Received: 30 January 2018 | Revised: 7 August 2018 | Accepted: 16 August 2018

DOI: 10.1002/fes3.150

ORIGINAL RESEARCH

WILEY Food and Energy Security Open Access

Assessing the performance of commercial farms in England and Wales: Lessons for supporting the sustainable intensification of agriculture

Les G. Firbank[1] | **John Elliott**[2] | **Rob H. Field**[3] | **John Michael Lynch**[4] | **Will J. Peach**[3] | **Stephen Ramsden**[4] | **Carla Turner**[2]

[1]School of Biology, University of Leeds, Leeds, UK

[2]RSK ADAS Ltd, Leeds, UK

[3]RSPB Centre for Conservation Science, Sandy, UK

[4]School of Biosciences, University of Nottingham, Nottingham, UK

Correspondence
Les G. Firbank, School of Biology, University of Leeds, Leeds, UK.
Email: l.firbank@leeds.ac.uk

Present address
John Michael Lynch, Atmospheric, Oceanic and Planetary Physics, University of Oxford, Oxford, UK

Funding information
Defra

Abstract

Understanding the trade-offs between yield, ecosystem services, and other societal benefits is a fundamental prerequisite for the sustainable intensification of agriculture. Here, we develop and test an holistic approach to assessing farm performance across production, social, financial, and environmental dimensions. A longlist of potential indicators was reduced to a smaller subset of Headline Indicators, covering financial performance, levels of food production (standardized in terms of energy content), social characteristics of the farmer (including age, level of education, and degree of business cooperation), hours worked on the farm and provision of public access, and environmental quality (including impacts on climate regulation and water quality). A new index for biodiversity was created and validated, based on land use and management. Data were collected from 59 English and Welsh farms, using a questionnaire structured to be similar to the UK Farm Business Survey. Data were analyzed per farm and per unit area. The main overall variation in Headline Indicators was due to positive relationships between production, profitability and predicted levels of nitrate and GHG emissions, while social variables and biodiversity were generally unrelated to production. Cereal production was associated with relatively low levels of GHG emissions per unit of food production. There were strong differences in indicator profiles between farm types. Such metrics have value in helping understand how best to drive sustainable intensification, especially as it should involve reducing the pollution footprint of food production.

1 | INTRODUCTION

The case for the sustainable intensification (SI) of agriculture in order to meet rising demand for food while supporting ecosystem services, livelihoods, and wellbeing is widely accepted (Godfray & Garnett, 2014), despite some debate concerning the usefulness of the term (e.g. Gunton, Firbank, Inman, & Winter, 2016). It is therefore essential to be able to measure farm performance across the range of factors that contribute to SI, namely productivity, economics, human wellbeing, environmental impact and social characteristics (Smith et al., 2017). Most current sets of SI indicators address levels of food production and environmental pollution, following earlier framings of SI just in terms of food and environment. For example, Firbank, Elliott, Drake, Cao, and Gooday (2013) adopted a simplified set of SI indicators that were intended to measure performance across an efficiency frontier, considering food production (expressed in terms of energy content), modeled emissions of nitrates to watercourses, modeled ammonia and greenhouse gases (GHGs) to air and an indicator for biodiversity, drawn from data on habitats and land management. Other indicator sets include animal welfare (Kuneman et al., 2014), socioeconomic properties (Smith et al., 2017), and developmental goals (Musumba, Grabowski, Palm, & Snapp, 2017). Any of these approaches could be used to assess the performance of commercial farms on at least some aspects of SI.

However, there is no real consensus as to which variables should be included in SI assessments, nor about how the variables should be integrated and interpreted. This reflects in part the wide range of uses of SI metrics, and the different understandings about what actually constitutes SI: thus agricultural productivity can be defined in terms of financial value, energy value (Firbank, Elliott, et al., 2013), nutritional value (Godfray & Garnett, 2014), or values of the brand to the consumer. The range of environmental and social variables to be included varies greatly, as does the choice of units; furthermore, very different impressions can be given by scaling metrics per unit area (Firbank, Elliott, et al., 2013) as opposed to per unit product (Zhou et al., 2014). The choice of method of integration and presentation of data also has a strong influence on the perception of sustainability; variables can be integrated using financial values (Glendining et al., 2009; Rodriguez-Ortega et al., 2014), visualization (Elliott, Firbank, Drake, Cao, & Gooday, 2013) or integrated analysis (Coelli & Rao, 2005; Del Prado et al., 2011).

Here, we develop a new approach to measuring SI using a novel indicator set developed through consultation with a diverse range of stakeholders, including a new indicator for farm biodiversity derived without the need for site-specific survey data. We demonstrate and test this indicator set through the collection of one of the most comprehensive and large-scale SI surveys of commercial farms undertaken to date. This approach is designed to integrate with the routine collection of farm performance data within the EU Farm Accountancy Data Network (FADN) (Kelly et al., 2018; Lynch, Skirvin, Wilson, & Ramsden, 2018), and is therefore relevant to wider international performance monitoring, and has the potential to be used in ongoing data collection programs over a large number of farms.

2 | HEADLINE INDICATORS OF FARM PERFORMANCE

A long list of potential indicators of SI was prepared by collating those used in previous studies (Supporting Information Material 1). During a workshop with researchers and stakeholders, this list was reduced to reflect the availability and reliability of primary data, while considering the data needs and potential sensitivity to SI interventions (also in Supporting Information Material 1). The reduced list of indicators was further refined while designing and testing the process of data collection, and a subset of these variables was selected to act as Headline Indicators of the major aspects of farm performance (Table 1). These indicators covered the main goods, services, and disservices provided by the farm over the year. All were measurable at whole farm scales, but could also be reported per unit area, product or profit as appropriate.

2.1 | Farm description

Farms were classified into Defra Farm Types (Defra 2014). Virtual land area was used to account for all land actually farmed by the business, an estimate of land area used to grow animal feed imported onto the farm (following Firbank, Elliott, et al., 2013), along with a standardized 25% of all common land accessible to the farm.

2.2 | Farm financial performance

While the SI debate has not focused on the financial performance of farms, it is axiomatic that the financial objectives of the farm have to be met for it to be sustainable as a business. Two Headline Indicators were calculated from farm financial data, one for the proportion of income arising from farm sales, as opposed to Government support and other forms of income, and one for farm profit. Profit was calculated from data provided by the farmers as total income less livestock imports, feeds, fertilizers and pesticides, but not accounting for costs of labor, power, rent, insurance, or interest. More complete calculations of profit were not possible because there were too many gaps in the data.

2.3 | Food production

Food production is presented in terms of energy content, thus standardizing across different products but not between farming systems, as this measure favors the production of energy-dense foods, notably cereals. Data covering the export of foodstuffs from the farm per annum were obtained either from farm management software or by interview. Crop production was provided from areas and yields per crop. Data on forage production were often lacking, but it was assumed to be used on farm and therefore did not need to be measured separately. Milk yields were provided directly, while meat production was given as the net weight of animals exported from the farm. These exports were converted to a single production figure of energy production ha^{-1}, using standard composition tables following Firbank, Elliott, et al. (2013). It

TABLE 1 Headline Indicators of farm performance. See text for details

Category	Issue	Indicator	Description
Farm description			
	Farm Type	Farm Type	Using Defra list of farm types. Note that one farm classed as “mixed upland” was reclassified as “Grazing Livestock LFA”
	Farm area, including that used to grow feed imported to farm	Virtual Farm Area (ha)	Adjusted Total Farm Area with estimates of area used to grow any animal feed imported onto the farm
Farm financial performance			
	Profitability	Profit excluding indirect costs (£)	Include all sources of income less in direct costs
	Reliance on farm sales for income	Proportion of income arising from sales of farm goods	Income from farm sales/all income
Production			
	Quantity of production	Net Energy content GJ removed from the farm	Used to standardize net agricultural production, using total yields for each food type (net of imports of livestock to the farm), and standard tables of energy contents. Note that forage is not included as it used on farm
	Animal welfare and quality assurance	Farm Assurance Score	0 = no assurance; 1 = Red Tractor; 2 higher level
Social characteristics			
	Farmer age	Farmer age (y)	From farmer interview
	Farmer education	Farmer education level	Scored from farmer interview, from school to postgraduate qualification
	Farm labor	Total hours worked by all staff on the farm (h)	From farm records
	Investment in training	Total hours spent on staff training (h)	From farm records
	Engagement with other farmers	Cooperative farming score	Scored according to the variety of forms of cooperation
	Provision for social goods	Length of footpaths across the farm (km)	From farm records
		Area of open access land (ha)	From farm records
Environmental quality			
	Impact on climate regulation	Potential GHG emissions ($kgCO_2$ eq)	Modeled using Farmscoper from inputs, outputs, and relevant management details using a combination of IPCC tier 1 and tier 2 methods
	Impacts on air and water quality	Potential nitrate losses to water (Kg)	Modeled using a disaggregated modification of NEAP-N, plus nonfield losses, within Farmscoper from data provided by farmer on physical inputs, outputs, land management, and soil characteristics
	Biodiversity	Biodiversity score	Weighted scoring system on basis of land cover

was not possible to do the same for protein or other aspects of food composition. Membership of farm assurance schemes was used to provide evidence of commitment to product quality and animal welfare (Pandolfi, Stoddart, Wainwright, Kyriazakis, & Edwards, 2017). Farms were scored according to whether there was no scheme membership (Score = 0), Red Tractor (score = 1) or higher level certification scheme, here including Organic, RSPCA assured, and the Maedi Visnae health scheme for sheep, given scores of 2.

2.4 | Social characteristics

Data were collected on the social aspects of the farmer, the farm business, and potential impacts of the farm to wider society. We recorded the age and highest education level attained by the farmer (indicated using a score, 1 = School education (Left at 16 or before); 2 = A Levels; 3 = Technical qualification (NVQs, BTEC, OND, HND, etc.); 4 = Undergraduate degree; 5 = Postgraduate degree and 0, Prefer not to disclose). Information about the workforce was summarized as the total number of hours worked over the year, and numbers of hours spent on staff training. Data were also used on levels of engagement by the farmer with others, through membership of networks including buying groups. This was done because collaboration between farmers builds social capital (Bchir, 2011; Gomez-Limon, Vera-Toscano, & Garrido-Fernandez, 2014) with potential economic and environmental benefits including mutual learning and strengthening relationships and networks (Wynne-Jones, 2017). The levels of cooperation may influence the adoption of SI interventions, especially those that rely on more than one farm, e.g. catchment management (Waterton et al., 2015). The score was derived according to the variety of business engagements, with one point for each approach to shared working, excluding contracting, including membership of a buying group, a co-operative or producer group, collaborative environmental management, share farming, sharing labor, sharing machinery, swapping manure, and lending sires. Membership of a discussion group was not included in the score.

One of the major cultural services from agriculture is the provision of settings for leisure for exercise, enjoying the landscape, observing wildlife, hunting and fishing, or other reasons (Millennium Ecosystem Assessment 2005). Such recreation has benefits for human health (Barton & Pretty, 2010) as well as local economies. Length of footpaths and areas of open access land were used to indicate the farm's contribution to rural recreation.

2.5 | Environmental quality

Environmental indicators distinguish between flows and stocks. Flows are, broadly speaking, those ecological processes that underpin ecosystem services. They include the biogeochemical gains and losses in a farming system; the gains are typically nutrient additions by the farmer, but can also include carbon sequestration. Losses to the environment are inevitable for nearly all farming systems, though are increased when resource use efficiency is poor, with the losses typically behaving as pollutants, influencing climate regulation, air and/or water quality. Stocks include the biophysical resources available to the farm. Some of these, notably soil quality, act as natural capital and pay dividends to the farmer into the future (Pretty, 2008), while others, such as biodiversity, can support cultural and spiritual services of the enjoyment of nature, as well as provide direct benefits to human health and continued food production (Firbank, Bradbury, McCracken, & Stoate, 2013). Pesticide use was not included as a high level indicator, because of the sensitivity of environmental impact to the choice of compound, adjuvant and application method, as well as to the timing and conditions of spraying.

2.5.1 | Impacts on climate regulation

Globally, agriculture is responsible for approximately 30-35% of GHG emissions (Foley et al., 2011). In the United Kingdom, agriculture-linked GHG emissions are primarily in the form of nitrous oxide (N_2O) from fertilized soils, methane (CH_4) produced by livestock and livestock slurries and manures, and carbon dioxide (CO_2) produced through energy consumption, including on farm energy use and embedded within the production of and transport of inputs. Agriculture may also sequester carbon in soil or plants, if appropriate management activities are undertaken (Smith et al., 2008). Improving energy use efficiency can increase both economic and environmental sustainability by decreasing the costs alongside decreasing GHG emissions (Alluvione, Moretti, Sacco, & Grignani, 2011).

Collecting data on absolute physical usage of fuels and electricity is relatively easy on farm as these are normally monitored, or their expenditure is available from accounts records. Models are used to estimate GHG emissions from particular agricultural activities, including changes in land use. They are broadly categorized into three levels of complexity (IPCC 2006). Tier 1 uses international emissions factors; Tier 2 uses national emissions factors within more complex IPCC modeling methodologies, while Tier 3 may use approved national models or methodologies. Here, the tool FARMSCOPER (Gooday et al., 2014) version 3 was used to estimate GHG emissions from agricultural management and energy use around the farm, which includes Tier 2 methods where possible, otherwise Tier 1.

2.5.2 | Impacts on air and water quality

Agriculture can compromise air and water quality through losses of nitrogen and phosphorus compounds, pesticides, and microorganisms. The pollutant loadings of potential losses of ammonia to air, nitrate and phosphorus to watercourses can be estimated via the mechanistic models PSYCHIC, for phosphorus (Davison, Withers, Lord, Betson, & Stromqvist, 2008); the NEAP-N catchment-scale nitrate model (Lord & Anthony, 2000) and combining models for ammonia (Chambers, Lord, Nicholson, & Smith, 1999; Webb et al., 2006). Outputs from these models have been incorporated into FARMSCOPER as a detailed set of coefficients that use secondary data on local physical environment (soil type, precipitation, temperature) and physical inputs (e.g. fertilizer applications, livestock excreta) to predict losses for a given farm (Gooday & Anthony, 2010). Risks from emissions of toxic microbes can be inferred from modeling the flows of fecal indicator organisms (Kay et al., 2010). While it is also possible to estimate losses of pesticides using similar models (Gooday et al., 2014), their interpretation is difficult because of the great variation in the products and their ecological effects. Here, the potential losses of nitrate to water courses, as estimated by FARMSCOPER V 3, are used as a Headline Indicator of pollution and risk to water quality.

2.5.3 | Biodiversity

The mosaic of farmland in Europe has provided a habitat rich in biodiversity; however, agricultural intensification has been strongly linked with a widespread decline of biodiversity in recent decades (Stoate et al., 2001). Designing comprehensive, scientifically justified biodiversity indicators is a significant challenge given that different taxa have different requirements of habitat type, quality and configuration (Benton, Vickery, & Wilson, 2003), that biodiversity of many taxa depends not simply on the characteristics of an individual farm, and that no taxonomic group is a good indicator of all others (Billeter et al., 2008). There is currently no consensus indicator for farmland biodiversity suitable for farm-scale studies that can be obtained solely from records of land use and farm management. Therefore, a new biodiversity scoring system was developed using an approach backed by industry and conservation bodies, in which points are given for particular interventions and management practices: weightings helped ensure that the score was not systematically higher for particular farm types or for larger farms (Table 2). The method was validated using bird data collected from a separate sample of English farms (see Supporting Information Material 2).

TABLE 2 Allocation of values for the Biodiversity Score. Habitat areas/lengths are multiplied by the weighting value and summed to provide a single value for each farm, which can then divided by virtual area of the farm if required. See Supporting Information Material Table S2.1 for full details

Habitat	Unit	Value
Arable noncropped habitats	ha	2
Arable field boundary	km	1
Arable grass margins	ha	1
Arable flower rich habitats	ha	2
Arable seed rich habitats	ha	2
Arable spring sown crops, excluding cereals	ha	1
Livestock noncropped habitats	ha	2
Livestock field boundary	ha	1
Livestock rough grazing	ha	0.5
Livestock flower rich	ha	2
Spring cereals	ha	1
Root crops	ha	1
Forage crops excluding maize (e.g. Lucerne)	ha	1

3 | METHODS

Data were collected from two surveys of farmers: an initial survey explored farmer behavior, while the more detailed follow-up survey was designed to collect most of the management data, designed to be capable of being integrated with the Farm Business Survey. The sample frame included commercial farms from six areas of England and Wales, chosen to capture the range of farm types from upland to lowland, livestock to arable. Specialist pig, poultry, and horticultural businesses were excluded. Fifty-nine validated surveys were undertaken by face-to-face interviews between July and November 2015, addressing production during 2014; 46 farms provided complete data for the calculation of the selected Headline Indicators (Table 3), and the other farms were included in analyses that were not affected by the data gaps. The data were analyzed to identify covariation among the Headline Indicators across the farms, and especially between farm types, both at the farm scale and, where appropriate, per unit area. Interrelationships among the Headline Indicators were also explored, using Principal Components Analysis (PCA) among other approaches. The sample size is very small for this analysis (Guadagnoli & Velicer, 1988). The approach is justified here because there is no intention to generalize the results to a wider population (cf MacCallum, Widaman, Preacher, & Hong, 2001), rather to help with data interpretation and to inform the selection of other analyses. All statistical analyses were conducted using SPSS Version 21.

4 | RESULTS

4.1 | Variation across all farms

The main variation in the Headline Indicators of farm performance across farms in the sample was explored using Principal Components Analysis (PCA). At the whole farm level (Figure 1a), the first axis (that accounted for 21% of overall variation) related to variation in commercial productivity and levels of pollution, as it was highly correlated with nitrate losses (0.88), profit (0.79), and GHG emissions (0.67). The second axis (13%) drew out farm size, as it was correlated most strongly with virtual area (0.60) and biodiversity score (0.71). The third axis (also 13%) appeared to have reflected an upland extensive/lowland intensive split, as it was correlated with area of open access land (0.68), farm assurance score (0.611), and energy content of food produced (-0.59). The fourth component (explaining 11% of variation) related to the structure of the farm business, and was correlated with proportion of income from farm scales (0.50), farm assurance score (0.52), and farmer education level (0.61). Dairy farms showed the least variation in Headline Indicators (Figure 1).

TABLE 3 Categorization of returns from farm survey by (A) farm type and (B) SIP study area. Note that one of the cereal farms lacked basic data on yields and finances, so was excluded from all analyses

(A) Numbers of farms of different types	Farm type: Cereals	Dairy	Grazing livestock Less Favored Area (LFA)	Grazing livestock lowland	Mixed	Total
Total	11	5	21	10	12	59
Total that provided complete data	6	5	20	6	9	46
(B) Numbers of farms in each study region						
Avon			6			
Conwy			14			
Eden			6			
Nafferton			5			
Taw			7			
Upper Welland			16			
Wensum			5			

Some Headline Indicators (profit, food energy, hours worked, GHG, nitrate and biodiversity scores) were also analyzed per unit area (using virtual area, to take into account land used to grow feeds imported onto the farm). The overall patterns were similar to those at the whole farm scale, but explained a higher proportion of variation in the data. The first axis of the resulting PCA, that accounted for 43% of the variation, corresponded with variation in commercial productivity and levels of pollution, as it was highly correlated with nitrate losses ($r = 0.93$), profit (0.84), and GHG emissions (0.77), although it was highly influenced by two farms (Figure 1b). The second axis accounted for 25% of the variation and was strongly correlated with food production (0.77) and biodiversity (0.72); cereal and mixed farms had the highest scores on this axis.

4.2 | Variation between and within farm types

As one would expect, there were substantial differences in mean indicator values between farm types. In this sample, cereal farms were the largest and most profitable farms, produced the most food (in terms of embedded energy), had the highest biodiversity scores, and highest levels of nitrate emissions (Figure 2a). Per unit area, cereal farms generated the most food energy and lowest levels of GHG emissions; LFA livestock farms were the least productive in terms of food energy, but had the lowest nitrate losses and highest biodiversity scores while dairy and mixed farms were the most profitable but contributed the highest GHG emissions (Figure 2b). Such differences are consistent with what is already known (Firbank, Elliott, et al., 2013), and reflect the very different levels of potential food production between farm types and environments. Performance when scaled per unit food energy is highly dependent on farming system (Figure 2c); scaling performance against profitability (Figure 2d) is difficult to interpret because of the sensitivity to input and output price fluctuations (see also Supporting Information Material 3 for numerical values).

Levels of variability varied strongly between farm types and indicators. Dairy farms were the least variable in performance across most indicators (Figure 3a). At the whole farm scale, there was much more variation in public access, biodiversity and training compared with farmer age and emissions of pollutants (Figure 3a). These differences were less apparent when corrected for virtual area of the farm, which emphasizes variation in food production among the livestock farms, biodiversity, and the hours worked (Figure 3b).

4.3 | Relationships between variables describing farm performance in environmental, financial, and productivity terms

The PCA suggested strong relationships between food production, profitability, and levels of pollution, with weaker relationships with biodiversity; here, these relationships are explored in more detail. When considered per unit area, the relationships between GHG emissions and both food production and profit showed a strong increase across livestock farms, but no real relationship within cereal farms: mixed farms showed a reduction in GHG emissions with increasing food production, possibly reflecting the varying balance between livestock

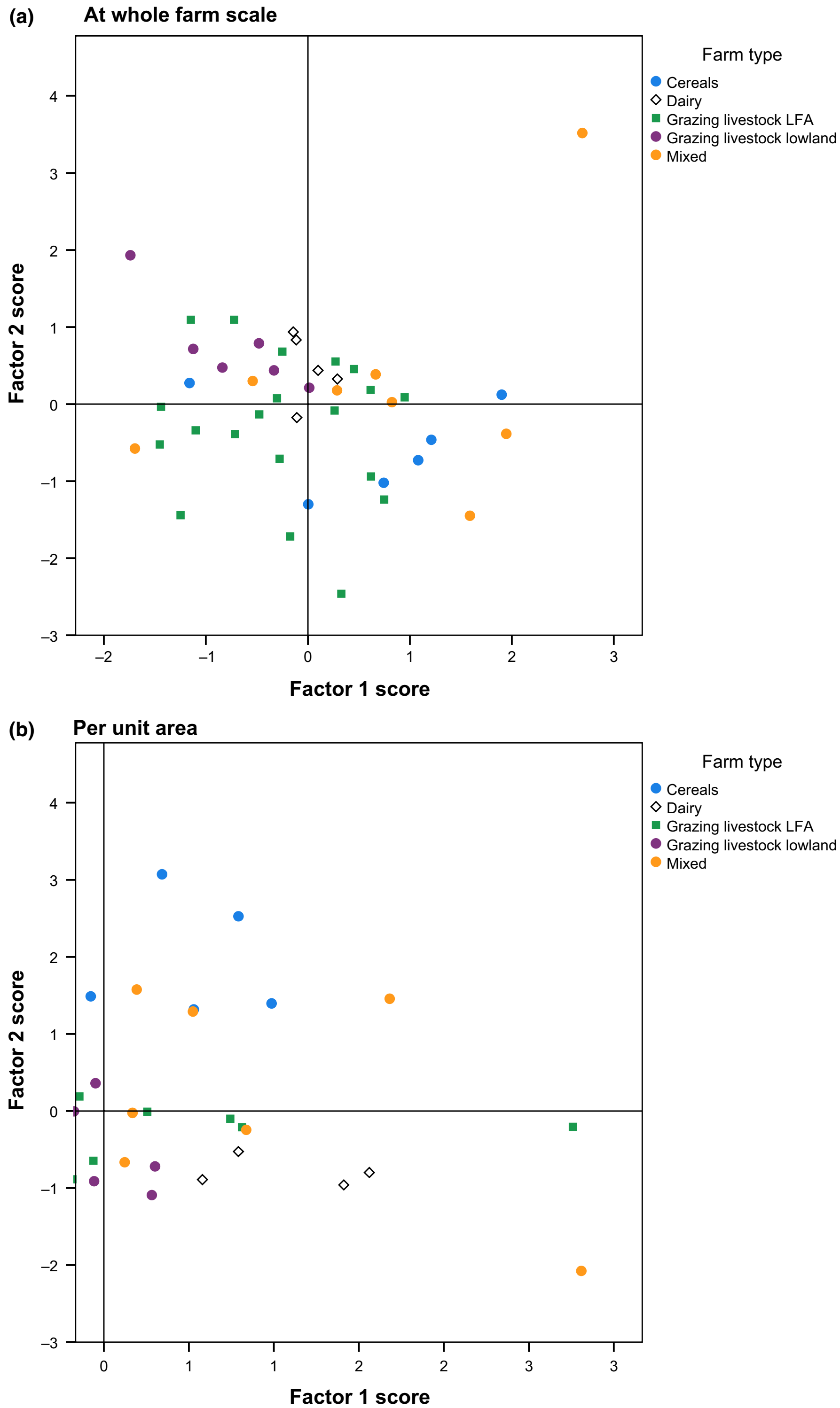

FIGURE 1 Principal component analysis of financial, production, social, and environmental characteristics of all farms, with data provided at (a) whole farm basis and (b) per unit area. In (a), the calculation uses all Headline Indicators given in Table 1, with points representing individual farms indicated by farm type. For (b), a subset of Headline Indicators (profit, food energy, hours worked, GHG, nitrate, and biodiversity scores) was analyzed per unit virtual farm area. Cereal farms are dark blue filled circles; dairy, black, open diamonds; Less Favored Area (LFA) livestock, green, filled squares; lowland livestock, purple, filled circles and mixed farms orange, filled circles

and crop production (Figure 4a,d). The relationships between nitrate emissions and both food production and profit were strongly positive across all farm types, again with less variation within the farm types than between them (Figure 4b,e, see also Supporting Information Material 4 and 5 for all correlation results). There were no clear relationships between the biodiversity scores and either profit or food production when scaled per unit area (Figure 4c,f). Significant correlations among the various social variables were few: in particular, there were no significant correlations between farmer age, education and cooperation and levels of food production, pollution nor profitability (Supporting Information Material 2).

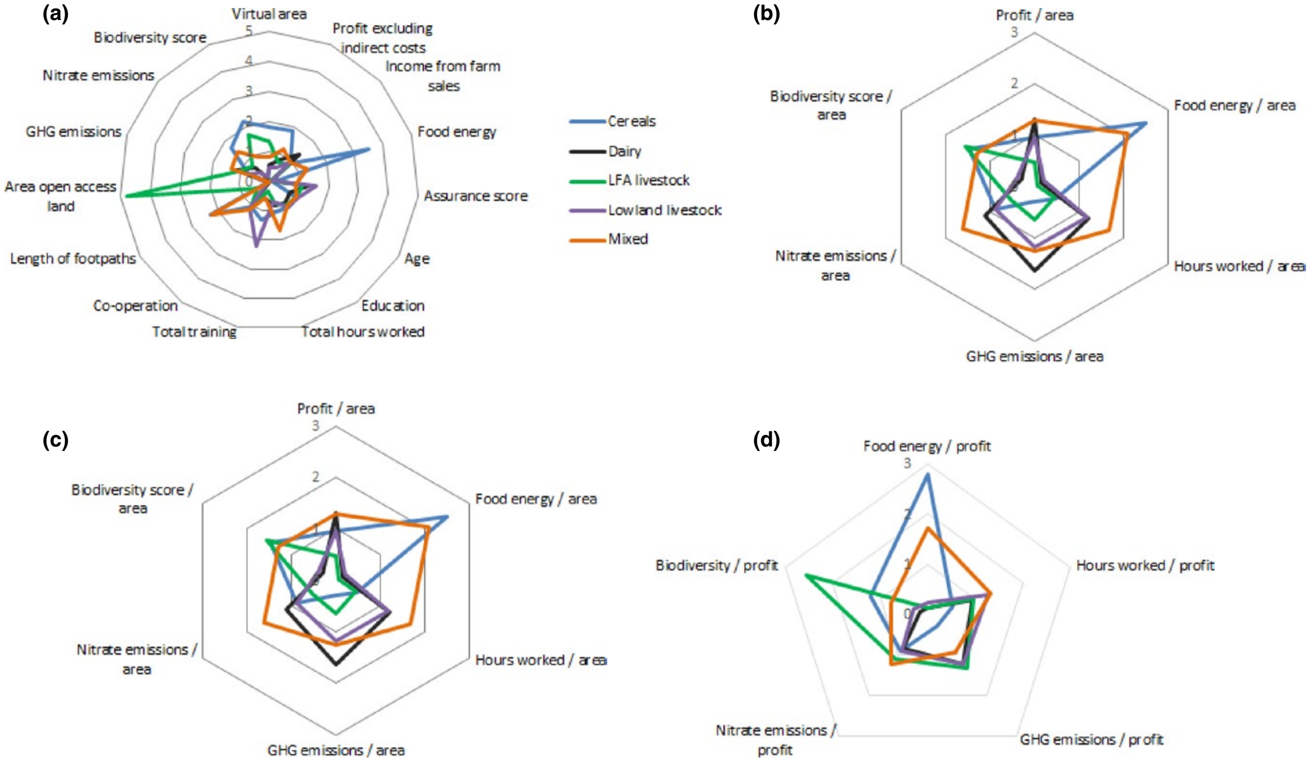

FIGURE 2 Radar plots of farm performance, in terms of per farm (a), per unit area (b), per unit food production (c), and per unit profit (d). The values plotted are the ratios of the mean value for each indicator on each farm type over the mean values of these means across all farm types for the indicators; the plots therefore visualize the relative performance of the different farm types for the different indicators. Cereal farms in dark blue, dairy in black, Less Favored Area (upland) livestock farms in green, lowland livestock in purple, and mixed farms in orange

5 | DISCUSSION

It is increasingly recognized that agricultural sustainability is not simply about profit, production, and environment, but also includes human wellbeing (not least health and nutrition) and social sustainability. These aspects of farming have been called the ‘five domains of sustainability’ (Smith et al., 2017), and are reflected in the Headline Indicators used here. There are a variety of methods of assessing some or all of these domains at the farm scale (Gunton et al., 2016; Mahon, Crute, Simmons, & Islam, 2017; Smith et al., 2017), which can differ in scale as well as objective (Gunton et al., 2016), and will often reflect the ease of data collection; thus here we did not collect enough data to consider the costs of power and energy in our calculations of profit. Those indicators used here were taken from a combination of direct data collection from the farmers, and simple relationships and models to generate some variables, including emissions of pollution, biodiversity levels, and virtual areas. Such models are prone to errors at the scale of the individual farm, as the fine details of farm environment and management cannot be accounted for. Thus actual emissions of GHGs and water pollution depend on the weather and timing in ways that cannot be currently be captured by the models used; reporting food production in terms of energy does not address issues of nutritional quality, and the estimation of virtual farm area oversimplifies the actual use of common land and the assumptions of standard relationships between land use and livestock feed type. Furthermore, the interpretation of the indicators depends much on how they are scaled: environmental effects can look very different if scaled per unit land area than if scaled per unit product.

Farm performance using these indicators is strongly differentiated by farm types. Such influence is not surprising; farming systems are typically located according to the capability of the land (Firbank, Elliott, et al., 2013; Musumba et al., 2017), and some metrics are sensitive to the type of food produced (Firbank, Elliott, et al., 2013). It appears that some farm types display greater uniformity than others, reflecting the greater biophysical variation and diversity in income streams in extensive upland compared to dairy enterprises, for example. Over all of the farms of this study however, there were broad positive correlations among productivity, profitability and modeled levels of pollution (with the notable exception of cereals and GHG emissions, Figure 4). This result seems surprising; one might expect the uptake of technology such as precision farming and genetic improvement to disrupt these relationships by reducing inputs without sacrificing yields. However, such changes are hard to observe from a single dataset measured at one

Food and Energy Security Open Access —WILEY

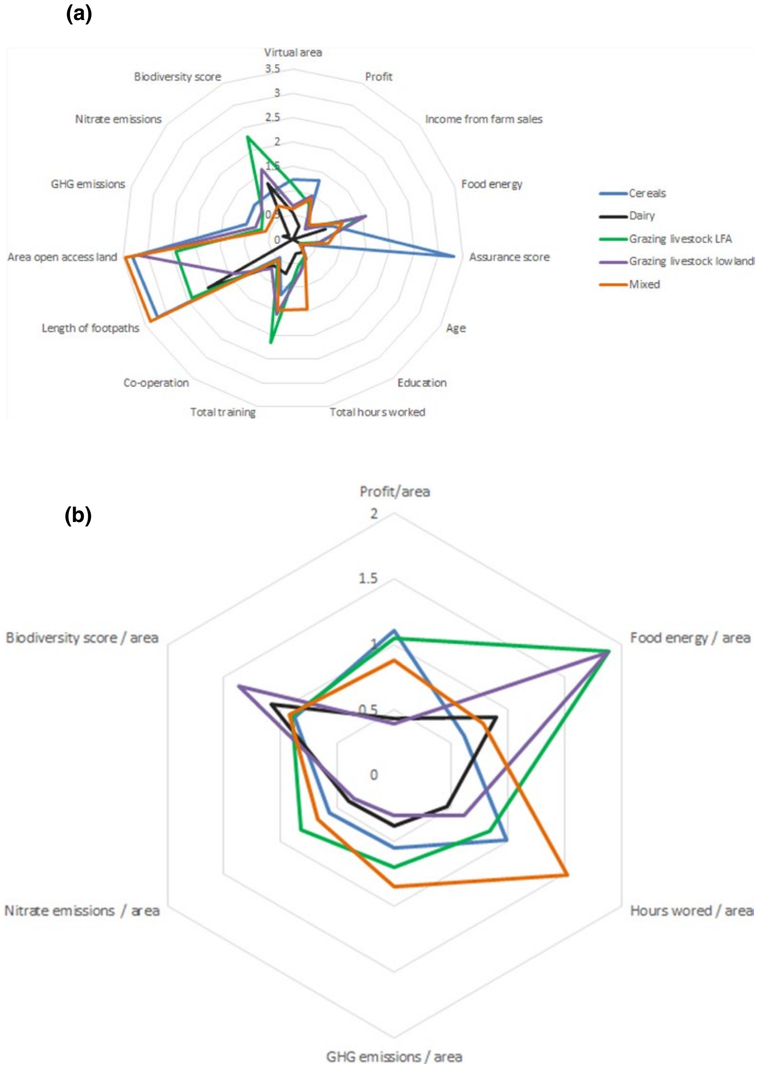

FIGURE 3 Radar plots of the variability of farm performance, in terms of per farm (a) and per unit area (b). Values shown are the coefficients of variation for each indicator across all farms of each farm type. No transformation or normalization was required. Cereal farms in dark blue, dairy in black, Less Favored Area (upland) livestock farms in green, lowland livestock in purple, and mixed farms in orange

time, rather than observing trends from the same farms over time. Furthermore, while there are many ways for farmers to reduce pollution from livestock, modeled emissions are currently driven largely by livestock numbers: more work is necessary to capture actual emissions. The same issue applies to pollution where impact is premised on input use rather than the systems and technologies or mitigation used to recycle/capture potential losses. By contrast, the relationships between production, profit, and biodiversity scores are not statistically significant (Figure 4). Support for biodiversity is seen by some farmers as a cost to business, to be paid through the public purse (Firbank, Elliott, et al., 2013), even though there is evidence that biodiversity can support food production and add value to farm performance (Pywell et al., 2015). If agrienvironmental support is to become more restricted, the economic and social arguments based on ecosystem services from farmland biodiversity may need to be strengthened (Reed et al., 2017) and alternative methods of incentivizing farmers considered (Hanley, Banerjee, Lennox, & Armsworth, 2012).

Social variables were also poorly related to production and profitability. This result is surprising, given that many views of SI involve social factors (Struik & Kuyper, 2017), and that adoption of best practice can vary with social characteristics of the farmers (Liu, Bruins, & Heberling, 2018). It is possible that the social variation among these particular farmers was too small to reveal effects that can be found among more diverse groups.

Collecting these indicators for the same farms over time, e.g. using an extension to the FADN (Buckley, Wall, Moran, & Murphy, 2015; Lynch et al., 2018), will identify the resilience of farm performance to external change, as well as identify trends and their relationships to potential drivers. These will include on-farm variables, exogenous changes to markets and weather, and the multiple public policy interventions. Such work will support change within each farm type, especially if used to target knowledge exchange and supported by benchmarking, and will particularly encourage SI by increasing resource use efficiency. However, the transition toward a truly sustainable agricultural system requires a more radical

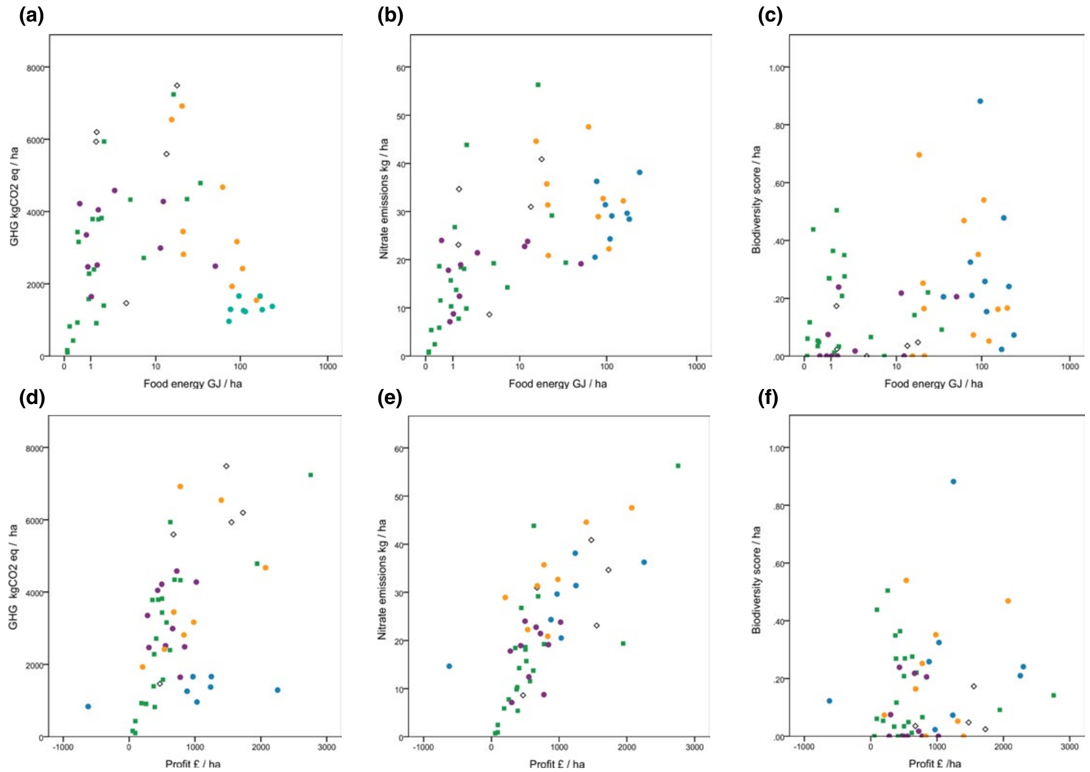

FIGURE 4 The relationships between food production and (a) GHG emissions ($r = -0.299$, $n = 53$, $p < 0.05$), (b) nitrate emissions ($r = 0.406$, $n = 53$, $p < 0.01$), (c) biodiversity score ($r = 0.212$, $n = 58$, n.s.); and profits and (d) GHG emissions (0.525, $n = 51$, $p < 0.001$), (e) nitrate emissions $r = 0.720$, $n = 51$, $p < 0.001$), and (f) biodiversity score ($r = 0.088$, $n = 53$, n.s.). The indicators are as shown in Table 1, shown per unit virtual area. Log scales are used to help visualize the relationships across all farm types. See Figure 1 for key; cereal farms are dark blue filled circles; dairy, black, open diamonds; LFA livestock, green, filled squares; lowland livestock, purple, filled circles and mixed farms orange, filled circles

approach that takes a more holistic approach to food security, provision of ecosystem services, and increasing resilience to external trends, including policy, trade, social and environmental change (Norton, 2016). New approaches to quantify desirable levels of particular land uses (Firbank, 2017) coupled with place-based support schemes (Reed et al., 2017) are showing how this can be achieved.

ACKNOWLEDGMENTS

We thank Carol Morris, Susanne Jarratt, Matt Lobley, and Rebecca Wheeler for making available data and contact details for the farm survey and Mark Else, John Kazer, Stuart Knight, Matt Lobley, Tom Macmillan, and Chris Winney for their comments on this work. We thank the Defra Survey Control Unit for their input to survey design and conduct, thereby ensuring that appropriate ethical standards were met. This was funded by Defra within the Sustainable Intensification Research Platform (SIP), a multipartner research program comprising farmers, industry experts, academia, environmental organizations, policymakers, and other stakeholders. This paper contains public sector information licensed under the Open Government Licence v3.0.

ORCID

Les G. Firbank http://orcid.org/0000-0003-1242-8293
Rob H. Field http://orcid.org/0000-0002-0194-6872
John Michael Lynch http://orcid.org/0000-0001-7863-1767
Stephen Ramsden http://orcid.org/0000-0001-5652-3749
Will J. Peach http://orcid.org/0000-0002-4242-910X

REFERENCES

Alluvione, F., Moretti, B., Sacco, D., & Grignani, C. (2011). EUE (energy use efficiency) of cropping systems for a sustainable agriculture. *Energy*, *36*, 4468–4481. https://doi.org/10.1016/j.energy.2011.03.075

Barton, J., & Pretty, J. (2010). What is the best dose of nature and green exercise for improving mental health? A multi-study analysis. *Environmental Science & Technology*, *44*, 3947–3955. https://doi.org/10.1021/es903183r

Bchir, M. A. (2011). What cooperative behaviour for farmers? Challenging experimental economics with field investigation. *Cahiers Agricultures*, *20*, 92–96.

Benton, T. G., Vickery, J. A., & Wilson, J. D. (2003). Farmland biodiversity: Is habitat heterogeneity the key? *Trends in Ecology & Evolution*, *18*, 182–188. https://doi.org/10.1016/S0169-5347(03)00011-9

Billeter, R., Liira, J., Bailey, D., Bugter, R., Arens, P., Augenstein, I., … Edwards, P. J. (2008). Indicators for biodiversity in agricultural landscapes: A pan-European study. *Journal of Applied Ecology*, *45*, 141–150.

Buckley, C., Wall, D. P., Moran, B., & Murphy, P. N. C. (2015). Developing the EU Farm Accountancy Data Network to derive indicators around the sustainable use of nitrogen and phosphorus at farm level. *Nutrient Cycling in Agroecosystems*, *102*, 319–333. https://doi.org/10.1007/s10705-015-9702-9

Chambers, B. J., Lord, E. I., Nicholson, F. A., & Smith, K. A. (1999). Predicting nitrogen availability and losses following application of organic manures to arable land: MANNER. *Soil Use and Management*, *15*, 137–143.

Coelli, T. J., & Rao, D. S. P. (2005). Total factor productivity growth in agriculture: A Malmquist index analysis of 93 countries, 1980–2000. *Agricultural Economics*, *32*, 115–134. https://doi.org/10.1111/j.0169-5150.2004.00018.x

Davison, P. S., Withers, P. J. A., Lord, E. I., Betson, M. J., & Stromqvist, J. (2008). PSYCHIC - A process-based model of phosphorus and sediment mobilisation and delivery within agricultural catchments. Part 1: Model description and parameterisation. *Journal of Hydrology*, *350*, 290–302. https://doi.org/10.1016/j.jhydrol.2007.10.036

Defra (2014). *Farm classification in the United Kingdom*. London, UK: Defra.

Del Prado, A., Misselbrook, T., Chadwick, D., Hopkins, A., Dewhurst, R. J., Davison, P., … Scholefield, D. (2011). SIMS(DAIRY): A modelling framework to identify sustainable dairy farms in the UK. Framework description and test for organic systems and N fertiliser optimisation. *Science of the Total Environment*, *409*, 3993–4009. https://doi.org/10.1016/j.scitotenv.2011.05.050

Elliott, J., Firbank, L. G., Drake, B., Cao, Y., & Gooday, R. (2013). *Exploring the concept of sustainable intensification*. Report to the Land Use Policy Group.

Firbank, L. G. (2017). The beef with sustainability. *Nature Ecology & Evolution*, *2*(1), 5–6.

Firbank, L. G., Bradbury, R. B., McCracken, D. I., & Stoate, C. (2013). Delivering multiple ecosystem services from enclosed farmland in the UK. *Agriculture, Ecosystems and Environment*, *166*, 65–75. https://doi.org/10.1016/j.agee.2011.11.014

Firbank, L., Elliott, J., Drake, B., Cao, Y., & Gooday, R. (2013). Evidence of sustainable intensification among British farms. *Agriculture, Ecosystems and Environment*, *173*, 58–65. https://doi.org/10.1016/j.agee.2013.04.010

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., … Zaks, D. P. M. (2011). Solutions for a cultivated planet. *Nature*, *478*, 337–342. https://doi.org/10.1038/nature10452

Glendining, M. J., Dailey, A. G., Williams, A. G., van Evert, F. K., Goulding, K. W. T., & Whitmore, A. P. (2009). Is it possible to increase the sustainability of arable and ruminant agriculture by reducing inputs? *Agricultural Systems*, *99*, 117–125. https://doi.org/10.1016/j.agsy.2008.11.001

Godfray, H. C. J., & Garnett, T. (2014). Food security and sustainable intensification. *Philosophical Transactions of the Royal Society B-Biological Sciences*, *369*, 20120273. https://doi.org/10.1098/rstb.2012.0273

Gomez-Limon, J. A., Vera-Toscano, E., & Garrido-Fernandez, F. E. (2014). Farmers' contribution to agricultural social capital: Evidence from Southern Spain. *Rural Sociology*, *79*, 380–410. https://doi.org/10.1111/ruso.12034

Gooday, R., & Anthony, S. (2010). *Mitigation method-centric framework for evaluating cost-effectiveness*. Defra Project WQ0106 (Module 3). pp. 75. ADAS, Wolverhampton.

Gooday, R. D., Anthony, S. G., Chadwick, D. R., Newell-Price, P., Harris, D., Duethmann, D., … Winter, M. (2014). Modelling the cost-effectiveness of mitigation methods for multiple pollutants at farm scale. *Science of the Total Environment*, *468*, 1198–1209. https://doi.org/10.1016/j.scitotenv.2013.04.078

Guadagnoli, E., & Velicer, W. (1988). Relation of sample size to the stability of component patterns. *Psychological Bulletin*, *103*, 265–275. https://doi.org/10.1037/0033-2909.103.2.265

Gunton, R. M., Firbank, L. G., Inman, A., & Winter, D. M. (2016). How scalable is sustainable intensification? *Nature Plants*, *2*, 16065. https://doi.org/10.1038/nplants.2016.65

Hanley, N., Banerjee, S., Lennox, G. D., & Armsworth, P. R. (2012). How should we incentivize private landowners to 'produce' more biodiversity? *Oxford Review of Economic Policy*, *28*, 93–113. https://doi.org/10.1093/oxrep/grs002

IPCC. (2006). *IPCC Guidelines for National Greenhouse Gas Inventories Volume 4 Agriculture, Forestry and Other Land Use*. IGES, Japan.

Kay, D., Anthony, S., Crowther, J., Chambers, B. J., Nicholson, F. A., Chadwick, D., … Wyer, M. D. (2010). Microbial water pollution: A screening tool for initial catchment-scale assessment and source apportionment. *Science of the Total Environment*, *408*, 5649–5656. https://doi.org/10.1016/j.scitotenv.2009.07.033

Kelly, E., Latruffe, L., Desjeux, Y., Ryan, M., Uthes, S., Diazabakana, A., … Finn, J. (2018). Sustainability indicators for improved assessment of the effects of agricultural policy across the EU: Is FADN the answer? *Ecological Indicators*, *89*, 903–911. https://doi.org/10.1016/j.ecolind.2017.12.053

Kuneman, G., Fellus, E., Ywema, E., Elferink, E., dervan Wal, E., vanVliet, J., … van der Schans, F. (2014). *Sustainability performance assessment version 2.0: towards consistent measurement of sustainability at farm level*. pp. 69. CLM/SAI Platform.

Liu, T. T., Bruins, R. J. F., & Heberling, M. T. (2018). Factors influencing farmers' adoption of best management practices: A review and synthesis. *Sustainability*, *10*, 432. https://doi.org/10.3390/su10020432

Lord, E. I., & Anthony, S. G. (2000). MAGPIE: A modelling framework for evaluating nitrate losses at national and catchment scales. *Soil Use and Management*, *16*, 167–174.

Lynch, J., Skirvin, D., Wilson, P., & Ramsden, S. (2018). Integrating the economic and environmental performance of agricultural systems: A demonstration using Farm Business Survey data and Farmscoper. *Science of the Total Environment*, *628–629*, 938–946. https://doi.org/10.1016/j.scitotenv.2018.01.256

MacCallum, R. C., Widaman, K. F., Preacher, K. J., & Hong, S. (2001). Sample size in factor analysis: The role of model error. *Multivariate Behavioral Research*, *36*, 611–637. https://doi.org/10.1207/S15327906MBR3604_06

Mahon, N., Crute, I., Simmons, E., & Islam, M. M. (2017). Sustainable intensification - "oxymoron" or "third-way"? A systematic review. *Ecological Indicators*, *74*, 73–97. https://doi.org/10.1016/j.ecolind.2016.11.001

Millennium Ecosystem Assessment (2005). *Synthesis report*. Washington, DC: Island Press.

Musumba, M., Grabowski, P., Palm, C., & Snapp, S. (2017). *Guide for the sustainable intensification assessment framework*. Manhattan, KS: Kansas State University.

Norton, L. R. (2016). Is it time for a socio-ecological revolution in agriculture? *Agriculture Ecosystems & Environment*, *235*, 13–16. https://doi.org/10.1016/j.agee.2016.10.007

Pandolfi, F., Stoddart, K., Wainwright, N., Kyriazakis, I., & Edwards, S. A. (2017). The "Real Welfare' scheme: Benchmarking welfare outcomes for commercially farmed pigs. *Animal*, *11*, 1816–1824. https://doi.org/10.1017/S1751731117000246

Pretty, J. (2008). Agricultural sustainability: Concepts, principles and evidence. *Philosophical Transactions of the Royal Society B-Biological Sciences*, *363*, 447–465. https://doi.org/10.1098/rstb.2007.2163

Pywell, R. F., Heard, M. S., Woodcock, B. A., Hinsley, S., Ridding, L., Nowakowski, M., & Bullock, J. M. (2015). Wildlife-friendly farming increases crop yield: Evidence for ecological intensification. *Proceedings of the Royal Society B-Biological Sciences*, *282*, 20151740. https://doi.org/10.1098/rspb.2015.1740

Reed, M. S., Allen, K., Attlee, A., Dougill, A. J., Evans, K. L., Kenter, J. O., … Whittingham, M. J. (2017). A place-based approach to payments for ecosystem services. *Global Environmental Change-Human and Policy Dimensions*, *43*, 92–106. https://doi.org/10.1016/j.gloenvcha.2016.12.009

Rodriguez-Ortega, T., Oteros-Rozas, E., Ripoll-Bosch, R., Tichit, M., Martin-Lopez, B., & Bernues, A. (2014). Applying the ecosystem services framework to pasture-based livestock farming systems in Europe. *Animal*, *8*, 1361–1372. https://doi.org/10.1017/S1751731114000421

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., … Smith, J. (2008). Greenhouse gas mitigation in agriculture. *Philosophical Transactions of the Royal Society B-Biological Sciences*, *363*, 789–813. https://doi.org/10.1098/rstb.2007.2184

Smith, A., Snapp, S., Chikowo, R., Thorne, P., Bekunda, M., & Glover, J. (2017). Measuring sustainable intensification in smallholder agroecosystems: A review. *Global Food Security-Agriculture Policy Economics and Environment*, *12*, 127–138. https://doi.org/10.1016/j.gfs.2016.11.002

Stoate, C., Boatman, N. D., Borralho, R. J., Carvalho, C. R., de Snoo, G. R., & Eden, P. (2001). Ecological impacts of arable intensification in Europe. *Journal of Environmental Management*, *63*, 337–365. https://doi.org/10.1006/jema.2001.0473

Struik, P. C., & Kuyper, T. (2017). Sustainable intensification in agriculture: The richer shade of green. A review. *Agronomy for Sustainable Development*, *37*, Article Number: 39 DOI: 10.1007/s13593-017-0445-7.

Waterton, C., Maberly, S. C., Tsouvalis, J., Watson, N., Winfield, I. J., & Norton, L. R. (2015). Committing to place: The potential of open collaborations for trusted environmental governance. *PLoS Biology*, *13*, e1002081. https://doi.org/10.1371/journal.pbio.1002081

Webb, J., Ryan, M., Anthony, S. G., Brewer, A., Laws, J., Aller, M. F., & Misselbrook, T. H. (2006). Cost-effective means of reducing ammonia emissions from UK agriculture using the NARSES model. *Atmospheric Environment*, *40*, 7222–7233. https://doi.org/10.1016/j.atmosenv.2006.06.029

Wynne-Jones, S. (2017). Understanding farmer co-operation: Exploring practices of social relatedness and emergent affects. *Journal of Rural Studies*, *53*, 259–268. https://doi.org/10.1016/j.jrurstud.2017.02.012

Zhou, M. H., Zhu, B., Bruggemann, N., Bergmann, J., Wang, Y. Q., & Butterbach-Bahl, K. (2014). N_2O and CH_4 emissions, and NO_3 (−) leaching on a crop-yield basis from a subtropical rain-fed wheat-maize rotation in response to different types of nitrogen fertilizer. *Ecosystems*, *17*, 286–301. https://doi.org/10.1007/s10021-013-9723-7

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Firbank LG, Elliott J, Field RH, et al. Assessing the performance of commercial farms in England and Wales: Lessons for supporting the sustainable intensification of agriculture. *Food Energy Secur*. 2018;e00150. https://doi.org/10.1002/fes3.150