1 **Integrating the economic and environmental performance of agricultural systems: a**

2 **demonstration using Farm Business Survey data and Farmscoper**

3 John Lynch[a,*], David Skirvin[b], Paul Wilson[a], Stephen Ramsden[a]

4 [a] Division of Agricultural and Environmental Sciences, University of Nottingham, Sutton

5 Bonington Campus, College Road, Sutton Bonington, Loughborough, LE12 5RD, United

6 Kingdom

7 [b] RSK ADAS Ltd, Titan 1 Offices, Coxwell Avenue, Wolverhampton Science Park, Stafford

8 Road, Wolverhampton, WV10 9RT, United Kingdom

9 * Corresponding author, current address: Teagasc, Rural Economy and Development Centre,

10 Mellows Campus, Athenry, Co. Galway, H65 R718, Ireland

11 **Abstract**

12 There is a continued need to monitor the environmental impacts of agricultural systems while

13 also ensuring sufficient agricultural production. However, it can be difficult to collect relevant

14 environmental data on a large enough number of farms and studies that do so often neglect to

15 consider the financial drivers that ultimately determine many aspects of farm management and

16 performance. This paper outlines a methodology for generating environmental indicators from

17 the Farm Business Survey (FBS), an extensive annual economic survey of representative farms

18 in England and Wales. Data were extracted from the FBS for a sample of East Anglian cereal

19 farms and south western dairy farms and converted where necessary to use as inputs in

20 'Farmscoper'; farm-level estimates of nitrate, phosphorus and sediment loadings and ammonia

21 and greenhouse gas emissions were generated using the Farmscoper model. Nitrate losses to

22 water, ammonia and greenhouse gas emissions were positively correlated with food energy

23 production per unit area for both farm types; phosphorus loading was also correlated with food

24   energy on the dairy farms. Environmental efficiency indicators, as measured by either total

25   food energy or financial output per unit of negative environmental effect, were calculated;

26   greenhouse gas emission efficiency (using either measure of agricultural output) and nitrate

27   loading efficiency (using financial output) were positively correlated with profitability on

28   cereal farms. No other environmental efficiency measures were significantly associated with

29   farm profitability and none were significant on the dairy farms. These findings suggest that an

30   improvement in economic performance can also improve environmental efficiency, but that

31   this depends on the farm type and negative environmental externality in question. In a wider

32   context, the augmentation of FBS-type data to generate additional environmental indicators

33   can provide useful insights into ongoing research and policy issues around sustainable

34   agricultural production.

35   **Keywords:** Farm level modelling, Sustainable Intensification, Farm Accountancy Data

36   Network, Profitability, Environmental impacts

1. Introduction

Contemporary agricultural production systems face a significant challenge if an acceptable balance between production and environmental impact is to be achieved (Foley et al., 2011). To gain some sort of level of acceptable 'food security', agriculture needs to provide for both a growing and increasingly affluent global population (Godfray et al., 2010). However, security of food supply is increasingly threatened by environmental challenges and competition for resources, particularly land for non-food uses such as biomass for fuel (Tilman et al., 2011). These production challenges must therefore be met at the same time as managing the environmental impacts of farming. The significant negative environmental effects of agriculture, such as greenhouse gas emissions and nutrient loss to water, must be limited to some extent (Balmford et al., 2012), while provision of beneficial ecosystem services, for example supporting and regulating services such as soil formation and pollination, must be enhanced (Firbank, 2009).

Addressing these challenges requires consideration of multiple effects that act on multiple components of complex agricultural systems: systems that also involve people − farmers, advisors and other stakeholders − who have economic and other objectives that they wish to fulfil. In order to assess these integrated impacts and appraise changes in agricultural practices or policy interventions, quantitative metrics or *indicators* are needed, for all outcomes of interest - for example, greenhouse gas emissions as a measure of environmental impact. Direct on-farm measurement on a sufficient number of farms would require significant financial and technological investment in monitoring equipment and is especially difficult for non-point source environmental pollutants, such as those associated with agricultural inputs like nitrogen (nitrous oxide, nitrate, ammonia). To overcome these difficulties, *mechanistic modelling* of agricultural systems can be used to estimate values of important pollutant loads from available farm information. In the UK, the decision support tool 'Farmscoper' (Farm SCale Optimisation

62   of Pollutant Emission Reductions) uses farm structure and physical input information to

63   estimate production of a range of pollutants at individual farm level from a range of mechanistic

64   models (Gooday and Anthony, 2010).

65   The mechanistic modelling approach is dependent on the quality and availability of direct (on-

66   farm), or secondary information sources. Collection of on-farm information through surveys

67   or other approaches tailored to specific model requirements will generate a richer dataset for

68   modelling (Firbank *et al.*, 2013), but can be time consuming for the assessor and/or farmer and

69   presents challenges in ensuring sufficient scope in farm types and farm locations visited.

70   Furthermore, it is difficult to collect realistic and comprehensive economic information without

71   access to – what are from the farmer's perspective – sensitive farm financial records. As noted

72   above, agents involved in agriculture, most notably farmers, will have economic (and social

73   objectives) that will influence their willingness to adopt practices that have the potential to

74   enhance or mitigate the positive and negative effects of agriculture on the environment. Thus,

75   the environmental enhancement of an *existing*, economically rich data set is an attractive

76   option.

77   The Farm Accountancy Data Network (FADN) was launched in 1965, following EU Council

78   Regulation 79/65, to provide business information on European agricultural holdings and

79   assess the effects of the Common Agricultural Policy (CAP) on farm incomes: of the five

80   original objectives of the CAP, the main social objective was and in practice continues to be

81   "to ensure a fair standard of living for farmers" (European Parliament, 2017). To these ends,

82   FADN data are collected at the individual farm level and are primarily composed of

83   accountancy records, but some physical information and details of farm structure are also

84   available. FADN now represents a large resource of agricultural information, with almost 50

85   years of economic data. The consistency of the FADN dataset allows assessment over time and

86   between different EU member states. Data collection is handled by liaison agencies within each

87   state. In the United Kingdom this organisation is the Department for Environment, Food and

88   Rural Affairs, and in England and Wales FADN data is collected through the Farm Business

89   Survey (FBS). The FBS surveys *circa* 2300 farms every year, covering a representative sample

90   of farm types and sizes, providing an excellent agricultural data resource.

91   A great advantage of generating environmental indicators using the FBS and more widely,

92   FADN or other accounting data, is that it enables both economic and environmental

93   performance to be measured. This is particularly helpful as it helps to operationalise concepts

94   such as 'Sustainable Intensification' (SI). SI has been interpreted in different ways, but a useful

95   definition from the perspective of potential users of the concept – most obviously farmers and

96   extension agents - is given by the RISE Foundation: "Sustainable Intensification means

97   simultaneously improving the productivity and environmental management of agricultural

98   land" (Buckwell, 2014). Although measurement of productivity is in principle straightforward

99   – the change over time in output per unit of agricultural resources used to produce that output

100   – in agriculture this is quite difficult to achieve in practice. Indeed, the fundamental concept

101   driving FADN is the difficult task of relating inputs to their specific outputs on farms with

102   mixed enterprises and production periods that span months, in the case of poultry, or years, in

103   the case of more extensive beef production systems. Measurement of the effect of

104   environmental management - across a wide enough range of environmental impacts - is more

105   difficult without some form of modelling approach. Therefore, it would be attractive if the

106   mechanistic modelling described above could be used to enhance or 'augment' the quality of

107   the environmental information available for individual farms within the FADN and FBS

108   databases and this is the approach that we use here, using the Farmscoper tool as an example.

109   If the resulting information is sufficiently reliable, farmers, extension agents or other

110   stakeholders can assess the extent to which performance is improving across both

111   environmental and economic performance measures.

112   Most farmers in the UK are familiar with the idea of benchmarking performance through what

113   are termed 'unit costs of production' – cost per tonne of wheat or litre of milk for example.

114   Expressing environmental impact per unit of output is thus an attractive way of presenting

115   environmental information to farmers. This also captures the spirit of SI as described by

116   Buckwell et al., 2014: an improvement in SI can be achieved through either an increase in

117   output for a given environmental impact; or a reduction in environmental impact for a given

118   output. Furthermore, by comparing these environmental efficiency indicators with farm

119   structural information, economic performance or social factors such as membership of buying

120   groups or level of education, we can begin to grasp why some farms may perform better than

121   others, in order to highlight the ways in which SI might be improved, through policy

122   instruments or knowledge exchange programmes.

123   The aim of this study was therefore to develop a methodology for using available farm

124   management data in mechanistic environmental impact models and to demonstrate how the

125   results can be used as environmental efficiency metrics. To this end, we describe a

126   methodology for using FADN as a source of secondary data for an external environmental

127   model, Farmscoper, with example FBS data for a subset of cereal and dairy farms. While

128   FADN data have been used in environmental impact analysis, a novel aspect of our approach

129   is that we adapt FADN-type data for use with mechanistic models, rather than e.g. using

130   nutrient balance approaches (e.g. Dalgaard et al., 2006; Buckley, 2015). Farmscoper is

131   restricted to generating results for agricultural diffuse pollutants ('negative externalities') and

132   we do not consider positive impacts of agricultural management, such as biodiversity

133   provision, that are not covered by Farmscoper. Results obtained through this methodology are

134   linked with agricultural output, both physically (total food energy from a farm) and financially

135   (the value of farm physical output at market prices), to derive what Jan et al. (2012) refer to as

136   'partial environmental efficiency' indicators: that is, we generate a range of indicators, rather

137 than a composite, single index of sustainability. Partial environmental efficiency indicators are

138 also compared to farm profitability, as reported in the FBS, through the Management and

139 Investment Income (MII) measure of business performance. Our emphasis is on demonstrating

140 the approach with the example dataset; however, we consider the extent to which the results

141 can inform farmers on how to achieve SI objectives, particularly through improving their own

142 production efficiency. We conclude by discussing the potential utility and limitations of the

143 approach and make suggestions for improving the type of data collected through FADN and

144 the FBS.

145 **2. Methods**

146

147 2.1 Farmscoper

148 Farmscoper is a Microsoft Excel-based decision support tool, developed for the United

149 Kingdom Department for Environment, Food and Rural Affairs (Defra) to estimate multiple

150 diffuse pollutant losses and assess potential mitigation methods (Gooday and Anthony, 2010).

151 Farmscoper calculates pollutant loads through a number of mechanistic models simulating farm

152 systems and agricultural practices, including interactions with climate and soil type. The

153 mechanistic models used within Farmscoper are themselves validated methodologies which

154 have been employed in previous studies: PSYCHIC (Davison *et al.*, 2008; Strömqvist *et al.*,

155 2008), NEAP-N (Anthony *et al.*, 1996), NARSES (Webb and Misselbrook, 2004), MANNER

156 (Chambers *et al.*, 1999), and the IPCC methodologies for methane and nitrous oxide emissions

157 from agriculture (IPCC, 2006).

158 This study focuses on the use of Farmscoper to demonstrate appraisal of current farm

159 performance, rather than potential mitigations; thus, only current pollutant load and emissions

160 estimates were generated. The outputs were: nitrate loading, phosphorus loading, sediment

161 loading, ammonia emissions, methane emissions, nitrous oxide emissions, plus greenhouse gas

162 emissions associated with energy use and total farm greenhouse gas emissions. Loadings are

163 defined as kg of pollutant lost from farm to local water bodies annually. Emissions are defined

164 as kg of pollutant lost from farm to atmosphere annually, with greenhouse gases converted to

165 CO_2 equivalents assuming a Global Warming Potential (GWP) of 25 for methane and 298 for

166 nitrous oxide (as used in the most recent UK National Inventory Report). Further details on the

167 construction and operation of Farmscoper can be found in Gooday and Anthony, 2010 and

168 Gooday *et al.*, 2014.

169 2.2 Farm data

170 Farm data were obtained from the 2012 Farm Business Survey. In order to demonstrate the

171 utility of using FBS data in an external model, the concept must be shown to work for distinct

172 farm types; to this end, dairy and cereal farms were therefore selected as two contrasting types

173 of farm system. Within each farm type, a set of similar farms within the same area were

174 compared to increase the probability that estimated pollutant loads result from farm-specific

175 circumstances and management decisions and are not simply a reflection of farm type and

176 region. Cereal farms were selected from the eastern England counties of Norfolk, Suffolk and

177 Cambridgeshire, and dairy farms were taken from the south-western counties of Devon and

178 Somerset. To simplify data processing and ensure that reliable, standardised data were

179 available, farms with atypical arable crops or non-cattle livestock systems were excluded.

180 These conditions resulted in 38 predominantly cereal farms, covering nine different arable

181 enterprises (winter wheat, spring wheat, winter oilseed rape, triticale, winter barley, spring

182 barley, field beans, peas and potatoes) and 29 predominantly grass- and maize-based dairy

183 farms.

184 Three different approaches were employed to generate Farmscoper input data from the FBS

185 dataset depending on the data availability and model requirements: 1) extraction of physical or

186 structural farm data directly from the FBS; 2) conversion of indirect FBS data (from financial

187 or other indirect data sources) to an appropriate format for model input; and 3) use of additional

188 data from external geo-referenced datasets. Table 1 summarises these inputs. A number of

189 assumptions were made where data limitations became apparent. Most wheat in England is

190 winter sown; however, there was a small proportion of land on the FBS farms that was sown

191 to spring wheat: Farmscoper does not distinguish between winter and spring cropping for

192 wheat, and therefore all wheat was assumed to be winter sown. The FBS category 'other silage

193 cereals' does not record the type of grain; this was assumed to be whole crop wheat, the most

194 common form of whole crop cereal silage in England. The Farmscoper categories of

195 'permanent pasture' and 'rotational grassland' were assigned following FBS conventions

196 whereby any grass present for five years or more is considered permanent pasture. Electricity,

197 fuel, oil and water use were all estimated from expenditure as recorded in the FBS, using

198 relevant coefficients from contemporary agricultural advisory publications, as shown in Table

199 1. Electricity consumption was calculated by assuming a standard metered rate of £0.0069 per

200 kilowatt hour (SAC Consulting, 2012). The FBS data for 'machinery and vehicle fuels' was

201 assumed to represent agricultural ('red') diesel at a cost of £0.63 per litre, while 'heating fuels'

202 were assumed to be kerosene at a cost of £0.53 per litre (SAC Consulting, 2012). Metered water

203 use was calculated from FBS water costs at a rate of £0.95 per metre^3 (AHDB, 2011). Imported

204 (i.e. from off-farm) fertiliser applications were extracted directly from the FBS in the form of

205 N, P and K inputs in kilograms per hectare, while animal manure production and transfers

206 between farm enterprises were handled within Farmscoper as part of the MANNER sub-model.

207 Physical fertiliser import data were not collected for approximately 50% of farms in the 2012

208 FBS sample (data were not available for 11 of the cereal farms and 14 of the dairy farms);

209   however, value data were available for expenditure on fertiliser with no breakdown on

210   individual nutrients; furthermore, these data are available as a panel, opening up the potential

211   to track fertiliser related impacts over time, even when physical data are not available. A

212   methodology was therefore devised to convert expenditure data to physical data for use in

213   Farmscoper; this was used for N, P and K bought onto the farm, where fertiliser quantities were

214   not recorded. Total fertiliser expenditure for each enterprise was directly extracted from the

215   FBS; this was then divided by the area of that land use category to convert to expenditure per

216   unit area and subsequently scaled according to typical fertiliser costs for each enterprise. It was

217   assumed that individual N, P and K applications were applied in the same proportion as

218   standard rates (Agro Business Consultants, 2012; SAC Consulting, 2012) with these rates being

219   used to allocate N, P and K from the total fertiliser expenditure value. A similar approach was

220   used to convert expenditure on crop protection products to physical values. Analyses and

221   results presented thus use the whole sample of farms.

222   There are a number of farm business profitability measures within the FBS. For this study we

223   use 'Management and Investment Income' (MII) - this is the total value of all trading farm

224   outputs within a year, less total costs of production, including an imputed rent for owner-

225   occupied farms and an imputed cost for the manual labour of the farmer and spouse. It

226   represents the return to the farmer and spouse for their management of 'tenants' capital': this

227   excludes landlord-type capital such as land and buildings. The measure is before interest –

228   either earned or charged - of the business and allows a meaningful comparison to be made

229   between tenanted and owner-occupied farms. A useful heuristic for interpreting MII is that a

230   value of zero implies that an owner-occupied farm business would be no worse off if the farmer

231   and spouse were to realise their opportunity costs, i.e. to rent out their land and labour at going

232   market rates.

233   2.3 External geo-referenced data

234   Farmscoper incorporates local rainfall and soil type to model the movement of pollutants. This

235   data is not recorded in the FBS, and was therefore derived by correlating approximate farm

236   location with external geo-referenced datasets using ESRI ArcGIS desktop 10 (ESRI, 2014).

237   An illustration of the geo-referencing for the south-west farms is shown in Figure 1.

238   Long-term annual precipitation was derived using the Met Office UKCP09 gridded observed

239   climate dataset (UKCP09, 2015). A long-term average (average annual precipitation between

240   2002 and 2011) was used as 2012 precipitation data were not available when the study began,

241   and also to establish a precipitation map that could be used for future work exploring potential

242   mitigations and changes in management that were not tied to a specific year.

243   Dominant soil type for a farm's location was derived using the British Geological Survey Soil

244   Parent Material Model (British Geological Survey, 2011). Soil types classified as light or light

245   to medium under the Soil Parent Material Model were entered as 'permeable free draining

246   soils' in Farmscoper. Medium soils were entered as 'impermeable soils where artificial

247   drainage required for arable cultivation', and heavy soils as 'impermeable soils where artificial

248   drainage required for arable cultivation or grassland'.

249

250   (Figure 1 here)

251

252   2.4 Environmental efficiency indicators

253   Environmental efficiency was explored for each farm type using efficiency indicators

254   expressing each negative environmental impact generated per unit agricultural production, at

255   the whole farm level (an inverse approach following that of Jan *et al.*, 2012). Individual, rather

256   than aggregate, indicators were used as only a subset of negative environmental impacts were

257 generated here and food production is only one of several potential multifunctional benefits

258 provided by agriculture. Furthermore, some form of weighting would be needed if an aggregate

259 indicator were to be constructed and 'trade-offs' between different environmental outcomes

260 would be masked. Two different measures were used in order to capture different attributes of

261 agricultural production: total food energy of all agricultural outputs (in gigajoules, GJ) and the

262 value of these outputs (in £). The latter measure effectively weights different physical outputs

263 by their price: this reflects different nutritional contents to an extent (e.g. protein and oil in

264 oilseed rape) and also consumers' willingness to pay for different outputs. Food energy output

265 was calculated by extracting agricultural production data from the FBS and converting using

266 energy content coefficients following Firbank *et al.* (2013). Gross output (£) was taken directly

267 from the FBS, across all farm enterprises. Adjustments made for disposal of the previous year's

268 crop output were excluded so that only outputs generated within a given year (and hence

269 associated with the environmental impacts modelled) were included in the analysis. As

270 efficiency indicators based on food financial output and energy content still do not necessarily

271 take into account important nutritional and other aspects of food production, direct comparisons

272 between the two contrasting farm system types were not made.

273   2.5 Statistical analyses

274 The environmental impacts derived from Farmscoper were described using summary statistics

275 expressed per hectare, per GJ food energy and per £ of gross output. Following Jan *et al.*, 2012,

276 the relationship between per hectare farm environmental impact and food production was tested

277 using the Spearman's rank correlation coefficient. The relationship between the environmental

278 efficiency indicators (i.e. environmental impact per unit food production or gross output) was

279 then compared with farm financial performance, as measured by MII per hectare, also using

280 Spearman's rank correlation coefficient. All analyses were performed in R (R Core Team,

281 2016).

282   (Table 1 here)

283

284   **3. Results**

285

286   3.1 Summary of environmental impacts

287   The FBS-derived data were successfully run through Farmscoper and indicators for

288   environmental pollutants were estimated for individual farms where no data were previously

289   available. A summary of pollutant loadings and greenhouse gas emissions for the sample is

290   shown in Table 2 below. The broad range in results shown by the standard deviation for each

291   indicator, for both system types, suggests that the estimates derived from the FBS data were

292   sufficient to describe important differences in farm structure and management. Although it was

293   not possible in the scope of this study to validate these results with actual impacts as measured

294   on-farm, they are within the range of expected values. The average carbon footprint per litre of

295   milk from our sample was 1.38 kg CO_2e per litre, which is similar to the average result of 1.31

296   kg CO_2e per litre demonstrated in a UK dairy foot-printing study, and within the range of values

297   found (DairyCo, 2012). In a similar modelling study in one specific catchment, Zhang et al.

298   (2012) estimated slightly greater nitrate loadings than we found, (38 and 40 kg ha^{-1} year^{-1} for

299   cereal and dairy farms respectively), slightly lower phosphorus loadings (0.2 and 0.5 kg ha^{-1}

300   year^{-1}) and sediment loadings of 159 and 104 kg ha^{-1} year^{-1}. In a study of agricultural losses to

301   water from cereal farms in Eastern England, Taylor et al. (2016) presented estimates of annual

302   nitrate run-off between 3 and 12 kg ha^{-1} year^{-1}, somewhat lower than our result and highlighting

303   the variability in estimates.

304

305   (Table 2 here)

306

3.2 Environmental efficiency of food production

308   In order to relate the environmental metrics described above to food production, efficiency
309   indicators were generated describing the environmental impact per unit food produced (in both
310   food energy content and food financial output), as shown in Table 3 below.

311

312   (Table 3 here)

313

314   These results are in line with those found in another UK study which demonstrated similar
315   environmental impacts per unit of food energy produced, in this case using data collected from
316   individual study farms (Firbank et al, 2013); the authors also report a considerable range in the
317   metrics within similar farm types.

318

3.3 Farm-level production efficiency

320   The relationship between farm land use productivity, as measured by food energy content per
321   hectare of farmland and environmental impact per hectare is shown in Figure 2. For cereal
322   farms, nitrate loading ($r = 0.5$, $P < 0.001$), ammonia emissions ($r = 0.36$, $P = 0.03$) and total
323   greenhouse gas emissions ($r = 0.5$, $P < 0.01$) were all positively associated with increased
324   productivity, suggesting that more intensive production, associated with increased nitrogen
325   inputs, produced more food but at a greater environmental impact per unit area. Using financial
326   output rather than food energy content as a measure of agricultural production resulted in

327   similar relationships for nitrate loading ($r = 0.46$, $P < 0.01$) and greenhouse gas emissions ($r =$

328   0.24, $P < 0.01$), but ammonia emissions were no longer significant ($r = 0.24$, $P = 0.15$).

329   Sediment loading was not strongly associated with food production (in terms of £ output or GJ

330   food energy content) for either farm type and appeared more strongly driven by local

331   environment and climate rather than farm outputs; however, it should be noted that differences

332   in farm practice with a strong effect on sediment loading (e.g. form of tillage undertaken) were

333   not available from the 2012 FBS, and hence assumed the same for all farms.

334   For dairy farms, nitrate loading ($r = 0.66$, $P < 0.001$), phosphorus loading ($r = 0.53$, $P < 0.01$),

335   sediment loading ($r = 0.40$, $P = 0.03$), ammonia emissions ($r = 0.81$, $P < 0.001$) and total

336   greenhouse gas emissions ($r = 0.82$, $P < 0.001$) were associated with greater food energy

337   output, largely as a result of greater fertiliser application and higher stocking rates. Similar

338   relationships were seen when using financial output instead of food energy content, with nitrate

339   loading ($r = 0.59$, $P < 0.001$), phosphorus loading ($r = 0.48$, $P < 0.01$), ammonia emissions (r

340   $= 0.90$, $P < 0.001$) and total greenhouse gas emissions ($r = 0.88$, $P < 0.001$) again showing

341   significant relationships, although sediment loading was not associated with food financial

342   output ($r = 0.3$, $P = 0.1$). The relatively large and strong correlation between output value and

343   ammonia and greenhouse gases suggests that dairy farms with higher milk output are more

344   closely associated with higher emissions.

345

346   (Figure 2 here)

347

348   3.4 Environmental and economic performance of farms

349   Correlations between the environmental efficiency indicators and farm economic performance

350   (MII per farm) were mostly negative as shown in Table 4 below; indicating a pattern where

351   more profitable farms generate lower environmental impacts per unit food output. However,

352   only cereal farms showed a significant relationship and this only in greenhouse gas emissions

353   efficiency per unit food energy produced. Results were similar when gross output was used as

354   the measure of agricultural production instead of food energy content.

355

356   **4. Discussion**

357

358   4.1 Assessment of FBS (FADN) data in a generic farm mechanistic modelling tool

359   (Farmscoper)

360   The approach described in this study resulted in a number of important environmental

361   indicators for farms where this information had previously been unavailable. The heterogeneity

362   in performance across all indicators confirms that the farm input data provided are sufficiently

363   rich to detect differences between farms, as well as implying variation in performance that may

364   be important in the drive for sustainable intensification, discussed further in section 4.2 below.

365   The indicators illustrate how the approaches can be used to investigate both the local (e.g.

366   environmental impact per hectare for local problems such as sediment or nutrient loss) and

367   global (e.g. greenhouse gas emissions per unit of food produced) implications of SI. As noted

368   by (Franks, 2014), SI does not imply a uniform approach on all farms: while the primary goal

369   of sustainable intensification is to minimise the overall negative impacts of agricultural

370   production, local concerns, for example pollutant loadings entering a given catchment, may

371   override this objective in some cases.

372   As the farm input data came from the FBS and FADN, the assumptions made could be extended

373   to explore more farms and perform comparable analyses, both over time and across other

374   European nations. Previous studies have explored the use of FADN data to generate

375   environmental impacts, for example life cycle assessments of Dutch dairy farms (Thomassen

376   *et al.*, 2009) and nutrient balances for farms in Ireland (Buckley *et al.*, 2015). For the Farm

377   Business Survey, previous approaches have explored the environmental performance of FBS

378   farms, as demonstrated in the Agri-Environment Footprint index (Westbury *et al.*, 2011), and

379   incorporated some elements of environmental performance and sustainable intensification in

380   economic models (Gadanakis *et al.*, 2015), but this represents, to the knowledge of the authors,

381   the first use of FBS data to follow through for the specific environmental outputs demonstrated

382   here.

383   There are some weaknesses inherent in the approach as a result of FADN data being primarily

384   focussed on farm finances. Some management details are beyond the scope of standard data

385   collection and hence were assumed the same for all farms: for example the number and type of

386   field operations, which will have implications for a number of environmental impacts

387   (Townsend *et al.*, 2016). The use of geospatial referencing for some data is a convenient means

388   of acquiring additional data without further on-farm surveying, but may introduce some

389   inaccuracies due to the limits of resolution possible within farm confidentiality constraints. The

390   data are also limited to the whole farm level and differences between fields will also exist in

391   many instances, particularly in some regions of the UK where soil type can vary substantially

392   even within individual fields. As with all modelling approaches, care must be taken when

393   making inferences from model estimates, e.g., what seems an 'unexpected' result – our dairy

394   farms show greater sediment loadings than cereal farms, despite the probable greater extent of

395   tillage operations on the latter – can be explained by other factors, in this case partly by

396   precipitation differences between western and eastern England. However, we would emphasise

397   that better data, particularly on soil management, would help to give better results. On balance,

398   however, the compromises made greatly expands the number of farms available for analysis;

399   moreover, these farms form part of a representative sample for each EU country and have data

400   rich information on farm economic performance. The focus on accounts type data also means

401   that similar approaches could be used where farmers are willing to share data, as the

402   information required is likely to exist in similar forms in management accounts or other

403   electronic farm records. The use of FADN data also facilitates comparison with other

404   approaches that use FBS-type data sets, such as stochastic frontier and data envelopment

405   analysis. These seek to determine whole farm economic efficiency measures relative to a

406   feasible production 'frontier' - that is, feasible under existing technological conditions (see, for

407   example, Wilson *et al.*, 2001; Thirtle *et al.*, 2004; Barnes *et al.*, 2009; Gadanakis *et al.*, 2015).

408   The data extracted and generated from the FBS sample were demonstrated with the Farmscoper

409   tool as it provides a comprehensive range of outputs based on well-validated sub-models.

410   However, the approach shown here emphasises the use of generic data, so that alternative

411   models could also be employed, appropriate to specific policy issues or research questions.

412   Emerging topics of interest may require additional data collection where the current FBS

413   dataset cannot provide reliable estimates (for example, on management information for

414   biodiversity indicators) and these could be included in the future. The great advantage of

415   building on the existing dataset is that it contains detailed and accurate economic information

416   from a robust, representative sample of farms. This also allows scaling, for example, scaling

417   up representative farm-type impacts to catchment and national scales (e.g. Glithero *et al.*,

418   2013). Furthermore, the methodology presented here could readily be applied to alternative

419   farm accountancy or management data, and is not exclusive to the FBS or FADN. The main

420   data inputs, as listed in Table 1, could readily be obtained from typical farm records and used

421   in Farmscoper or alternative tools by researchers, farm advisors or individual farmers, either

422   directly (where sufficiently detailed data are already available) or following similar

423   assumptions and conversions to this study. We also suggest that the environmental efficiency

424   relationships demonstrated provide useful metrics that practitioners could use to benchmark

425   performance across farms, or for the same farm attempting to improve production practices

426   over time.

427

428   4.2 Implications for sustainable intensification

429   The concept, practicality and aims of sustainable intensification have prompted much debate

430   since its emergence as an important part of agricultural policy in the UK (Mahon *et al.*, 2017).

431   This paper demonstrates approaches and indicators that can contribute to the arguments

432   surrounding sustainable intensification by linking measures of farm productivity and

433   environmental impacts.

434   The correlations between food production and several environmental impacts highlight some

435   of the concerns around intensive agricultural production (Struik *et al.*, 2014), but provide useful

436   insight into the concept of sustainable intensification. Changes in the strength of these

437   relationships can be used to demonstrate levels of achievement towards the goal of sustainably

438   increasing production (or reducing environmental impact for existing levels of production) at

439   the farm level. The heterogeneity among farms in terms of environmental performance relative

440   to food production also suggests opportunities for some farms to sustainably intensify, with

441   different farms showing diverse levels of environmental pollution for the same output of food

442   energy. Further investigation of on-farm activities could identify which practices or biophysical

443   features make certain farms more or less environmentally efficient. This information could then

444   be used to highlight where technological or management interventions are of value for

445   enhancing sustainable intensification, as well as highlighting potential spatial differences and

446 ensuring appropriate production and environmental aims are sought for different farm

447 locations.

448 In addition to farm production and environmental impacts, it is important to consider economic

449 performance in assessing sustainable intensification, as without the economic pillar, it cannot

450 be claimed that farms are managed sustainably. Management practices and technologies

451 proposed for sustainable intensification will also only be widely taken up if individual farmers

452 can see the economic merit for their business, or at least that employing a given intervention

453 will not come at a significant cost. The extensive and robust economic data available within

454 the FBS therefore presents an additional advantage in using this dataset to assess sustainable

455 intensification. This study highlighted the relationship between cereal farm profitability and

456 increased greenhouse gas emission efficiency (represented by both the emissions per unit food

457 energy produced or financial output of crop production) and nitrate loadings (when measuring

458 emissions per unit agricultural financial output), demonstrating sustainable intensification

459 'win-wins', whereby more efficient nitrogen and fuel use results in greater farm incomes and

460 reduced emissions per food output. However, it is difficult to draw firm conclusions from the

461 limited dataset used here; as emphasised our main intention has been to demonstrate the

462 combined use of mechanistic models with FBS data to provide policy relevant metrics.

463 It is interesting to note that there were some differences in environmental efficiency indicators

464 depending on whether food energy or gross output was used as a measure of agricultural

465 production. As discussed by Elliott *et al.* (2013), food energy content is a useful indicator for

466 unifying different agricultural outputs, and can be considered as representing net contributions

467 to human food security. However, energy content also omits important differences between

468 food attributes, including further nutritional aspects or consumer preferences. Financial output

469 can be used to indicate overall societal valuation of different products, as distinct from human

470 dietary needs; however, this valuation will also be affected by non-consumer effects, including

471 'shocks' caused by e.g. weather events. Neither indicator fully captures the full range of

472 important food attributes, and so it is important to highlight this and consider the implications

473 of which indicator is used. It should be noted that although this study used food energy and

474 financial value to describe agricultural output, other metrics could also be used as appropriate

475 for future research questions or farm assessments, e.g. physical outputs of individual food

476 products (e.g. litres of milk produced or kg wheat yields).". Given the large number of farm

477 structural and management factors embodied in these indicators, the sample size examined here

478 was too small to reliably apply multivariate techniques in order to identify important drivers of

479 the environmental efficiency relationships, or explore differences between them. However, the

480 methodologies presented can be used in future work, on larger FBS and FADN datasets, over

481 time, to further investigate these important components of the sustainable intensification

482 debate.

483 Despite the positive relationship between emissions efficiency and profitability on cereal

484 farms, it is interesting to note that environmental efficiency was not associated with

485 profitability for any other indicator, including greenhouse gas emissions on dairy farms. This

486 is in contrast to some studies which found, for example, that economic performance was

487 correlated with environmental efficiency in a range of impacts (e.g. on Swiss dairy farms - Jan

488 et al., 2012), and that carbon footprint of milk was associated with profitability (e.g. on Irish

489 dairy farms - O'Brien et al., 2015). The Irish study, however, also demonstrated a considerable

490 range in carbon footprint across all levels of profitability, and further work across a wider

491 sample of farms would be required to confirm whether this relationship differs in the UK.

492 There are mixed implications for the results on our study farms with respect to achieving

493 sustainable intensification. On the one hand, it implies a lack of situations where farms show

494 both greater environmental and economic efficiency: as we would expect, there are trade-offs.

495 The environmental indicators under consideration are largely externalities, and if not associated

496 with increased profitability will offer no economic incentive for farmers to improve

497 environmental performance. At the same time, if there is also no economic disadvantage to

498 increasing environmental efficiency of food production, farmers may be willing to implement

499 sustainable intensification measures based on personal preference, policy tools or quality

500 assurance and marketing initiatives. There are a range of options for how sustainable

501 intensification could be practically achieved on farm (Franks, 2014), yet there is not currently

502 a clear overall policy strategy. Furthermore, the future of agri-environmental policy is

503 particularly uncertain in the United Kingdom as a result of the decision to leave the European

504 Union (Baldock *et al.*, 2016). Regardless of the route taken in agricultural policy, the

505 environmental and economic indicators as presented here remain a valuable means of assessing

506 the efficiency and impacts of the sector.

507 The establishment of a suite of environmental indicators derived from the Farm Business

508 Survey is especially valuable as the data is collected annually, allowing progress to be tracked

509 over time. It is important to note that each farm is a bio-physically unique unit, and therefore

510 has individual production possibilities that will relate to local environmental and economic

511 conditions. Furthermore, individual farms also differ in their social and management

512 dimensions based on their role within the local community, the individual farmer's objectives,

513 and the willingness and ability of the farm manager to invest in or change farm practices. These

514 can also be explored through the FBS (Wilson, 2014). A true measure of sustainable

515 intensification, over time, can be gained by revisiting these indicators to assess movement

516 across the various dimensions of farm performance.

517 **5. Conclusion**

518 This paper demonstrates a methodology for augmenting an economically rich dataset, using

519 sample farms from the 2012 English Farm Business Survey (FBS), to generate environmental

520 indicators for agricultural pollutants. These are compared to food production and farm

521 profitability measures, also derived from the FBS, to assess the sustainability of agricultural

522 production on the sample farms. Although this paper is primarily concerned with demonstrating

523 the approach, results show that there is wide variability across farms for all pollutants when

524 measured per hectare, per gigajoule of food energy and per £ value of agricultural output. There

525 was no significant relationship between environmental efficiency and profitability on the dairy

526 farm sample. Cereal farm profitability, as measured by the income generated by farm

527 management and investment, was positively and significantly correlated with better

528 greenhouse gas emission efficiency, as measured by both emissions per unit food energy and

529 per unit gross output; and nitrate loading when measured per unit of agricultural gross output.

530 The relationship between production, profit and environmental efficiency does not therefore

531 appear to apply to all farms; nor will it apply to all indicators - in particular, we have not

532 considered methods of quantifying biodiversity in this paper. However, there is evidence that

533 improved agricultural management in crop production, particularly of nitrogen fertilisers, can

534 generate both environmental and financial benefits to farmers, a message that will help

535 facilitate knowledge exchange activities. Finally, there are some limitations to the approach,

536 most notably the extent of the data available for modelling: this could be addressed in the future

537 through the collection of appropriate input data, through FADN and the FBS, for use in the

538 type of environmental models considered here, as well as other approaches to capturing the

539 environmental effects of 21st century agriculture.

Acknowledgements

544   UKCP09 projections are © Crown Copyright 2009. The UK Climate Projections data have

545   been made available by the Department for Environment, Food and Rural Affairs (Defra) and

546   Department for Energy and Climate Change (DECC) under licence from the Met Office,

547   Newcastle University, University of East Anglia and Proudman Oceanographic Laboratory .

548   These organisations accept no responsibility for any inaccuracies or omissions in the data, nor

549   for any loss or damage directly or indirectly caused to any person or body by reason of, or

550   arising out of, any use of this data.

References

552   Agro Business Consultants, 2012. The Agricultural Budgeting & Costing Book. 75th Edition.
553   AHDB, 2011. DairyCo DIY Full Water Audit Pack.
554   Anthony, S.G., Quinn, P., Lord, E., 1996. Catchment scale modelling of nitrate leaching. Aspects Appl.
555   Biol. 46, 23-32.
556   Baldock, D., Buckwell, A., Colsa-Perez, A., Farmer, A., Nesbit, M., Pantzar, M., 2016. The potential
557   policy and environmental consequences for the UK of a depature from the European Union. Institute
558   for European Environmental Policy.
559   Balmford, A., Green, R., Phalan, B., 2012. What conservationists need to know about farming.
560   Proceedings of the Royal Society B: Biological Sciences 279, 2714-2724.
561   Barnes, A.P., Moran, D., Topp, K., 2009. The scope for regulatory incentives to encourage increased
562   efficiency of input use by farmers. Journal of Environmental Management 90, 808-814.
563   British Geological Survey, 2011. BGS Soil Parent Material Database.
564   Buckley, C., Wall, D.P., Moran, B., Murphy, P.N.C., 2015. Developing the EU Farm Accountancy Data
565   Network to derive indicators around the sustainable use of nitrogen and phosphorus at farm level.
566   Nutrient Cycling in Agroecosystems 102, 319-333.
567   Buckwell, A., 2014. The Sustainable Intensification of European Agriculture. RISE.
568   Chambers, B.J., Lord, E.I., Nicholson, F.A., Smith, K.A., 1999. Predicting nitrogen availability and losses
569   following application of organic manures to arable land: MANNER. Soil Use and Management 15, 137-
570   143.
571   DairyCo, 2012. Greenhouse gas emissions on British dairy farms.
572   Dalgaard, R., Halberg, N., Kristensen, I.S., Larsen, I., 2006. Modelling representative and coherent
573   Danish farm types based on farm accountancy data for use in environmental assessments. Agriculture,
574   Ecosystems & Environment 117(4), 223-237.
575   Davison, P.S., Withers, P.J.A., Lord, E.I., Betson, M.J., Strömqvist, J., 2008. PSYCHIC – A process-based
576   model of phosphorus and sediment mobilisation and delivery within agricultural catchments. Part 1:
577   Model description and parameterisation. Journal of Hydrology 350, 290-302.
578   Elliott, J., Firbank, L.G., Drake, B., Cao, Y., Gooday, R., 2013. Exploring the Concept of Sustainable
579   Intensification. Land Use Policy Group.
580   ESRI, 2014. Environmental Systems Research Institute ArcGIS 10.2.2 for Desktop.
581   Firbank, L., 2009. Commentary: It's not enough to develop agriculture that minimizes environmental
582   impact. International Journal of Agricultural Sustainability 7, 151-152.
583   Firbank, L.G., Elliott, J., Drake, B., Cao, Y., Gooday, R., 2013. Evidence of sustainable intensification
584   among British farms. Agriculture, Ecosystems & Environment 173, 58-65.

585 Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D.,
586 O/'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C.,
587 Polasky, S., Rockstrom, J., Sheehan, J., Siebert, S., Tilman, D., Zaks, D.P.M., 2011. Solutions for a
588 cultivated planet. Nature 478, 337-342.
589 Franks, J.R., 2014. Sustainable intensification: A UK perspective. Food Policy 47, 71-80.
590 Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Evaluating the Sustainable Intensification of arable
591 farms. Journal of Environmental Management 150, 288-298.
592 Glithero, N.J., Wilson, P., Ramsden, S.J., 2013. Straw use and availability for second generation biofuels
593 in England. Biomass and Bioenergy 55, 311-321.
594 Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson,
595 S., Thomas, S.M., Toulmin, C., 2010. Food Security: The Challenge of Feeding 9 Billion People. Science
596 327, 812-818.
597 Gooday, R., Anthony, S.G., 2010. Mitigation method-centric framework for evaluating cost-
598 effectiveness. Defra Project WQ0106(3). Final Report.
599 Gooday, R.D., Anthony, S.G., Chadwick, D.R., Newell-Price, P., Harris, D., Duethmann, D., Fish, R.,
600 Collins, A.L., Winter, M., 2014. Modelling the cost-effectiveness of mitigation methods for multiple
601 pollutants at farm scale. Science of The Total Environment 468–469, 1198-1209.
602 IPCC, 2006. IPCC Guidelines for National Greenhouse Gas Inventories. Agriculture, Forestry and Other
603 Land Use. In: Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.).
604 Jan, P., Dux, D., Lips, M., Alig, M., Dumondel, M., 2012. On the link between economic and
605 environmental performance of Swiss dairy farms of the alpine area. The International Journal of Life
606 Cycle Assessment 17, 706-719.
607 Mahon, N., Crute, I., Simmons, E., Islam, M.M., 2017. Sustainable intensification – "oxymoron" or
608 "third-way"? A systematic review. Ecological Indicators 74, 73-97.
609 O'Brien, D., Hennessy, T., Moran, B., Shalloo, L., 2015. Relating the carbon footprint of milk from Irish
610 dairy farms to economic performance. Journal of Dairy Science 98, 7394-7407.
611 R Core Team, 2016. R: A language and environment for statistical computing. R Foundation for
612 Statistical Computing, Vienna, Austria.
613 SAC Consulting, 2012. The Farm Management Handbook 2012/13.
614 Strömqvist, J., Collins, A.L., Davison, P.S., Lord, E.I., 2008. PSYCHIC – A process-based model of
615 phosphorus and sediment transfers within agricultural catchments. Part 2. A preliminary evaluation.
616 Journal of Hydrology 350, 303-316.
617 Struik, P.C., Kuyper, T.W., Brussaard, L., Leeuwis, C., 2014. Deconstructing and unpacking scientific
618 controversies in intensification and sustainability: why the tensions in concepts and values? Current
619 Opinion in Environmental Sustainability 8, 80-88.
620 Taylor, S.D., He, Y., Hiscock, K.M., 2016. Modelling the impacts of agricultural management practices
621 on river water quality in Eastern England. Journal of Environmental Management 180, 147-163.
622 Thirtle, C., Lin Lin, L., Holding, J., Jenkins, L., Piesse, J., 2004. Explaining the Decline in UK Agricultural
623 Productivity Growth. Journal of Agricultural Economics 55, 343-366.
624 Thomassen, M.A., Dolman, M.A., van Calker, K.J., de Boer, I.J.M., 2009. Relating life cycle assessment
625 indicators to gross value added for Dutch dairy farms. Ecological Economics 68, 2278-2284.
626 Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification
627 of agriculture. Proceedings of the National Academy of Sciences 108, 20260-20264.
628 Townsend, T.J., Ramsden, S.J., Wilson, P., 2016. Analysing reduced tillage practices within a bio-
629 economic modelling framework. Agricultural Systems 146, 91-102.
630 UKCP09, 2015. UK Climate Projections 2009.
631 Webb, J., Misselbrook, T.H., 2004. A mass-flow model of ammonia emissions from UK livestock
632 production. Atmospheric Environment 38, 2163-2176.
633 Westbury, D.B., Park, J.R., Mauchline, A.L., Crane, R.T., Mortimer, S.R., 2011. Assessing the
634 environmental performance of English arable and livestock holdings using data from the Farm
635 Accountancy Data Network (FADN). Journal of Environmental Management 92, 902-909.

636   Wilson, P., 2014. Farmer characteristics associated with improved and high farm business
637   performance. International Journal of Agricultural Management 3, 191-199.
638   Wilson, P., Hadley, D., Asby, C., 2001. The influence of management characteristics on the technical
639   efficiency of wheat farmers in eastern England. Agricultural Economics 24, 329-338.
640   Zhang, Y., Collins, A.L., Gooday, R.D., 2012. Application of the FARMSCOPER tool for assessing
641   agricultural diffuse pollution mitigation methods across the Hampshire Avon Demonstration Test
642   Catchment, UK. Environmental Science & Policy 24, 120-131.

643