



Measuring sustainable intensification: combining composite indicators and efficiency analysis to account for positive externalities in cereal production

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Accepted Version

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Areal, F. J., Jones, P. J., Mortimer, S. R. and Wilson, P. (2018) Measuring sustainable intensification: combining composite indicators and efficiency analysis to account for positive externalities in cereal production. *Land Use Policy*, 75. pp. 314-326. ISSN 0264-8377 doi: <https://doi.org/10.1016/j.landusepol.2018.04.001> Available at <http://centaur.reading.ac.uk/76354/>

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To link to this article DOI: <http://dx.doi.org/10.1016/j.landusepol.2018.04.001>

Publisher: Elsevier

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1 **Measuring sustainable intensification: Combining composite indicators and** 2 **efficiency analysis to account for positive externalities in cereal production**

3 Abstract

4 We combine the use of a stochastic frontier analysis framework and composite
5 indicators for farm provision of environmental goods to obtain a farm level composite
6 indicator reflecting sustainable intensification. The novel sustainable intensification
7 composite indicator that is developed accounts for multidimensional market and non-
8 market outputs, namely the economic performance of cereal farms (i.e. market
9 production value) and the associated positive environmental impacts of production (e.g.
10 positive environmental externalities). The composite indicator integrates three different
11 indicators for the provision of environmental goods into a stochastic frontier analysis: a)
12 agri-environmental payments; b) the ratio of rough grassland and permanent pasture
13 area to total utilised agricultural area; and c) land use diversity, as measured by the
14 Shannon Index. We apply this approach to a panel of data for 106 cereal farms in
15 England and Wales during the period 2010-2012. Results indicate that farm rankings on
16 the indicator vary substantially depending on the weight given to the different
17 environmental aspects/indicators, suggesting that single indicators of the provision of
18 environmental goods may not provide a true reflection of the environmental
19 performance of farms. We illustrate a simple approach that captures the aspects of
20 sustainable intensification of farms in a much more holistic way, i.e. by producing a
21 distribution of sustainable intensification scores for each farm reflecting different
22 weightings of evaluation criteria. To reduce the dimensionality of this distribution farms
23 are classified into four distinct groups according to the shape of this distribution, with
24 some farms found to perform well under all combinations of weights for evaluation
25 criteria, while others always perform poorly. This distribution-based analysis provides a
26 greater depth of information than traditional approaches based on the generation of a
27 single sustainable intensification score.

28 29 **1. Introduction**

30 A growing awareness of the externalities associated with agricultural production has
31 been a key driver of the development of agricultural policies in the EU for more than 30
32 years (Potter and Goodwin, 1998). Following decades of policies oriented towards

33 increased productivity in the decades after 1945 (Stoate et al., 2001), without much
34 consideration for the environmental consequences of such an approach, the focus of EU
35 agricultural policy changed from the mid-1980s toward the promotion of a more
36 sustainable agriculture, through provision of incentives to farmers “to work in a
37 sustainable and friendly manner”, providing a “better balance between food production
38 and the environment” (European Commission, 2014; Buckwell et al., 2014). Initially,
39 such policies focussed on protection of natural resources, biodiversity and cultural
40 landscapes. In the last 10 years, since the volatility in commodity prices of 2007/8 and
41 growing concerns about food security, attention has moved towards measures aimed at
42 promoting ecosystem services beneficial to production (Plieninger et al., 2012;
43 Tiftonell, 2014) and their role in contributing to ‘sustainable intensification’ (Tilman et
44 al., 2011).

45 A narrow definition of ‘sustainable intensification’ (SI) is simply improved resource use
46 efficiency, i.e. ‘producing more with less’. However, a more complete understanding
47 has to encompass the positive and negative externalities of agriculture, i.e. the supply of
48 ecosystem services beyond provisioning. However, the interlinkages between
49 agricultural production and these environmental outputs, and the trade-offs between
50 them, are complex, making it extremely difficult to envision what sustainable
51 agriculture (or for this matter sustainable intensification) actually comprises (Pretty,
52 1997). The difficulty in generating models of sustainable intensification in agriculture is
53 compounded by two factors. First, the spatial heterogeneity of both the environments in
54 which agriculture operates and the production systems employed. Second, sustainable
55 intensification in agriculture is an anthropogenic concept that is also subject to
56 heterogeneity, as individuals and societies value the ecosystem services provided by
57 agriculture differently and have different levels of awareness and understandings of the
58 interlinkages and trade-offs between these ecosystem services. These differences mean
59 that the definition of sustainable intensification in agriculture, as a concept, varies, even
60 amongst international organisations, although some overlap exists. Thus, for example,
61 the Montpellier Panel and Save and Grow report (FAO, 2011) define sustainable
62 intensification as: “producing more outputs with more efficient use of all inputs - on a
63 durable basis - while reducing environmental damage and building resilience, natural
64 capital and the flow of environmental services”; The Royal Society (2009) defines
65 sustainable intensification as “... yields are increased without adverse environmental

66 impact and without the cultivation of more land”; and the UK Foresight Report
67 (Foresight Report, 2011) states, when referring to sustainable intensification,
68 “simultaneously raising yields, increasing the efficiency with which inputs are used and
69 reducing the negative environmental effects of production”. While the first and third
70 definitions are similar, the second definition highlights a slight but important difference,
71 i.e. that SI is considered to be achieved by increasing provisioning services while
72 simultaneously not increasing negative environmental externalities. Taking all these
73 definitions into account, and for the purposes of this study, sustainable intensification
74 can be understood as increasing the market-based dimension of sustainability (i.e.
75 agricultural yield) without decreasing the capacity to provide (largely) non-market
76 dimensions, i.e. environmental services. This understanding of SI evokes the more
77 generalised definition offered by Jules Pretty (Pretty, 1997) that SI represents:
78 “increasing food production from existing farmland while minimising pressure on the
79 environment”. These different interpretations of SI have generated a debate about the
80 pathways to achieving SI, with various models being put forward, including land
81 sparing, land sharing, and competitive advantage (Franks, 2014).

82 While there are different interpretations of what constitutes SI, and consequently
83 different proposed pathways to achieving it, all these approaches face the common
84 problem of how to measure success. The questions arising from this are: (a) what
85 dimensions of SI need to be measured; (b) what metrics are appropriate to capture these
86 dimensions; and (c) how can these metrics be combined into a composite measure of SI
87 that truly reflects the relative importance of each dimension, i.e. under what weighting
88 system?

89 It seems clear from the definitions above that any meaningful SI measure/metric needs
90 to take into account both provisioning outputs and the environmental impacts of land
91 management, i.e. the inclusion of environmental externalities into technical efficiency
92 analysis. Traditionally, metrics of the environmental dimension have focussed solely on
93 the negative externalities associated with agricultural production. However, there can
94 also be ‘positive’ environmental outputs associated with productive land management,
95 for example the provision, or improvement, of semi-natural habitats and the positive
96 effects on wildlife and biodiversity that result (Mattison and Norris, 2005; OECD,
97 1999). Therefore, measuring SI is not the same as measuring sustainability, as the SI
98 measure excludes some key dimensions of sustainability, such as social impacts. In part,

99 this results from limitations on the information available to produce SI, such as, for
100 example, the Defra Farm Business Survey (FBS) data, as used in this study.

101 Approaches to incorporating environmental externalities into technical efficiency
102 analysis began with Färe et al. (1989). While the focus of this early work was solely
103 directed towards the negative externalities associated with agricultural production (Färe
104 et al., 1989, 1996, 2001; Lansink and Reinhard, 2004; Murty et al., 2006; Reinhard and
105 Thijssen, 2000; Reinhard et al., 1999, 2002) more recent technical efficiency analysis
106 has also incorporated the provision of positive externalities (Omer et al., 2007; Areal et
107 al., 2012; Sipiläinen and Huhtala, 2013; van Rensburg and Mulugeta, 2016). More
108 recently, work by Ang et al. (2015) analysed the impact of dynamic profit maximisation
109 on biodiversity, for a sample of UK cereal farms, using a DEA approach.

110 The limitation of some of the approaches adopted to date, i.e. that use composite
111 indicators to account for different dimensions of SI, is that these composite indicators
112 can only reflect fixed and usually pre-determined relative weightings of these
113 dimensions. Some other approaches to developing composite indicators of SI have not
114 relied on pre-determined weights, but have used statistical procedures such as DEA and
115 factor analysis to determine them. For instance, Barnes and Thomson (2014) used a
116 form of factor analysis to provide weights to individual indicators to form composite
117 indicators of SI. However, the weights for SI indicators obtained in all these previous
118 studies are presented as a single set of numbers, based on the averages of the weight
119 distribution, while variation of these weights is not explored. This may give these
120 composite indicators a form of starting point bias and makes them of limited value to
121 policy makers, who would view the choice of weights for these dimensions as a fully
122 anthropogenic decision. This paper explores the potential for the use in composite SI
123 indicators of a number of different indicators of environmental outputs under multiple
124 weightings, on the basis that all of these alternatives capture some valid aspect of
125 environmental goods at the farm level. To explore the feasibility of constructing such an
126 indicator this study uses a stochastic frontier framework to undertake technical
127 efficiency analysis at the farm level to test a mechanism to create a composite indicator
128 of sustainable intensification combining provisioning outputs with indicators
129 representing multiple dimensions of environmental goods provision.

130 Since we face farms with multiple outputs (e.g. market and non-market/environmental
131 outputs) we estimate farm level efficiency through the use of an output distance
132 function (Coelli et al., 2005), where the farm production frontier directly accounts for
133 both market and non-market goods.

134 To overcome the problem of there being no single correct weighting of the relative
135 importance of the different dimensions of environmental output, we explore a method to
136 capture all potential integer weighting combinations within and between the multiple SI
137 indicator. We therefore estimate 66 efficiency stochastic frontier models that account
138 for different combinations of weights for the dimensions of environmental goods
139 provision, to create a single composite indicator for SI. This approach provides a much
140 more nuanced picture (i.e. a probability distribution) of SI at the farm level, than would
141 relying on the use of a single snap-shot, based on a single set of weights.

142 **Methods**

143 **1.1. Data**

144 The analysis reported here uses data in the form of a balanced panel of 106 specialist
145 cereals farms drawn from the annual Defra Farm Business Survey (FBS) for England and
146 Wales, between 2010 and 2012¹. Data were drawn solely for the ‘specialist cereals’ farm
147 type, to minimize the level of heterogeneity due to differences in farming system. While
148 the FBS provides financial data on each farm business, alongside crop, livestock and land
149 use data, it has been historically more limited with respect to environmental metrics (e.g.
150 metres of hedges or pond areas) and physical measures of inputs (e.g. kilograms of
151 nitrogen fertiliser). This has led to the analysis herein drawing on a more limited range
152 of data, and using environmental payments as a composite metric for some environmental
153 outputs, i.e. where these payments can reasonably be assumed to capture public benefit
154 from environmental activities. While drawing on such proxy metrics limits, in part, the
155 results generated, these data are sufficient to demonstrate an approach for quantifying SI
156 that can be further refined in the future through the use of better data. To illustrate, the
157 most recent FBS year (2016/17) captures, for the first time, the areas of certain landscape
158 features, including buffer strips, hedges and catch/green cover/nitrogen fixing crops.

¹ We selected all Specialist Cereals farms that were in the FBS within the period of the study that had all information required for the model (i.e. 106 farms).

159 Farm provisioning outputs were captured using two separate metrics: a) cereals enterprise
160 output (£)²; and b) other agricultural outputs, i.e. other crops and livestock (£)³. Farm
161 environmental outputs were captured by the three metrics described below. To capture
162 inputs, the following metrics were included: utilised agricultural area (ha); labour use
163 (hours per annum); machinery costs (£); other costs, including crop protection and animal
164 costs (£). Also employed, as explanatory variables in the modelling, were a set of socio-
165 economic variables, such as farmer age and education level, financial pressure (debt/asset
166 ratio) and membership of certification and assurance schemes. Farmer age has been
167 included as a covariate as this may be related to SI, with younger farmers being more
168 concerned about sustainability. We also hypothesise that more educated farmers may
169 have more knowledge of the approaches required to increase production in a sustainable
170 way. We hypothesise that farmers under financial pressure may de-emphasise
171 sustainability goals in favour of output, or profit-based, business goals, and so achieve
172 lower SI scores than farmers not under financial pressure. Additionally, these three
173 factors, have been previously identified as determinants of technical efficiency (Hadley,
174 2006; Wilson et al., 2001). Finally, assurance scheme membership has been included as
175 such schemes often include sustainability requirements, and so we hypothesise that
176 farmers with assurance schemes have higher SI scores. This last factor has, to our
177 knowledge, has not been examined as a potential driver of SI or efficiency in previous
178 studies.

179 The FBS contains information on the geographical location of the farm as associated with
180 the landscape type ('National Character Area')⁴ in which the farm lies. This information
181 has been used to identify and map any spatial influences on SI.

182 Summary descriptive statistics for the sample of farms, based on the variables used in
183 the analysis, can be found in Table 1.

² The FBS dataset reflects input use by farms primarily in value terms. For consistency sake, therefore, both outputs and inputs are denominated in value terms. However, for the purpose of this analysis these deflated data can be assumed to act as proxies for measures of volume. Data has been deflated using the agricultural price indices for inputs and outputs and the CPI for the environmental payments.

³ Although our data is obtained for specialised cereal farms, some of these farms will have livestock, although this will be a minority enterprise.

⁴ National Character Areas are landscape units defined by geology, topography, soil type, land cover, history, and cultural and economic activity. Their boundaries follow natural linear features in the landscape rather than administrative boundaries.

Variable	Mean	Std. Dev
Cereals (£)	237,417	274,964
Other output (£)	30,215	42,124
EI (Agri-env payments) (£)	15,737	22,790
EI (Permanent grassland) (proportion of UAA)	0.157	0.147
EI (Land use diversity) (Index)	0.598	0.134
UAA (ha)	333	313
Labour (number of hours per annum)	47,220	58,156
Machinery (£)	131,311	125,514
Crop and animal cost (£)	122,242	136,991

185 Table 1. Descriptive statistics for sample farms (average 2010-2012). Key: EI = Environmental Indicator,
186 UAA = Utilised Agricultural Area.

187 1.2.Measurement of efficiency

188 Buckwell et al. (2014) explored the use of such multi-dimensional composite indicators
189 within the framework of economic theory, and suggested that provisioning and
190 environmental dimensions can be seen as two dimensions of a production possibilities
191 frontier (PPF), where the PPF serves to ‘depict the challenge of sustainable
192 intensification’. We accept this principle in our analysis and incorporate composite
193 indicators for the provision of environmental goods as another dimension to the standard
194 technical efficiency analysis.

195 We use an output distance function approach to describe technology in a way that allows
196 efficiency to be measured for multi-input, multi-output farms (Coelli et al., 2005). More
197 specifically, we describe the degree to which a farm can expand its outputs given its input
198 vector.

$$199 \quad P(x) = \{y \in R_+^M : x \text{ can produce } y\} = \{y : (x, y) \in T\} \quad (1)$$

200 Where y refers to all $M = 3$ market-based, plus environmental outputs of the farm, where
201 environmental outputs are represented by either a single or composite indicator for the
202 provision of environmental goods; x represents all K inputs used in the farm; and T
203 represents the technological set. The distance function is defined on the output set $P(x)$
204 as

$$205 \quad D_o(x, y) = \min \left\{ \theta : \left(\frac{y}{\theta} \right) \in P(x) \right\} \text{ for all } x \in R_+^K \quad (2)$$

206

207 We posit that a translog function for the parametric distance function with M outputs and
 208 K inputs offers some attractive properties, such as flexibility and allowing the imposition
 209 of homogeneity, which makes it the preferred form in the literature (Lovell et al., 1994;
 210 Coelli and Perelman, 1999; Brümmer et al., 2002, 2006; Areal et al., 2012).

$$211 \quad \ln D_{Oi} = \alpha_0 + \sum_{m=1}^M \alpha_m \ln y_{mi} + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^K \beta_k \ln x_{ki} +$$

$$212 \quad + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^K \sum_{m=1}^M \delta_{km} \ln x_{ki} \ln y_{mi} ; i = 1, \dots, n \quad (3)$$

213 where i denotes the i th farm in the sample. Using linear homogeneity of the output
 214 distance function in outputs, equation (3) can be transformed into an estimable regression
 215 model by normalising the function by one of the outputs⁵ (Lovell et al, 1994). From
 216 Euler's theorem, homogeneity of degree one in output implies

$$217 \quad \sum_{m=1}^M \alpha_m + \sum_{m=1}^M \sum_{n=1}^M \alpha_{mn} \ln y_{ni} + \sum_{m=1}^M \sum_{k=1}^K \delta_{km} \ln x_{ki} = 1 \quad (4)$$

218 which will be satisfied if $\sum_{m=1}^M \alpha_m = 1$, $\sum_{m=1}^M \alpha_{mn} = 0$ for all n , and $\sum_{m=1}^M \delta_{km} = 0$
 219 for all k , which is equivalent to normalising by one of the outputs leading to

$$220 \quad \ln D_O \left(\frac{y_i}{y_{2i}}, x \right) = \ln D_O \frac{1}{y_{2i}} (y_i, x) \quad (5)$$

221 and

$$222 \quad -\ln y_2 = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \frac{y_{mi}}{y_{2i}} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \alpha_{mn} \ln \frac{y_{mi}}{y_{2i}} \ln \frac{y_{ni}}{y_{2i}} + \sum_{k=1}^K \beta_k \ln x_{ki} +$$

$$223 \quad + \frac{1}{2} \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^K \sum_{m=1}^{M-1} \delta_{km} \ln x_{ki} \ln \frac{y_{mi}}{y_{2i}} + \varepsilon_i - z_i \quad (6)$$

224 where ε_i is a symmetric random error term that accounts for statistical noise and z_i is a
 225 non-negative random variable associated with technical inefficiency.

226

227 **2.3 Indicators of the provision of environmental goods**

228 We make use of three indicators of the provision of environmental goods, with these being
 229 commonly employed in the literature: agri-environmental payments (Hasund, 2013); the
 230 area of rough grazing and permanent pasture as a proportion of the total utilised

⁵ We normalised the function using the cereals value.

231 agricultural area (Barnes et al. 2011; Areal et al., 2012; Barnes and Thomson, 2014) and
232 the widely used Shannon Index for land use diversity (LUD) (Westbury et al., 2011).

$$233 \quad LUD = -\sum_{c=1}^C a_c \times \ln(a_c), LUD \geq 0 \quad (7)$$

234 where a_c is the proportion of the area occupied by crop c and C is the total number of
235 crops. The Shannon index provides a metric of the number of land use classes on the
236 farm and their proportional representation. A high index value therefore indicates
237 higher crop diversity.

238 Although the data employed in this study is restricted to agricultural land uses and does
239 not capture total diversity of land cover on the farm, i.e. non-agricultural areas, there is
240 growing evidence that biodiversity is positively affected by heterogeneity in agricultural
241 crop types (Siriwardena et al. 2000; Benton et al. 2003). Indeed, it is for this reason that
242 a crop diversity requirement has been incorporated into the cross-compliance measures
243 of the 2015 CAP.

244

245 All the above three measures for the provision of environmental goods are relevant from
246 a policy viewpoint. For example, the latter two are reflected in the EU Common
247 Agricultural Policy (CAP), which makes receipt of direct payments contingent on a
248 minimum level of crop diversity and maintenance of the permanent grassland area.

249 Agri-environmental payments under Pillar II of the CAP are taken to reflect the positive
250 value attributed by society to the local provision of environmental goods through
251 modification of land management practices. These goods include protection of soil and
252 water resources, conservation of farmland biodiversity, protection of historic features and
253 cultural landscapes and the provision of opportunities for recreation and amenity.

254 The indicator capturing the ratio of permanent pasture plus rough grazing area⁶ to total
255 utilized agricultural area allows for the identification of farms undertaking low-intensity
256 management, which enhances the provision of areas of high nature value semi-natural
257 habitats. These areas provide a number of environmental benefits such as soil structure
258 improvement, renewal of ground water and flooding control through enhanced
259 infiltration, reductions in water runoff and higher soil organic carbon density (Altieri,
260 1999; Menta et al., 2011; Leifeld et al., 2005). Indicators based on the presence of

⁶ Permanent area refers to land used permanently, for 5 years or more, for herbaceous forage crops, either cultivated or growing wild (European Council, 2003) whereas rough grassland is non-intensive grazing grassland.

261 permanent grassland have been previously used in SI related studies by Areal et al. (2012)
262 and Barnes and Thomson (2014).

263

264 Undoubtedly, the three environmental indicators used here reflect the provision of a wide
265 range of environmental outputs associated with the management of agricultural land, with
266 each indicator capturing a different dimension of environmental provision, although there
267 is some overlap between them.

268

269 **2.4. Sustainable intensification indicators**

270 As discussed above, a number of indicators have been used in the literature to capture the
271 provision of environmental goods at the farm level. In this study we explore the extent to
272 which the use of different indicators of the provision of environmental goods leads to
273 different SI outcomes. To achieve this, we carry out a stochastic frontier analysis (SFA)
274 using each of these environmental indicators in separate models to estimate farm level
275 efficiency, see models M1-M4 shown in Table 2. The farm efficiency estimates obtained
276 from models M2-M4 we equate with three different indicators of SI, with each of these
277 indicators reflecting the provision of different environmental goods (i.e. different
278 components of the totality of farm provision of environmental goods). The use of
279 ‘efficiency’ measures as an indicator of ‘sustainable intensification’ follows the work of
280 Gadanakis et al. (2015), who used DEA to create a composite SI. Hence, we equate the
281 farm efficiency scores obtained from efficiency measures when augmented with
282 provision of environmental goods with what could be called eco-efficiency measures.
283 Eco-efficiency and SI indicators are therefore assumed to be synonymous, i.e. eco-
284 efficiency and SI are closely related concepts, where both are based on the same principle
285 of generating more output while using fewer resources and generating fewer
286 environmental externalities. The OECD defined eco-efficiency as: “Eco-efficiency is
287 reached by the delivery of competitively-priced goods and services that satisfy human
288 needs and bring quality of life, while progressively reducing ecological impacts and
289 resource intensity throughout the life cycle, to a level at least in line with the earth’s
290 estimated carrying capacity” OECD (1998). This is similar to the definitions of SI. Eco –
291 efficiency brings together environmental and economic goals contributing towards
292 sustainable development (OECD, 1998). The eco-efficiency literature also makes use of
293 holistic indicators. Indicators for eco-efficiency began by using ratios that relate the
294 economic value of goods and services produced to the environmental impacts or pressures

295 associated with the production process. These made use of simple, solitary indicators such
 296 as GDP/emissions of pollutants, or units of output per unit of environmental impact or
 297 pressure (Picazo-Tadeo et al., 2012). However, this type of ratio-based indicator was not
 298 suitable for the incorporation into the same indicator of a number of different outputs
 299 (economic output) and inputs (environmental impact). As a consequence of this
 300 limitation, new indicators were developed where a set of inputs and outputs were
 301 aggregated using weights, the values for which were typically assigned by a panel of
 302 experts, or individual assessment (i.e. no mathematical/statistical methods were used).
 303 Our approach integrates environmental indicators into efficiency analysis in a different
 304 way (i.e. incorporating a set of composite indicators for the provision of environmental
 305 goods into stochastic frontier analysis obtaining farm level distributions of SI rather than
 306 single ‘snap shot’ composite indicator.
 307 The comparison of SI indicators obtained from the models M1-M4 sheds light on both
 308 the quantity and the type of provisioning and environmental goods being provided by
 309 farms.

310
 311

Model	Description
M1	Baseline technical efficiency model not accounting for environmental externalities
M2	Technical efficiency plus provision of environmental goods using agri-environmental payments as indicator
M3	Technical efficiency plus the ratio of rough and permanent pasture area to total utilized agricultural area as an indicator of provision of environmental goods
M4	Technical efficiency plus LUD as an indicator of provision of environmental goods

SI Indicators

312 Table 2. Description of the models

313
 314

315 **2.5. Composite indicators**

316 When combining indicators into composites, the weights given to each indicator have a
317 significant bearing on the interpretation of that composite indicator (Barnes and
318 Thomson, 2014; OECD, 2008). Consequently, the allocation of weights needs to be well
319 informed to ensure that the composite indicator captures the ‘true’ or ‘optimal’ relative
320 importance of these dimensions of the environment, i.e. as reflected in human values.
321 However, there is often no way to judge the relative importance of different
322 environmental indicators, either because appropriate weights have never been
323 systematically generated, or because consensus on the relative importance of environment
324 dimensions cannot be reached (Mauchline et al., 2012). The default response in these
325 circumstances is to assume that each indicator represents a different but equally valid
326 dimension of environmental goods provision, regardless of whether this is actually the
327 case. As a means to circumventing this uncertainty, we apply a methodology developed
328 by Areal and Riesgo (2015), which obviates the need to manually, or statistically, allocate
329 weights to the components of aggregate indicators. This methodology is based on the
330 assumption that the use of a set of composite indicators using every possible weighting
331 combination accounts for both the range of possibilities that farmers have available to
332 provide environmental outputs and the range of values that society puts on those
333 environmental outputs. The validity of this approach is based on the further assumption
334 that sustainable agriculture is not achieved by delivering a combination of outputs in fixed
335 proportion, but rather can be achieved by a distribution across different combinations of
336 outputs.

337

338 We obtain only a partial picture of SI (i.e. the efficiency level once the provision of
339 environmental output is taken into consideration in the production function) from models
340 M2, M3, and M4, since each of these indicators only account for the provision of a
341 fraction of the environmental output generated by each farm (i.e. SI status will differ
342 depending on which indicator is used). We therefore build a 106×3 matrix EG using the
343 3 indicators for the provision of environmental goods. Each indicator is normalised using
344 the distance method $\left(EG_i = \frac{egi}{\max(eg)}\right)$, which measures the relative position of an
345 indicator to a reference point, in this case the maximum value of the indicator in the
346 sample. This allows us to rescale each indicator to a dimensionless scale (0, 1].

347 We weight and aggregate⁷ the individual indicator matrix EG as follows:

348

$$349 \quad CEG = EG \times W' \quad (8)$$

350

351 where the weighting matrix W is generated with the following features: each element of
352 the matrix can take values $\{0,0.1,0.2, \dots,1\}$, and the rows of the weighting matrix are a
353 combination of elements (weights) where the sum of elements in each row equals 1. The
354 total number of combinations holding these rules is 66, meaning that W is a 66×3
355 weighting matrix. We then obtain CEG , a 106×66 matrix. Finally, we estimate the
356 model from equation (6) using the matrix CEG of 66 composite indicators for the
357 provision of environmental values to create a composite indicator of SI, i.e. the Composite
358 Sustainable Intensification (CSI) indicator. Hence, we run 66 models using each of the
359 weighting combinations to obtain 66 CSI per farm. Farms are then ranked, relative to
360 other farms, according to how well they score in each of the 66 CSI . This information is
361 summarised in a farm rank distribution representing individual farm SI performance. As
362 an illustration of the possibilities of using this information for policy purposes, farms are
363 grouped into four distinct classes according to their performance on all 66 indicators.

364

365 **2.6. The Stochastic Frontier Analysis (SFA)**

366 We use a Bayesian Markov Chain Monte Carlo (MCMC) procedure (see Koop, 2003 for
367 a detailed explanation) for the model estimation. One advantage of the MCMC approach
368 is that the distribution of the individual farm inefficiencies is automatically mapped as
369 part of the estimation process, rather than having to be estimated ex-post as in the classical
370 approach. The standard stochastic output distance function model, and the extended
371 model to account for the provision of environmental outputs, can be specified as equations
372 9 and 10 (below) respectively.

$$373 \quad y_{it} = x_{it}\beta + \varepsilon_{it} - z_i \quad (9)$$

$$374 \quad y_{it} = x_{it}\beta + e_{it}\psi + \varepsilon_{it} - z_i \quad (10)$$

375 with the inefficiency term being common for both approaches

$$376 \quad z \sim G(K\phi, \omega) \quad (11)$$

⁷ Equation (8) implies that we use the additive aggregation rule for the sustainable intensification composite indicator.

377 where y_{it} is a vector of N observations of the logarithm of cereal production for farm i
378 in year t ; x_{it} is an $N \times m$ matrix of the logarithm of other outputs (excluding
379 environmental externalities) and inputs and interlinkages between them, given a
380 translog function for farm i in year t ; ei_{it} is a matrix for the environmental indicator
381 (i.e. provision of environmental goods indicator) and its interlinkages with other outputs
382 and inputs for farm i in year t ; ψ is the coefficient associated with the environmental
383 indicator; ε and z are vectors that account for a normally distributed error and farm
384 inefficiency respectively.

385 The farm inefficiency term z follows a gamma distribution with parameters α and farm
386 mean efficiency ($K\omega$); K is a $T \times r$ matrix of explanatory variables for inefficiency
387 and ω is an $r \times 1$ vector of parameters associated with the explanatory variables for
388 inefficiency.

389

390

391 **3 Results**

392 The Bayesian Markov Chain Monte Carlo (MCMC) procedure generated 30,000
393 random draws from the conditional distributions with, 5,000 draws discarded and
394 25,000 draws retained. These 25,000 draws can be considered as a sample from the joint
395 posterior density function of the parameters. Table 3 shows the coefficient estimates
396 obtained from the four models shown in Table 2.

397

398 As Table 3 shows, all models produced similar results for the coefficients associated
399 with production inputs. Thus, all coefficient signs are as expected. The UAA and crop
400 and animal costs were the two most important inputs in terms of cereal production,
401 excepting for M4 (land use diversity) where UAA and labour are the two most
402 important inputs. A percentage increase in these inputs leads to relatively high
403 increases in the outputs compared to other inputs such as labour, for example. Very
404 much as expected, the production of other outputs on the farm and rising values on the
405 environmental indicator(s) (i.e. a greater area of the two land-based EI measures and
406 less land cover specialisation) reduced the production of cereals, holding everything else
407 constant, i.e. there is a trade-off between market output (i.e. cereals) and the provision
408 of environmental goods, regardless of the type of environmental good. This is possibly
409 due to a redistribution of resources, especially of land, away from cereals production to

410 other uses, as is the case for model M3, where an increase in the proportion of UAA
411 given over to rough and permanent grassland reduces the area allocated to cereal
412 production. The results in Table 3 suggest that the environmental output draws land
413 away from cereals production, as land use diversity captures increasing complexity, i.e.
414 reducing reliance on one, or a few cereals crops.

415 Table 3 also shows the role of a number of potential explanatory variables in driving SI.
416 Past research into the impact of farmer age on efficiency has produced mixed results
417 (Wilson et al, 2001; Iraizoz et al., 2006). Replicating the findings of Tan et al. (2010)
418 this analysis finds a clear positive relationship between both age and level of education
419 with level of efficiency, irrespective of the model used. Conversely, Hadley (2006)
420 found a small but significant negative relationship between age and efficiency for cereal
421 farms in England and Wales.

422

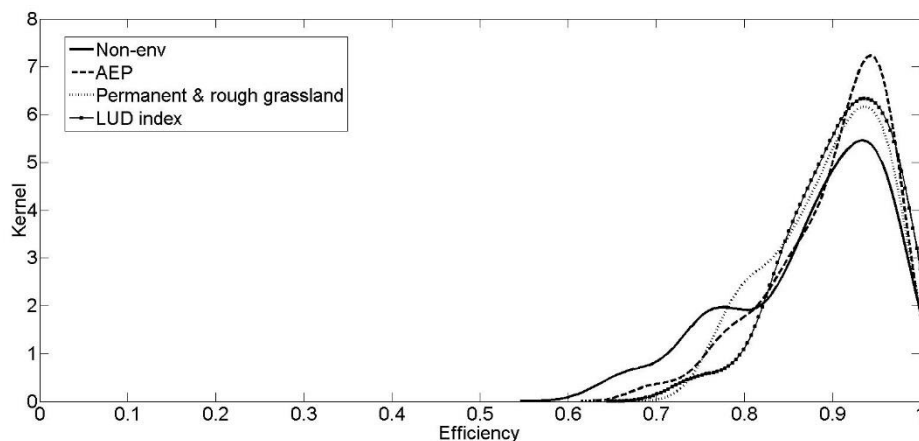
	M1 – Baseline (Non-env.)			M2 - AEP			M3- Grass			M4 - LUD		
	Coeff.	95% posterior coverage regions		Coeff.	95% posterior coverage regions		Coeff.	95% posterior coverage regions		Coeff.	95% posterior coverage regions	
Constant	0.112	0.080	0.143	0.059	0.035	0.092	0.064	0.036	0.098	0.090	0.058	0.100
Other outputs	-0.295	-0.351	-0.244	-0.214	-0.271	-0.161	-0.189	-0.251	-0.126	-0.102	-0.124	-0.060
EO (environmental output)				-0.193	-0.255	-0.128	-0.122	-0.163	-0.083	-0.667	-0.651	-0.506
UAA	0.597	0.441	0.757	0.731	0.600	0.652	0.587	0.444	0.765	0.257	0.218	0.394
Labour	0.063	0.003	0.142	0.050	0.002	0.127	0.044	0.002	0.114	0.024	-0.036	0.079
Machinery and general costs	0.014	3.E-04	0.051	0.010	4.E-04	0.039	0.011	5.E-04	0.039	0.007	-0.056	0.099
Crop and animal costs	0.214	0.095	0.328	0.105	0.026	0.192	0.169	0.049	0.300	0.014	-0.017	0.112
Constant	0.494	0.371	0.678	0.446	0.336	0.607	0.472	0.356	0.648	0.435	0.328	0.594
Farmer's age	-1.287	-1.705	-0.871	-1.233	-1.646	-0.817	-1.301	-1.725	-0.881	-1.268	-1.667	-0.868
Education	-0.849	-0.391	0.091	-0.546	-0.994	-0.072	-0.755	-1.233	-0.255	-0.641	-1.079	-0.180
Finance pressure	-1.118	-0.553	0.028	-0.583	-1.133	0.001	-0.352	-0.902	0.238	-0.716	-1.220	-0.167
Assurance Scheme	-0.253	0.642	1.742	0.631	-0.312	1.760	0.001	-0.963	1.163	0.567	-0.335	1.681

423

424 Table 3. Slope parameters for Models M1-M4

425

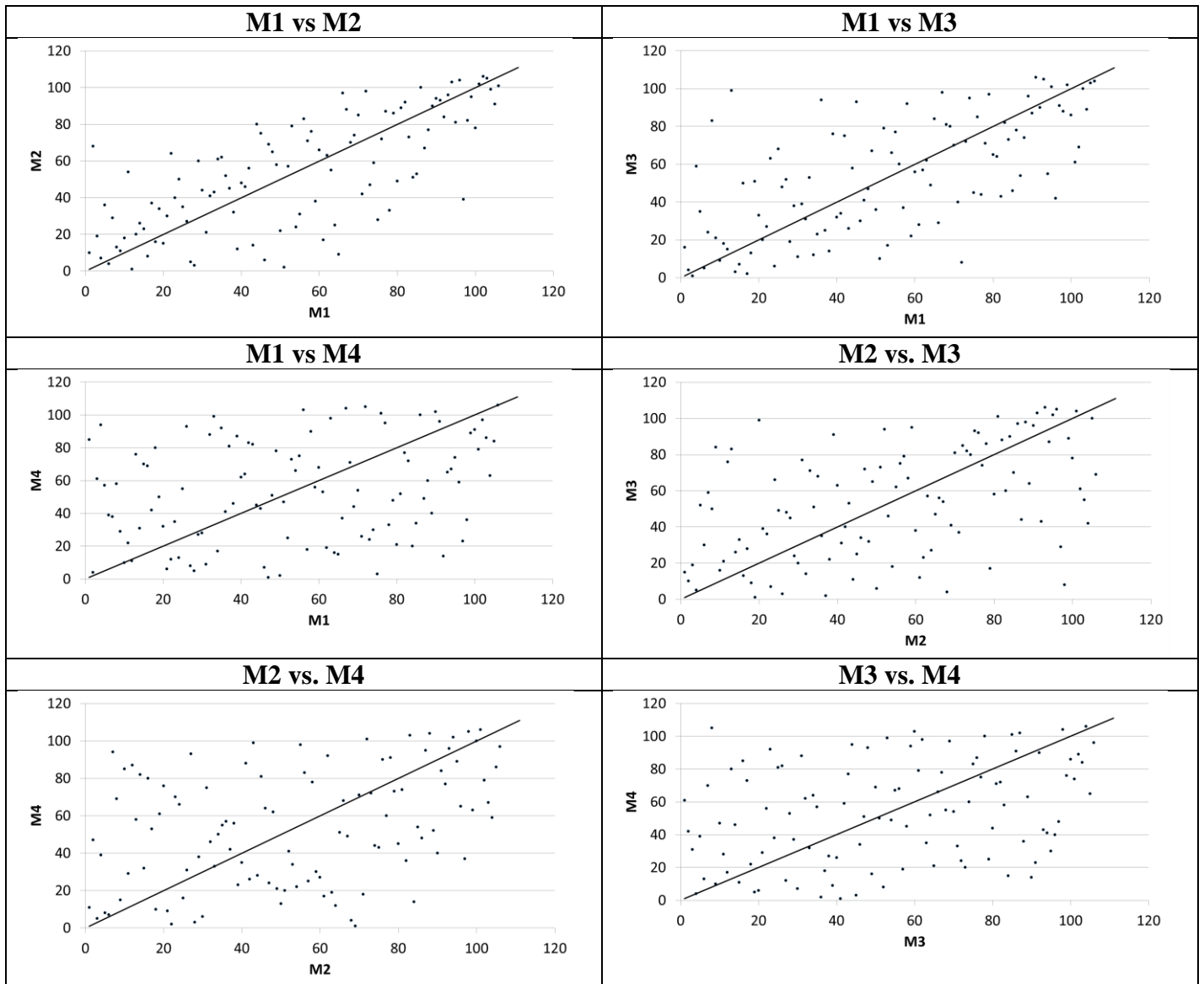
426 The average technical efficiency (TE) of the sample for the model that does not account
 427 for environmental outputs (M1) is 0.88 whereas for models M2, M3, and M4, efficiency
 428 (i.e. SI) is 0.90, 0.90 and 0.91 respectively. Sample medians are 0.90, 0.92, 0.91 and
 429 0.92 respectively. Figure 1 shows the kernel distributions of the posterior means of farm
 430 technical efficiency evaluated over models M1- M4. The results suggest that including
 431 environmental goods in total farm outputs shifts the efficiency distribution toward the
 432 right (i.e. the aggregate SI score of farms is, on average, higher with the addition of non-
 433 market outputs). This suggests that farmers are as efficient at producing environmental
 434 outputs as they are provisioning outputs, if not more efficient. However, it is worth
 435 noting that improving SI requires more than increasing the area of permanent pasture,
 436 land in stewardship or a greater diversity of crops diversification. In a wider sense, SI
 437 should also capture the farmer's use of the crop(s), and extending the analysis through
 438 the inclusion of this information into the model would improve the SI measure.



439
 440 Figure 1. Kernel distributions of the posterior means of technical efficiency across all
 441 farms for M1, M2, M3 and M4.

442
 443 As noted by Areal et al. (2012), when generating SI scores using different model
 444 specifications it is worth investigating their differential impacts on individual farm SI
 445 rankings. Figure 2 shows that farm efficiency rankings (i.e. farm SI rankings) vary
 446 across the four models. These figures allow us to see the extent to which the addition of
 447 the different environmental outputs changes the farm efficiency score. As is apparent,
 448 the addition of the agri-environment indicator has least impact on farm efficiency score,
 449 i.e. the data points are fairly tightly clustered along the no-change line. Conversely,
 450 models M3 and M4, i.e. using the ratio of rough and permanent pasture area to total

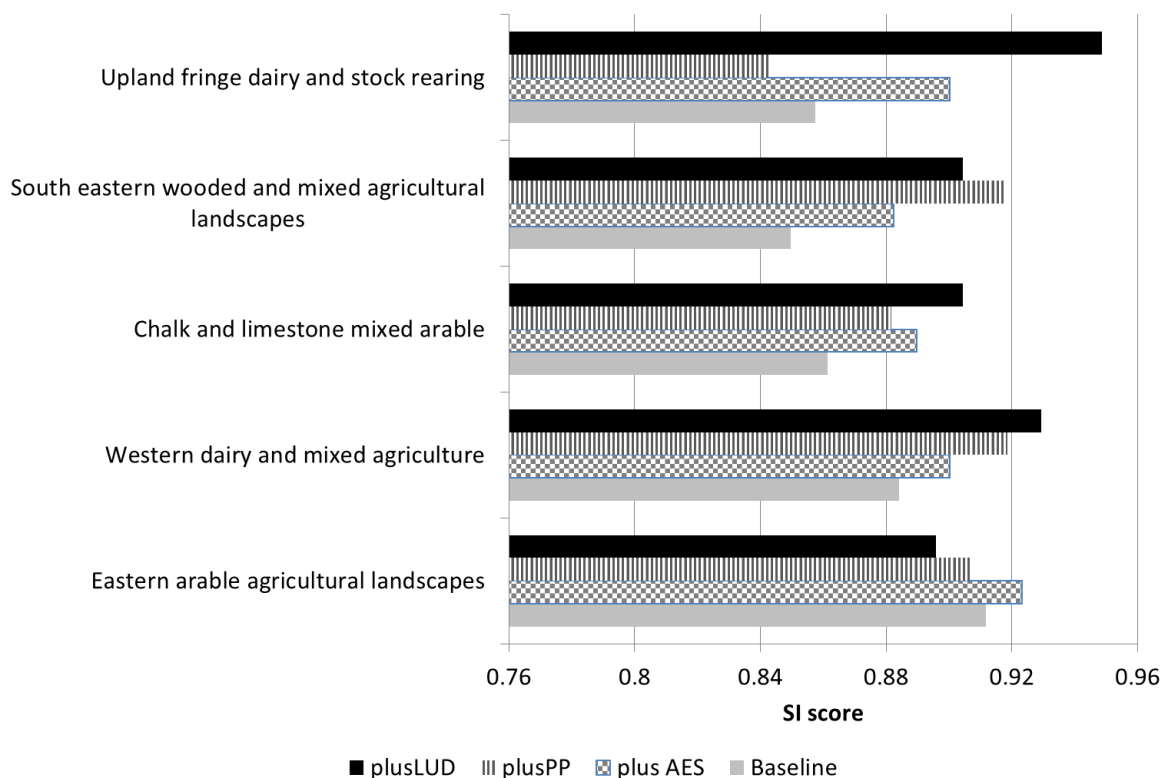
451 agricultural area and the LUD indicator respectively, produce the most widely
 452 distributed data points, indicating significant changes in farm efficiency score.
 453
 454



455
 456 Figure 2. Scatter plots of rankings of efficiency scores
 457
 458

459
 460
 461 Figure 2 shows that farm SI scores vary markedly on the basis of the environmental
 462 indicator chosen. Farm SI scores also vary according to the type of landscape in which
 463 the farm is located. To explore this issue further, we analysed changes in SI and SI
 464 rankings after grouping farms according to landscape type, following the Swanwick

465 typology of the 159 National Character Areas in England (Swanwick et al., 2007)⁸.
 466 Figure 3 shows that when using the LUD indicator, SI scores are higher for farms in
 467 upland fringe dairy and stock rearing landscape types than they are in other landscape
 468 types. However, this same region is the least efficient when the other environmental
 469 indicators are considered. Eastern arable landscapes are consistently efficient, except
 470 when weighting heavily for LUD, as there is greater specialisation of farming systems
 471 here and simpler crop rotations with more focus on cereals.

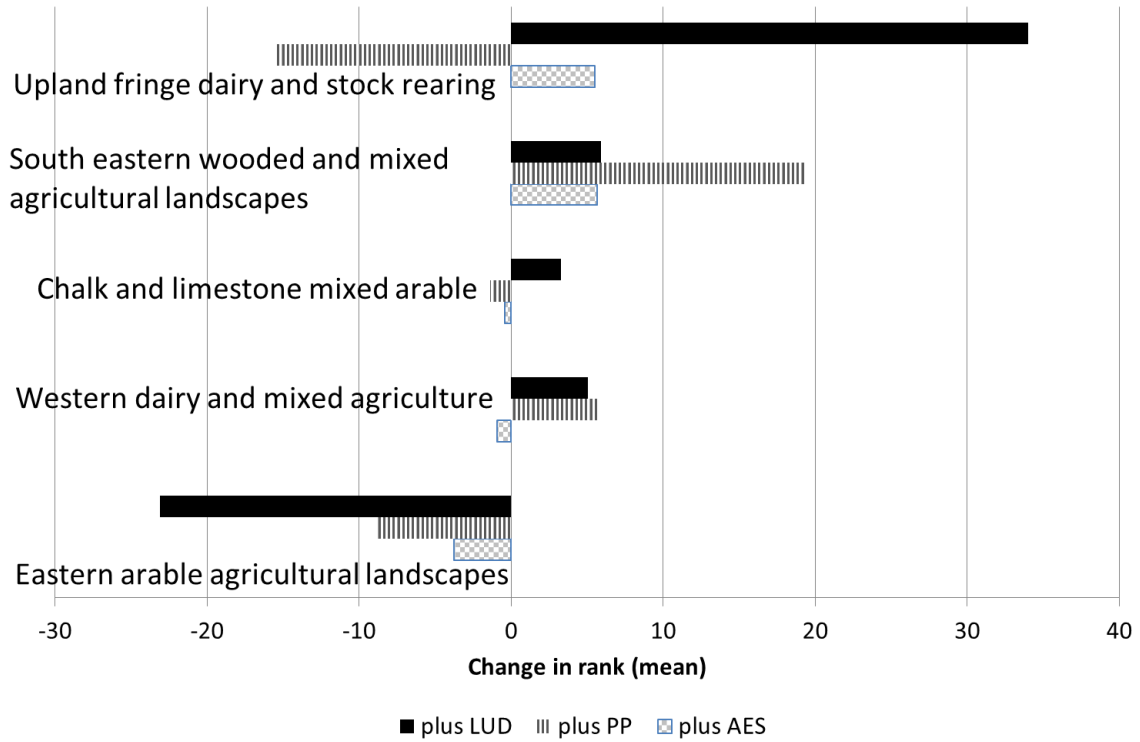


472
 473 Figure 3. SI scores by model and landscape type

474
 475
 476 Figure 4 shows how farms change in average efficiency within each landscape type
 477 when different environmental indicators are added to farm outputs. The figure shows
 478 that farms in the intensive arable eastern claylands significantly drop in SI rank, and
 479 those in the upland fringes increase in SI rank, when using LUD as the indicator of
 480 provision of environmental goods (M4). When the permanent and rough grassland
 481 indicator is added (M3) farms in south eastern wooded and mixed agricultural

⁸ Note that the FBS farm classification (i.e. cereal farms) is different from the landscape type classification.

482 landscapes tend to increase in SI ranking, whereas farms in the upland fringes decrease
 483 in SI rank. These findings present compelling evidence that the use of different
 484 indicators for the provision of environmental goods may lead to different SI rankings at
 485 the farm level, and that the extent of this variation depends to some extent on landscape
 486 type.

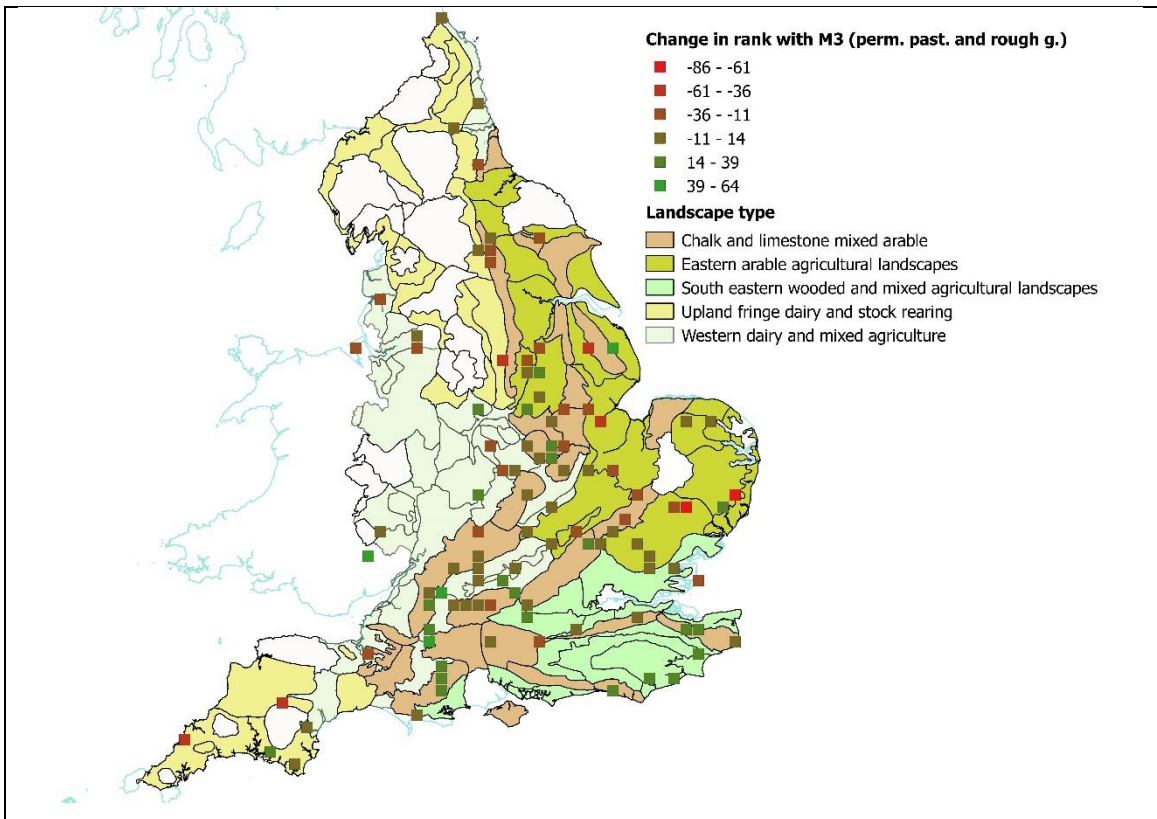


487
 488 Figure 4. Changes in SI rank resulting from the inclusion of environmental outputs,
 489 compared to the baseline model (M1) by landscape type

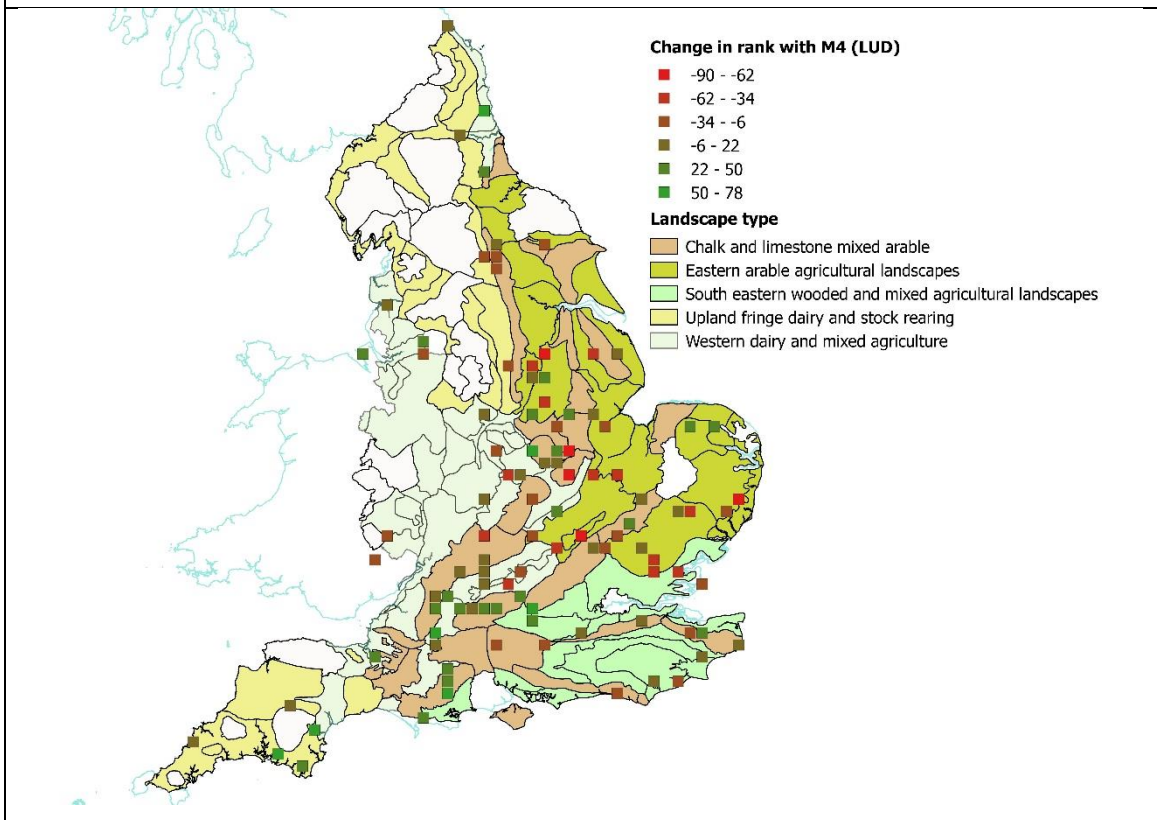
490
 491 Figure 5 shows the extent of changes in SI ranking, when provision of environmental
 492 goods (permanent grassland and LUD) is accounted for, in interaction with landscape
 493 type

494

5a: Permanent pasture and rough grazing (M3)



5b: Land use diversity (M4)



495 Figure 5. Spatial distribution of the extent of changes in SI ranking when provision of
496 environmental goods (permanent grassland and LUD) is accounted for⁹ in interaction
497 with landscape type.

498

499 Farms were found to exhibit different patterns in SI scores under different indicator
500 weightings. Figure 6 shows the kernel distributions of rankings for 6 individual farms
501 under the 66 SI indicators. These six farms have been selected to be representative of
502 different farm classes, where the classification is based on the way in which their
503 efficiency changes through the addition to farm outputs, under different environmental
504 indicator weights. As can be seen from the figures, some farms receive very high ranks,
505 for example farms 2 and 38, regardless of how their environmental indicators are
506 ranked. The radar diagrams show why this occurs. Both farms 2 and 38 score well on
507 provisioning outputs, while at the same time scoring either well, or moderately well, on
508 all three environmental indicators.

509 Some farms, i.e. farms 5 and 7, have much more heterogeneity of ranks, leading to
510 broader kernel distributions. This suggests that under some weighting conditions, i.e. for
511 some environmental outputs, they score highly, but in other cases they score poorly.
512 The radar diagram for farm 5 shows that again, provisioning outputs are relatively high,
513 and output on one of the environmental indicators is good, but there is very little output,
514 or no output at all, on the other two environment indicators. When these absent
515 environmental outputs are heavily weighted, therefore, the farm's SI rank suffers.

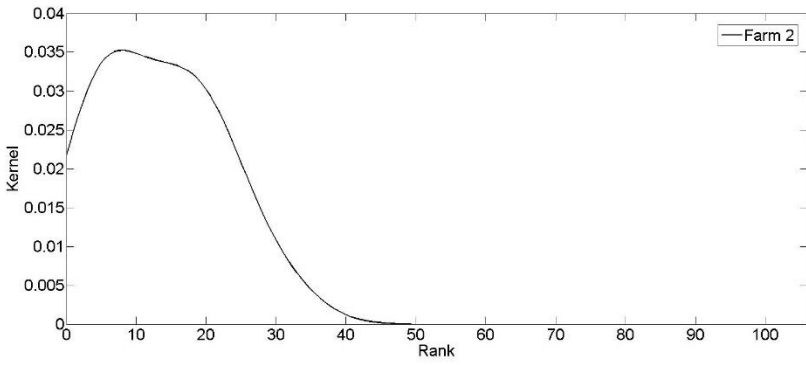
516 Farms 51 and 100 illustrate the final class of farms, where SI rank score is poor
517 regardless of the way in which the environmental indicators are weighted. In both these
518 cases environmental outputs are low, but not non-existent. However, in this class of
519 farms, even if performance on one environmental indicator is reasonable, the SI rank
520 remains low due to the very low rate of provisioning output per hectare.

521 Another interesting outcome is that most farms do well in the case of at least one of the
522 environmental indicators, i.e. there is evidence of some sort of provision of
523 environmental goods on most farms.

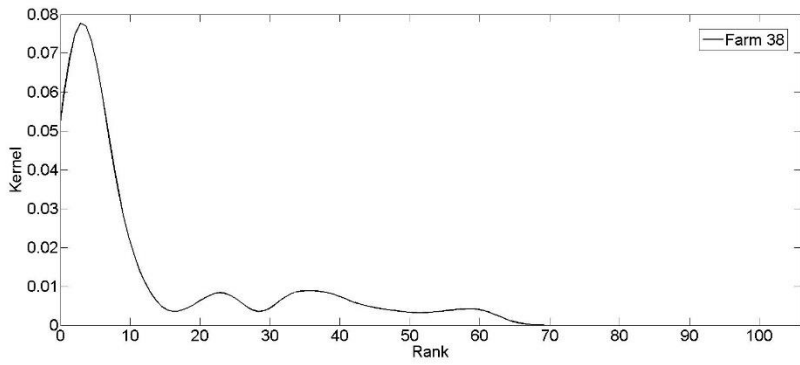
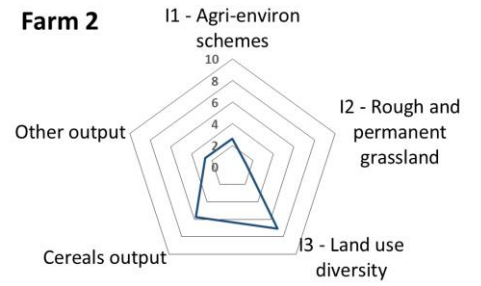
⁹ The location of the farms are only approximate random locations within the county in which the farm is located. Location of the farms has only been constrained to the farm's landscape type.

524

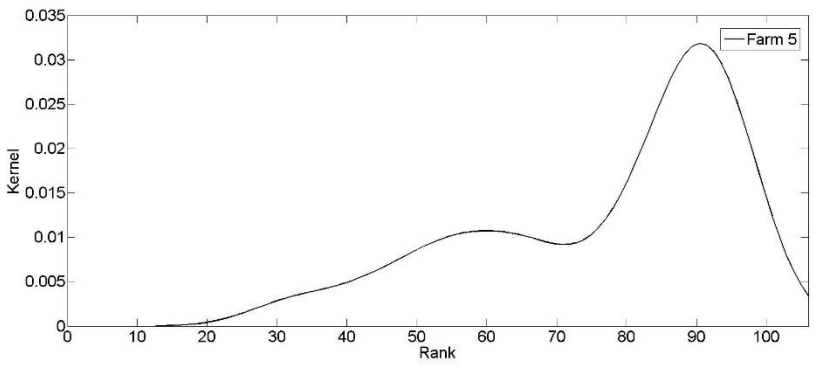
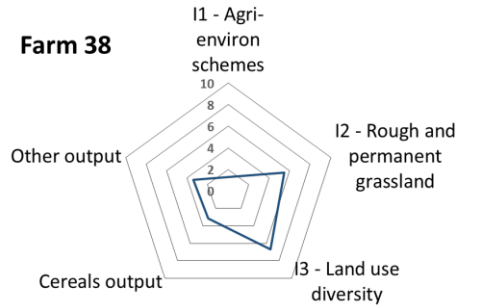
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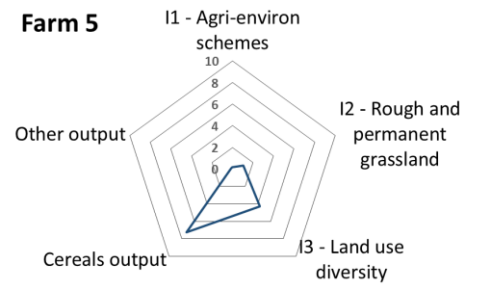
Farm 2

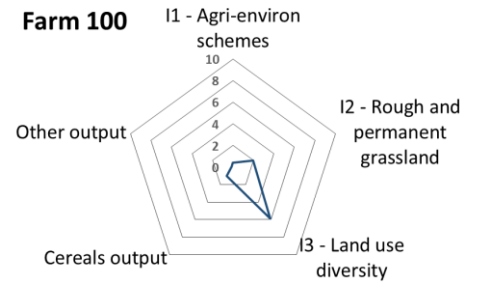
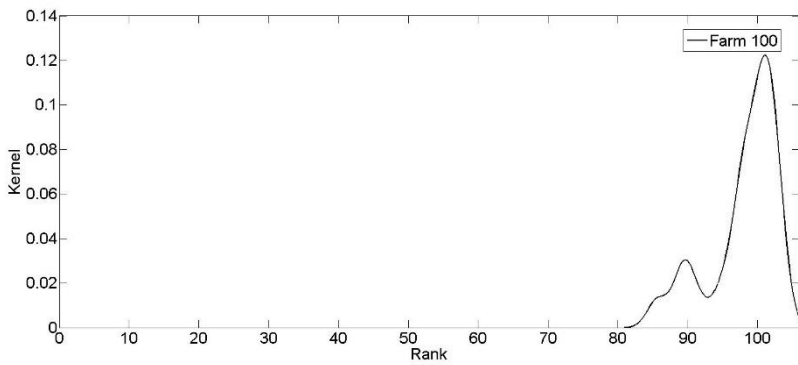
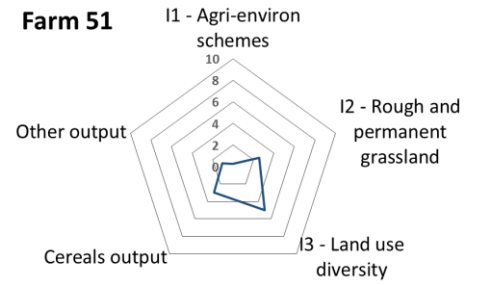
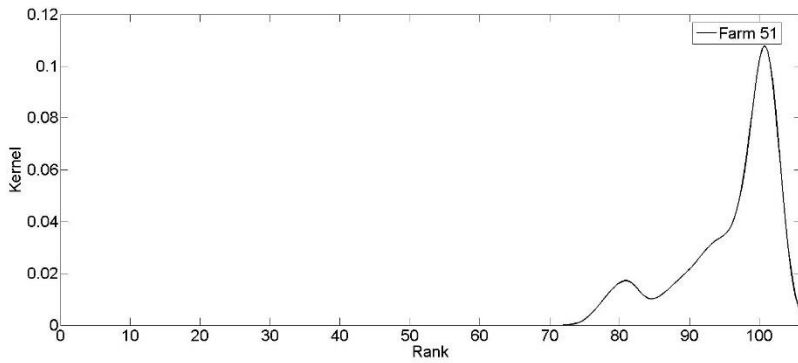
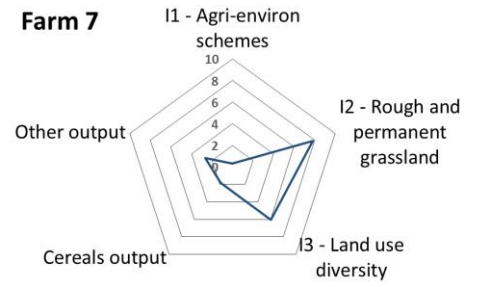
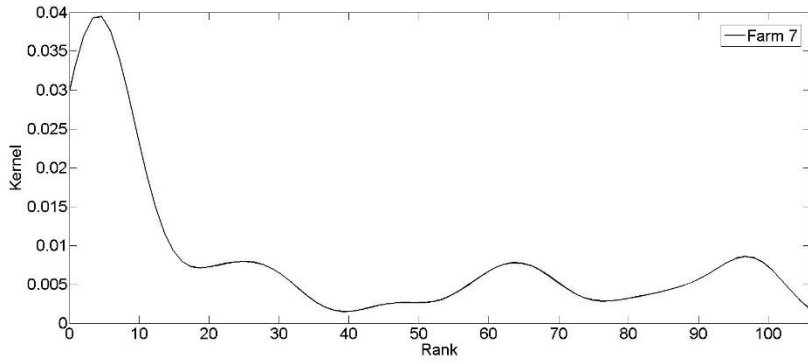


Farm 38



Farm 5





526

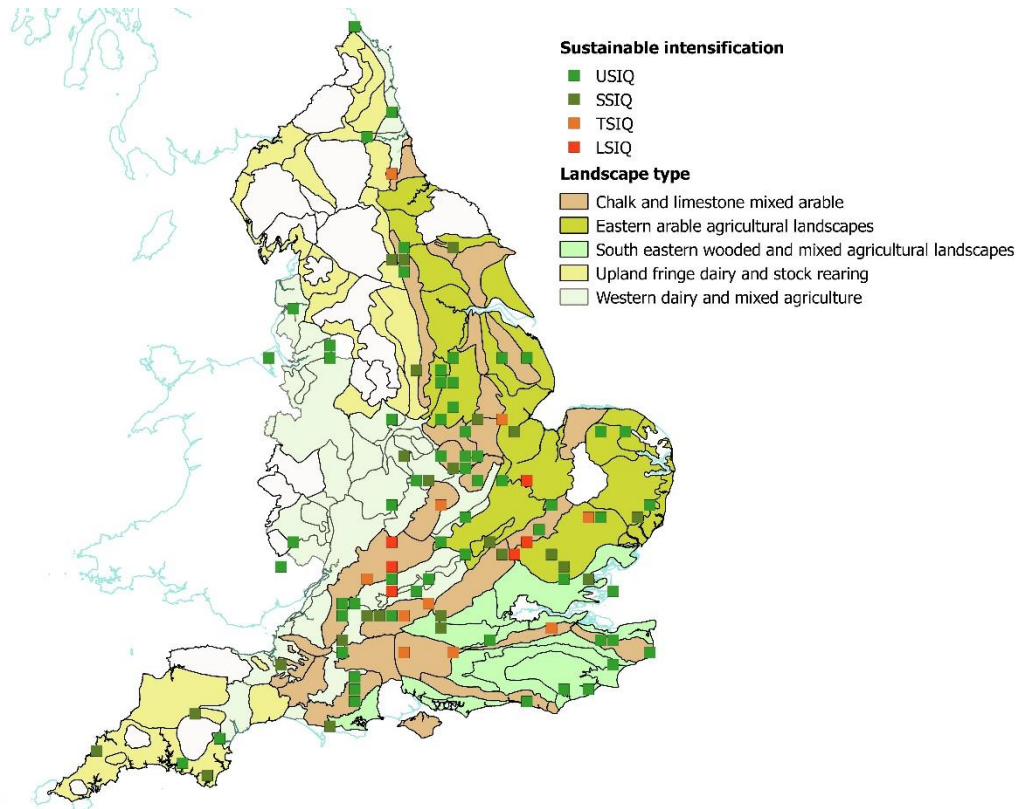
527 Figure 6. Kernel distributions of individual farm ranking based on efficiency scores,
 528 plus radar diagrams showing the scale of a range of provisioning and environmental
 529 farm outputs.

530

531 The results shown in Figures 5 and 6 raise a question about how robustly farms can be
532 classified according to their SI performance using simple fixed weight composite SI
533 indicators of the type that have appeared in the literature to date. Specifically, how can
534 policy makers, based on the use of such indicators, reward farmers for their
535 environmental outputs, or decide on the nature of the goals to set for farms in different
536 regions to enhance their SI performance?

537 One way in which the outputs of the current estimation approach could be used for
538 policy analysis would be to classify farms according to their SI distributions. For
539 example, a sample of farms could be divided into quartiles on the basis of SI
540 performance under all environmental outputs : a) the upper SI quartile (USIQ), i.e.
541 farms that are within the first quartile of the distribution under at least one sustainable
542 intensification indicator; b) the second SI quartile (SSIQ), i.e. farms that are not in the
543 first quartile but fall into the second quartile under at least one indicator; c) the third SI
544 quartile (TSIQ), i.e. those that are not in the first two quartiles but are in the third
545 quartile under at least one environmental indicator; and d) the lower SI quartile (LSIQ),
546 i.e. farms that always fall into the fourth quartile irrespective of the environmental
547 indicator used.

548 Figure 7 demonstrates that, using this approach, high and low levels of sustainable
549 intensification can be found in all landscape types except for south eastern wooded and
550 mixed agricultural landscapes, where all farms in the area are ranked within USIQ
551 (upper quartile) or SSIQ (second quartile) on the basis of our analyses. Most of the
552 TSIQ and LSIQ farms are located in chalk and limestone mixed arable landscapes. It
553 might be argued that these differences in SI performance are heavily determined by the
554 underlying geology and topology that form these landscapes, via constraints on the
555 environmental outputs that can be delivered from the farms within these areas. This
556 further highlights the policy complexity surrounding SI (Wilson, 2014; Barnes and
557 Thomson, 2014) and strongly suggests that incentives to promote increases in SI,
558 inclusive of environmental outputs, need to be context-specific (Armsworth et al., 2012)
559 and feasible within the landscape or catchment where the farm exists. Promoting
560 policies which encourage SI based on a narrowly defined concept, or measurement, of
561 SI, i.e. a ‘one-size-fits-all’ model, are inherently flawed and likely to lead to irrational
562 policy goals and impacts in some areas due to the heterogeneous nature of landscapes.
563 This is as true in England, as in the rest of the world.



564

565 Figure 7. Spatial distribution of farm SI¹⁰ performance by quartiles and landscape type

566 **4 Conclusions**

567 Accounting for the interlinkages between ecological and agricultural systems in
 568 economic analysis is crucial to provide useful recommendations to policy makers.
 569 However, such relationships are difficult to model, making economic analysis of agro-
 570 ecological systems and related issues challenging. Given this complexity, two main
 571 issues arguably arise in the policy context. First, what form should metrics of SI take in
 572 order to provide robust comparison between farm types in different locations? Second,
 573 how can policy makers draw upon these metrics of SI in order to implement evidence-
 574 based policies for the benefit of society through improvements in sustainability?
 575 Examining the first question, the results of this analysis demonstrate that while the
 576 choice of SI metric has clear impacts on the relative SI performance of farms, most
 577 farms are seen to be contributing to sustainability through the provision of at least one
 578 environmental output. Because the composite SI index generated in this study
 579 incorporates multiple types of environmental output without prejudicing any, it is

¹⁰ The location of the farms are only approximate random locations within the county in which the farm is located. Location of the farms has only been constrained to the farm’s landscape type.

580 arguable that this novel, holistic metric of SI, is an improvement on existing metrics of
581 SI performance. The study has also shown that it is important to place any SI metric
582 used within the context of the landscape in which the farm business operates (Koochafan
583 et al., 2012). However, this novel approach to SI construction would surely go some
584 way to allowing policy makers to design policies that are context specific, i.e. targeted
585 towards location-specific outcomes (Armsworth et al., 2012). Complementary
586 approaches that can add value to policy decisions based on this novel composite SI
587 indicator include the development of typology mapping of location-indicator data
588 (Raymond et al., 2009; Andersen et al., 2007). While these approaches do need to be
589 implemented with prior knowledge of feasible outcome possibilities to avoid
590 unintentional consequences, this limitation can usually be overcome by embedding local
591 knowledge within action plans and, moreover, from a bottom-up approach to enhancing
592 positive environmental outcomes from agricultural land (Posthumus and Morris, 2010).
593 The results of the modelling exercise simply reveal a level of complexity (with regard to
594 the type and extent of environmental outputs provision) that policy makers should
595 address in policy design. The statistical approach taken here could itself be developed
596 and used by policy makers and/or their advisors to map regional, or farm system SI, or
597 environmental outputs provision.

598 Although it is widely acknowledged that measuring SI may be a challenging task, since
599 definitions of sustainability and SI are, in and of themselves, broad and unspecific, the
600 alternative of failing to acknowledge context-specifics in SI estimation severely limits
601 the value of such SI metrics, especially where these have been derived through the
602 arbitrary choice of a single weighting system for environmental outputs within the
603 indicator (EI), rather than registering a range of both environmental indicators and
604 associated weights, as proposed here.

605 **Acknowledgment**

606 This work was supported by a grant award from the Rural Business Research
607 Consortium.

608

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769 **Appendix**

770 **A.1 The conditional likelihood function**

771 We assume a normal distribution with mean 0 and covariance matrix $h^{-1}I$ for the
772 likelihood function; X_i is vector of fixed non-stochastic variables, which include inputs
773 and all other outputs; z_i and ε_j (i.e. the error term and the farm inefficiency) are

774 independent of each other for all i and j . The conditional likelihood functions for
 775 expressions (9) and (10), with $p(\cdot)$ referring to the density and $p(\cdot|\cdot)$ to the conditional
 776 density, areⁱ:

$$777 \quad p(y|\beta, h, z) \propto h^{\frac{N}{2}} \exp \left[-\frac{h}{2} (y_i - X_i\beta)'(y_i - X_i\beta) \right] \quad (12)$$

778

779 **A.2 The priors**

780 The likelihood function must be complemented with a prior distribution on the
 781 parameters $(\rho, \beta, \psi, h, \mu_z^{-1})$ to conduct Bayesian inference. An independent Normal-
 782 Gamma prior is used for the coefficients in the production frontier and the error
 783 precision h . We follow the approach used by Fernández et al. (2000) and Koop et al.
 784 (1997) regarding the prior for z . Hence, an r -dimensional parameter vector $\phi =$
 785 (ϕ_1, \dots, ϕ_r) is added where each of the elements of the parameter vector ϕ measures the
 786 effect of the inefficiency explanatory variables k_{ij} on the inefficiency distribution.

787 Given ϕ , z has a probability density function given by

$$788 \quad p(z_i|\mu_z^{-1}(\phi)) = \frac{z_i^{\alpha-1}}{\mu_j \Gamma(\alpha)} \exp(-\mu_z^{-1}(\phi)z_i) \quad (13)$$

789 where $\Gamma(\cdot)$ indicates the Gamma function and $f_G(z_i|\alpha, \mu_z^{-1}(\phi))$ is the Gamma density
 790 with parameters α and $\mu_z^{-1}(\phi)$, mean $\mu_z(\phi)$, variance $\mu_z^2(\phi)$; being $\mu_z^{-1}(\phi) =$
 791 $\prod_{j=1}^r \phi_j^{k_{ij}}$ where k_{ij} are dummy variables and $k_{i1} = 1$. An exponential distribution (i.e.
 792 $\alpha = 1$) is commonly assumed in the literature (Areal et al., 2012; Fernández et al.,
 793 2000; Koop et al., 1997; van den Broeck et al., 1994) which makes the prior for z

$$794 \quad p(z_i|\mu_z^{-1}(\phi)) \propto \exp(-\mu_z^{-1}(\phi)z_i) \quad (14)$$

795 The priors for each of the elements of the vector ϕ are taken to be independent and
 796 follow a Gamma density with hyperparameters $e_j = 1$ and $g_j = -\ln(r^*)$ with $r^* =$
 797 0.80 being consistent with farms expected to be close to the frontier under a competitive
 798 market (van den Broeck et al., 1994).

799

800 **A.3 The joint posterior and conditional posteriors**

801 The Bayesian model is defined through the following joint posterior distribution.

$$802 \quad p(\beta, \psi, h, \mu_z^{-1}, z, |y) \propto p(y|\beta, \psi, h, \mu_z^{-1}(\phi), z)p(\beta)p(\psi)p(h)p(z|\mu_z^{-1}(\phi))p(\phi) \quad (15)$$

803 After extracting the kernel for β, ψ from expression (14) the conditional posterior for
 804 β, ψ are normal distributions

$$805 \quad p(\beta, \psi | h, \mu_z^{-1}(\phi), z, y) \sim N(b, \bar{V}) \quad (16)$$

806 The conditional posterior for h is a Gamma distribution

$$807 \quad p(h | \beta, \psi, \mu_z^{-1}(\phi), z, y) \sim G(\bar{s}^{-2}, \bar{v}) \quad (17)$$

808 The conditional posterior for ϕ follows a Gamma distribution

$$809 \quad p(\phi_j | y, \beta, \psi, h, \mu_z^{-1}(\phi), z) = f_G(\phi_j | e_j + \sum_{i=1}^N w_{ij}, g_j + \sum_{i=1}^N w_{ij} z_i \prod_{s \neq j} \phi_s^{w_{is}}) \quad (18)$$

810 The conditional posterior for z_i is

$$811 \quad p(z_i | \beta, \psi, h, \mu_z^{-1}(\phi), y) \propto \exp\left(-\frac{hT}{2} \left(z_i - \bar{X}_i \beta - \bar{e}l_i \psi + \bar{y}_i + \frac{\mu_z^{-1}(\phi)}{Th}\right)^2\right) \quad (19)$$

812 where $\bar{y}_i = \sum_{t=1}^T \frac{y_{it}}{T}$, $\bar{X}_i = \sum_{t=1}^T \frac{x_{it}}{T}$, $\bar{e}l_i = \sum_{t=1}^T \frac{e_{lit}}{T}$

813
