Integrating the economic and environmental performance of agricultural systems: a demonstration using Farm Business Survey data and Farmscoper

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

[a] Division of Agricultural and Environmental Sciences, University of Nottingham, Sutton Bonington Campus, College Road, Sutton Bonington, Loughborough, LE12 5RD, United Kingdom

[b] RSK ADAS Ltd, Titan 1 Offices, Coxwell Avenue, Wolverhampton Science Park, Stafford Road, Wolverhampton, WV10 9RT, United Kingdom

* Corresponding author, current address: Teagasc, Rural Economy and Development Centre, Mellows Campus, Athenry, Co. Galway, H65 R718, Ireland

Abstract

There is a continued need to monitor the environmental impacts of agricultural systems while also ensuring sufficient agricultural production. However, it can be difficult to collect relevant environmental data on a large enough number of farms and studies that do so often neglect to consider the financial drivers that ultimately determine many aspects of farm management and performance. This paper outlines a methodology for generating environmental indicators from the Farm Business Survey (FBS), an extensive annual economic survey of representative farms in England and Wales. Data were extracted from the FBS for a sample of East Anglian cereal farms and south western dairy farms and converted where necessary to use as inputs in 'Farmscoper'; farm-level estimates of nitrate, phosphorus and sediment loadings and ammonia and greenhouse gas emissions were generated using the Farmscoper model. Nitrate losses to water, ammonia and greenhouse gas emissions were positively correlated with food energy production per unit area for both farm types; phosphorus loading was also correlated with food energy on the dairy farms. Environmental efficiency indicators, as measured by either total food energy or financial output per unit of negative environmental effect, were calculated; greenhouse gas emission efficiency (using either measure of agricultural output) and nitrate loading efficiency (using financial output) were positively correlated with profitability on cereal farms. No other environmental efficiency measures were significantly associated with farm profitability and none were significant on the dairy farms. These findings suggest that an improvement in economic performance can also improve environmental efficiency, but that this depends on the farm type and negative environmental externality in question. In a wider context, the augmentation of FBS-type data to generate additional environmental indicators can provide useful insights into ongoing research and policy issues around sustainable agricultural production.

Keywords: Farm level modelling, Sustainable Intensification, Farm Accountancy Data 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 of Pollutant Emission Reductions) uses farm structure and physical input information to estimate production of a range of pollutants at individual farm level from a range of mechanistic models (Gooday and Anthony, 2010).

The mechanistic modelling approach is dependent on the quality and availability of direct (on-farm), or secondary information sources. Collection of on-farm information through surveys or other approaches tailored to specific model requirements will generate a richer dataset for modelling (Firbank *et al.*, 2013), but can be time consuming for the assessor and/or farmer and presents challenges in ensuring sufficient scope in farm types and farm locations visited. Furthermore, it is difficult to collect realistic and comprehensive economic information without access to – what are from the farmer's perspective – sensitive farm financial records. As noted above, agents involved in agriculture, most notably farmers, will have economic (and social objectives) that will influence their willingness to adopt practices that have the potential to enhance or mitigate the positive and negative effects of agriculture on the environment. Thus, the environmental enhancement of an *existing*, economically rich data set is an attractive option.

The Farm Accountancy Data Network (FADN) was launched in 1965, following EU Council Regulation 79/65, to provide business information on European agricultural holdings and assess the effects of the Common Agricultural Policy (CAP) on farm incomes: of the five original objectives of the CAP, the main social objective was and in practice continues to be "to ensure a fair standard of living for farmers" (European Parliament, 2017). To these ends, FADN data are collected at the individual farm level and are primarily composed of accountancy records, but some physical information and details of farm structure are also available. FADN now represents a large resource of agricultural information, with almost 50 years of economic data. The consistency of the FADN dataset allows assessment over time and between different EU member states. Data collection is handled by liaison agencies within each state. In the United Kingdom this organisation is the Department for Environment, Food and Rural Affairs, and in England and Wales FADN data is collected through the Farm Business Survey (FBS). The FBS surveys *circa* 2300 farms every year, covering a representative sample of farm types and sizes, providing an excellent agricultural data resource.

A great advantage of generating environmental indicators using the FBS and more widely, FADN or other accounting data, is that it enables both economic and environmental performance to be measured. This is particularly helpful as it helps to operationalise concepts such as ‘Sustainable Intensification’ (SI). SI has been interpreted in different ways, but a useful definition from the perspective of potential users of the concept – most obviously farmers and extension agents - is given by the RISE Foundation: “Sustainable Intensification means simultaneously improving the productivity and environmental management of agricultural land” (Buckwell, 2014). Although measurement of productivity is in principle straightforward – the change over time in output per unit of agricultural resources used to produce that output – in agriculture this is quite difficult to achieve in practice. Indeed, the fundamental concept driving FADN is the difficult task of relating inputs to their specific outputs on farms with mixed enterprises and production periods that span months, in the case of poultry, or years, in the case of more extensive beef production systems. Measurement of the effect of environmental management - across a wide enough range of environmental impacts - is more difficult without some form of modelling approach. Therefore, it would be attractive if the mechanistic modelling described above could be used to enhance or ‘augment’ the quality of the environmental information available for individual farms within the FADN and FBS databases and this is the approach that we use here, using the Farmscoper tool as an example. If the resulting information is sufficiently reliable, farmers, extension agents or other stakeholders can assess the extent to which performance is improving across both environmental and economic performance measures.

Most farmers in the UK are familiar with the idea of benchmarking performance through what are termed ‘unit costs of production’ – cost per tonne of wheat or litre of milk for example. Expressing environmental impact per unit of output is thus an attractive way of presenting environmental information to farmers. This also captures the spirit of SI as described by Buckwell et al., 2014: an improvement in SI can be achieved through either an increase in output for a given environmental impact; or a reduction in environmental impact for a given output. Furthermore, by comparing these environmental efficiency indicators with farm structural information, economic performance or social factors such as membership of buying groups or level of education, we can begin to grasp why some farms may perform better than others, in order to highlight the ways in which SI might be improved, through policy instruments or knowledge exchange programmes.

The aim of this study was therefore to develop a methodology for using available farm management data in mechanistic environmental impact models and to demonstrate how the results can be used as environmental efficiency metrics. To this end, we describe a methodology for using FADN as a source of secondary data for an external environmental model, Farmscoper, with example FBS data for a subset of cereal and dairy farms. While FADN data have been used in environmental impact analysis, a novel aspect of our approach is that we adapt FADN-type data for use with mechanistic models, rather than e.g. using nutrient balance approaches (e.g. Dalgaard et al., 2006; Buckley, 2015). Farmscoper is restricted to generating results for agricultural diffuse pollutants (‘negative externalities’) and we do not consider positive impacts of agricultural management, such as biodiversity provision, that are not covered by Farmscoper. Results obtained through this methodology are linked with agricultural output, both physically (total food energy from a farm) and financially (the value of farm physical output at market prices), to derive what Jan et al. (2012) refer to as ‘partial environmental efficiency’ indicators: that is, we generate a range of indicators, rather than a composite, single index of sustainability. Partial environmental efficiency indicators are also compared to farm profitability, as reported in the FBS, through the Management and Investment Income (MII) measure of business performance. Our emphasis is on demonstrating the approach with the example dataset; however, we consider the extent to which the results can inform farmers on how to achieve SI objectives, particularly through improving their own production efficiency. We conclude by discussing the potential utility and limitations of the approach and make suggestions for improving the type of data collected through FADN and the FBS.

2. Methods

2.1 Farmscoper

Farmscoper is a Microsoft Excel-based decision support tool, developed for the United Kingdom Department for Environment, Food and Rural Affairs (Defra) to estimate multiple diffuse pollutant losses and assess potential mitigation methods (Gooday and Anthony, 2010). Farmscoper calculates pollutant loads through a number of mechanistic models simulating farm systems and agricultural practices, including interactions with climate and soil type. The mechanistic models used within Farmscoper are themselves validated methodologies which have been employed in previous studies: PSYCHIC (Davison *et al.*, 2008; Strömqvist *et al.*, 2008), NEAP-N (Anthony *et al.*, 1996), NARSES (Webb and Misselbrook, 2004), MANNER (Chambers *et al.*, 1999), and the IPCC methodologies for methane and nitrous oxide emissions from agriculture (IPCC, 2006).

This study focuses on the use of Farmscoper to demonstrate appraisal of current farm performance, rather than potential mitigations; thus, only current pollutant load and emissions estimates were generated. The outputs were: nitrate loading, phosphorus loading, sediment loading, ammonia emissions, methane emissions, nitrous oxide emissions, plus greenhouse gas emissions associated with energy use and total farm greenhouse gas emissions. Loadings are defined as kg of pollutant lost from farm to local water bodies annually. Emissions are defined as kg of pollutant lost from farm to atmosphere annually, with greenhouse gases converted to CO_2 equivalents assuming a Global Warming Potential (GWP) of 25 for methane and 298 for nitrous oxide (as used in the most recent UK National Inventory Report). Further details on the construction and operation of Farmscoper can be found in Gooday and Anthony, 2010 and Gooday *et al.*, 2014.

2.2 Farm data

Farm data were obtained from the 2012 Farm Business Survey. In order to demonstrate the utility of using FBS data in an external model, the concept must be shown to work for distinct farm types; to this end, dairy and cereal farms were therefore selected as two contrasting types of farm system. Within each farm type, a set of similar farms within the same area were compared to increase the probability that estimated pollutant loads result from farm-specific circumstances and management decisions and are not simply a reflection of farm type and region. Cereal farms were selected from the eastern England counties of Norfolk, Suffolk and Cambridgeshire, and dairy farms were taken from the south-western counties of Devon and Somerset. To simplify data processing and ensure that reliable, standardised data were available, farms with atypical arable crops or non-cattle livestock systems were excluded. These conditions resulted in 38 predominantly cereal farms, covering nine different arable enterprises (winter wheat, spring wheat, winter oilseed rape, triticale, winter barley, spring barley, field beans, peas and potatoes) and 29 predominantly grass- and maize-based dairy farms.

Three different approaches were employed to generate Farmscoper input data from the FBS dataset depending on the data availability and model requirements: 1) extraction of physical or structural farm data directly from the FBS; 2) conversion of indirect FBS data (from financial or other indirect data sources) to an appropriate format for model input; and 3) use of additional data from external geo-referenced datasets. Table 1 summarises these inputs. A number of assumptions were made where data limitations became apparent. Most wheat in England is winter sown; however, there was a small proportion of land on the FBS farms that was sown to spring wheat: Farmscoper does not distinguish between winter and spring cropping for wheat, and therefore all wheat was assumed to be winter sown. The FBS category 'other silage cereals' does not record the type of grain; this was assumed to be whole crop wheat, the most common form of whole crop cereal silage in England. The Farmscoper categories of 'permanent pasture' and 'rotational grassland' were assigned following FBS conventions whereby any grass present for five years or more is considered permanent pasture. Electricity, fuel, oil and water use were all estimated from expenditure as recorded in the FBS, using relevant coefficients from contemporary agricultural advisory publications, as shown in Table 1. Electricity consumption was calculated by assuming a standard metered rate of £0.0069 per kilowatt hour (SAC Consulting, 2012). The FBS data for 'machinery and vehicle fuels' was assumed to represent agricultural ('red') diesel at a cost of £0.63 per litre, while 'heating fuels' were assumed to be kerosene at a cost of £0.53 per litre (SAC Consulting, 2012). Metered water use was calculated from FBS water costs at a rate of £0.95 per metre^3 (AHDB, 2011). Imported (i.e. from off-farm) fertiliser applications were extracted directly from the FBS in the form of N, P and K inputs in kilograms per hectare, while animal manure production and transfers between farm enterprises were handled within Farmscoper as part of the MANNER sub-model. Physical fertiliser import data were not collected for approximately 50% of farms in the 2012 FBS sample (data were not available for 11 of the cereal farms and 14 of the dairy farms);

however, value data were available for expenditure on fertiliser with no breakdown on individual nutrients; furthermore, these data are available as a panel, opening up the potential to track fertiliser related impacts over time, even when physical data are not available. A methodology was therefore devised to convert expenditure data to physical data for use in Farmscoper; this was used for N, P and K bought onto the farm, where fertiliser quantities were not recorded. Total fertiliser expenditure for each enterprise was directly extracted from the FBS; this was then divided by the area of that land use category to convert to expenditure per unit area and subsequently scaled according to typical fertiliser costs for each enterprise. It was assumed that individual N, P and K applications were applied in the same proportion as standard rates (Agro Business Consultants, 2012; SAC Consulting, 2012) with these rates being used to allocate N, P and K from the total fertiliser expenditure value. A similar approach was used to convert expenditure on crop protection products to physical values. Analyses and results presented thus use the whole sample of farms.

There are a number of farm business profitability measures within the FBS. For this study we use ‘Management and Investment Income’ (MII) - this is the total value of all trading farm outputs within a year, less total costs of production, including an imputed rent for owner-occupied farms and an imputed cost for the manual labour of the farmer and spouse. It represents the return to the farmer and spouse for their management of ‘tenants’ capital’: this excludes landlord-type capital such as land and buildings. The measure is before interest – either earned or charged - of the business and allows a meaningful comparison to be made between tenanted and owner-occupied farms. A useful heuristic for interpreting MII is that a value of zero implies that an owner-occupied farm business would be no worse off if the farmer and spouse were to realise their opportunity costs, i.e. to rent out their land and labour at going market rates.

2.3 External geo-referenced data

Farmscoper incorporates local rainfall and soil type to model the movement of pollutants. This data is not recorded in the FBS, and was therefore derived by correlating approximate farm location with external geo-referenced datasets using ESRI ArcGIS desktop 10 (ESRI, 2014). An illustration of the geo-referencing for the south-west farms is shown in Figure 1.

Long-term annual precipitation was derived using the Met Office UKCP09 gridded observed climate dataset (UKCP09, 2015). A long-term average (average annual precipitation between 2002 and 2011) was used as 2012 precipitation data were not available when the study began, and also to establish a precipitation map that could be used for future work exploring potential mitigations and changes in management that were not tied to a specific year.

Dominant soil type for a farm's location was derived using the British Geological Survey Soil Parent Material Model (British Geological Survey, 2011). Soil types classified as light or light to medium under the Soil Parent Material Model were entered as 'permeable free draining soils' in Farmscoper. Medium soils were entered as 'impermeable soils where artificial drainage required for arable cultivation', and heavy soils as 'impermeable soils where artificial drainage required for arable cultivation or grassland'.

(Figure 1 here)

2.4 Environmental efficiency indicators

Environmental efficiency was explored for each farm type using efficiency indicators expressing each negative environmental impact generated per unit agricultural production, at the whole farm level (an inverse approach following that of Jan *et al.*, 2012). Individual, rather than aggregate, indicators were used as only a subset of negative environmental impacts were generated here and food production is only one of several potential multifunctional benefits provided by agriculture. Furthermore, some form of weighting would be needed if an aggregate indicator were to be constructed and 'trade-offs' between different environmental outcomes would be masked. Two different measures were used in order to capture different attributes of agricultural production: total food energy of all agricultural outputs (in gigajoules, GJ) and the value of these outputs (in £). The latter measure effectively weights different physical outputs by their price: this reflects different nutritional contents to an extent (e.g. protein and oil in oilseed rape) and also consumers' willingness to pay for different outputs. Food energy output was calculated by extracting agricultural production data from the FBS and converting using energy content coefficients following Firbank *et al.* (2013). Gross output (£) was taken directly from the FBS, across all farm enterprises. Adjustments made for disposal of the previous year's crop output were excluded so that only outputs generated within a given year (and hence associated with the environmental impacts modelled) were included in the analysis. As efficiency indicators based on food financial output and energy content still do not necessarily take into account important nutritional and other aspects of food production, direct comparisons between the two contrasting farm system types were not made.

2.5 Statistical analyses

The environmental impacts derived from Farmscoper were described using summary statistics expressed per hectare, per GJ food energy and per £ of gross output. Following Jan *et al.*, 2012, the relationship between per hectare farm environmental impact and food production was tested using the Spearman's rank correlation coefficient. The relationship between the environmental efficiency indicators (i.e. environmental impact per unit food production or gross output) was then compared with farm financial performance, as measured by MII per hectare, also using Spearman's rank correlation coefficient. All analyses were performed in R (R Core Team, 2016).

(Table 1 here)

3. Results

3.1 Summary of environmental impacts

The FBS-derived data were successfully run through Farmscoper and indicators for environmental pollutants were estimated for individual farms where no data were previously available. A summary of pollutant loadings and greenhouse gas emissions for the sample is shown in Table 2 below. The broad range in results shown by the standard deviation for each indicator, for both system types, suggests that the estimates derived from the FBS data were sufficient to describe important differences in farm structure and management. Although it was not possible in the scope of this study to validate these results with actual impacts as measured on-farm, they are within the range of expected values. The average carbon footprint per litre of milk from our sample was 1.38 kg CO_2e per litre, which is similar to the average result of 1.31 kg CO_2e per litre demonstrated in a UK dairy foot-printing study, and within the range of values found (DairyCo, 2012). In a similar modelling study in one specific catchment, Zhang et al. (2012) estimated slightly greater nitrate loadings than we found, (38 and 40 kg ha^{-1} year^{-1} for cereal and dairy farms respectively), slightly lower phosphorus loadings (0.2 and 0.5 kg ha^{-1} year^{-1}) and sediment loadings of 159 and 104 kg ha^{-1} year^{-1}. In a study of agricultural losses to water from cereal farms in Eastern England, Taylor et al. (2016) presented estimates of annual nitrate run-off between 3 and 12 kg ha^{-1} year^{-1}, somewhat lower than our result and highlighting the variability in estimates.

(Table 2 here)

3.2 Environmental efficiency of food production

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

(Table 3 here)

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

3.3 Farm-level production efficiency

The relationship between farm land use productivity, as measured by food energy content per hectare of farmland and environmental impact per hectare is shown in Figure 2. For cereal farms, nitrate loading ($r = 0.5$, $P < 0.001$), ammonia emissions ($r = 0.36$, $P = 0.03$) and total greenhouse gas emissions ($r = 0.5$, $P < 0.01$) were all positively associated with increased productivity, suggesting that more intensive production, associated with increased nitrogen inputs, produced more food but at a greater environmental impact per unit area. Using financial output rather than food energy content as a measure of agricultural production resulted in similar relationships for nitrate loading (r = 0.46, $P < 0.01$) and greenhouse gas emissions (r = 0.24, $P < 0.01$), but ammonia emissions were no longer significant (r = 0.24, P = 0.15). Sediment loading was not strongly associated with food production (in terms of £ output or GJ food energy content) for either farm type and appeared more strongly driven by local environment and climate rather than farm outputs; however, it should be noted that differences in farm practice with a strong effect on sediment loading (e.g. form of tillage undertaken) were not available from the 2012 FBS, and hence assumed the same for all farms.

For dairy farms, nitrate loading (r = 0.66, $P < 0.001$), phosphorus loading (r = 0.53, $P < 0.01$), sediment loading (r = 0.40, P = 0.03), ammonia emissions (r = 0.81, $P < 0.001$) and total greenhouse gas emissions (r = 0.82, $P < 0.001$) were associated with greater food energy output, largely as a result of greater fertiliser application and higher stocking rates. Similar relationships were seen when using financial output instead of food energy content, with nitrate loading (r = 0.59, $P < 0.001$), phosphorus loading (r = 0.48, $P < 0.01$), ammonia emissions (r = 0.90, $P < 0.001$) and total greenhouse gas emissions (r = 0.88, $P < 0.001$) again showing significant relationships, although sediment loading was not associated with food financial output (r = 0.3, P= 0.1). The relatively large and strong correlation between output value and ammonia and greenhouse gases suggests that dairy farms with higher milk output are more closely associated with higher emissions.

(Figure 2 here)

3.4 Environmental and economic performance of farms

Correlations between the environmental efficiency indicators and farm economic performance (MII per farm) were mostly negative as shown in Table 4 below; indicating a pattern where more profitable farms generate lower environmental impacts per unit food output. However, only cereal farms showed a significant relationship and this only in greenhouse gas emissions efficiency per unit food energy produced. Results were similar when gross output was used as the measure of agricultural production instead of food energy content.

4. Discussion

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

The approach described in this study resulted in a number of important environmental indicators for farms where this information had previously been unavailable. The heterogeneity in performance across all indicators confirms that the farm input data provided are sufficiently rich to detect differences between farms, as well as implying variation in performance that may be important in the drive for sustainable intensification, discussed further in section 4.2 below. The indicators illustrate how the approaches can be used to investigate both the local (e.g. environmental impact per hectare for local problems such as sediment or nutrient loss) and global (e.g. greenhouse gas emissions per unit of food produced) implications of SI. As noted by (Franks, 2014), SI does not imply a uniform approach on all farms: while the primary goal of sustainable intensification is to minimise the overall negative impacts of agricultural production, local concerns, for example pollutant loadings entering a given catchment, may override this objective in some cases.

As the farm input data came from the FBS and FADN, the assumptions made could be extended to explore more farms and perform comparable analyses, both over time and across other European nations. Previous studies have explored the use of FADN data to generate environmental impacts, for example life cycle assessments of Dutch dairy farms (Thomassen *et al.*, 2009) and nutrient balances for farms in Ireland (Buckley *et al.*, 2015). For the Farm Business Survey, previous approaches have explored the environmental performance of FBS farms, as demonstrated in the Agri-Environment Footprint index (Westbury *et al.*, 2011), and incorporated some elements of environmental performance and sustainable intensification in economic models (Gadanakis *et al.*, 2015), but this represents, to the knowledge of the authors, the first use of FBS data to follow through for the specific environmental outputs demonstrated here.

There are some weaknesses inherent in the approach as a result of FADN data being primarily focussed on farm finances. Some management details are beyond the scope of standard data collection and hence were assumed the same for all farms: for example the number and type of field operations, which will have implications for a number of environmental impacts (Townsend *et al.*, 2016). The use of geospatial referencing for some data is a convenient means of acquiring additional data without further on-farm surveying, but may introduce some inaccuracies due to the limits of resolution possible within farm confidentiality constraints. The data are also limited to the whole farm level and differences between fields will also exist in many instances, particularly in some regions of the UK where soil type can vary substantially even within individual fields. As with all modelling approaches, care must be taken when making inferences from model estimates, e.g., what seems an ‘unexpected’ result – our dairy farms show greater sediment loadings than cereal farms, despite the probable greater extent of tillage operations on the latter – can be explained by other factors, in this case partly by precipitation differences between western and eastern England. However, we would emphasise that better data, particularly on soil management, would help to give better results. On balance, however, the compromises made greatly expands the number of farms available for analysis; moreover, these farms form part of a representative sample for each EU country and have data rich information on farm economic performance. The focus on accounts type data also means that similar approaches could be used where farmers are willing to share data, as the information required is likely to exist in similar forms in management accounts or other electronic farm records. The use of FADN data also facilitates comparison with other approaches that use FBS-type data sets, such as stochastic frontier and data envelopment analysis. These seek to determine whole farm economic efficiency measures relative to a feasible production 'frontier' - that is, feasible under existing technological conditions (see, for example, Wilson *et al.*, 2001; Thirtle *et al.*, 2004; Barnes *et al.*, 2009; Gadanakis *et al.*, 2015).

The data extracted and generated from the FBS sample were demonstrated with the Farmscoper tool as it provides a comprehensive range of outputs based on well-validated sub-models. However, the approach shown here emphasises the use of generic data, so that alternative models could also be employed, appropriate to specific policy issues or research questions. Emerging topics of interest may require additional data collection where the current FBS dataset cannot provide reliable estimates (for example, on management information for biodiversity indicators) and these could be included in the future. The great advantage of building on the existing dataset is that it contains detailed and accurate economic information from a robust, representative sample of farms. This also allows scaling, for example, scaling up representative farm-type impacts to catchment and national scales (e.g. Glithero *et al.*, 2013). Furthermore, the methodology presented here could readily be applied to alternative farm accountancy or management data, and is not exclusive to the FBS or FADN. The main data inputs, as listed in Table 1, could readily be obtained from typical farm records and used in Farmscoper or alternative tools by researchers, farm advisors or individual farmers, either directly (where sufficiently detailed data are already available) or following similar assumptions and conversions to this study. We also suggest that the environmental efficiency relationships demonstrated provide useful metrics that practitioners could use to benchmark performance across farms, or for the same farm attempting to improve production practices over time.

4.2 Implications for sustainable intensification

The concept, practicality and aims of sustainable intensification have prompted much debate since its emergence as an important part of agricultural policy in the UK (Mahon *et al.*, 2017). This paper demonstrates approaches and indicators that can contribute to the arguments surrounding sustainable intensification by linking measures of farm productivity and environmental impacts.

The correlations between food production and several environmental impacts highlight some of the concerns around intensive agricultural production (Struik *et al.*, 2014), but provide useful insight into the concept of sustainable intensification. Changes in the strength of these relationships can be used to demonstrate levels of achievement towards the goal of sustainably increasing production (or reducing environmental impact for existing levels of production) at the farm level. The heterogeneity among farms in terms of environmental performance relative to food production also suggests opportunities for some farms to sustainably intensify, with different farms showing diverse levels of environmental pollution for the same output of food energy. Further investigation of on-farm activities could identify which practices or biophysical features make certain farms more or less environmentally efficient. This information could then be used to highlight where technological or management interventions are of value for enhancing sustainable intensification, as well as highlighting potential spatial differences and ensuring appropriate production and environmental aims are sought for different farm locations.

In addition to farm production and environmental impacts, it is important to consider economic performance in assessing sustainable intensification, as without the economic pillar, it cannot be claimed that farms are managed sustainably. Management practices and technologies proposed for sustainable intensification will also only be widely taken up if individual farmers can see the economic merit for their business, or at least that employing a given intervention will not come at a significant cost. The extensive and robust economic data available within the FBS therefore presents an additional advantage in using this dataset to assess sustainable intensification. This study highlighted the relationship between cereal farm profitability and increased greenhouse gas emission efficiency (represented by both the emissions per unit food energy produced or financial output of crop production) and nitrate loadings (when measuring emissions per unit agricultural financial output), demonstrating sustainable intensification 'win-wins', whereby more efficient nitrogen and fuel use results in greater farm incomes and reduced emissions per food output. However, it is difficult to draw firm conclusions from the limited dataset used here; as emphasised our main intention has been to demonstrate the combined use of mechanistic models with FBS data to provide policy relevant metrics.

It is interesting to note that there were some differences in environmental efficiency indicators depending on whether food energy or gross output was used as a measure of agricultural production. As discussed by Elliott *et al.* (2013), food energy content is a useful indicator for unifying different agricultural outputs, and can be considered as representing net contributions to human food security. However, energy content also omits important differences between food attributes, including further nutritional aspects or consumer preferences. Financial output can be used to indicate overall societal valuation of different products, as distinct from human dietary needs; however, this valuation will also be affected by non-consumer effects, including ‘shocks’ caused by e.g. weather events. Neither indicator fully captures the full range of important food attributes, and so it is important to highlight this and consider the implications of which indicator is used. It should be noted that although this study used food energy and financial value to describe agricultural output, other metrics could also be used as appropriate for future research questions or farm assessments, e.g. physical outputs of individual food products (e.g. litres of milk produced or kg wheat yields).”. Given the large number of farm structural and management factors embodied in these indicators, the sample size examined here was too small to reliably apply multivariate techniques in order to identify important drivers of the environmental efficiency relationships, or explore differences between them. However, the methodologies presented can be used in future work, on larger FBS and FADN datasets, over time, to further investigate these important components of the sustainable intensification debate.

Despite the positive relationship between emissions efficiency and profitability on cereal farms, it is interesting to note that environmental efficiency was not associated with profitability for any other indicator, including greenhouse gas emissions on dairy farms. This is in contrast to some studies which found, for example, that economic performance was correlated with environmental efficiency in a range of impacts (e.g. on Swiss dairy farms - Jan et al., 2012), and that carbon footprint of milk was associated with profitability (e.g. on Irish dairy farms - O’Brien et al., 2015). The Irish study, however, also demonstrated a considerable range in carbon footprint across all levels of profitability, and further work across a wider sample of farms would be required to confirm whether this relationship differs in the UK.

There are mixed implications for the results on our study farms with respect to achieving sustainable intensification. On the one hand, it implies a lack of situations where farms show both greater environmental and economic efficiency: as we would expect, there are trade-offs. The environmental indicators under consideration are largely externalities, and if not associated with increased profitability will offer no economic incentive for farmers to improve environmental performance. At the same time, if there is also no economic disadvantage to increasing environmental efficiency of food production, farmers may be willing to implement sustainable intensification measures based on personal preference, policy tools or quality assurance and marketing initiatives. There are a range of options for how sustainable intensification could be practically achieved on farm (Franks, 2014), yet there is not currently a clear overall policy strategy. Furthermore, the future of agri-environmental policy is particularly uncertain in the United Kingdom as a result of the decision to leave the European Union (Baldock *et al.*, 2016). Regardless of the route taken in agricultural policy, the environmental and economic indicators as presented here remain a valuable means of assessing the efficiency and impacts of the sector.

The establishment of a suite of environmental indicators derived from the Farm Business Survey is especially valuable as the data is collected annually, allowing progress to be tracked over time. It is important to note that each farm is a bio-physically unique unit, and therefore has individual production possibilities that will relate to local environmental and economic conditions. Furthermore, individual farms also differ in their social and management dimensions based on their role within the local community, the individual farmer's objectives, and the willingness and ability of the farm manager to invest in or change farm practices. These can also be explored through the FBS (Wilson, 2014). A true measure of sustainable intensification, over time, can be gained by revisiting these indicators to assess movement across the various dimensions of farm performance.

5. Conclusion

This paper demonstrates a methodology for augmenting an economically rich dataset, using sample farms from the 2012 English Farm Business Survey (FBS), to generate environmental indicators for agricultural pollutants. These are compared to food production and farm profitability measures, also derived from the FBS, to assess the sustainability of agricultural production on the sample farms. Although this paper is primarily concerned with demonstrating the approach, results show that there is wide variability across farms for all pollutants when measured per hectare, per gigajoule of food energy and per £ value of agricultural output. There was no significant relationship between environmental efficiency and profitability on the dairy farm sample. Cereal farm profitability, as measured by the income generated by farm management and investment, was positively and significantly correlated with better greenhouse gas emission efficiency, as measured by both emissions per unit food energy and per unit gross output; and nitrate loading when measured per unit of agricultural gross output. The relationship between production, profit and environmental efficiency does not therefore appear to apply to all farms; nor will it apply to all indicators - in particular, we have not considered methods of quantifying biodiversity in this paper. However, there is evidence that improved agricultural management in crop production, particularly of nitrogen fertilisers, can generate both environmental and financial benefits to farmers, a message that will help facilitate knowledge exchange activities. Finally, there are some limitations to the approach, most notably the extent of the data available for modelling: this could be addressed in the future through the collection of appropriate input data, through FADN and the FBS, for use in the type of environmental models considered here, as well as other approaches to capturing the environmental effects of 21st century agriculture.

Acknowledgements

This research was funded as part of the Defra Sustainable Intensification Platform (SIP: Project Code LM0201). The authors would also like to thank the staff of the Farm Business Survey, and all farmers who participate in it.

UKCP09 projections are © Crown Copyright 2009. The UK Climate Projections data have been made available by the Department for Environment, Food and Rural Affairs (Defra) and Department for Energy and Climate Change (DECC) under licence from the Met Office, Newcastle University, University of East Anglia and Proudman Oceanographic Laboratory . These organisations accept no responsibility for any inaccuracies or omissions in the data, nor for any loss or damage directly or indirectly caused to any person or body by reason of, or arising out of, any use of this data.

References

Agro Business Consultants, 2012. The Agricultural Budgeting & Costing Book. 75th Edition.

AHDB, 2011. DairyCo DIY Full Water Audit Pack.

Anthony, S.G., Quinn, P., Lord, E., 1996. Catchment scale modelling of nitrate leaching. Aspects Appl. Biol. 46, 23-32.

Baldock, D., Buckwell, A., Colsa-Perez, A., Farmer, A., Nesbit, M., Pantzar, M., 2016. The potential policy and environmental consequences for the UK of a depature from the European Union. Institute for European Environmental Policy.

Balmford, A., Green, R., Phalan, B., 2012. What conservationists need to know about farming. Proceedings of the Royal Society B: Biological Sciences 279, 2714-2724.

Barnes, A.P., Moran, D., Topp, K., 2009. The scope for regulatory incentives to encourage increased efficiency of input use by farmers. Journal of Environmental Management 90, 808-814.

British Geological Survey, 2011. BGS Soil Parent Material Database.

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.

Buckwell, A., 2014. The Sustainable Intensification of European Agriculture. RISE.

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.

DairyCo, 2012. Greenhouse gas emissions on British dairy farms.

Dalgaard, R., Halberg, N., Kristensen, I.S., Larsen, I., 2006. Modelling representative and coherent Danish farm types based on farm accountancy data for use in environmental assessments. Agriculture, Ecosystems & Environment 117(4), 223-237.

Davison, P.S., Withers, P.J.A., Lord, E.I., Betson, M.J., Strömqvist, 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.

Elliott, J., Firbank, L.G., Drake, B., Cao, Y., Gooday, R., 2013. Exploring the Concept of Sustainable Intensification. Land Use Policy Group.

ESRI, 2014. Environmental Systems Research Institute ArcGIS 10.2.2 for Desktop.

Firbank, L., 2009. Commentary: It's not enough to develop agriculture that minimizes environmental impact. International Journal of Agricultural Sustainability 7, 151-152.

Firbank, L.G., Elliott, J., Drake, B., Cao, Y., Gooday, R., 2013. Evidence of sustainable intensification among British farms. Agriculture, Ecosystems & Environment 173, 58-65.

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O/'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockstrom, J., Sheehan, J., Siebert, S., Tilman, D., Zaks, D.P.M., 2011. Solutions for a cultivated planet. Nature 478, 337-342.

Franks, J.R., 2014. Sustainable intensification: A UK perspective. Food Policy 47, 71-80.

Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Evaluating the Sustainable Intensification of arable farms. Journal of Environmental Management 150, 288-298.

Glithero, N.J., Wilson, P., Ramsden, S.J., 2013. Straw use and availability for second generation biofuels in England. Biomass and Bioenergy 55, 311-321.

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C., 2010. Food Security: The Challenge of Feeding 9 Billion People. Science 327, 812-818.

Gooday, R., Anthony, S.G., 2010. Mitigation method-centric framework for evaluating cost-effectiveness. Defra Project WQ0106(3). Final Report.

Gooday, R.D., Anthony, S.G., Chadwick, D.R., Newell-Price, P., Harris, D., Duethmann, D., Fish, R., Collins, A.L., Winter, M., 2014. Modelling the cost-effectiveness of mitigation methods for multiple pollutants at farm scale. Science of The Total Environment 468–469, 1198-1209.

IPCC, 2006. IPCC Guidelines for National Greenhouse Gas Inventories. Agriculture, Forestry and Other Land Use. In: Eggleston, H.S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.).

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

Mahon, N., Crute, I., Simmons, E., Islam, M.M., 2017. Sustainable intensification – “oxymoron” or “third-way”? A systematic review. Ecological Indicators 74, 73-97.

O’Brien, D., Hennessy, T., Moran, B., Shalloo, L., 2015. Relating the carbon footprint of milk from Irish dairy farms to economic performance. Journal of Dairy Science 98, 7394-7407.

R Core Team, 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

SAC Consulting, 2012. The Farm Management Handbook 2012/13.

Strömqvist, J., Collins, A.L., Davison, P.S., Lord, E.I., 2008. PSYCHIC – A process-based model of phosphorus and sediment transfers within agricultural catchments. Part 2. A preliminary evaluation. Journal of Hydrology 350, 303-316.

Struik, P.C., Kuyper, T.W., Brussaard, L., Leeuwis, C., 2014. Deconstructing and unpacking scientific controversies in intensification and sustainability: why the tensions in concepts and values? Current Opinion in Environmental Sustainability 8, 80-88.

Taylor, S.D., He, Y., Hiscock, K.M., 2016. Modelling the impacts of agricultural management practices on river water quality in Eastern England. Journal of Environmental Management 180, 147-163.

Thirtle, C., Lin Lin, L., Holding, J., Jenkins, L., Piesse, J., 2004. Explaining the Decline in UK Agricultural Productivity Growth. Journal of Agricultural Economics 55, 343-366.

Thomassen, M.A., Dolman, M.A., van Calker, K.J., de Boer, I.J.M., 2009. Relating life cycle assessment indicators to gross value added for Dutch dairy farms. Ecological Economics 68, 2278-2284.

Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. Proceedings of the National Academy of Sciences 108, 20260-20264.

Townsend, T.J., Ramsden, S.J., Wilson, P., 2016. Analysing reduced tillage practices within a bio-economic modelling framework. Agricultural Systems 146, 91-102.

UKCP09, 2015. UK Climate Projections 2009.

Webb, J., Misselbrook, T.H., 2004. A mass-flow model of ammonia emissions from UK livestock production. Atmospheric Environment 38, 2163-2176.

Westbury, D.B., Park, J.R., Mauchline, A.L., Crane, R.T., Mortimer, S.R., 2011. Assessing the environmental performance of English arable and livestock holdings using data from the Farm Accountancy Data Network (FADN). Journal of Environmental Management 92, 902-909.

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