In Step 2.1 the
439 RAM model was run for *each* system (CSS, OSS). In Step 2.2 the EIs and outputs of
440 each farm in each system were projected onto their efficient levels with the formulae
441 in 4. In Step 2.3 the RAM model was re-run for the *whole* sample (both CSS and
442 OSS) using the projected data from Step 2.2. Step 2.4 tested for differences in the
443 new eco-efficiency scores between the two systems and between the three feeding
444 strategies with non-parametric rank tests. Unlike Phase 1, in Phase 2, systems and
445 feeding strategies were exposed to the full eco-efficiency potential that the data
446 showed to be possible for these groups.

447 There are distinct differences between Phase 1 and 2. Although Phase 1 did
448 not differentiate between regional and managerial factors, it helped to evaluate the
449 185 French specialized farms under their *observed* levels of EIs and outputs, as
450 reported in Table 2. In other words, Phase 1 evaluated farms 'as they *actually*
451 performed' and not 'as they *could* be performing', as in the 'corrective' methodology
452 described in Phase 2. Phase 1 is therefore useful for efficiency comparisons between
453 and within farms in terms of the whole population, without correcting for potential
454 systematic differences between groups (defined by region in this case). Phase 2 is
455 appropriate for testing the hypothesis that systematic unavoidable differences
456 between groups will affect efficiency performance. Phases 1 and 2 are therefore
457 independent but complementary. See Brockett *et al.* (2004) who also conducted their
458 analysis in two stages analogous to the two Phases employed here.

459

460 Figure 3: about here

461

462 All calculations were run with the R language (<http://www.R-project.org/>). The
463 R function for RAM was developed by the first author of this article. The Kruskal-
464 Wallis test is available in the standard version of R. Dunn's test is available by the R
465 package 'dunn.test' (<https://cran.r-project.org/web/packages/dunn.test/dunn.test.pdf>).

466

467 **Results**

468 *Eco-efficiency scores and slacks per system and feeding strategy when accounting*
469 *for managerial inefficiencies*

470 The results for the eco-efficiency scores and slacks presented in this sub-section
471 were calculated *before* applying the 'corrective' methodology (Phase 1 in Figure 3).

472

473 *Eco-efficiency scores.* Statistics for the eco-efficiency scores and their mean ranks
474 per system and feeding strategy are presented in Table 3. The mean, median and
475 mean ranks of eco-efficiency scores were higher for OSS than CSS. However, the
476 Kruskal-Wallis test did not identify significant differences between CSS and OSS in
477 terms of the eco-efficiency scores' mean ranks ($P = 0.105$). The three feeding
478 strategies ranked as follows in terms of mean, median and mean ranks of eco-
479 efficiency scores: (<10% maize) > (10-30% maize) > (>30% maize). The Kruskal-
480 Wallis test identified significant differences between the three feeding strategies in
481 terms of the eco-efficiency scores' mean ranks ($P = 0.001$). Specific differences were
482 identified with Dunn's test. Differences were significant between DMUs with <10%
483 maize and >30% maize in the total forage area ($P < 0.001$) and between DMUs with
484 10-30% maize and >30% maize ($P = 0.011$). No differences were found between
485 DMUs with >10% maize and 10-30% maize in the total forage area ($P = 0.083$).

486

487 Table 3: about here

488

489 *EI and output slacks.* Table 4 summarizes the optimal EI and output slacks from

490 model 2 per system, expressed as proportions of their respective ranges i.e.

491 s_{io}^*/R_i ($i = 1, \dots, m$) and s_{ro}^*/R_r ($r = 1, \dots, s$). That way, it was possible to ‘decompose’ the

492 eco-efficiency scores in Table 3 in order to detect the EIs and outputs with the

493 highest relative contribution to a DMU’s inefficiency. (Averaging each system’s input

494 and output inefficiencies in Table 4 and then subtracting them from 1 equals the

495 mean efficiency scores presented in Table 3.) The EIs with the highest contribution to

496 CSS systems’ inefficiency were eutrophication potential, land use and acidification

497 potential. By contrast, eutrophication potential was the EI with the by-far-largest

498 contribution to OSS systems’ inefficiency. In terms of output inefficiency, meat and

499 milk were by far the largest contributors to the inefficiency of both OSS and CSS.

500 Notably, for both OSS and CSS the mean input inefficiencies were much higher than

501 the mean output inefficiencies.

502

503 Table 4: about here

504

505 *Eco-efficiency scores per system and feeding strategy after eliminating managerial*

506 *inefficiencies*

507 The eco-efficiency results per system and feeding strategy presented in this section

508 were obtained *after* eliminating all managerial inefficiencies (i.e. slacks) from the 59

509 CSS farms and 126 OSS farms, based on the ‘corrective’ methodology (Phase 2 in

510 Figure 3). Statistics for the eco-efficiency scores and their mean ranks per system

511 and feeding strategy are presented in Table 5. The mean and mean ranks of eco-

512 efficiency scores were higher for OSS than CSS and the medians of both systems
513 equalled 1. The Kruskal-Wallis test identified significant differences between the eco-
514 efficiency scores' mean ranks of the two systems ($P < 0.001$). The three feeding
515 strategies had almost-equal mean and equal median eco-efficiency scores. The
516 Kruskal-Wallis test did not identify significant differences between feeding strategies
517 in terms of mean ranks of the eco-efficiency scores ($P = 0.767$).

518

519 Table 5: about here

520

521 **Discussion**

522 This study is aimed at researchers, advisors and policy makers searching for tools
523 that can address the challenges of increasing farm output and reducing EIs,
524 especially given the recent trend towards sustainable intensification of agriculture
525 (see Foresight, 2011). Our framework contributes to the stream of literature
526 employing methodologies able to capture several aspects in order to ensure that
527 development is in fact 'sustainable'. Dairy farming was used as an exemplar to
528 demonstrate the framework, which is expandable to other agricultural settings.

529

530 *Not 'just LCA' but 'DEA and LCA'*

531 According to recent guidelines by the Livestock Environmental Assessment and
532 Performance Partnership (LEAP, 2015, p.6), *'[i]n order to prevent shift of burden from*
533 *[one] environmental issue to another, no environmental improvement*
534 *option should be recommended without having [...] assessed [...] the effects on*
535 *resource use and those other environmental impacts targeted as relevant for*
536 *livestock supply chains [...]*'. In other words, the LEAP guidelines themselves

537 implicitly acknowledge the issue of substitution possibilities between LCA eco-
538 efficiency ratios, mentioned in the introduction to this study. The implications of this
539 issue can be demonstrated by looking at the results of LCA eco-efficiency studies
540 comparing dairy farms with different proportions of land devoted to maize silage (e.g.
541 Basset-Mens *et al.*, 2009, Rotz *et al.*, 2010). According to these studies, because
542 grassland requires less fertilization than arable land, lower impacts from
543 eutrophication, acidification, greenhouse gas emissions and non-renewable energy
544 use have been observed on grass-based farms. However, arable crops such as
545 maize silage have higher yields per hectare. It is therefore impossible to conclude
546 that a particular feeding strategy has a higher eco-efficiency potential than another
547 one, unless all feeding strategies are evaluated at the *aggregate* level, as was done
548 in this study. Indeed, feeding the LCA variables into the RAM model showed that the
549 eco-efficiency of farms with >30% maize was lower, favouring more grass-based
550 systems.

551

552 *Regional differences*

553 Higher eco-efficiency scores were expected for OSS systems over CSS because the
554 bio-physical conditions in West France are more favourable. Specifically, the climate
555 conditions in West France favour the production of high quality forages which are
556 essential for dairy production. These differences in climate conditions between West
557 and Continental France were implicitly examined in this study by removing
558 managerial inefficiencies from CSS and OSS with the 'corrective' methodology.
559 Indeed, Jan *et al.* (2012) emphasized that DEA results should be interpreted with
560 care as inefficiencies may be attributed to factors that are beyond managerial control.
561 Hence, removing managerial factors with the 'corrective' methodology revealed each

562 system's true eco-efficiency potential that the projected data showed to be possible,
563 solely as a result of the different bio-physical conditions between West and
564 Continental France. OSS systems then ranked significantly higher, on average, than
565 CSS in terms of eco-efficiency scores (Table 5).

566

567 *Identifying specific sources of eco-'inefficiency'*

568 Examining the slacks (Table 4) can help prioritize the reduction (increase) of those
569 EIs (outputs) most responsible for the eco-inefficiency of CSS and OSS. For
570 example, CSS systems had a quite large acidification slack. In fact, in CSS systems
571 cows are generally offered more protein concentrates, potentially to avoid any protein
572 shortages, which tends to increase ammonia emissions (Faverdin *et al.*, 2014). It is
573 noteworthy that CSS also had a large land use slack (Table 4). These systems
574 devoted a larger part of on-farm land to crop production at the expense of lower milk
575 and meat production than OSS (compare mean crops-milk and crops-meat ratios per
576 system, which can be easily derived from Table 2). This, in turn, explains the lower
577 crops slack, and higher milk and meat slacks, of CSS in comparison with OSS (Table
578 4). Finally, note that for both systems the largest slack was eutrophication, as
579 opposed to the relatively low global warming potential slacks. This agrees with the
580 findings of Bava *et al.* (2014) that livestock systems are often responsible for
581 important local EIs.

582

583 *Methodological aspects*

584 *Eco-efficiency as a relative measure to improve sustainability.* It can be argued that
585 improving eco-efficiency does not guarantee sustainability. Because eco-efficiency is
586 a relative measure, improvements can be achieved if either EIs are reduced or

587 outputs are increased. Furthermore, the absolute environmental pressure can still
588 exceed the ecosystem's carrying capacity (Kuosmanen and Kortelainen, 2005). For
589 example, there is a high concentration of dairy farms in West France and the main
590 production regions are located near environmentally sensitive areas (Chatellier and
591 Pflimlin, 2006). Thus, although OSS systems had higher eco-efficiency, this does not
592 necessarily mean that they operated within the local ecosystem's carrying capacity.

593 Nevertheless, eco-efficiency is often cost-effective so it makes economic
594 sense to exploit it to the utmost (Kuosmanen and Kortelainen, 2005). In this study the
595 RAM model helped identify such options through the relative EI and output slacks
596 (Table 4). Prioritizing those EIs and outputs with the largest relative slacks can result
597 in notable eco-efficiency improvements. This is advantageous because policies
598 targeted at eco-efficiency improvements tend to be easier to adopt, and politically
599 easier to implement, than policies restricting the level of economic activity
600 (Kuosmanen and Kortelainen, 2005).

601
602 *Comparing RAM with alternative methods.* This study considered RAM's ranking
603 property as one of its main advantages. Besides RAM, there are several promising
604 methods to rank DMUs. See the reviews by Adler *et al.* (2002) and Markovits-
605 Somogyi (2011) regarding the methods mentioned hereafter. Other ranking methods
606 missing from both reviews exist, such as the 'global efficiencies' (GLE) approach by
607 Despotis (2002) which, like RAM, uses a common weighting scheme across all
608 DMUs. These ranking methods can be roughly classified as having at least one of
609 the following characteristics: (i) they require modifications to the original DEA model
610 (e.g. when imposing weights restrictions); (ii) they involve supplementary analyses
611 with tools such as multivariate statistics (e.g. canonical correlation analysis for

612 ranking) or multiple-criteria decision making (e.g. GLE), which translates to additional
613 computational time and/or coding effort; (iii) the original DEA model cannot be easily
614 solved (e.g. fuzzy DEA); and (iv) there is no correspondence between the DMUs'
615 efficiency scores and their ranks (e.g. GLE). While some of these issues can be dealt
616 with fairly easily (e.g. the weights restrictions), to the best of our knowledge, RAM is
617 the only simple, readily available linear DEA model with a ranking property that does
618 not involve (i-iv). Note that RAM can only rank inefficient DMUs. In fact, ranking
619 efficient DMUs was not desirable here because rankings can differ between methods
620 (see Adler *et al.*, 2002), possibly affecting the results of the non-parametric rank
621 statistics.

622 Additive models (such as RAM) are not the only DEA models able to
623 simultaneously minimise EIs (and/or inputs) and maximise output. Another example
624 is the directional distance function (DDF) whereby the minimization of EIs and inputs,
625 and maximization of outputs, is made via a 'direction vector' that reflects different
626 stakeholder preferences. For example, the direction vector may be set to minimize
627 EIs for the given outputs, maximize outputs for the given EIs or do both
628 simultaneously. Several other choices are also possible (see Beltrán-Estevé *et al.*,
629 2014, Berre *et al.*, 2014). For instance, Berre *et al.* (2014) argued that a sustainable
630 intensification scenario would seek to reduce pollution and increase outputs with a
631 possible *increase* in inputs. The RAM model can also allow for input increases
632 because it can handle negative values (see Cooper *et al.*, 1999): simply assign a
633 negative sign to the inputs to be increased.

634 DDFs are advantageous over RAM when the objective is not only to calculate
635 the input and output adjustments necessary for a DMU to operate efficiently, but also
636 to determine how 'far' these adjustments are from an input-output combination

637 maximizing profits (provided that input and output prices are known) for this particular
638 DMU (Färe and Grosskopf, 2000). This ‘allocation’ problem cannot be modelled with
639 RAM. Nonetheless, RAM is appropriate when it is desirable to decompose efficiency
640 scores into variable-specific scores through the slacks (as was done here) because,
641 unlike DDFs, RAM does not assume proportional adjustments in inputs and outputs
642 (some recently developed DDFs that relax this assumption have in fact an additive
643 structure; see Chen *et al.*, 2015). Note that there are several normalization options
644 for the slacks (other than by division by the variables’ ranges as was done here) that
645 create opportunities for further analyses (Cooper *et al.*, 1999 discuss a range of
646 choices). For example, when input prices are known, input slacks can be ‘priced’ to
647 determine the proportion of each input’s cost to the total cost (see Soteriades *et al.*,
648 2015).

649 Finally, we draw attention to the alternative definitions of ‘data-driven’ weights
650 in models 1 and 2. In model 1 the weights are calculated by the model itself. This
651 may result in large weights for EIs of secondary importance, leaving a negligible or
652 zero weight for more important EIs (Kuosmanen and Kortelainen, 2005). This can be
653 fixed by restricting *a priori* the weights’ values to admissible ranges (see Kuosmanen
654 and Kortelainen, 2005). By contrast, with RAM (model 2) the weights are not
655 *calculated* but *given*, because the model uses the variable’s ranges as weights,
656 which are always non-zero. Therefore, reliance on subjective weights restrictions as
657 in model 1 is not necessary with RAM.

658

659 *Choice of DEA variables.* Choice of input and output variables used is a key aspect
660 of DEA methodology. Past studies on dairy farm eco-efficiency with DEA often use
661 one aggregate output indicator to avoid too many DMUs on the efficient frontier. For

662 example, Pérez Urdiales *et al.* (2015) defined output as economic value added [(milk
663 sales + value of on-farm consumption of milk) – direct costs]. On the other hand, Jan
664 *et al.* (2012) argued that economic value added might bias the results as an increase
665 in the market price of a given commodity would lead to higher eco-efficiency. Instead,
666 they aggregated all farm outputs into a single output of digestible energy content.
667 However, with this method it is assumed that any form of energy in human diets can
668 be substituted by any other, provided that energy requirements are met. Also, milk,
669 meat and crops have different nutritional values in addition to energy content.
670 Therefore, in this study it was deemed more appropriate to keep milk, meat and
671 crops as three separate outputs.

672 Furthermore, in this study the eco-efficiency measure did not include
673 operational inputs (e.g. labour, capital, on-farm electricity use) and ‘undesirable’
674 outputs (e.g. kg CO₂-equivalents, wastewater) because the idea was to aggregate
675 *altogether* the two elements used in LCA ratios: EIs and outputs. In other words, we
676 were concerned with the EIs rather than the amount of operational inputs and
677 undesirable outputs of DMUs (see Jan *et al.*, 2012, p.715, but also Kuosmanen and
678 Kortelainen, 2005). An alternative way of conducting eco-efficiency analysis by also
679 involving operational inputs and undesirable outputs is with the ‘LCA+DEA method’
680 (see Vázquez-Rowe and Iribarren, 2015). With LCA+DEA, ‘target’ LCA impacts are
681 obtained by adjusting the operational inputs to their optimal values via DEA and re-
682 performing the LCA exercise. Therefore, in LCA+DEA the DEA exercise is an
683 intermediate step that helps determine the DMUs’ benchmarks and thus the target
684 EIs. Alternatively, target EIs can be obtained directly from RAM’s optimal slacks. This
685 reduces potential dimensionality issues because the set of DEA variables will
686 generally be smaller than that with LCA+DEA (Jan *et al.*, 2012, p.715).

687

688 **Conclusion**

689 Combining LCA with RAM, the 'corrective' methodology and non-parametric rank
690 tests can significantly improve (dairy) farm eco-efficiency assessments compared to
691 previous studies using partial ratios or coupling LCA with DEA. The modelling
692 framework was demonstrated with LCA data for French specialized dairy farms.
693 Results showed that OSS systems ranked higher, on average, than CSS systems in
694 terms of eco-efficiency. Also, the average eco-efficiency rank of farms with lower
695 proportions of maize silage in the total forage area was higher, on average, than
696 farms with higher proportions of maize. These results helped identify the eco-
697 efficiency potential of each region and feeding strategy and could therefore aid
698 advisors and policy makers at farm or region/sector level. This demonstration also
699 highlights the capacity of the proposed multiple-EI, multiple-output framework to
700 measure and understand eco-efficiency, and to compare different groups, which
701 makes it a promising multiple-criteria tool towards the achievement of greater yet
702 sustainable agricultural production.

703

704 **Acknowledgements**

705 The authors would like to express their gratitude to two anonymous referees whose
706 constructive comments helped significantly improve an earlier version of this
707 manuscript. The authors take responsibility for any errors that may remain. We
708 acknowledge feedback from staff at SRUC (Scotland), INRA (St Gilles, France) and
709 Idele (Le Rheu, France) and also from Dr Philippe Lecomte (CIRAD, France) and Dr
710 Marc Metzger (University of Edinburgh). Likewise, thank you to Professor Mette
711 Asmild (University of Copenhagen) and Professors Jean-Philippe Boussemart and

712 Hervé Leleu at IÉSEG (Lille, France) for the fruitful discussions on DEA, as well as to
713 Dr Jiayi Liu and Dr Giles Innocent (BioSS, Scotland) for their tips in statistics. This
714 project is jointly funded by SRUC (via Scottish Government's Rural Affairs and the
715 Environment Strategic Research programme) and the PHASE division of INRA.

716

717 **References**

718 Adler N, Friedman L and Sinuany-Stern, Z 2002. Review of ranking methods in the
719 data envelopment analysis context. *European Journal of Operational Research*
720 140, 249-265.

721 Basset-Mens C, Ledgard S and Boyes M 2009. Eco-efficiency of intensification
722 scenarios for milk production in New Zealand. *Ecological Economics* 68, 1615-
723 1625.

724 Bava L, Sandrucci A, Zucali M, Guerci M and Tamburini A 2014. How can farming
725 intensification affect the environmental impact of milk production? *Journal of*
726 *Dairy Science* 97, 4579-4593.

727 Béguin E, Bonnet J, Dollé J-B, Charroin T and Ferrand M 2008. Les différents postes
728 de consommation en énergie et les pistes d'économie en élevage bovin laitier.
729 *Rencontres Recherches Ruminants* 15, 217-220.

730 Beltrán-Esteve M, Picazo-Tadeo A and Reig-Martínez E 2014. A metafrontier
731 directional distance function approach to assessing eco-efficiency. *Journal of*
732 *Productivity Analysis* 41, 69-83.

733 Berre D, Blancard S, Boussemart JP, Leleu H and Tillard E 2014. Finding the right
734 compromise between productivity and environmental efficiency on high input
735 tropical dairy farms: a case study. *Journal of Environmental Management* 146,
736 235-244.

737 Bogetoft P and Otto L 2011. Benchmarking with DEA, SFA, and R. Springer, New
738 York, NY, US.

739 Brockett PL, Cooper WW, Golden LL, Rousseau JJ and Wang YY 2004. Evaluating
740 solvency versus efficiency performance and different forms of organization and
741 marketing in US property - liability insurance companies. European Journal of
742 Operational Research 154, 492-514.

743 Brockett PL and Golany B 1996. Using rank statistics for determining programmatic
744 efficiency differences in data envelopment analysis. Management Science 42,
745 466-472.

746 Casey JW and Holden NM 2005. The relationship between greenhouse gas
747 emissions and the intensity of milk production in Ireland. Journal of
748 Environmental Quality 34, 429-436.

749 Charroin T, Palazon R, Madeline Y, Guillaumin A and Tchakerian E 2005. Le
750 système d'information des Réseaux d'Elevage français sur l'approche globale
751 de l'exploitation. Intérêt et enjeux dans une perspective de prise en compte de
752 la durabilité. Rencontres Recherches Ruminants 12, 335-338.

753 Chatellier V and Pflimlin A 2006. Dairy systems in the European regions of the
754 Atlantic area. In Proceedings of the Final Seminar of the Green Dairy Project,
755 13-14 December 2006, Rennes, France pp. 11-30.

756 Chen PC, Yu MM, Chang CC, Hsu SH and Managi S 2015. The enhanced Russell-
757 based directional distance measure with undesirable outputs: numerical
758 example considering CO₂ emissions. Omega 53, 30-40.

759 Conover WJ 1999. Practical nonparametric statistics, 3rd edition. John Wiley & Sons
760 Inc, New York, NY, US.

761 Cooper WW, Park KS and Pastor JT 1999. RAM: A range adjusted measure of
762 inefficiency for use with additive models, and relations to other models and
763 measures in DEA. *Journal of Productivity Analysis* 11, 5-42.

764 Cooper WW, Seiford LM and Tone K 2007. *Data envelopment analysis: a*
765 *comprehensive text with models, applications, references and DEA-Solver*
766 *software, 2nd edition*. Springer Science+Business Media, LLC, New York, NY,
767 US.

768 CORPEN- Comité d'orientation pour de pratiques agricoles respectueuses de
769 l'environnement 1999. Estimation des flux d'azote, de phosphore et de
770 potassium associés aux vaches laitières et à leur système fourrager : influence
771 de l'alimentation et du niveau de production. Ministère de l'Écologie, de
772 l'Énergie, du Développement durable et de la Mer, Ministère de l'Agriculture,
773 France.

774 Despotis DK 2002. Improving the discriminating power of DEA: focus on globally
775 efficient units. *Journal of the Operational Research Society* 53, 314-323.

776 EMEP/CORINAIR- European Monitoring and Evaluation Programme/Core Inventory
777 of Air Emissions in Europe 2002. Atmospheric emission inventory guidebook,
778 3rd edition. European Environment Agency, Copenhagen, Denmark.

779 ESCAP- Economic and Social Commission for Asia and the Pacific 2009. Eco-
780 efficiency indicators: measuring resource-use efficiency and the impact of
781 economic activities on the environment. ESCAP, Bangkok, Thailand.

782 Färe R and Grosskopf S 2000. Theory and applications of directional distance
783 functions. *Journal of Productivity Analysis* 13, 93-103.

784 Faverdin P, Baratte C, Perbost R, Thomas S, Ramat E and Peyraud J-L 2014. A web
785 tool to simply assess feed autonomy and nitrogen excretion of dairy herds:
786 CowNex. Rencontres Recherches Ruminants 21, 391-394.

787 Foresight 2011. The future of food and farming. The Government Office for Science,
788 London, UK.

789 Gac A, Deltour L, Cariolle M, Dollé J-B, Espagnol S, Flénet F, Guingand N, Lagadec
790 S, Le Gall A, Lellahi A, Malaval C, Ponchant P and Tailleur A 2010a. GES'TIM,
791 Guide méthodologique pour l'estimation des impacts des activités agricoles sur
792 l'effet de serre. Version 1.2. Institut de l'Élevage, Paris, France.

793 Gac A, Manneville V, Raison C, Charroin T and Ferrand M 2010b. L'empreinte
794 carbone des élevages d'herbivores : présentation de la méthodologie
795 d'évaluation appliquée à des élevages spécialisés lait et viande. Rencontres
796 Recherches Ruminants 17, 335-342.

797 Guerci M, Bava L, Zucali M, Sandrucci A, Penati C and Tamburini A 2013. Effect of
798 farming strategies on environmental impact of intensive dairy farms in Italy.
799 Journal of Dairy Research 80, 300-308.

800 Guinée JB, Gorrée M, Heijungs R, Huppes G, Kleijn R, Koning A de, Oers L van,
801 Wegener Sleeswijk A, Suh S, Udo de Haes HA, Bruijn H de, Duin R van and
802 Huijbregts MAJ 2002. Handbook on life cycle assessment. Operational guide to
803 the ISO standards. I: LCA in perspective. IIa: Guide. IIb: Operational annex. III:
804 Scientific background. Kluwer Academic Publishers, Dordrecht, The
805 Netherlands.

806 IPCC- Intergovernmental Panel on Climate Change 2007. Climate Change 2007: the
807 physical science basis. Contribution of Working Group I to the Fourth

808 Assessment Report of the Intergovernmental Panel on Climate Change.
809 Cambridge University Press, Cambridge, UK.

810 Jan P, Dux D, Lips M, Alig M and Dumondel M 2012. On the link between economic
811 and environmental performance of Swiss dairy farms of the alpine area.
812 International Journal of Life Cycle Assessment 17, 706-719.

813 Kuosmanen T and Kortelainen M 2005. Measuring eco-efficiency of production with
814 data envelopment analysis. Journal of Industrial Ecology 9, 59-72.

815 LEAP- Livestock Environmental Assessment and Performance Partnership 2015.
816 Developing sound tools for transition to sustainable food and agriculture. LEAP
817 partnership life cycle assessment guidelines on livestock supply chains:
818 methodological notes. Draft version 1 for public review. LEAP, Rome, Italy.

819 Markovits-Somogyi R 2011. Ranking efficient and inefficient decision making units in
820 data envelopment analysis. International Journal for Traffic and Transport
821 Engineering 1, 245-256.

822 Nemecek T and Kägi T, 2007, Life cycle Inventories of Swiss and European
823 agricultural production systems. Final report ecoinvent V2.0 No. 15a. Agroscope
824 Reckenholz-Taenikon Research Station ART, Zurich, Switzerland.

825 Pérez Urdiales M, Oude Lansink A and Wall A 2015. Eco-efficiency among dairy
826 farmers: the importance of socio-economic characteristics and farmer attitudes.
827 Environmental and Resource Economics, doi:10.1007/s10640-015-9885-1,
828 Published online by Springer Netherlands 20 February 2015.

829 Ramli NA and Munisamy S 2015. Eco-efficiency in greenhouse emissions among
830 manufacturing industries: a range adjusted measure. Economic Modelling 47,
831 219-227.

832 Rotz CA, Montes F and Chianese DS 2010. The carbon footprint of dairy production
833 systems through partial life cycle assessment. *Journal of Dairy Science* 93,
834 1266-1282.

835 Sheskin DJ 1997. *Handbook of parametric and nonparametric statistical procedures*.
836 CRC Press LLC, Boca Raton, FL, US.

837 Soteriades AD, Faverdin P, March M and Stott AW 2015. Improving efficiency
838 assessments using additive data envelopment analysis models: an application
839 to contrasting dairy farming systems. *Agricultural and Food Science* 24, 235-
840 248.

841 van Calster KJ, Berentsen PBM, Giesen GWJ and Huirne RBM 2008. Maximising
842 sustainability of Dutch dairy farming systems for different stakeholders: a
843 modelling approach. *Ecological Economics* 65, 407-419.

844 Vázquez-Rowe I and Iribarren D 2015. Review of life-cycle approaches coupled with
845 data envelopment analysis: launching the CFP. *The Scientific World Journal*.
846 doi.org/10.1155/2015/813921.

847 **Table 1** *On-farm emissions due to different sources of the farming system*

	Source and emissions													
	Enteric	Building			Storage			Fertilization		Crop			N ² leaching (NO ₃)	P ³ runoff (PO ₄)
		CH ₄ , NH ₃ ,		NH ₃ ,	N ₂ O,	N ₂ O,	Min. ¹	Organic	Grazing	residue	Indirect	Combustion		
		CH ₄	N ₂ O											
CH ₄	N ₂ O	NO	CH ₄	N ₂ O	NO	NO	NH ₃	NO	CH ₄	NO	N ₂ O	N ₂ O	PO ₄	
Milk yield, fat %	X													
Livestock units	X	X							X					
% time indoors		X	X						X	X				
Building type		X												
Manure type				X	X			X						
Animal N exc. ⁴			X		X	X	X	X			X			
MS (time & vol.) ⁵				X										
N/P fertilization								X						X
Energy use													X	
Inputs													X	

	Farm N surplus			X		X	
	Crop rot. ⁶		X	X		X	X
848	¹ Mineral.						
849	² Nitrogen.						
850	³ Phosphorous.						
851	⁴ Animal nitrogen excretion.						
852	⁵ Time and volume of manure storage (MS).						
853	⁶ Crop rotation.						
854							

855 **Table 2** *Statistics of dairy farm environmental impacts and outputs per system, in both years 2007 and 2008*

Data	CSS ¹ (n = 59)				OSS ² (n = 126)			
	Min	Max	Mean	SD	Min	Max	Mean	SD
EI ³								
Non-renewable energy (10 ³ MJ)	580	5256	1643	846	343	4223	1406	709
Land use (ha)	48	351	133	67	48	268	101	43
Eutrophication (kg PO ₄)	625	10890	3200	2241	425	10070	3200	2058
Acidification (kg SO ₂)	2189	11780	4728	1982	1543	8413	3798	1419
GWP ⁴ (kg CO ₂)	163500	1431000	535000	257097	91400	1330000	507200	218404
Outputs								
Milk (kg protein)	2210	10540	5218	1957	2080	10900	5195	1907
Meat (kg live weight)	0	73410	21700	13401	0	92210	23330	11644
Crops (10 ³ MJ)	614	10930	3488	2683	0	8152	2142	1848

856 ¹ Continental Specialized Systems.

857 ² Oceanic Specialized Systems.

858 ³ Environmental impact.

859 ⁴ Global warming potential.

Table 3 *Statistics for eco-efficiency scores per system and feeding strategy before removal of managerial inefficiencies*

System	Eco-efficiency scores					
	Min	Max	Median	Mean	SD	Mean rank
CSS ¹	0.840	1.000	0.934	0.938	0.047	83.814
OSS ²	0.762	1.000	0.950	0.949	0.050	97.302
Feeding strategy						
<10% maize ³	0.841	1.000	0.966	0.964	0.038	113.795 ^a
10-30% maize ³	0.840	1.000	0.954	0.950	0.045	98.596 ^a
>30% maize ³	0.762	1.000	0.930	0.932	0.053	78.310 ^b

¹ CSS: Continental Specialized Systems.

² OSS: Oceanic Specialized Systems.

³ Maize area as % of total forage area on farm.

^{a,b} Values within a column with different superscripts differ significantly at $P < 0.05$.

Table 4 Mean slack values per system expressed as a proportion of their corresponding ranges

	CSS ¹	OSS ²
Environmental impacts		
Non-renewable energy	0.066	0.060
Land use	0.100	0.041
Eutrophication	0.107	0.141
Acidification	0.090	0.053
GWP ³	0.060	0.069
Mean	0.085	0.073
Outputs		
Crops	0.003	0.007
Milk	0.033	0.019
Meat	0.040	0.022
Mean	0.025	0.016

¹OSS: Oceanic Specialized Systems.

²CSS: Continental Specialized Systems.

³GWP: global warming potential.

Table 5 *Statistics for eco-efficiency scores per system and feeding strategy after removal of managerial inefficiencies*

System	Eco-efficiency scores					
	Min	Max	Median	Mean	SD	Mean rank
CSS ¹	0.908	1.000	0.995	0.985	0.022	67.059 ^a
OSS ²	0.890	1.000	1.000	0.994	0.018	105.147 ^b
Feeding strategy						
<10% maize ³	0.934	1.000	1.000	0.991	0.017	88.614
10-30% maize ³	0.928	1.000	1.000	0.993	0.016	94.991
>30% maize ³	0.890	1.000	1.000	0.991	0.024	93.946

¹ CSS: Continental Specialized Systems.

² OSS: Oceanic Specialized Systems.

³ Maize area as % of total forage area on farm

^{a,b} Values within a column with different superscripts differ significantly at $P < 0.05$.

1 **Figure 1** Description of the dairy farming system used for the Life Cycle Analysis
2 (LCA) calculations.

3

4 **Figure 2** An efficient frontier ABC in the case of a single environmental impact (EI)
5 and a single output. Inefficient decision-making unit D seeks maximal EI reduction
6 and output expansion and thus is projected on ABC at point B.

7

8 **Figure 3** Description of the modelling framework adopted in this study. DEA: Data
9 Envelopment Analysis. LCA: Life Cycle Analysis.