Defra Sustainable Intensification Research Platform

SIP Project 1: Integrated Farm Management for Improved Economic, Environmental and Social Performance (LM0201)

Objective 1.1: Developing improved indicators and standardised methodologies for land managers and their advisers to measure the economic, environmental and social performance of farms

Work Package 1.1B: Developing augmented efficiency and productivity measures to form a basis for integrated Sustainable Intensification metrics

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The Sustainable Intensification Research Platform (SIP) is a multi-partner research programme comprising farmers, industry experts, academia, environmental organisations, policymakers and other stakeholders. The platform has explored the opportunities and risks of Sustainable Intensification (SI) from a range of perspectives and scales across England and Wales, through three linked and transdisciplinary research projects:

SIP Project 1	Integrated Farm Management for improved economic, environmental and social performance
SIP Project 2	Opportunities and risks for farming and the environment at landscape scales
SIP Project 3	A scoping study on the influence of external drivers and actors on the sustainability and productivity of English and Welsh farming

Projects 1 and 2 have investigated ways to increase farm productivity while reducing environmental impacts and enhancing the ecosystem services that agricultural land provides to society.

Project 1 partners are: NIAB (lead), IBERS (Aberystwyth University), ADAS, Agri-Food and Biosciences Institute (AFBI), Bangor University, Biomathematics and Statistics Scotland (BioSS), University of Bristol, University of Cambridge, Carbon Trust, Centre for Ecology and Hydrology (CEH), Duchy College, University of Exeter, Fera, Game and Wildlife Conservation Trust (GWCT), Glasgow Caledonian University, Harper Adams University, University of Hertfordshire, Linking Environment And Farming (LEAF), University of Leeds, Newcastle University, NIAB EMR, University of Nottingham, Organic Research Centre, University of Reading, Rothamsted Research, Royal Society for the Protection of Birds (RSPB), Scotland's Rural College (SRUC), Soil Association and Velcourt.

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The data used for this publication was created as part of the SIP, and is freely available (subject to data embargo) at the Agricultural and Environmental Data Archive (AEDA) owned by the Freshwater Biological Association (FBA). All data is owned by Defra.

ABBREVIATIONS

CAP	Common Agricultural Policy
DEA	Data Envelopment Analysis
Defra	Department for Environment, Food and Rural Affairs
ES	Ecosystem Services
FADN	Farm Accountancy Data Network
FBS	Farm Business Survey
GHG	Greenhouse Gas
Ha	Hectares
IFM	Integrated Farm Management
ISM	Integrated sustainable intensification methodology
KE	Knowledge Exchange
LEAF	Linking Environment And Farming
LFA	Less Favoured Areas
N	Nitrogen
OECD	Organisation for Economic Co-operation and Development
P	Phosphorus
SI	Sustainable Intensification
SIP	Sustainable Intensification Research Platform
SFA	Stochastic Frontier Analysis
TFP	Total Factor Productivity

EXECUTIVE SUMMARY

This work has shown how Sustainable Intensification (SI) can be assessed through efficiency and productivity measures that are augmented with positive and negative environmental externalities. These provide a better assessment of the performance of farms in relation to the broader objectives of agricultural policy than can be achieved with conventional measures.

We applied Data Envelopment Analysis (DEA) using data for cereal farms in the Farm Business Survey (FBS) as well as data collected through the survey of study area commercial farms undertaken in Work Package 1.2A. A number of measures were developed to account for environmental aspects related to agricultural production: a) sustainable efficiency, a SI measure that combines the production of conventional output, pollution and environmental goods associated with the conventional production by farms; b) environmental inefficiency, a SI measure that assesses the overuse of nitrogen fertiliser compared to a pollution-minimising benchmark; and c) sustainable productivity, a measure of productivity that incorporates information on sustainable efficiency to provide a dynamic picture of SI.

We found that incorporating positive and negative environmental externalities in the production technology of the industry (*i.e.* the production frontier used to define the relationship between inputs and outputs) showed a different picture of how efficient farms are on average compared to standard approaches. In fact, this resulted in lower overall sustainable efficiency scores[1]. The different DEA conducted showed that the FBS cereal farms had an average sustainable efficiency of 0.69 and 0.59 in 2012 and 2013, respectively, and that in 2012 on average 53 kg of nitrogen per hectare was overused compared to the pollution-minimising benchmark. These figures suggest that the cereal farms were below their potential sustainable performance. On average, the cereal farms produced around 70% of the output and environmental goods that were produced by the best performing cereal farms, given the inputs used and their negative impacts on the environment. Our productivity analysis applied to the FBS cereal farms suggests that there was a decline (0.93) in sustainable productivity between 2012 and 2013 due to a decline in efficiency (0.88), which was partly offset by an increase in technical change (1.11)[2]. This means that the FBS cereal farms producing the maximum potential output given their inputs (*i.e.* farms on the production frontier[3]) increased their performance with regard to SI (*i.e.* sustainable productivity), but that the inefficient farms did not manage to keep up with the frontier farms, and declined in terms of SI.

We also attempted to contextualise the differences in sustainable efficiency for the FBS cereal farms. We found that sustainable efficiency is positively associated with farm size, and that cereal farms in Less Favoured Areas and on upland soils had a lower SI efficiency. Caution is required in interpreting the latter result because the number of farms surveyed in these areas was small (n = 43) and the sample was very heterogeneous, consisting of mixed as well as specialised farms. When we extended our analysis to include additional measures of sustainability using data from the farms in the Work Package 1.2A survey we found an average sustainable efficiency of 0.64. Whilst this figure is not directly comparable to the figures from the FBS farms, as different

[1] Sustainable efficiency scores are based on efficiency measures that can take any value in the range [0,1]

[2] The productivity analysis conducted yields results on productivity change. Values of productivity change greater than 1 indicate an increase in productivity; values smaller than 1 indicate a decrease in productivity; values equal to 1 indicate no productivity change.

[3] Production frontier reflects the current state of technology in the industry and represents the maximum output attainable from each input level (Coelli *et al.*, 2005). The production frontier can be used to identify technically efficient farms, *i.e.* those on the frontier, and inefficient farms, *i.e.* those below the frontier (Coelli *et al.*, 2005).

sustainable indicators were used, the fact that including additional measures of sustainability reduced measured efficiency suggests that there is considerable scope for improvements to be made in SI.

Furthermore, we reviewed the literature on shadow-pricing of positive and negative environmental externalities (*i.e.* calculating the opportunity cost of increasing (decreasing) the positive (negative) environmental externality by one unit). The key message from this review was that shadow-pricing externalities critically depends on how the externality is represented in the production economics framework. While the literature has largely treated environmental goods as conventional outputs in a production economics framework, we have shown that this approach has limitations. Addressing the problems of computing the shadow-price of crop diversification, we developed a new measure and found that crop diversification was positively associated with an increase in long-term profit. This is in contrast with other studies, which assume that there always is a trade-off between conventional production and the production of environmental goods, but it accords with conventional wisdom, which holds that crop diversification yields benefits to farms.

This report shows that the efficiency and productivity framework is flexible in that it can easily be enriched with more and better data on the positive and negative environmental externalities. Our main recommendation is that methods of incorporating more data within the framework supported by the FBS should be explored. In particular, it is critical that we are able to connect data on soil quality and biodiversity to the data that focus on more conventional measures of business performance in the FBS. Improved measures of soil quality would substantially improve the measurement of SI. We believe it is worthwhile to create a more detailed account of the spatial characteristics of environmental externalities. In addition, future studies would benefit from spatially specific nutrient coefficients that reflect the differences in cost of nutrient leaching. This would increase the ability of analysts to accurately identify farms with scope to improve their SI, and also to identify drivers of SI, which is crucial information for policy makers.

1. INTRODUCTION

1.1 Overview of Objective 1.1

In Objective 1.1 we sought to review current methodologies for assessing the environmental and social performance of farm businesses and to identify suitable indicators for further development into an integrated sustainable intensification methodology (ISIM) that was 'rooted in standard economic theories of production and the environment'. This would be replicable and open to refinement as new data became available. From an initial literature review, which was reported in the SIP Project 1 Scoping Study (Knight *et al.* 2014), we identified a range of suitable indicators for use with a core dataset provided by the Farm Business Survey (FBS) for England and Wales. The FBS is part of the European Farm Accountancy Data Network (FADN) and thus the methods that we employ can be extended to other European countries and projects. The ISIM has two integrated 'Strands' that both use FBS data; by using two approaches, we overcome some of the limitations of each individual approach.

1.1.1 Strand 1 (Work Package 1.1A)

Strand 1 (described in full in the Work Package 1.1A final report) used a sub-set of FBS data for 2012, together with a suite of mechanistic environmental models to generate economic, social and environmental indicators for individual FBS farms.

1.1.2 Strand 2 (Work Package 1.1B)

Strand 2 used the full FBS data-set for 2012 and 2013 (including the Strand 1 sub-set data) to generate farm level efficiency indicators for different farm types within the FBS. These indicators show the position of each farm relative to a 'frontier' representing the best performing farms under current technological conditions (*e.g.* on cereal farms, with current varieties of cereals). We calculate the efficiency of farms in relation to conventional inputs (land, labour and capital) and outputs (agricultural production), and also positive environmental externalities (or 'environmental goods', using the Shannon index for crop diversity as an indicator) and negative environmental externalities (using nitrogen and phosphorus surplus as an indicator).

By incorporating positive and negative environmental externalities into the efficiency analysis we obtain farm efficiency levels that can be interpreted as Sustainable Intensification (SI) metrics for the farm (*i.e.* accounting not only for conventional inputs and outputs but also for environmental goods and negative environmental externalities associated with the production of conventional outputs). Examples of such an extension of the efficiency analysis by incorporating non-conventional outputs are the extent of wetland and interior forest (Macpherson, Principe and Smith 2010), six key indicators of biotic integrity of watershed data (Bellenger and Herlihy 2009, Bellenger and Herlihy 2010), the extent of permanent grassland (Areal, Tiffin and Balcombe 2012), cultural services, biodiversity, carbon sequestration and the extent of arable and grassland (Ruijs *et al.* 2015, Ruijs *et al.* 2013), the Shannon index for crop diversity (Sipiläinen and Huhtala 2013) and wetland quality (Bostian and Herlihy 2014).

A key aspect of SI is to farm in ways that ensure that 'natural' features that can contribute to productivity, such as soil quality, are enhanced. We therefore extend the efficiency framework by incorporating these features through the use of indicators such as the Shannon index for crop diversity. We have also considered ways in which measurement of SI can be extended to capture the social dimension of sustainability. The framework that we have presented to incorporate the environmental dimension is based on a conceptualisation of the processes that link the natural and managed ecosystems. This approach is less suited to the social dimension where the processes are less clear. We have therefore used social indicators to provide context for the differences in efficiency scores.

To give an indication of the flexibility of our approach, and to show how it might be extended, we applied our efficiency methods to the data collected from the survey of study area commercial farms undertaken in Work Package 1.2A. This shows that more detailed data on positive and negative environmental externalities can easily be incorporated in our efficiency and productivity measures.

Finally, we reviewed the literature on shadow-pricing environmental goods and negative environmental externalities (*i.e.* calculating the opportunity cost of increasing the environmental good or decreasing the negative environmental externality by one unit) and developed a novel measure to assess the opportunity cost of crop diversification.

1.2 Aim and Objectives

The overall **aim** of Objective 1.1 was to develop improved indicators and standardised methodologies for land managers and their advisers to measure the economic, environmental and social performance of farms. The main objective of Work Package 1.1B (covered by this report) was to develop augmented efficiency and productivity measures to form a basis for integrated SI metrics.

1.3 Deliverables and Tasks

The key deliverables for Work Package 1.1B were integrated SI metrics that can be used on-farm to assess how well a farming system is delivering economic, environmental and social outcomes, and where there is opportunity to improve. The key tasks undertaken were to:

1.1B1 Conduct an augmented efficiency analysis of FBS farms

1.1B2 Develop a prototype 'environmental efficiency' tool

1.1B3 Analyse factors contributing to good SI performance

1.1B4 Compare results with the commercial farm survey from Work Package 1.2A

1.1B5 Extend Total Factor Productivity to include non-conventional in/outputs

1.1B6 Review methods for incorporating shadow values

2. GENERAL METHODOLOGY

2.1 Data Envelopment Analysis

We use 'Data Envelopment Analysis' (DEA) to compute efficiency and productivity measures for cereal farms in the FBS. This method imposes minimal restrictions on the production technology that is assumed to transform inputs into outputs, environmental goods and negative environmental externalities. The method constructs a frontier to represent the performance of the most efficient farms in the data set and compares the performance of other farms to this. A number of measures have been developed to account for environmental aspects related to agricultural production: a) sustainable efficiency, an SI measure that combines the production of conventional output, pollution and environmental goods associated with the conventional production by farms; b) environmental inefficiency, an SI measure that assesses the overuse of nitrogen compared to a pollution-minimising benchmark; and c) sustainable productivity, a measure of productivity that incorporates the information on sustainable efficiency to provide a dynamic picture of SI. One disadvantage is that all deviations from the technological frontier are explained as farm inefficiency. Alternatively, one could employ Stochastic Frontier Analysis (SFA), which allows for disentangling deviations from the frontier into components of technical inefficiency and random noise. This comes at the price of more restrictive assumptions regarding the production technology. The DEA method is further explained in the appendices of each section concerned.

2.2 Farm Business Survey Data

The Farm Business Survey (FBS) provides the basis of our work. The FBS dataset provides statistically representative, farm-level information on economic and physical characteristics. The FBS dataset is especially rich in terms of economic data (economic values of inputs and outputs), as it was not originally designed to record environmental factors. Since 2012-2013, fertiliser surveys were conducted as part of the FBS which record the fertiliser applied to a crop. By comparing this data with the theoretical nitrogen (N) and phosphorus (P) requirements of the crop, nutrient surpluses can be calculated. We regard surpluses as a negative environmental externality as their increase has a detrimental effect for society through their impacts on water quality for example.[4] Data on environmental goods such as biodiversity are harder to obtain, although more details will be soon available in the light of the greening of the CAP (*e.g.* buffer strips and hedgerows). We have made use of the Shannon index for crop diversity as a proxy of biodiversity.

Data are taken from the FBS dataset for 2012 and 2013. To obtain a homogenous sample, we consider cereal farms that do not produce any livestock, but note that our method can also be used for livestock farms if more details on the nutrient contents of the feed inputs are available. The farms are geographically spread throughout England and Wales. All size classes are represented. We only include the farms that completed the fertiliser survey.

Table 1 lists the variables that we use in the model. Most variables are expressed as (deflated) expenditures in £. The number of farms varies according to the analysis that we perform and details are therefore given in the relevant section of the report.

[4] It is possible that a negative 'surplus' may arise in which case the farmer is depleting the natural stock of the nutrient.

Table 1: Variables used in the analysis

Variables	Directly from FBS?	Units
Conventional Outputs		
Wheat	Yes	£
Barley	Yes	£
Oats	Yes	£
Beans	Yes	£
Peas	Yes	£
Potatoes	Yes	£
Sugar beets	Yes	£
Other	Yes	£
Conventional variable inputs		
Land	Yes	Hectares
Variable inputs	Yes	£
Seed and planting stock	Yes	£
Fertiliser	Yes	£
Crop protection	Yes	£
Electricity	Yes	£
Heating fuel	Yes	£
External labour	Yes	Annual working hours
Management	Yes	Annual working hours
Other variable inputs	Yes	£
Conventional capital inputs		
Buildings	Yes	£
Machinery	Yes	£
Negative Environmental Externalities		
Nitrogen surplus	No	Kg
Phosphorus surplus	No	Kg
Environmental goods		
Shannon index for crop diversity	No	Unitless

The nitrogen (N) and phosphorus (P) surplus and the Shannon index of crop diversity are derived from the information obtained from the FBS dataset.

The **nitrogen and phosphorus surplus** are calculated as follows. Consider a firm that transforms a vector of $m = 1 \dots M$ variable inputs, $x \in \mathbb{R}_+^M$ to a vector of $n = 1 \dots N$ outputs, $y \in \mathbb{R}_+^N$. We assume that inputs and outputs have a fixed proportionate content of the single polluting nutrient given by the $(M \times 1)$ and $(N \times 1)$ vectors of non-negative pollutant coefficients a and b. The nitrogen and phosphorus surpluses are calculated as the difference between the levels of the pollutant in the outputs and inputs given by the material balance equation:

$$z(a, b) = a'x - b'y.$$

The nutrient coefficients for both inputs, a, and outputs, b, are obtained from the EUROSTAT (2015) website. Results obtained using these coefficients are consistent with the UK coefficients used in the soil surface method.

Crop diversity has been shown to be linked with *inter alia* long-term stability of the carbon stock in the soil (Henry *et al.* 2009), improved nutrient balance (Pimentel *et al.* 2005) and landscape diversity (Westbury *et al.* 2011). The **Shannon index for crop diversity** $S(L_m)$ is computed as follows:

$$S(L_m) = -\sum_{m=1}^{M} \left[\frac{L_m}{L} * \ln \frac{L_m}{L}\right]$$

where L_m is the area of land allocated to growing the m-th crop and L is total land area. The index increases with the number of species and as they are present in increasingly equal proportions. For instance, if the farms in the sample produce seven crops, a farm maximizes its Shannon index by producing seven crops evenly on the land. It is a well-established measure with many applications focusing on the farm level (Spellerberg and Fedor 2003). In the context of crop production, it measures the crop diversity by representing the number of crop types and evenness of the area covered by the crops. Various studies in the economics literature use the Shannon index for crop diversity as an environmental good (*e.g.*, Di Falco and Chavas 2008, Sipiläinen and Huhtala 2013, Weitzman 2000). Despite these appealing characteristics, we note that crop diversity is a contested measure of environmental goods (it is only one element of biodiversity). We made our choice because of the constraints imposed by the use of the FBS. The measure we present demonstrates the potential to extend efficiency measurement to capture environmental goods. As better measures of these outputs become available, they can be used to replace the Shannon index.

3. METHODS, RESULTS AND DISCUSSION

3.1 Sustainable Efficiency

We develop an augmented efficiency measure which rewards conventional production and crop diversity (measured by the Shannon index), and penalises fertiliser N and P surpluses (Appendix 1). The measure is expressed as a number between 0 and 1, where 1 denotes maximum sustainable efficiency. For example, an augmented efficiency score of 0.80 means that the farm operates at 80% of its potential in simultaneously increasing production of conventional goods and the Shannon index for crop diversity, and reducing N and P surplus.

In line with Murty, Russell and Levkoff (2012), we make use of **network Data Envelopment Analysis** (DEA) for a balanced sample of 93 specialised cereal farms for the years 2012 and 2013. We use an intersection of the conventional technology (with conventional inputs and outputs), polluting technology (which generates N and P surplus), and environmental-good-generating technology (which generates the Shannon index for crop diversity) to compute overall environmental efficiency (Appendix 2). In practice, this means that we compute three partial efficiency scores (one for each sub-technology) and that we compute the mean of the three partial efficiency scores to obtain the eventual sustainable efficiency score.

Two key features of the approach that we adopt are as follows. First, we quantify pollution rigorously by deriving the N and P surplus so that it is consistent with the material balance condition. Second, we recognise that it is the change in natural capital stock that is the relevant outcome variable when assessing SI. Thus we treat the Shannon index for crop diversity as a conventional output for the current year, and as an input for the subsequent year. The latter is in line with the concept of a natural capital stock yielding ecosystem services. Ecosystem services are yielded simultaneously with conventional production, and part of the natural capital stock can be carried over as inputs for future production.

Table 2 shows that the average sustainable efficiency scores are 0.69 and 0.59 for 2012 and 2013, respectively.

Table 2: Sustainable efficiency scores

Year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2012	0.44	0.60	0.68	0.69	0.78	1
2013	0.31	0.51	0.57	0.59	0.67	1

Figure 1 shows a plot of the probability density function for the two years. It shows that the reduction in the mean score is broadly the consequence of a leftward shift in the distribution. It is apparent also that some farms towards the high end of the distribution are less affected by the shift than is generally the case. Overall, 2011/12 was a wet year in comparison to 2012/13 but the conditions in winter 2012/13 were particularly wet, which meant that the area of winter sown crops was lower than normal in that year.

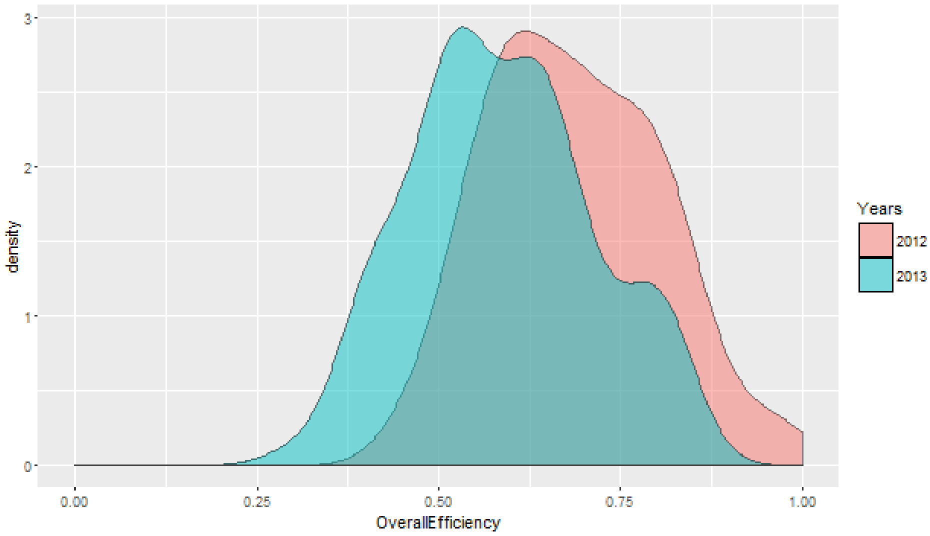

Figure 1: Probability density function for Overall Sustainable Efficiency (2012-2013)

The change in overall sustainable efficiency can be decomposed into changes in efficiency for the conventional technology (Figure 2), technology for the production of nutrient surplus (Figure 3) and technology for the 'production' of the Shannon index (Figure 4). Figures 2 and 3 show that in relation to conventional technologies and nutrient surplus a comparatively large number of farms are on the frontier. Regarding the conventional technology, the distribution shifts leftwards between 2012 and 2013. It is also evident that there is a collection of farms that are relatively close the frontier and with efficiencies greater than 90%. There is a second group that have efficiencies close to 80% with an extended tail of farms with efficiencies below this. In 2013 the second group is more affected by the reduction in efficiency. A possible explanation may be that these were farms that are located on heavier soils that are difficult to manage in the autumn/winter. This would make them appear less efficient in all years and more severely affected when conditions are particularly wet as they were in 2012/13. However, since we lack information about the specific farm locations we cannot confirm this is the case.

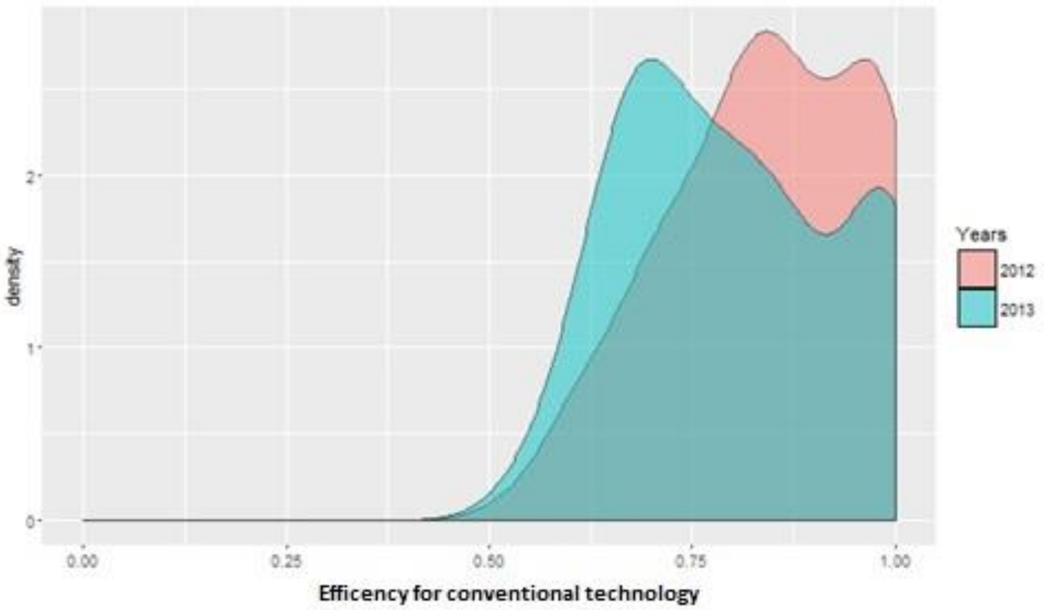

Figure 2: Efficiency of conventional technology

Figure 3 shows that the nutrient surplus generating technology also has relatively large numbers of farms on the frontier. There are again two groups, one with very high levels of efficiency and another with levels around 50%. In contrast with the conventional technology, the reduction in efficiency largely affects farms that are close to the frontier. This suggests that the challenging conditions in winter 2012/13 affected those farms that had relatively low levels of nutrient wastage given the levels at which they are being applied. This may be a consequence of those farms that are normally very good at timing fertiliser application to coincide with key growth stages being forced to apply fertiliser at sub-optimal times as a result of the poor weather. Or the farms may have over-estimated their fertiliser requirement, either because they under-estimated the supply from the soil or because they over-estimated crop requirement.

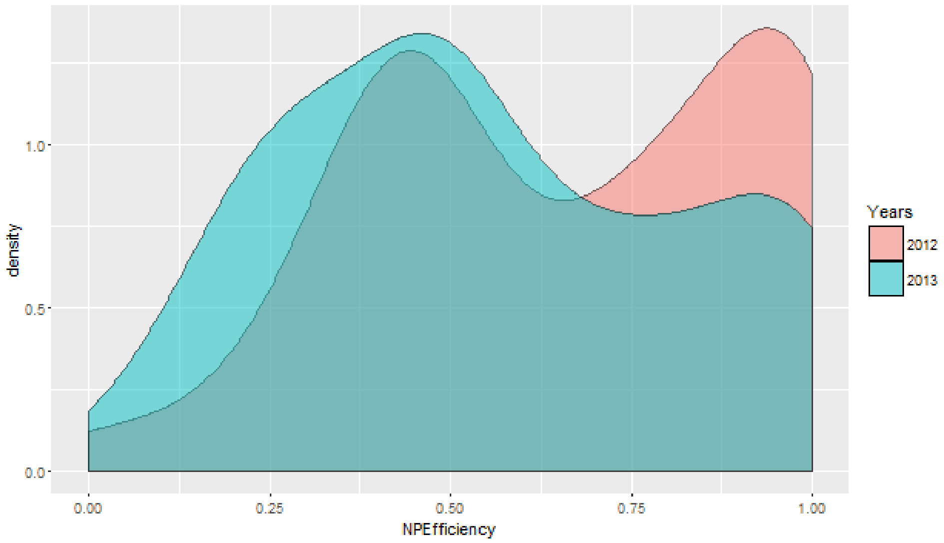

Figure 3: Efficiency of technology that generates negative environmental externalities (N and P surplus)

Figure 4 shows a somewhat different picture for the Shannon index technology. There are only a very small number of farms on the frontier with the bulk of the population having efficiency levels of below 50%. The most efficient farms according to this measure achieve a high level of crop diversity given the input levels that they are using and the crop diversity of the previous year. The highly efficient farms may therefore just be those where there is a change in the crop rotation in the years for which the analysis is conducted.

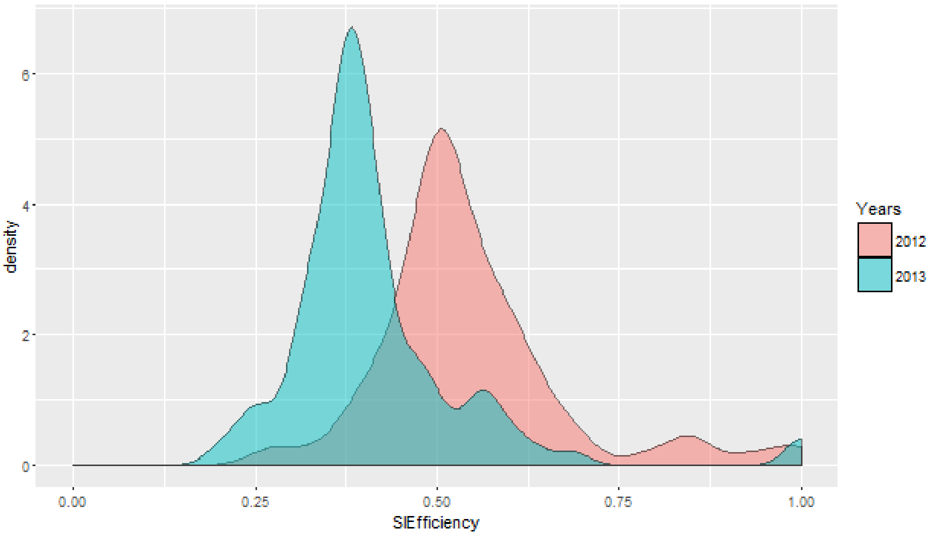

Figure 4: Efficiency of technology that generates and uses environmental goods (Shannon index)

3.2 Environmental inefficiency

In line with Coelli, Lauwers and Van Huylenbroeck (2007), we develop an environmental inefficiency measure that indicates the overuse of N compared to a pollution-minimising benchmark. Environmental inefficiency is expressed in terms of kg N overuse per hectare. The technological frontier is defined in input-output space. Thus a firm that is on the frontier is unable to produce a higher yield than they currently do, given the level of N use. Such a farm may however not be on a pollution-minimising point of the frontier (*i.e.* an efficient farm could remain efficient but minimise pollution). There are many combinations of inputs and outputs that lead to efficient outcomes. However, only one of those outcomes can be pollution-minimising. This gives rise to two components of an efficiency score, the first measuring distance off the frontier and the second measuring distance from the pollution minimising point. Because of the analogy with profit maximisation, we term these sources of inefficiency (technical and allocative respectively).

A full version of this work is being prepared for submission to the *European Journal of Operational Research*. Appendix 2 provides a technical explanation of the method.

We found that for our sample of 115 cereal farms, environmental inefficiency is on average 53 kg N per hectare ranging from 0 to 174 kg N per hectare for the year 2012. This measures the amount by which N surplus can be reduced by adopting the technology and nitrogen-yield ratio of the environmentally efficient farm. Figure 5 shows the histogram for the number of farms achieving varying levels of environmental inefficiency. It also shows the number of farms where this is due to technical inefficiency in the sense that they are inside the frontier, and allocative inefficiency where the firms are on the frontier but not at the pollution-minimising point. 78 farms are technically inefficient and 35 farms are allocatively inefficient. The remaining 2 farms are on the frontier and minimise pollution[5].

[5] Note that they are not on the same spot. This is possible as the nutrient coefficients of the seeds are different per farm and land is assumed to be a fixed factor.

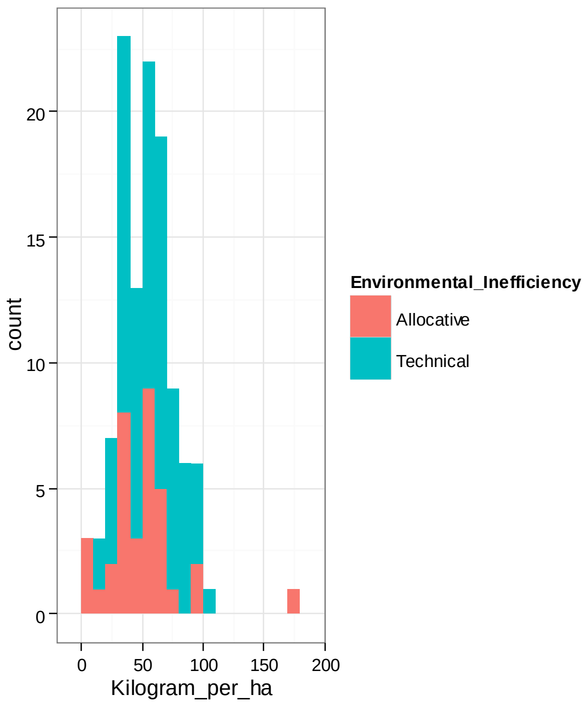

Figure 5: Environmental inefficiency, technical inefficiency and allocative inefficiency.

3.3 Sustainable productivity growth

Our sustainable efficiency measure assesses sustainable performance across farms within a given year. However, the term 'Sustainable *Intensification*' suggests that one also needs to assess how sustainable performance *dynamically changes over time.* Building on the static efficiency framework developed in section 3.1, we introduce a dynamic, sustainable productivity measure that assesses SI[6]. The framework is based on the Malmquist productivity index (Caves, Christensen and Diewert 1982). It uses the same distance function framework as in section 3.1 *i.e.* an intersection of the conventional technology (with conventional inputs and outputs), polluting technology (which generates N and P surplus), and environmental-good-generating technology (which generates the Shannon index for crop diversity to compute overall environmental efficiency). However, it also compares observations of the current year with the technology of the subsequent year and *vice versa*.

The sustainable productivity measure has a straightforward interpretation. Sustainable productivity growth (decline) yields a number higher (lower) than one. This measures how the farmers' ability to simultaneously deal with conventional production and production of negative environmental externalities and environmental goods changes over time. The measure can be decomposed into efficiency changes and technical changes. The latter indicates shifts of the technological sustainability frontier. Growth in a component is indicated by a number higher than one, and decline by a number lower than one.

A full version of this work is being prepared for submission to *Ecological Economics*. Appendix 3 provides a technical explanation of the method.

Table 3 and Figure 6 show that there was a sustainable productivity decline (0.93) in 2012-2013 due to a decline in efficiency (0.88), which was partly offset by an increase in technical change (1.11). This means that farms on the frontier increased their performance with regard to SI, but that the inefficient farms did not manage to keep up with the frontier farms and even deteriorated in terms of SI. The decline in sustainable productivity can mainly be explained by exceptionally bad weather conditions in 2013, which have an impact on the majority of the farms. The sustainable productivity measure thus provides nuance about what happened in terms of SI. It shows that the decline in sustainable efficiency is only one part of the story, with frontier farms actually improving in terms of SI in spite of the conditions, but most farms unable to keep up with the frontrunners.

Table 3: Sustainable productivity change, technical change and efficiency change for 2012-2013

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Productivity change	0.79	0.87	0.92	0.93	0.97	1.23
Technical change	0.64	0.95	1.09	1.11	1.21	1.82
Efficiency change	0.46	0.78	0.85	0.88	0.97	1.46

[6] Although we take into account the intertemporal character of the Shannon index (as it simultaneously serves as an input for the next year and as an output for the current year), efficiency measures are in essence still static. They do not provide any information on how the technological frontier and technical efficiency have shifted in time.

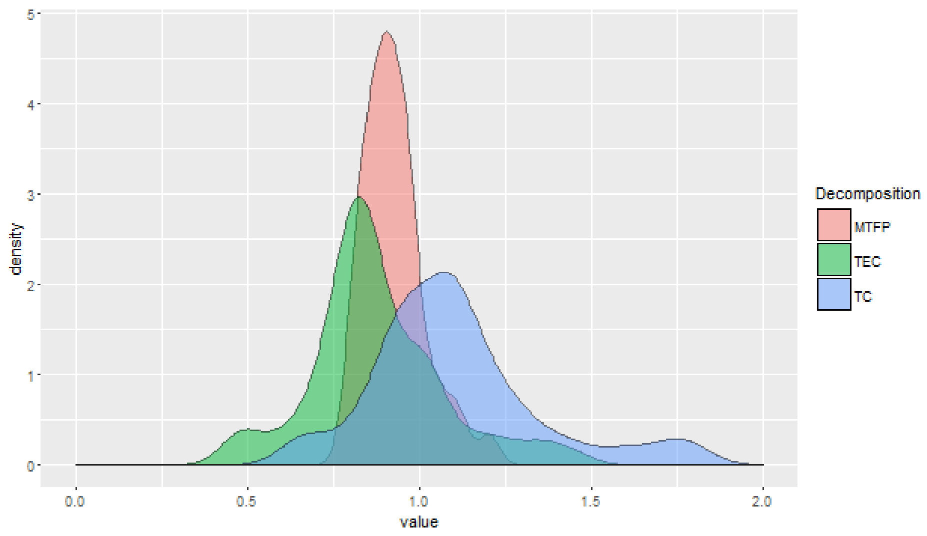

Figure 6: Probability density distribution of sustainable productivity change (MTFP) and its decomposition into technical efficiency change (TEC) and technical change (TC) for 2012-2013

3.4 Contextualising differences in sustainable efficiency

In order to contextualise the differences in sustainable efficiency we divided up the results by relevant contextual aspects. Table 4 shows the mean sustainable efficiency scores per farm size class, age class of the farmer, soil type according to the English Nature soil type qualification, membership of LEAF (Linking Environment And Farming) and Less Favoured Area (LFA) status. According to the Wilcoxon signed-rank tests, there are some significant differences (at the 10% level) for size class, upland soils and LFAs. The results suggest that sustainable efficiency is positively associated with size, and that farms in LFAs and on upland soils have a lower sustainable efficiency. It is noted that cereal farming is not typically the main enterprise on upland farms.

We emphasise that this exercise should be regarded as a rough contextualisation rather than a rigorous assessment of the drivers of SI. For many variables, it is difficult to infer a causal connection due to confounding factors and/or reverse causality. Moreover, the sample size might be too small to make robust conclusions. In this sense, we adhere to the cautious interpretation that correlation does not necessarily imply causation.

Table 4: Mean and standard deviation (between brackets) of sustainable efficiency for contextual variables.

CONTEXTUAL VARIABLES		**SUSTAINABLE EFFICIENCY**
Size	0-33 percentile	0.62 (0.13)
	33-67 percentile	0.63 (0.12)
	67-100 percentile	0.67 (0.15)
Age	0- percentile	0.65 (0.16)
	33-67 percentile	0.64 (0.13)
	67-100 percentile	0.62 (0.11)
Soil type	Flood Plain Lowland	0.63 (0.12)
	Upland	0.50 (0.06)
	Mixed Lowland	0.66 (0.14)
	Calcareous Lowland	0.64 (0.14)
	Acidic Lowland	0.64 (0.15)
LEAF	Yes	0.66 (0.14)
	No	0.64 (0.13)
LFA	Yes	0.53 (0.08)
	No	0.64 (0.13)

3.5 Using our model for collected survey data

3.5.1 Sustainable efficiency

A number of environmental indicators can be used in the models developed (*i.e.* the models are flexible enough to make use of different environmental indicators) to obtain the SI measure. In this section we use GHG emissions, a different environmental indicator than the ones used in previous sections, areas aimed at promoting biodiversity, plus the Shannon index for crop diversity as previously used.

Using the approach developed in Section 3.1, we compute the sustainable efficiency scores for a number of commercial farms within the study areas from survey data collected within Work Package 1.2A (which will be reported separately). Essentially, we employ an intersection of the conventional technology (with conventional inputs and outputs), polluting technology, and environmental-good-generating technology. We adjust our model to the data availability of the new context by using GHG emissions as indicators of negative environmental externalities, and the Shannon index for crop diversity and areas aimed at promoting biodiversity as indicators for provisioning environmental goods.

First, as FARMSCOPER allows us to obtain a detailed assessment of the composition of GHG emissions relevant to agricultural production, we focus on overall GHG emission by aggregating methane production and nitrous oxide by their global warming potential expressed in CO_2 equivalents. Feed, agrochemicals, fertilisers and herd size are assumed to be the inputs that generate GHG emissions. Second, the Shannon index for crop diversity and areas promoting biodiversity (livestock area of non-cropped habitats being managed sympathetically for wildlife, rough and lightly grazed grassland, flower-rich habitat area and arable crops on livestock farms) are the environmental goods in our model. We treat the environmental goods as 'weakly disposable' outputs, meaning that these are assumed to be simultaneously inputs for lower levels of the environmental good and outputs for higher levels. This is in contrast with our intertemporal model in Section 3.1, which treats the environmental good as an input for the production of the subsequent period and as an output for the production of the current period. This simplification was unavoidable, as we only have data for one year. On the other hand, we believe that the combination of the two environmental goods allows us to represent the positive environmental externalities produced by the farms in a more accurate way. Third, the sample includes crop-only, mixed as well as livestock farms. The final dataset contained 43 farms.

Table 5 shows the summary statistics of the sustainable efficiency scores for the collected survey data. The average sustainable efficiency score is 0.64, which is within the range of the FBS results.

Table 5: Sustainable efficiency scores for collected survey data

Year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2015	0.34	0.48	0.65	0.64	0.76	0.97

Figure 7 shows distributions for the overall sustainable efficiency scores and their decomposition into the technology of conventional production, GHG emission and environmental goods. As with the FBS results, (partial) conventional efficiency is higher than (partial) efficiency with regard to GHG emissions and environmental goods. Note, however, that the results are not fully comparable as the farm sample, the year considered and the indicator set are all different.

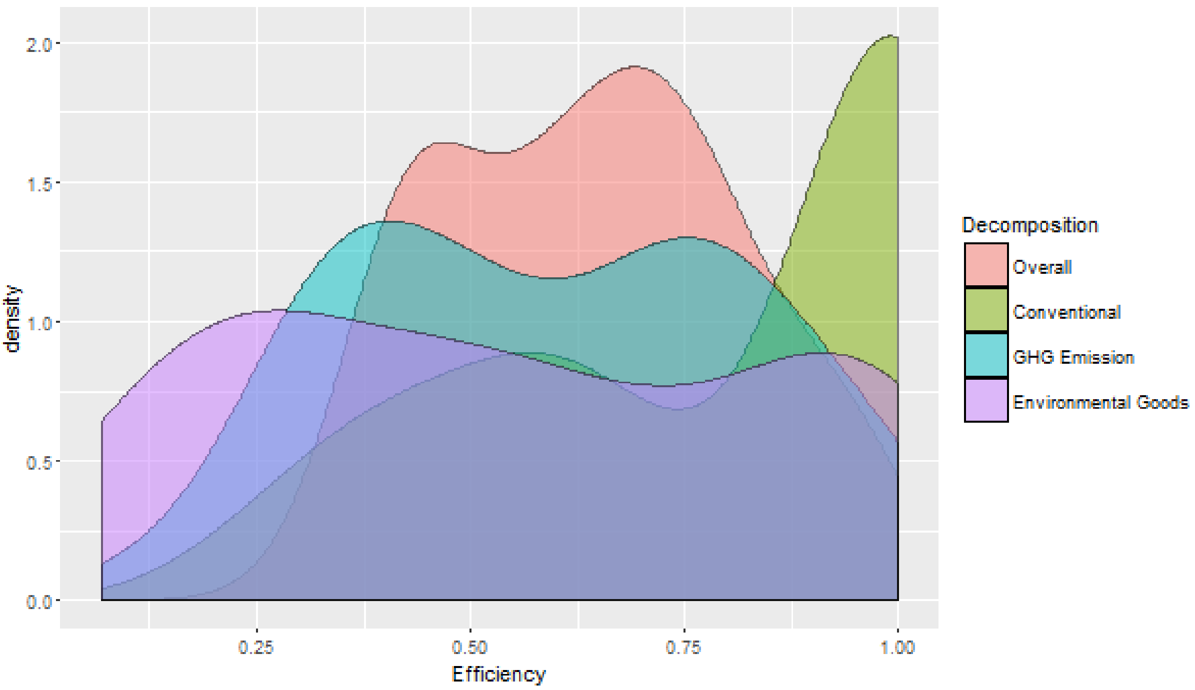

Figure 7: Overall sustainable efficiency, conventional efficiency, GHG emission efficiency and environmental goods efficiency

3.5.2 Contextualising differences in sustainable efficiency

Work Package 1.2A also collected data on the farms' characteristics and IFM/SI practices. The *caveat* of Section 3.4 holds even more as the sample size is smaller and the heterogeneity of the sample is larger: this exercise should be seen as a rough contextualisation rather than a rigorous assessment of the drivers of SI. Table 7 focuses on the IFM/SI practices implemented. There are no statistical differences between the groups.

Table 5: Mean and standard deviation (between brackets) of sustainable efficiency for IFM/SI practices[7]

IFM/SI PRACTICES	ALREADY CARRIED OUT (N=39)	WOULD CONSIDER (N=30)	WOULD NOT CONSIDER (N=21)	N/A (N=34)
TOLERANT VARIETIES	0.63 (0.18)	0.66 (0.19)	0.82 (0.10)	0.61 (0.17)
REDUCED TILLAGE	0.70 (0.17)	0.63 (0.22)	0.60 (0.24)	0.59 (0.15)
COVER CROPS	0.60 (0.18)	0.69 (0.17)	0.76 (0.16)	0.61 (0.18)
NUTRITION	0.60 (0.16)	0.67 (0.21)	0.90 (0.03)	0.74 (0.13)
RESEED PASTURE	0.63 (0.18)	0.65 (0.13)	0.63 (0.25)	0.73 (0.17)
PREDICT DISEASE OUTBREAKS	0.65 (0.19)	0.56 (0.18)	0.68 (0.12)	0.65 (0.18)
PRECISION FARMING	0.68 (0.17)	0.64 (0.21)	0.78 (0.17)	0.55 (0.12)
ENERGY USE	0.62 (0.20)	0.64 (0.16)	0.71 (0.19)	0.61 (0.07)
OPIMISE MARGINAL LAND FOR ES	0.64 (0.17)	0.62 (0.24)	0.92 (NA)	NA
TRAINING	0.67 (0.17)	0.70 (0.24)	0.92 (NA)	0.60 (NA)

[7] N= sum of the observations per column (N = 39 means that summing up all observations carrying out the IFM/SI practices is equal to 39)

Table 6 shows the results for perceived involvement (either formally or informally) in cooperation or joint-working with other farmers as an approximation of social capital. Again, we do not find statistical differences between the groups.

Table 6: Mean and standard deviation (between brackets) of sustainable efficiency for involvement variables

SOCIAL CAPITAL	CURRENTLY INVOLVED (N=37)	PREVIOUSLY INVOLVED (N=13)	WOULD CONSIDER (N=17)	NOT INVOLVED (N=39)	DOES NOT REGARD AS COOPERATION (N=5)
BUYING GROUP	0.70 (0.16)	0.53 (0.14)	0.74 (0.24)	0.61 (0.17)	NA
DISCUSSION GROUP	0.63 (0.17)	0.70 (0.38)	0.66 (0.23)	0.67 (0.16)	NA
PRODUCER ORG. / COOPERATIVE	0.72 (0.14)	NA	0.68 (0.18)	0.58 (0.17)	0.97 (NA)
TRADE UNION	0.63 (0.18)	NA	0.71 (NA)	0.69 (0.21)	0.74 (NA)
COMMONS	0.61 (0.23)	0.69 (NA)	NA	0.65 (0.17)	NA
ENVIRONMENTAL MANAGEMENT	0.63 (0.20)	NA	0.60 (0.15)	0.64 (0.17)	0.92 (NA)
CONTRACT LIVESTOCK	0.81 (NA)	NA	0.64 (0.20)	0.64 (0.18)	NA
CONTRACT CROPS	0.75 (0.21)	0.73 (0.04)	0.70 (0.37)	0.61 (0.16)	0.64 (0.33)
S-T KEEP OF LIVESTOCK	0.66 (0.19)	0.39 (NA)	0.55 (0.14)	0.66 (0.17)	NA
SHARE FARMING	0.70 (0.14)	0.73 (0.13)	0.61 (0.28)	0.63 (0.17)	NA
SHARING LABOUR	0.68 (0.18)	NA	0.71 (0.28)	0.61 (0.16)	NA
SHARING MACHINERY	0.69 (0.17)	0.78 (0.13)	0.42 (0.02)	0.60 (0.17)	NA
SWAPPING MANURE	0.70 (0.08)	NA	0.70 (0.38)	0.64 (0.18)	0.40 (NA)

In the light of the lack of significant differences, we are very cautious to make conclusions about the contextual variables of sustainable efficiency. There could be several reasons for these insignificant results. The sample size is small for the number of groups. Moreover, in contrast to our analysis focusing on FBS cereal farms, the sample is very heterogeneous.[8]

[8] We have also conducted a second-stage Ordinary Least Squares regression including farmers' age, the ratio of subsidies to revenues and education. However, the results remain overwhelmingly insignificant. Most likely, the sample is too small to find the drivers of sustainable efficiency.

3.6 Shadow-pricing environmental goods and negative environmental externalities

Note: a full version of this is being prepared for submission to *Land Economics*. Appendix 5 provides a review of shadow-pricing of positive and negative environmental externalities, a technical explanation of the method and a detailed discussion of the results.

3.6.1 A technical review

Understanding firms' marginal costs and benefits of positive and negative environmental externalities is essential for an effective policy intervention. Therefore, we conducted a review of shadow prices of positive and negative environmental externalities. The shadow price indicates the opportunity cost of increasing the environmental good, or decreasing the negative environmental externality, by one unit. The key message from this review is that shadow-pricing of positive and negative environmental externalities critically depends on how the externality is implemented in the production economics framework. Only recently, the literature has begun to gain a more complete understanding about how negative environmental externalities could be rigorously implemented in such a framework to calculate the shadow price. The literature on environmental goods is scarcer and seems to make the same mistakes as the original literature on negative environmental externalities: various *ad hoc* assumptions are being made without any theoretical justification. In fact, the ecological literature seems to strongly suggest that the current common practice of implementing an environmental good as a conventional output within a convex environmental technology set may be too restrictive (Chavas and Di Falco, 2012; Di Falco and Chavas, 2009; Ruijs et al., 2013; Ruijs *et al.*, 2015).

3.6.2 A method to assess the opportunity cost of crop diversification

We developed a new method to measure the opportunity cost of crop diversification for a balanced sample of 44 FBS cereal farms covering 2007-2013. Instead of implementing the environmental good (Shannon index for crop diversity) as a conventional output, we only implement conventional inputs and outputs in our production economics framework. As such, we refrain from making questionable assumptions about the properties of the environmental good. We calculate maximum long-run, 'dynamic' profit for the current land allocation and for the optimal land allocation. This enables us to express the opportunity cost of crop diversification in terms of foregone long-term profit due to misallocation of land use.

Table 6 shows the computed opportunity costs of the Shannon index for crop diversity. In what follows, we express the opportunity cost as the average cost (in constant 2007 £) of increasing the Shannon index by 0.1 unit per hectare. The average opportunity cost is -£101 for the period, ranging from -£244 (in 2009) to +£34 (in 2007). Only in the year 2007 was there an average positive opportunity cost, which may be due to the fact that it was the last year of 'set-aside'. Over the whole period, farms are on average 'willing to pay' for crop diversification. The opportunity costs of (almost) dynamically profit-maximizing farms are on average positive. Their average opportunity cost is £4 for the period, ranging from -£14 (in 2013) to £50 (in 2008).

67% of farms would gain from crop diversification and so might be willing to pay for it (technically 67% of the full sample of farms have a negative opportunity cost for crop diversification). 19% of the calculated opportunity costs are zero, and only 15% are positive. This proportion is consistent for the whole time period. The results also indicate that optimal reallocation of land use, which would have maximized long-run profit, would have led to increased compliance (by on average 26%) with the CAP's recently introduced '2 or 3 crop rule'. The standard deviations are very large. This means that there is substantial heterogeneity in the opportunity costs of crop diversification. Despite the consistency of the trends, there seems to be variability in the actual values of the computed opportunity costs. The usual approach of assessing the opportunity cost of providing an additional unit of the environmental good imposes non-negativity (*e.g.*, Sipiläinen and Huhtala 2013). This would always lead to the policy implication that farmers should be compensated for increasing the environmental good. Our results are thus important, as they suggest that most farms do not need to be compensated for crop diversification and are even willing to pay for this as it could increase long-run profits.

Table 7. Opportunity costs of the Shannon index for crop diversification per 0.1 ha using the proposed method, 2007-2013

Year	Number of farms	Average (in constant 2007 £)	Std. Dev. (in constant 2007 £)	Share		
				Negative	0	Positive
2007	44	34	290	55%	25%	20%
2008	44	-149	830	73%	18%	9%
2009	44	-244	1531	77%	18%	5%
2010	44	-21	159	59%	23%	18%
2011	44	-110	481	59%	18%	23%
2012	44	-105	564	66%	16%	18%
2013	44	-113	257	80%	11%	9%
Period	308	-101	730	67%	19%	15%

4. CONCLUSIONS, RECOMMENDATIONS AND FURTHER WORK

This report describes how SI can be assessed through efficiency and productivity measures that are augmented with positive and negative environmental externalities. These measures enable us to identify farms that have scope to improve in relation to SI. Using DEA, our empirical application focused on FBS cereal farms as well as (different types of) farm data collected through the survey of study area farms undertaken as part of Work Package 1.2A.

Various general lessons can be drawn from our research. First, augmenting efficiency measures with positive and negative environmental externalities shows a more holistic picture of farm performance. Conventional efficiency scores may be lower than augmented sustainable efficiency scores leading to a misleading picture of farm sustainability. Second, augmented productivity measures are conceptually in line with 'Sustainable *Intensification*' in the sense that they assess how sustainable performance *dynamically changes over time.* A particularly convenient feature is that this builds theoretically and empirically on the sustainable efficiency framework. It shows how sustainable efficiency as well as the sustainable frontier changes over time. Third, our approach shows the importance of taking into account the intertemporal character of environmental factors. This has long been recognised by ecological economists, who suggested that one should consider the natural capital stock yielding ecosystem services. Our approach takes into account that ecosystem services are yielded simultaneously with conventional production, and part of the natural capital stock can be carried over as inputs for future production. Fourth, our research illustrates that one should be wary of 'hidden' assumptions about how positive and negative environmental externalities are implemented in the efficiency and productivity framework. We have shown that modelling environmental goods as conventional outputs leads to the assumption that increases of the environmental good are always costly for the farmer. Our empirical application to crop diversity suggests that long-term profit maximization is in fact positively associated with crop diversity. A more flexible approach to deployment of incentives and rewards might thus be needed. Fifth, this report shows that our efficiency and productivity framework is flexible in that it can be easily enriched with more and better data on the positive and negative environmental externalities, as evidenced by the application of our model to farm data collected through the Work Package 1.2A survey.

Regarding the efficiency analysis applied to the FBS cereal farms, we found that the 53 kg of nitrogen per hectare is overused compared to the pollution-minimising benchmark. The average sustainable efficiency of the FBS cereal farms decreased from 2012 (0.69) to 2013 (0.59). Our productivity measure provides more detailed information about this shift: it suggests that there was a sustainable productivity decline (0.93) in 2012-2013 due to a decline in efficiency (0.88), which was partly offset by an increase in technical change (1.11). This means that the FBS cereal farms on the frontier increased their performance with regard to SI, but that the inefficient farms did not manage to keep up with the frontier farms and even deteriorated in terms of SI. We also tried to contextualise the differences in sustainable efficiency for the FBS cereal farms. We found that sustainable efficiency is positively associated with size and that cereal farms in LFAs and upland soils have a lower SI efficiency. Nevertheless, we emphasise that caution is required to interpret these results given the small sample size. The sustainable efficiency for the data collected through the survey from Work Package 1.2A was on average 0.64. We could not find robust conclusions about the drivers, most likely due to the heterogeneity of the dataset and small sample size.

Furthermore, we reviewed the literature on shadow-pricing positive and negative environmental externalities (*i.e.* calculating the opportunity cost of increasing the environmental good, or decreasing the negative externality, by one unit). The most important message of this review is that shadow-pricing of positive and negative environmental externalities critically depends on how the externality is represented in the production economics framework. Addressing the problems of computing the shadow-price of crop diversification, we developed a new measure and found that for many farms crop diversification is generally associated with an increase in long-run profit. This is in contrast with the state-of-the-art of the academic literature, which assumes that crop diversification is always costly for farmers. A more flexible approach to deployment of incentives and rewards might thus be needed.

Our approach is in line with the ongoing developments of agricultural policy-oriented research. The OECD currently has a working group which explicitly recommends 'greening' of productivity measures. The working group points out that an appropriate representation of pollutants in the production technology is necessary. It advocates doing so by taking into account the material balance and/or using a network model. Moreover, the working group has suggested taking into account the intertemporal characteristics of environmental factors that can be carried over from year to year. Our approach is clearly in line with these recommendations. Using the terms of the latest G20 Meeting of Agricultural Chief Scientists on 25 April 2016, our approach can be seen as a shift of focus on Total Factor Productivity (TFP, which only incorporates marketed inputs and outputs) to 'Total Resource Productivity' (which in addition includes non-marketed inputs and outputs).

Our main recommendation is to collect additional, more detailed data. We believe it is worthwhile to make a more detailed account of the spatial and temporal characteristics of positive and negative environmental externalities. Appropriately assessing soil quality would substantially improve the analysis of providing environmental goods. In particular, this would more closely align our framework with the concept of a natural capital stock yielding ecosystem services. This would realistically model the intertemporal trade-off faced by farmers between using soil carbon for current production and for future production. In addition, future studies would benefit from spatially specific nutrient coefficients. This would enable analysts to increase the accuracy of identifying farms with scope to improve in relation to SI and the identification of drivers of SI.

5. KEY MESSAGES

1. Farm sustainability can be measured and assessed by augmenting efficiency measures with positive and negative environmental externalities.
2. The approach taken can be seen as a shift of focus from Total Factor Productivity to 'Total Resource Productivity' (which in addition to market input and outputs includes non-marketed inputs and outputs).
3. We found that long-term profit maximization is positively associated with crop diversity.
4. Generally FBS cereal farms can both improve their efficiency levels and minimise their nitrogen use. We found that FBS cereal farms overused 53 kg of nitrogen per hectare compared to the pollution-minimising benchmark
5. Efficient FBS cereal farms increased their SI performance in 2013 with respect to 2012. However, inefficient farms did not manage to keep up with the efficient farms and even deteriorated in terms of SI.
6. A more detailed account of the spatial and temporal characteristics of positive and negative environmental externalities would be required to provide accurate information to decision makers on farm SI performance.

6. LIST OF OUTPUTS AND PUBLICATIONS

Knowledge Exchange

Aspects of this research have been presented at the following conferences:

- Agricultural Economics Society Conference. Warwick, April 2015
- 14th European Workshop on Efficiency and Productivity Analysis Helsinki, June 2015
- Agricultural and Applied Economics Association Annual Meeting. San Francisco, July 2015
- SIP Science meetings held in Leamington Spa (March 2015) and Bangor (April 2016)

Academic Papers

Papers currently in preparation are as follows:

- European Journal of Operational Research (environmental inefficiency)
- Ecological Economics (sustainable productivity growth)
- Land Economics (shadow pricing environmental goods and bads)

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8. APPENDICES

Appendix 1 Sustainable efficiency

Data

All quantitative data are taken from the FBS dataset for the years 2012-13 and 2013-14. In order to obtain a homogenous sample, our application considers 93 pure cereal farms that do not produce any livestock. The farms are geographically spread throughout England and Wales. All size classes are represented. We only include the farms that have completed the fertiliser survey.

We use data on variable inputs, quasi-fixed inputs, fixed factors and outputs. Land and labour are considered fixed factors. Aggregated cereal output is our conventional output. Variable inputs, quasi-fixed inputs and outputs are expressed in constant 2012 £. Land and labour are expressed in annual work hours and hectares, respectively. Table 1 presents the summary statistics of our dataset. The nutrient coefficients for both inputs and outputs are obtained from the OECD (2015) database (also see Appendix 2). This allows us to compute the nitrogen (N) and phosphorus (P) surplus.

Table 1: Summary statistics of dataset.

Variables	Unit	Mean	Minimum	Maximum	Std. dev.
Total Variable Inputs	2012 £	182,099	22,832	971,518	156,548
Capital Replacement Cost	2012 £	2,569,220	39,884	13,041,065	2,440,613
Land	Hectares	178	14	697	142
Labour	Annual Work Hours	4,105	250	27,310	3,662
Cereal Output	2012 £	428,888	59,194	2,534,420	376,514
Nitrogen Surplus	kg	21,287	-2,301	218,737	24,951
Phosphorus Surplus	kg	4,062	-8,977	248,258	18,436

Method

Murty, Russell and Levkoff (2012) show how one can take into account the material balances concerns coined by Coelli, Lauwers and Van Huylenbroeck (2007) in a distance function approach by separately modelling the conventional and polluting technology. Serra, Chambers and Oude Lansink (2014) adapt this approach to a context of Spanish cereal farms. We extend their work to a dynamic context of environmental productivity growth. This approach has two distinct advantages compared to the original approach of Coelli, Lauwers and Van Huylenbroeck (2007). First, the measure can more adequately incorporate multiple pollutants. Instead of assigning subjective weights to the environmental impact, it seeks a coordinate-wise maximum average expansion of production of conventional outputs simultaneously with a coordinate-wise maximum average reduction of N surplus as well as P surplus. Second, it allows for a more natural representation of potential abatement. Capital and labour can be used to decrease the N and P surplus, but need not to be perfect substitutes of the latter.

There are J firms, $j \in \Re_+^J$. We define a technology set that includes a vector of N non-polluting inputs (*e.g.* labour), $x \in \Re_+^N$, a vector of K polluting inputs (*e.g.* fertilisers, seeds), $r \in \Re_+^K$, a vector of M conventional outputs (*e.g.* cereals produced), $y \in \Re_+^M$, a vector of runoff outputs from the polluting inputs (*e.g.* N and P surplus), $z \in \Re_+^N$, and a vector of environmental goods $e \in \Re_+^O$.

The general technology is defined as:

(1) $$T = \{(x_t, r_t, y_t, z_t, e_{t-1}, e_t): (x_t, r_t, e_{t-1})\ can\ produce\ (y_t, z_t, e_t)\}$$

The material balance condition (*i.e.* nutrient runoff) is defined as the nutrients in the inputs, r_k, minus the nutrients absorbed by the outputs, p_k:

(2) $$z_k = r_k - p_k$$

The nutrients absorbed by the outputs, p_k, can be treated as an input. Moreover, we assume that the production of environmental goods in the previous year serves as inputs of the conventional production of the current year. The production technology T^Y is modelled as:

(3) $$T^Y = \left\{(x_t, r_t, y_t, z_t, e_{t-1}): \left(x_t, r_{t,1} - z_{t,1}, \ldots, r_{t,k} - z_{t,k}, e_{t-1}\right)\ can\ produce\ y_t\right\}$$

The polluting technology transforms the vector of polluting and non-polluting inputs to a vector of runoff outputs. It is thus assumed that non-polluting inputs such as labour and capital have a (negative) differential impact on the runoff outputs. The polluting technology T^Z is modelled as:

(4) $$T^Z = \{(x, r, y, z): (x, r)\ can\ produce\ z\}$$

For the environmental-good-producing technology T^E, we assume that the production of environmental goods in the previous year serves as inputs of the production of environmental goods in the current year. Moreover, we assume that there is a trade-off between the production of environmental goods and the production of conventional outputs in the same year. It is modelled as:

(5) $$T^E = \{(y_t, e_{t-1}, e_t): (-y_t, e_{t-1})\ can\ produce\ e_t\}$$

The general technology is modelled as the intersection of a production technology and polluting technology:

(6) $$T = T^Y \cap T^Z \cap T^E$$

We use Data Envelopment Analysis (DEA) to approximate Eqs. (3)-(6). The time periods of the technology and of the observation are denoted by respectively s and t. Assuming that there is one conventional output, an efficiency measure for the production technology in Eq. (3) is estimated as:

(7) $$\min_{\beta,\lambda} \beta^{s,t}\ \ s.t. \textstyle\sum_{j=1}^{J} \lambda^{j,s} x^{j,s} \leq x^t, \sum_{j=1}^{J} \lambda^{j,s}\left(r_k^{j,s} - z_k^{j,s}\right) \leq r_k^t - z_k^t, \sum_{j=1}^{J} \lambda^{j,s} y^{j,s} \geq y^{j,t}/\beta$$

Assuming that there are two runoff outputs (N and P surplus in our application), an efficiency measure for the polluting technology in Eq. (4) is estimated as:

(8) $$\min_{\gamma_1,\gamma_2,\mu} \frac{\gamma_1^{s,t}+\gamma_2^{s,t}}{2}\ s.t. \textstyle\sum_{j=1}^{J} \mu^{j,s} x^{j,s} \leq x^t, \sum_{j=1}^{J} \mu^{j,s} z_k^{j,s} \leq \gamma_k z_k^t, \sum_{j=1}^{J} \mu^{j,s} r_k^j \geq r_k^t$$

An efficiency measure for the technology regarding the environmental goods in Eq. (5) is estimated as:

(9) $$\min_{\delta,\lambda} \delta^{s,t}\ \ s.t. \textstyle\sum_{j=1}^{J} \lambda^{j,s} e^{j,s-1} \leq e^{t-1}, \sum_{j=1}^{J} \lambda^{j,s} e^{j,s} \geq e^{j,t}/\delta, \sum_{j=1}^{J} \lambda^{j,s} y^{j,s} \geq y^{j,t}/\delta$$

The Färe-Grosskopf-Lovell index is computed as the arithmetic average of Eqs (8)-(10) to describe the general technology:

(10) $$E^{s,t}(x, r, y, z, e) = \frac{1}{3}\left(\beta^{s,t} + \frac{\gamma_1^{s,t}+\gamma_2^{s,t}}{2} + \delta^{s,t}\right)$$

To calculate sustainable efficiency, we compute $E^{t,t}(x, r, y, z, e)$ with $s = t$.

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Appendix 2 Environmental efficiency

Consider a firm that transforms a vector of $m = 1 \ldots M$ inputs, $x \in \mathbb{R}_+^M$, to a vector of $n = 1 \ldots N$ outputs, $y \in \mathbb{R}_+^N$.

The feasible set is defined as:

$$P = \{(y, x): x\ can\ produce\ y\} \quad (1)$$

Assuming that P satisfies the standard properties of convexity, compactness and strong disposability of inputs and outputs, the directional distance function is defined as (Chambers *et al.*, 1996):

$$\vec{D}_T(x, y; g_x, g_y) = \max_{\beta} \{\beta: (x - \beta g_x, y + \beta g_y) \in P)\} \quad (2)$$

where g_x and g_y are the directional vectors that specify the direction of respectively input contraction and output expansion towards the frontier. $\vec{D}_T(.)$ is a measure of technical inefficiency as it assesses the distance to the frontier in the direction of (g_x, g_y). The directional vectors are exogenously chosen by the researcher.

The firm also emits pollutants. We assume that some or all inputs and outputs have a proportionate content of the single polluting nutrient given by a and b which are $(M \times 1)$ and $(N \times 1)$ vectors of non-negative nutrient coefficients (Coelli *et al.*, 2007). Pollution is defined by the difference between the levels of the polluting nutrient in the outputs and inputs given by the material balance equation, $z = a'x - b'y$.[9]

From an environmental perspective it is appropriate to minimise pollution. This is translated to

$$-z^*(x, y) = \max_{x,y} \{x, y: b'y - a'x \in P\} \quad (3)$$

which makes the analogy to profit maximisation explicit.

Solving Eq. (3) yields the input and output levels that minimise pollution. Analogous to profit inefficiency (Chambers *et al.*, 1996), environmental inefficiency is defined as (Van Meensel and Lauwers, 2013):

$$EI = \frac{(a'x - b'y) - z^*(x,y)}{a'g_x + b'g_y} \quad (4)$$

where environmental inefficiency EI is the normalised deviation between actual and minimised pollution.

Continuing the analogy, environmental inefficiency can be decomposed into technical and allocative components (Van Meensel and Lauwers, 2013):

$$\frac{(a'x - b'y) - z^*(x,y)}{a'g_x + b'g_y} = D_T(x, y; g_x, g_y) + EAI \quad (5)$$

where EAI denotes environmental allocative inefficiency.

To define the environmentally optimal directional vector, we adapt the Zofio *et al.* (2013) measure of profit inefficiency and introduce an environmental inefficiency measure where the directional vectors point towards the pollution-minimising benchmark.

[9] It is theoretically possible to decrease pollution by using abatement technology. In practice, however, cereal farms do not incur additional costs on technology to decrease the nitrogen surplus.

First, we obtain the usual directional distance function for firm $j = 1, \dots, J$ by solving the following Data Envelopment Analysis (DEA) problem[10]:

$$\vec{D}_T^1(x, y, L;\ g_x, g_y) = \max_{\beta,\gamma} \beta \tag{6}$$

s.t.

$$\sum_{j=1}^{J} \gamma^j x^j \leq x_m - \beta g_{x_m}, m = 1, \dots, M$$

$$y_n + \beta g_{y_n} \leq \sum_{j=1}^{J} \gamma^j y^j\ , n = 1, \dots, N$$

$$\sum_{j=1}^{J} \gamma^j = 1$$

$$\gamma^j \geq 0, j = 1, \dots, J$$

Second, we obtain the directional distance function with optimal environmental directional vectors for firm $j = 1, \dots, J$ by solving the following DEA problem:

$$\vec{D}_T^2(x, y, L;\ g_{x_m}^*, g_{y_n}^*) = \max_{\beta,\gamma,g_{x_m}^*,g_{y_n}^*} \beta \tag{7}$$

s.t.

$$\sum_{j=1}^{J} \gamma^j x^j \leq x_m - \beta g_{x_m}^*, m = 1, \dots, M$$

$$y_n + \beta g_{y_n}^* \leq \sum_{j=1}^{J} \gamma^j y^j\ , n = 1, \dots, N$$

$$\sum_{m=1}^{M} a_m g_{x_m}^* + \sum_{n=1}^{N} b_n g_{y_n}^* = 1$$

$$\sum_{j=1}^{J} \gamma^j = 1$$

$$\gamma^j \geq 0, j = 1, \dots, J$$

In contrast to Eq. (6), Eq. (7) endogenises the directional vectors by the third constraint. The directional vectors are optimised in such a way that they point towards the pollution-minimising benchmark while

[10] In line with Zofio *et al.* (2013), we choose $g_{x_m} = g_{y_n} = 1/(\sum_{m=1}^{M} a_m + \sum_{n=1}^{N} b_n)$.

ensuring that $(g_x^*, g_x^*) \neq (0_M, 0_N)$ and $\sum_{m=1}^{M} a_m g_{x_m}^* + \sum_{n=1}^{N} b_n g_{y_n}^* = 1$. If $\vec{D}_T^2(.) > 0$, the firm is environmentally inefficient and can curb pollution. Eq. (6) shows the source of environmental inefficiency. If $\vec{D}_T^1(.) > 0$, environmental inefficiency is due to technical inefficiency. This inefficiency may be caused by wrong engineering practices. If $\vec{D}_T^1(.) = 0$, environmental inefficiency is due to environmental allocative inefficiency. In this case, the firm lies on the frontier, but divert their inputs and outputs away from the pollution-minimising benchmark given the proportionate nitrogen contents.

Although Eq. (7) is a non-linear program, it can be linearised without changing the objective function by setting $\mu_{x_m} = \beta g_{x_m}^*$ and $\mu_{y_n} = \beta g_{y_n}^*$. As a result, $\sum_{m=1}^{M} a_m g_{x_m}^* + \sum_{n=1}^{N} b_n g_{y_n}^* = 1$ becomes $\sum_{m=1}^{M} a_m \mu_{x_m} + \sum_{n=1}^{N} b_n \mu_{y_n} = \beta$. This modification is equivalent if and only if $\beta > 0$ (Zofio *et al.*, 2013).

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Appendix 3 Sustainable productivity growth

Data

We refer to Appendix 1 (Sustainable efficiency) for a description of the data.

Method

Our approach is based on the distance functions in $E(.)$ developed in Appendix 1 (Sustainable efficiency).

We use the environmental Malmquist productivity index to assess environmental productivity. An example of an application of the Malmquist index in an environmental context can be found in Hoang and Coelli (2011). The environmental Malmquist productivity index for time period u is computed as:

$$(1) \qquad M_u(.) = \frac{E^{u,u+1}(.)}{E^{u,u}(.)}$$

The environmental Malmquist productivity index for time period $u+1$ is computed as:

$$(2) \qquad M_{u+1}(.) = \frac{E^{u+1,u+1}(.)}{E^{u+1,u}(.)}$$

The environmental Malmquist productivity change between u and $u+1$ is the geometric mean of Eqs (9) and (10):

$$(3) \qquad MC_{u,u+1}(.) = \left[\frac{E^{u,u+1}(.)}{E^{u,u}(.)} \times \frac{E^{u+1,u+1}(.)}{E^{u+1,u}(.)}\right]^{\frac{1}{2}}$$

Eq. (11) can be decomposed into technical efficiency change and technical change. Technical efficiency change is defined as:

$$(4) \qquad TEC_{u,u+1}(.) = \frac{E^{u+1,u+1}(.)}{E^{u,u}(.)}$$

$TEC_{u,u+1}(x, r, y, z)$ is always larger than zero. If it is higher (lower) than unity, technical efficiency has improved (worsened) in time.

Technical change is defined as:

$$(5) \qquad TC_{u,u+1}(.) = \left[\frac{E^{u,u}(.)}{E^{u+1,u}(.)} \times \frac{E^{u,u+1}(.)}{E^{u+1,u+1}(.)}\right]^{\frac{1}{2}}$$

$TC_{u,u+1}(x, r, y, z)$ is also always larger than zero. If it is higher (lower) than unity, the firm experiences technical progress (regress).

Figure 1 shows environmental productivity growth in (z, r) dimension. Firm A has an allocation of (z, r) of A^1 and A^2 at time 1 and time 2, respectively. The corresponding technology sets are denoted by $T^{Z,1}$ and $T^{Z,2}$. The technical efficiency changes from $\frac{|O^1B^1|}{|O^1A^1|}$ to $\frac{|O^2B^2|}{|O^2A^2|}$. As a result, $TEC_{1,2}(.) = \frac{|O^1B^1|}{|O^1A^1|} / \frac{|O^2B^2|}{|O^2A^2|} > 1$, indicating an increase in technical efficiency. The technical change is the geometric mean of $\frac{|O^1B^1|}{|O^1B^{2\prime}|}$ and

$\frac{|O^2B^{1'}|}{|O^2B^2|}$. As a result, $TEC_{1,2}(.) = \sqrt{\frac{|O^1B^1|}{|O^1A^1|}\Big/\frac{|O^1B^{2'}|}{|O^1A^1|} \times \frac{|O^2B^{1'}|}{|O^2A^2|}\Big/\frac{|O^2B^2|}{|O^2A^2|}} > 1$. The technical frontier shifts downwards, indicating technical progress in (z, r) dimension[11].

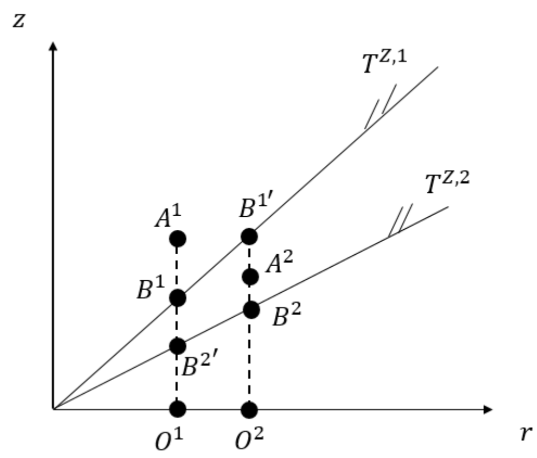

Figure 1: Environmental productivity growth in (z, r) dimension.

Reference List

Hoang V-N, Coelli T. 2011. Measurement of agricultural total factor productivity growth incorporating environmental factors: A nutrients balance approach. *Journal of Environmental Economics and Management* 62:462-474.

[11] The best-practice benchmark can generate less runoff (*e.g.* N surplus) for a given level of polluting input (*e.g.* fertiliser).

Appendix 4 Collected survey data – Sustainable efficiency

Method

Our model is based on Appendix 1 (Sustainable efficiency). However:

There are J firms, $j \in \Re_{+}^{J}$. We define a technology set that includes a vector of N non-polluting inputs (*e.g.* labour), $x \in \Re_{+}^{N}$, a vector of K polluting inputs (*e.g.* fertilisers, seeds), $r \in \Re_{+}^{K}$, a vector of M conventional outputs (*e.g.* cereals produced), $y \in \Re_{+}^{M}$, a vector of runoff outputs from the polluting inputs (*e.g.* greenhouse gas (GHG) emission), $z \in \Re_{+}^{N}$, and a vector of environmental goods $e \in \Re_{+}^{O}$.

The general technology is defined as:

(1) $$T = \{(x_t, r_t, y_t, z_t, e_t): (x_t, r_t)\ can\ produce\ (y_t, z_t, e_t)\}$$

The material balance condition (*i.e.* GHG emission) is obtained from the FARMSCOPER model.

We assume that conventional outputs are generated by conventional inputs. Moreover, this process produces environmental goods as by-products, which we treat as weakly disposable outputs. The conventional technology T^Y is modelled as:

(2) $$T^Y = \{(x_t, y_t, e_t): x_t\ can\ produce\ (y_t, e_t)_t\}$$

The polluting technology transforms the vector of polluting inputs to a vector of runoff outputs. The polluting technology T^Z is modelled as:

(3) $$T^Z = \{(x, r, z): (x, r)\ can\ produce\ z\}$$

For the environmental-good-producing technology T^E, we assume that the production of environmental goods is driven by a sub-vector of inputs $x_{t,E}$ that generate the environmental goods. Moreover, we assume that there is a trade-off between the production of environmental goods and the production of conventional outputs. This is modelled as:

(4) $$T^E = \left\{(y_t, e_t): \left(-y_t, x_{t,E}\right)\ can\ produce\ e_t\right\}$$

The general technology is modelled as the intersection of a production technology and polluting technology:

(5) $$T = T^Y \cap T^Z \cap T^E$$

We use Data Envelopment Analysis (DEA) to approximate Eqs. (3)-(5). Assuming that there is one conventional output, an efficiency measure for the production technology in Eq. (3) is estimated as:

(6) $$\min_{\beta,\lambda} \beta^{s,t}\ \ s.t. \textstyle\sum_{j=1}^{J} \lambda^{j,s} x^{j,s} \le x^t, \sum_{j=1}^{J} \lambda^{j,s} y^{j,s} \ge \frac{y^{j,t}}{\beta}, \sum_{j=1}^{J} \lambda^{j,s} e^{j,s} = e^t$$

Assuming that there is one runoff output (GHG emission), an efficiency measure for the polluting technology in Eq. (4) is estimated as:

(7) $$\min_{\gamma_1,\mu} \gamma_1^{s,t}\ \ s.t. \textstyle\sum_{j=1}^{J} \mu^{j,s} z_k^{j,s} \le \gamma_k z_k^t, \sum_{j=1}^{J} \mu^{j,s} r_k^j \ge r_k^t$$

An efficiency measure for the technology regarding the environmental goods in Eq. (5) is estimated as:

(8) $$\min_{\delta,\lambda} \delta^{s,t}\ \ s.t. \textstyle\sum_{j=1}^{J} \lambda^{j,s} x_E^{j,s} \le x_E^{j,s}, \sum_{j=1}^{J} \lambda^{j,s} e^{j,s} \ge e^{j,t}/\delta, \sum_{j=1}^{J} \lambda^{j,s} y^{j,s} \ge y^{j,t}/\delta$$

The Färe-Grosskopf-Lovell index is computed as the arithmetic average of Eqs. (6)-(8) to describe the general technology:

(9) $E^{s,t}(x,r,y,z,e) = \frac{1}{3}\left(\beta^{s,t} + \gamma_1^{s,t} + \delta^{s,t}\right)$

To calculate sustainable efficiency, we compute $E^{t,t}(x,r,y,z,e)$ with $s = t$.

Appendix 5 Environmental Goods as Conventional Outputs in a Distance Function

Theoretical Background

Consider a firm that transforms a vector of $m = 1 \dots M$ inputs, $x \in \mathbb{R}_+^M$ to a vector of $n = 1 \dots N$ outputs, $y \in \mathbb{R}_+^N$. This transformation also yields a vector of $d = 1 \dots D$ environmental goods, $e \in \mathbb{R}_+^D$. In analogy to treating pollutants as inputs in the tradition of Baumol and Oates (1988), environmental goods are commonly assumed to have the same axiomatic properties as outputs. All feasible combinations of inputs, outputs and environmental goods (x, y, e) are characterised by the primitive technology set T:

$$(1) \qquad T = \{(x, y, e) : x \text{ can produce } (y, e)\}$$

T is assumed to be a closed, bounded and convex technology set with strongly disposable inputs, outputs and environmental goods. Most reviewed studies employ an output set, holding inputs constant. However, this keeps the relationship between inputs and environmental goods implicit. The primitive technology set encompasses the output set and makes this relationship explicit (Färe and Grosskopf, 2005). Following Chambers *et al.* (1996), Chambers *et al.* (1998), Eq. (1) can be equally represented by the directional distance function $\vec{D}_T(x, y, e; g_x, g_y, g_e)$:

$$(2) \qquad \vec{D}_T(x, y, e; g_x, g_y, g_e) = \max_{\beta} \{\beta : (x - \beta g_x, y + \beta g_y, e + \beta g_e) \in T\}$$

where g_x, g_y and g_e are the directional vectors that specify the direction of respectively input contraction, output expansion and environmental good expansion towards the frontier. $\vec{D}_T(.) \geq 0$ is differentiable and measures the distance to the frontier in the direction of (g_x, g_y, g_e).

The derivative of $\vec{D}_T(.)$ with respect to outputs is:

$$(3) \qquad \nabla_y \vec{D}_T(x, y, e; g_x, g_y, g_e) \leq 0$$

The derivative of $\vec{D}_T(.)$ with respect to inputs is:

$$(4) \qquad \nabla_x \vec{D}_T(x, y, e; g_x, g_y, g_e) \geq 0$$

The derivative of $\vec{D}_T(.)$ with respect to environmental goods is:

$$(5) \qquad \nabla_e \vec{D}_T(x, y, e; g_x, g_y, g_e) \leq 0$$

Although environmental goods are non-marketed, we can assess the unknown shadow price u by exploiting the directional distance function's dual relationship to the profit function and using the envelope theorem. The profit function $\Pi(w, p, u)$ maximises profit for prices (w, p, u) given $P(x)$ (Chambers *et al.*, 1996, Chambers *et al.*, 1998):

$$(6) \qquad \Pi(w, p, u) = \max_{x,y,e} \{x, y, e : p'y + u'e - w'x \in T\}$$

The Trade-Off between Environmental Goods and Conventional Outputs

The trade-off between environmental goods and conventional outputs can be inferred using the envelope theorem (Chambers *et al.*, 1996, Chambers *et al.*, 1998):

$$(7) \qquad -\frac{\nabla_e \vec{D}_T(x,y,e;g_x,g_y,g_e)}{\nabla_y \vec{D}_T(x,y,e;g_x,g_y,g_e)} = -\frac{u}{p} \leq 0$$

Eq. (7) assumes that the shadow price u is positive and the relationship between marketable outputs and environmental goods is competitive for *all* levels of the environmental good. Figure 1 shows the production possibility frontier for one environmental good e_1 and one marketable output y_1, holding other environmental goods, other outputs and inputs constant.

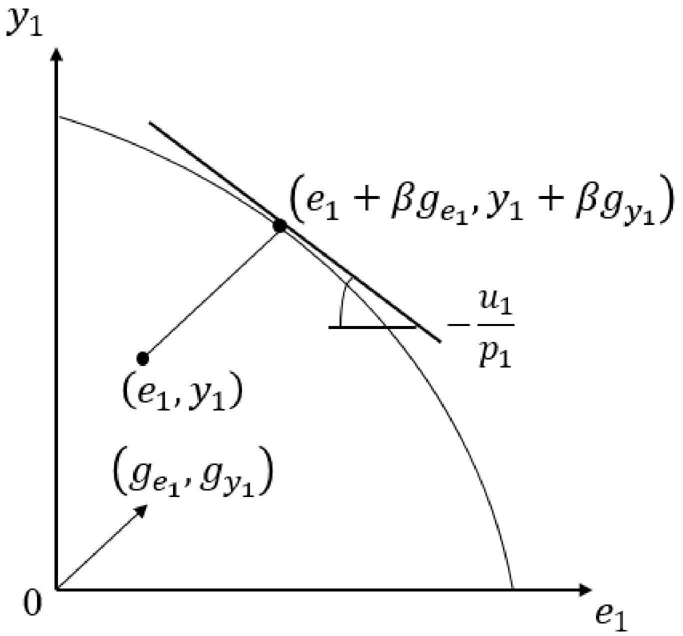

Figure 1. Trade-off between one marketable output y_1 and one environmental good e_1, holding other outputs, other environmental goods and inputs constant.

Färe *et al.* (2001), Bellenger and Herlihy (2010), Ruijs *et al.* (2013), Sipiläinen and Huhtala (2013), Bostian and Herlihy (2014) and Ruijs *et al.* (2015) use Eq. (7) to calculate the shadow price of environmental goods. To our surprise, only few studies that use an augmented distance function discuss or check the assumption of a competitive relationship between marketable outputs and environmental goods in depth. Macpherson *et al.* (2010) conduct a correlation analysis and do not find a robust negative competitive relationship between the environmental goods and marketable outputs. Sipiläinen and Huhtala (2013) briefly mention that crop diversification has a private value, as it is a way to hedge against uncertainty. Ruijs *et al.* (2013) and Ruijs *et al.* (2015) empirically check the transformation function between marketable outputs and environmental goods by parametric estimation and confirm a competitive relationship. Bostian and Herlihy (2014) expect that agricultural production contributes to the degradation of wetland condition due to drainage, channelling and runoff, but qualify this by claiming that the biophysical relationship is not exactly known.

The assumed competitive relationship has been contested in recent literature. Several contributions argue that some environmental goods are complementary to conventional production for lower levels of the environmental good, and competitive for higher levels (Hodge, 2008). Such a complementary-competitive relationship is hypothesised for *inter alia* the environmental quality of grassland and livestock production (Vatn, 2002), pollinator habitat and crop production (Wossink and Swinton, 2007), and the entire ecosystem on the farm and total agricultural production (Hodge, 2000).

There is nonetheless only limited empirical evidence of this relationship. Peerlings and Polman (2004) arrive at a competitive relationship between milk production on the one hand, and wildlife and landscape services on the other hand. Havlik *et al.* (2005) find evidence of a complementary-competitive relationship between grassland biodiversity and cattle production. Sauer and Wossink (2013) approximate a 'bundled' environmental good as the total green payments provided by the CAP. They apply a flexible transformation function and obtain a complementary relationship for most farms and a competitive relationship for a minority of farms.

The Trade-Off between Inputs and Environmental Goods
Using the envelope theorem, the trade-off between inputs and environmental goods can also be inferred (Chambers *et al.*, 1996, Chambers *et al.*, 1998):

$$-\frac{\nabla_x \vec{D}_T(x,y,e;g_x,g_y,g_e)}{\nabla_e \vec{D}_T(x,y,e;g_x,g_y,g_e)} = \frac{w}{u} \geq 0 \tag{8}$$

By treating an environmental good as a conventional output, it is implicitly assumed that the provision of *any* environmental good is non-decreasing for increases in *any* input. Figure 2 shows the production possibility frontier for one input x_1 and one environmental good e_1, holding other inputs, other environmental goods and outputs constant. Eq. (8) can in principle be used to compute the shadow price u. However, as most studies focus on the trade-off between environmental goods and marketable outputs, Eq. (8) has not been of interest in practice.

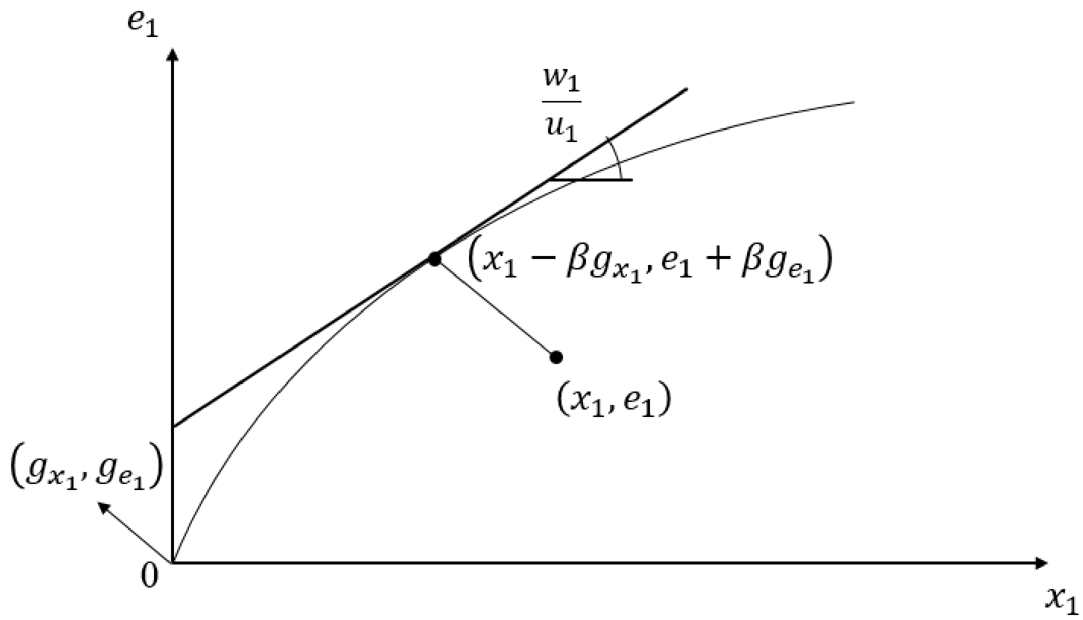

Figure 2. Trade-off between one input x_1 and one environmental good e_1, holding other inputs, other environmental goods and outputs constant.

The augmented production economics approach

Färe *et al.* (2001), Areal *et al.* (2012) and Sipiläinen and Huhtala (2013) augment a conventional production economics framework (with marketable inputs and outputs) with respectively the characteristics of public land conservation (the number of conservation sites, the area at each site and the total area available for fishing), the share of grassland, and the Shannon index for crop diversification. This *'augmented production economics approach'* is intuitive for economists as it is an extension of familiar neoclassical models. Interestingly, none of these studies elaborates on the implicit assumption that the provision of an environmental good is non-decreasing in the inputs if one models an environmental good as a conventional output.

One may argue that this assumption would hold for inputs that compete for environmental goods jointly produced with marketable outputs. For example, farmers may set aside land and some other inputs to produce conservation buffers and cover crops that could also have been used to produce marketable outputs (Wossink and Swinton, 2007). However, as both inputs and environmental goods are heterogeneous, we argue that the expected relationship between input use and provision of environmental goods may also be non-positive or unclear. We expect a non-positive relationship for inputs that contain environmentally damaging substances. Fertiliser use may lead to nitrogen leaching in the soil and eventually to lower groundwater quality. It may also volatilise into nitrous oxide, a greenhouse gas (Reinhard *et al.*, 1999). Pesticide use is expected to have a negative impact on farm biodiversity as it suppresses beneficial organisms such as beetles and birds (Skevas *et al.*, 2012). The relationship may depend on the environmental good. For instance, although fertiliser use may decrease groundwater quality, its impact on farm biodiversity is uncertain.

Augmented production economics approaches have focused on the output distance function, holding inputs constant. This may be the reason why the implicit assumption of the non-negative relationship between inputs and environmental goods has not been motivated. Nevertheless, the underlying production technology still depends on inputs. An incorrect assumption about the relationship between inputs and environmental goods also leads to an incorrect computation of the output distance function. Unfortunately, making such an *a priori* assumption is no trivial task.

The biophysical approach

Several studies veer from the augmented production economics approach. The *'biophysical approach'* considers marketable outputs and environmental goods, but no marketable inputs. Although environmental, non-marketable inputs are generally chosen more sparingly and carefully than in the augmented production economics approach, this is necessarily done on an *ad hoc* basis, which compromises economic intuition. Macpherson *et al.* (2010) consider four environmental inputs (percentage edge forest, percentage of impervious surface, percentage of riparian agriculture and road density). Explicitly stating that "this model specification lacks the clarity of the input–output relationship of a typical model in production economics" (p. 1921), they conduct a correlation analysis with the outputs (per capita income, population density, percentage of wetland and percentage of interior forest) as a robustness test and only partly confirm a positive relationship. Bostian and Herlihy (2014) solely implement joint land use as an input. Bellenger and Herlihy (2009), Bellenger and Herlihy (2010) and Ruijs *et al.* (2013) do not even consider any inputs.

Convexity

More and more studies argue that the environmental technology set is non-convex (Chavas and Di Falco, 2012, Di Falco and Chavas, 2009). The convexity assumption is invoked for analytical rather than theoretical reasons (Pope and Johnson, 2013). Again, Ruijs *et al.* (2013) and Ruijs *et al.* (2015) are the only authors that empirically test the convexity assumption. They do not find evidence of convexity. This implies that their resulting opportunity cost does not maximize benefits and cannot be used to design a pricing mechanism.

Lessons from the Debate on Environmental Bads

It is interesting to compare our concerns to the heated debate on how environmental bads (*i.e.* pollutants) should be implemented in a distance function framework. Environmental bads are traditionally implemented directly in a conventional production economics framework with marketable inputs and outputs. Earlier contributions suggest that pollutants should be modelled as conventional inputs, as these are assumed to be complements of marketable outputs (*e.g.* Baumol and Oates, 1988, Hailu and Veeman, 2001, Reinhard et al., 1999, 2000). However, this approach unrealistically assumes that fixed amounts of inputs can produce an unlimited amount of pollutants (Färe and Grosskopf, 2003). Most authors therefore treat pollutants as weakly disposable outputs that have complementary characteristics for lower levels of pollution and competitive characteristics for higher levels of pollution (*e.g.* Färe *et al.*, 2005, 2014, Pittman, 1983). The rationale is that conventional production increases with pollution, but that clean-up opportunity costs arise for higher pollution levels. This implies that the shadow price of pollution can also become negative. This has been contested by Hailu and Veeman (2001) who therefore model pollution as an input. Färe and Grosskopf (2003) claim that this is a conflation of the choice of the production technology and the directional vector. They propose that although pollution should be modelled as a weakly disposable output, it is still possible to choose a directional vector that points towards the complementary part of the frontier, which would result in positive shadow prices.

According to recent contributions, implementing a pollutant as an input or weakly disposable output may also lead to unacceptable implications for trade-offs among inputs, outputs and pollutants (Førsund, 2009). Coelli *et al.* (2007) introduce an environmental efficiency measure that complies with the material balance condition. Instead of adding pollution as an additional variable, polluting inputs and outputs are chosen in a pollution-minimising way. Murty *et al.* (2012) model the polluting technology as the intersection of an intended-output technology and a residual-generation technology.

Environmental goods are now commonly modelled as conventional outputs in a distance function framework, analogous to how pollutants have been modelled as conventional inputs in the earlier environmental economics literature. This assumes that there is a competitive relationship with marketable outputs for all levels of the environmental good and that the shadow price of an environmental good is non-negative. Recent studies have put forward that an environmental good may also be complementary to marketable outputs. Treating an environmental good as a conventional output also implies that the provision of an environmental good is assumed to be non-decreasing in the inputs. For the augmented production economics approach, which includes all marketable inputs, this assumption may be incorrect for at least some inputs. Clearly, inputs such as fertilisers and pesticides decrease the provision of some environmental goods. This critique is somewhat analogous to Murty *et al.* (2012), who argue that treating a pollutant as an input incorrectly implies that the trade-off between a pollution-generating input and a pollutant is assumed to be non-positive. One could adapt a biophysical approach and focus on environmental, non-marketable inputs. However, inputs are then chosen ad hoc, which compromises economic intuition. An additional difficulty is that environmental goods are considerably more heterogeneous than environmental bads, where the axiomatic properties are better understood.

A potentially complementary-competitive relationship between environmental goods and marketable outputs calls into question whether the weak disposability assumption should be invoked for an environmental good (Van Huylenbroeck *et al.*, 2007), as has been frequently done for pollutants. This would imply that the shadow price of an environmental good could be negative or positive (Wossink and Swinton, 2007). The empirical evidence of a complementary-competitive relationship is however only limited. Moreover, the sheer heterogeneity of inputs and environmental goods complicates the a priori assumption about the trade-off between inputs and environmental goods. Finally, convexity of a technology set augmented with environmental goods is an assumption contested by the ecological literature.

We have thus identified several problems in the increasingly common practice of augmenting a distance function with an environmental good treated as a conventional output. The weak disposability assumption is faced with similar problems. The shadow prices obtained by exploiting the distance function's dual relationship to the value function may therefore also be flawed. A fundamental problem is that the exact axiomatic properties of environmental goods are difficult to verify.

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Appendix 6 Instructions to compute sustainable efficiency, environmental inefficiency and sustainable productivity

Download the R package on http://www.r-project.org/. It is completely free.

Prepare the data for usage in R:

Structure the data as follows (the order and name of ID, inputs and outputs do not matter, as long as they are in the first row and do not contain any spaces):

ID	Input1	Input2	Output1	Output2	Input1	Input2	Output1	Output2
1	200	30000	10000	10	0.5	0.4	0.7	0.9
2	26	400000	4500	13	0.5	0.4	0.7	0.9
3	186	510000	1000	17	0.5	0.4	0.7	0.9
4	154	68000	6700	18	0.5	0.4	0.7	0.9
5	320	90120	8500	19	0.5	0.4	0.7	0.9

The file should be saved as a txt-file.

Open the relevant main file

Follow the instructions in the workspace.

There are four main files:

MasterfileGoodsBads.R (see Sections 3 and 5)

MasterfileNutrient.R (see Section 4)

MasterfileGoodsBadsSurvey.R (see Section 7)

Biodiversity4.R (see Section 8)

To make the main files fully operational, one also needs to save the auxiliary files in the same directory. The auxiliary files are:

Bbad.R, Bgood.R and Bprod.R (belonging to MasterfileGoodsBads.R and MasterfileGoodsBadsSurvey.R)

DynNut1.R and DynNut2.R (belonging to MasterfileNutrient.R)

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