Farm eco-efficiency: can sustainable intensification make the difference?

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Agricultural Land Markets – Efficiency and Regulation

Farm eco-efficiency: can sustainable intensification make the difference?

Meike Weltin [*], Silke Hüttel [**]

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Abstract

Sustainable intensification measures promise ecological improvements of farming while maintaining profitability. That is, farms should be able to produce at a higher ecological efficiency without losses in economic efficiency. Based on a theoretical framework, we investigate this promise empirically by analysing the environmental improvement potential of sustainable intensification. We thereby focus on quantifying biodiversity gains using a directional meta-frontier approach and farm survey data from the northern German Plain. We compare eco-efficiency scores in an ecological direction between adopters and matched non-adopters to identify the causal relationship between these gains and sustainable intensification. We find that adopters determine the system frontier. Despite higher mean eco-efficiency scores, most adopters do not yet fully exploit the potential of ecological improvements through sustainable intensification.

Keywords: environmental sustainability, eco-efficiency, directional data envelopment analysis, matching

JEL codes: Q12, Q15, Q57

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1 Introduction

Increasing population raising food demand, triggered by changing diets (Tilman et al. 2011), to be satisfied by limited land and natural resources (Cordell et al. 2009, Popp et al. 2014) engender a main future challenge. Food production systems, however, suffer increasingly from environmental problems, such as a loss of biodiversity or groundwater contamination. Intense farming systems have been argued to be a major driver (Foley et al. 2011). Coincidently increasing societal awareness has raised the demand for environmentally sustainable and climate-friendly food production (Feldmann and Hamm 2015). Ecological improvements in farming, typically associated with extensive or organic production, often cannot maintain productivity levels. Not surprisingly, rather smart combinations of organic and more intense systems have been pursued as potential solutions (Meemken and Qaim 2018). The concept of sustainable intensification (SI), originally proposed to foster sustainable growth in developing countries (e.g., Pretty 1997), has been postulated as part of this solution (Godfray and Garnett 2014), and has already been noticed by policymakers (Foresight 2011, Buckwell et al. 2014). This concept aims to balance the trade-off between production economics and environmental sustainability. From a farm perspective, this could be achieved by production measures to improve either economic or environmental outcomes without one reducing the other (Pretty and Bharucha 2014). Resource-saving crop production by utilising a wider crop rotation, reduced tillage, integrated pest management with buffer strips and technological solutions for improved input management, such as precision agriculture denote important examples (Weltin et al. 2018). Overall, these production systems target reducing environmental harm without additional land (Pretty 2018), offering the potential to contribute to closing yield gaps (Mueller et al. 2012), offsetting negative effects of agricultural land use (Baulcombe et al. 2009) and ensuring stable farm incomes to sustain vital rural economies (Godfray and Garnett 2014).

Given these promises, surprisingly, empirical evaluations of SI practices have been based mainly on field trial data (e.g., Paul et al. 2015, Townsend et al. 2016) or simulation-based approaches (e.g., Mao et al. 2015, Devkota et al. 2016) with focus on yield effects. Holistic farm-level approaches particularly for the global North, however, seem underrepresented. Some studies for developing countries find improvements in farms' performance by sustainable intensification (e.g., Kassie et al. 2015) and a recent study by Barnes and Thomson (2014) presents indicators to monitor the progress of SI for Scottish beef farms, though without farm performance assessment.

Farms in the global North aim more at improving a beneficial ecological output without sacrificing the economic performance when opting for sustainably intense practices (Godfray and Garnett 2014) and thus, focusing on single yield effects would not be sufficient. Agricultural production produces in addition to economic goods, either a beneficial ecological production output (Areal et al. 2012) or an undesirable environmental harm (Dakpo et al. 2016) within a complex relationship. Sidhoum et al. (2019) underline the importance of considering this multidimensionality of outcomes and even distinguish the technical, social and environmental performance of farms.

Against this backdrop, we rely on the concept of eco-efficiency when evaluating SI measures to acknowledge this complexity. Reaching eco-efficiency means producing more output using fewer resources with reduced environmental harm (Schmidheiny 1993). Applying this concept at the firm level, eco-efficiency captures the improvement of environmental outcome while maintaining economic output in a cost-effective manner (cf. Kuosmanen and Kortelainen 2005). Using static and dynamic production frontier models, for instance, Callens and Tyteca (1999), Tyteca (1999), Kuosmanen and Kortelainen (2005) and Kortelainen (2008) propose a radial eco-efficiency measure based on non-parametric Data Envelopment Analysis (DEA). These approaches have been applied to agricultural production, for instance, by Gadanakis et al. (2015) and Pérez Urdiales et al. (2016). As one of the few exceptions relating eco-efficiency to SI, Gadanakis et al. (2015) find that arable farms in the United Kingdom can reduce eco-inefficiencies by sustainable farming practices; however, their approach lacks explicit causal interpretation.

Our study aims at evaluating how sustainable intensification measures can improve eco-efficiency in lowland farming systems in north-western Europe. We rely on rich survey data from the northern German Plain as a representative region collected in 2017 (Weltin et al. 2019). Following the idea of Asmild and Hougaard (2006), farm managers might be first interested in achieving technical efficiency and improving in the economic output dimension. After meeting a certain threshold, depending on their environmental preferences, improving the environmental output as a secondary goal becomes relevant. We model this improvement potential in the ecological direction within sequential preferences guiding decisions by using directional DEA eco-efficiency measures. Eco-inefficiency then reflects the distance of actual to potential production in either direction, economic or ecological, while maintaining the other and thus an improvement potential (Picazo-Tadeo et al. 2012). We are specifically interested in quantifying how SI measures reduce the ecological improvement potential that is, to provide more ecological output at no economic cost. Treating SI as a different technology with highest possible ecological output compared to other farming practises, we hypothesize both technologies enveloped by a system frontier. For defining the system production frontier, we apply a meta-frontier approach (cf. O'Donnell et al. 2008). The system frontier offers highest possible outcomes in either direction, where farms adopting SI are hypothesized to largely determine the system frontier in ecological direction. The ecological output on the system frontier will serve as a reference to identify improvement potentials, where SI farms exploiting the potential of sustainable farming practises will have considerably lower improvement potentials.

Observed differences in the ecological improvement potential between groups might not only be associated with sustainable practices; these could also be related to structural differences of adopters and non-adopters, such as natural and socio-economic conditions (e.g., Kassie et al. 2015) or environmental preferences and awareness (e.g., Omer et al. 2010). In line with Mayen et al. (2010), linking the technology adoption decision and eco-efficiency analysis is a pre-condition to identify causal relationships. By enhancing the theoretical framework of Chabé-Ferret and Subervie (2013), we acknowledge the role of farmers' preferences and presume a representative farmer will decide first on whether to opt for the SI technology. Subsequently, the farm household maximizes its utility, where adopters voluntarily constrain production to reduce the improvement potential compared to a non-SI reference situation. We account for such selectivity issues by comparing eco-efficiency scores of SI farms with farms of a matched control sample (cf. Bogetoft and Kromann 2018).

The contribution of our paper is threefold. Firstly, to the best of our knowledge, we are the first authors providing a meta-frontier approach to measure improvement potentials in the direction of the ecological output. Secondly, based on a theoretical framework, we use a matching algorithm to generate a control sample that reduces potential biases and, thus, offer a causal interpretation of differences in eco-efficiency measures through SI. Thirdly, by means of this approach, we are able to disentangle differences in improvement potentials between SI adopters and non-adopters into a *technology* and a *performance* effect: Differences between the group-specific frontiers of adopters and non-adopters allows us to investigate whether SI is promising at all by offering a frontier, which is closer to the meta-frontier (*technology effect*). How efficiently a farm operates within its chosen technology in either direction reflects the *performance effect*, which is important to understand for policy implications regarding to what extent adopters exploit the production possibilities offered by the SI technology. An enhanced understanding of improvement potentials through such rather easy to take up agronomic practices offers a key to develop policy measures beyond agri-environmental payment schemes and shows the relevance.

The remainder is structured as follows: we continue elaborating the theoretical background and derive hypotheses (section 2). We next describe the data, sampling and the empirical model (section 3), followed by a detailed presentation and discussion of the results (section 4). We draw conclusions in section 5.

2 Theoretical framework

The behavioural model of Chabé-Ferret and Subervie (2013) serves as a basis which we enhance to frame the decision to adopt sustainable intensification (SI) measures to identify the causal impact of SI on farms' eco-efficiency and to derive the hypotheses.

Presuming representative farm i to produce output $\boldsymbol{Y}$ with an economic Y_{econ} and ecological dimension Y_{ecol}, the use of agronomic SI measures implies a different technology compared to non-adopters. The respective production technology sets are denoted by Ψ_j with $j = [0;\ 1]$, where $j = 0$ indicates production without SI and $j = 1$ the SI-adjusted production system. In both cases, farm i chooses variable input X and on-farm labour H. Fixed inputs $\boldsymbol{I}$, such as human and physical capital, as well as unobserved factors $\boldsymbol{\varepsilon}$, such as land quality, weather conditions and managerial ability, enter the production possibility sets[1]:

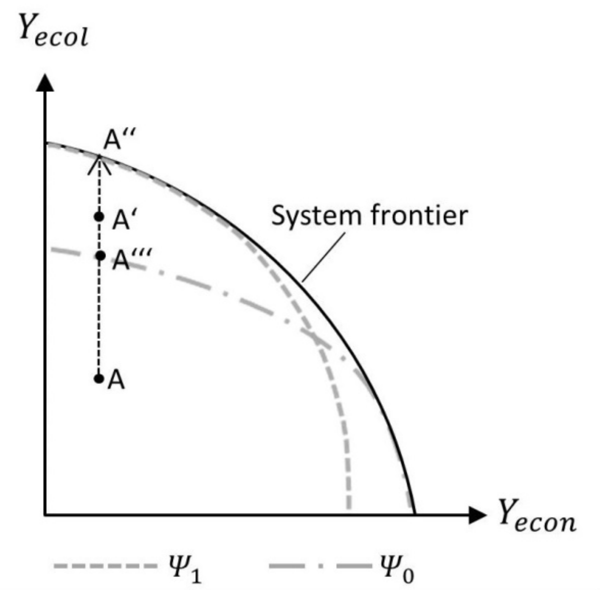
$$\Psi_j = [(X, H, \boldsymbol{I}, \boldsymbol{\varepsilon}, \boldsymbol{Y})\,|\,X, H, \boldsymbol{I}, \boldsymbol{\varepsilon}\ can\ produce\ \boldsymbol{Y}] \tag{1}$$

Following O'Donnell et al. (2008), the group-specific technologies determine a common production system frontier, Ψ_m, enveloping the SI and non-SI production frontiers; see Figure 1, where the solid black line exemplarily represents the system frontier in a two-output setting enveloping two technologies shown by the dashed lines. Farms producing on the system frontier will be eco-efficient. The distance between a farm's actual production and the system

[1] The farm index i is suppressed where possible for notational simplicity.

frontier will capture this farm's improvement potential, that is, eco-inefficiency. Since we are particularly interested in how SI adoption can improve production in the ecological direction, we measure the eco-efficiency as the distance of actual production in the direction of the potential ecological output, while maintaining the economic outcome within a directional distance function (e.g., Picazo-Tadeo et al. 2012). Following Figure 1, the distance between A and A'' denotes the improvement potential for an exemplary non-SI farm and a respective improvement potential when applying SI is given by A' to A''.

Figure 1. System frontier and the two group-specific frontiers, non-SI ($\boldsymbol{\Psi_0}$) and SI ($\boldsymbol{\Psi_1}$)



Ecological improvement potential is $\overline{AA''}$ under non-SI and $\overline{A'A''}$ under SI. Eco-efficient production implies an improvement potential of $\overline{A'''A''}$ under non-SI and $\overline{A''A''}$ under SI.

Eco-efficient production under Ψ_1 should provide higher or, at least, the same ecological output for the same economic output level compared to Ψ_0. We denote the resulting difference in improvement potentials as the *technology effect* of SI. That is, eco-efficiently producing farms under Ψ_0 (cf. Figure 1, point A''') can still improve in the ecological direction by $\overline{A'''A''}$. Under Ψ_1, eco-efficient production at A'' means producing on the system frontier and fully exploiting the improvement potential in the ecological direction. We frame the technology effect in the first hypothesis:

Hypothesis 1: The SI frontier locates in the direction of the ecological output closer to the system frontier. Hence, the system frontier is largely determined by SI adopters in this direction.

Switching technology by adopting SI measures, thus, offers to reduce the ecological improvement potential compared to farms' respective counterfactual situation without SI. As such, the observed and measurable respective improvement potential of a farm, denoted $\tilde{Y}_j$, results from two sequential decisions: firstly, the farm household decides whether to adopt SI, determining the possible improvement in the ecological direction. Secondly, the farm makes a choice regarding inputs allocation and intensity, on how eco-efficiently to operate within their respective technology.

Following Chabé-Ferret and Subervie (2013) and solving backwards, based on maximising a utility function U, the farm household evaluates optimized production input levels X_j^* and on-farm labour time allocation H_j^* for both the SI and non-SI technology. These optimized production levels determine optimal outputs and, thus, improvement potentials $\tilde{Y}_j^*$ for both cases. Both are functions of the exogenous variables, such as prices, consumption shifters, preferences and fixed inputs, g_j and h_j, respectively. Deciding upon the adoption of SI measures, we presume the farm household aims at a reduction of the improvement potential in the ecological direction compared to the respective non-SI reference situation. Farms use results from previous years and their experience to estimate the reference improvement potential: $\tilde{Y}_0^* = \tilde{Y}_0(X_0^*, H_0^*)$.

This farm household's utility maximisation problem is given by:

$$\max_{C,L,H,H_{off},X} U(C, L, H, X, \boldsymbol{S}, \boldsymbol{\eta}) \tag{2}$$

subject to:

$$Y_{econ} = f_j(X, H, \boldsymbol{I}, \boldsymbol{\varepsilon}, Y_{ecol}) \tag{3}$$

$$C = pY_{econ} - p_x X + wH_{off} \tag{4}$$

$$T = L + H + H_{off} \tag{5}$$

Utility U depends on levels of consumption C, leisure L, variable input X and on-farm labour hours H, reflecting the dependence of utility on the farmers' (dis)taste for certain input compositions due to preferences. Consumption shifters $\boldsymbol{S}$, such as age or education, and unobservable taste shifters $\boldsymbol{\eta}$, such as ecological preferences or idiosyncratic non-farm profit opportunities, also enter U. Utility maximization is subject to the production possibilities, where equation (3) gives the transformation function in an explicit form regarding Y_{econ} according to the implicit function theorem (e.g., Sauer and Wossink 2013). The consumption constraint in equation (4) states that the farm household sells Y_{econ} for price p with input costs at price p_x and quantities X. The farm generates additional income from H_{off} hours of off-farm work remunerated by wage rate w. Finally, equation (5) constrains the total available time T of hours for on- and off-farm labour and leisure time.

Optimal input levels under non-SI are, thus, given by:

$$X_0^* = g_0(p, p_x, w, T, \boldsymbol{I}, \boldsymbol{S}, \boldsymbol{\eta}, \boldsymbol{\varepsilon}) \tag{6}$$

and $H_0^* = h_0(p, p_x, w, T, \boldsymbol{I}, \boldsymbol{S}, \boldsymbol{\eta}, \boldsymbol{\varepsilon})$ (7)

When applying SI, the farm's input allocation will be guided such that the improvement potential in the ecological direction, $\tilde{Y}_1$, will not exceed the optimized improvement potential of the reference situation, $\tilde{Y}_0^*$. This gives an additional voluntary constraint to the utility maximization problem, where the reference improvement potential enters as a constant:

$$D(\tilde{Y}_1(X, H, \boldsymbol{I}, \boldsymbol{\varepsilon}, \boldsymbol{Y}) - \tilde{Y}_0^*) \leq 0 \tag{8}$$

This voluntary constraint of equation (8) enters the first-order conditions:

$$\frac{\partial U}{\partial C}(p\frac{\partial f_j}{\partial X} - p_x) + \frac{\partial U}{\partial X} - \lambda\left(\frac{\partial \tilde{Y}_1(X,H,\boldsymbol{I},\boldsymbol{\varepsilon},\boldsymbol{Y})}{\partial X}\right)D = 0 \quad (9)$$

$$\frac{\partial U}{\partial C}(p\frac{\partial f_j}{\partial H} - w) + \frac{\partial U}{\partial H} - \lambda\left(\frac{\partial \tilde{Y}_1(X,H,\boldsymbol{I},\boldsymbol{\varepsilon},\boldsymbol{Y})}{\partial H}\right)D = 0 \quad (10)$$

where λ denotes the respective Lagrangean multiplier.

The optimized input choices under SI ($D = 1$) will, thus, depend on the reference situation's improvement potential, $\tilde{Y}_0^*$. This counterfactual improvement potential works as a lower bound against which farms compare the respective ecological outcome expected upon which the improvement potential under SI is calculated. If the constraint is binding ($\lambda \neq 0$), the farm household will adjust X and H but may be compensated by increases in utility. If the constraint is not binding ($\lambda = 0$), the farmer has no costs in terms of constrained use of X and H when applying SI. Optimized input and labour allocation under SI are given by:

$$X_1^* = g_1(p, p_x, w, T, \boldsymbol{I}, \boldsymbol{S}, \boldsymbol{\eta}, \boldsymbol{\varepsilon}, \tilde{Y}_0^*) \quad (11)$$

and labour $H_1^* = h_1(p, p_x, w, T, \boldsymbol{I}, \boldsymbol{S}, \boldsymbol{\eta}, \boldsymbol{\varepsilon}, \tilde{Y}_0^*)$ (12)

Note, if a farm's expected improvement potential under SI, $\tilde{Y}_1^*$, remains insufficiently large to increase utility compared to $\tilde{Y}_0^*$ according to the environmental preferences, the farm will not adopt ($D = 0$) and equation (8) will not be relevant.

We only observe the outcome of the decision process and measure the improvement potential observed, $\tilde{Y}_j$, which depends on whether the farm chooses to apply SI measures. The farm household decides on SI based on the indirect utilities, V_1 and V_0, depending on the same variables as $\tilde{Y}_1^*$ and $\tilde{Y}_0^*$. The implementation of SI may, however, induce a disutility V from search, implementation or information cost, potentially varying with education and experience. The household will adopt SI ($D = 1$) when the expected increase in indirect utility outweighs the cost of adoption:

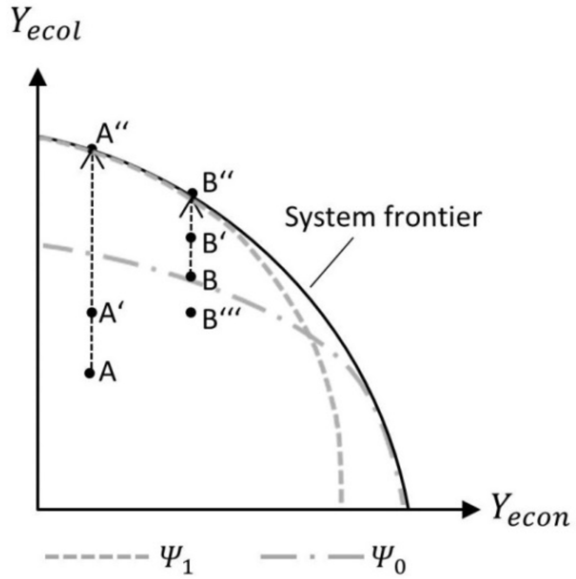
$$D=\mathbf{1}[E[V_1 - V_0|Z] - V \geq 0]] \quad (13)$$

where $\boldsymbol{Z}$ denotes determinants of the household's adoption decision. These may coincide with determinants of input choices, such as environmental preferences, consumption shifters or fixed inputs. As such, likely adopters and non-adopters might systematically differ, particularly regarding the environmental preferences. This shows the necessity of ensuring comparability when comparing outcomes observed.

Thus far, we have assumed efficient production under the respective technology. In the short-run, however, inefficiencies within the technology may occur and even be tolerated in terms of adjustment costs in the process of technology adoption (Ang and Oude Lansink 2017). Ignoring the inefficiencies of SI-adopters within technology particularly would bias the eco-inefficiencies retrieved. A fully efficient non-SI farm, for instance, could have a lower improvement potential compared to weakly efficient SI-farm.

We illustrate this *performance effect* in Figure 2, where farm A reduces the improvement potential when choosing SI; at best, the farm achieves A'', that is, is fully eco-efficient to the system frontier. In this case, the improvement potential turns to zero. However, farm A might only be able to reduce the improvement potential up to a point A' due to eco-inefficiencies within the SI technology. This corresponds to a level that farm A might also achieve when improving performance in the non-SI case. The distance to the SI group-specific frontier for A' is larger than the distance in the non-SI reference situation A to the non-SI group-specific frontier. The improvement potential for farm A still reduces when choosing SI, but that does not necessarily have to be the case. Farm B is eco-efficient within the non-SI technology but might exhibit eco-inefficiencies in the SI technology in such a way that B is not able to move to a point B' that reduces the improvement potential. A possible performance B''' under SI corresponding to the ecological output level of A' would even increase the improvement potential.

Figure 2. Improvement potentials for different reference situations A and B



SI adoption may shift farm production to A' and B' with reductions in improvement potential. B''' represents a situation when eco-inefficiencies in the SI technology increase the improvement potential compared to B.

Taken together, we single out two hypotheses on the impact of SI adoption on farmers' ecological improvement potential acknowledging a performance effect:

Hypothesis 2a: At the mean, for the same economic outcome, SI farms produce at a lower improvement potential (higher eco-efficiency score) to the ecological dimension compared to comparable non-SI adopters.

Hypothesis 2b: If adopters cannot fully exploit their reduction in the improvement potential of the SI-technology (low within technology eco-efficiency score), a high within-technology performance of comparable non-adopters can lead to lower improvement potentials under non-SI.

3 Data and empirical approach

3.1 Survey data and sampling

We use farm survey data that covers the northern German Plain in areas with an abundance of peatlands for the empirical approach. These areas demand adaptions in farming practice to fulfil climate protection and biodiversity goals (TEEB 2015). In this study, we focus primarily on farmland and crop diversity as the core biodiversity harm of agricultural intensification (Benton et al. 2003, Herbst et al. 2017). Another advantage is that these can be measured at the local level (Matson et al. 1997).

The survey questions embrace sustainable intensification measures and policy instruments for climate-friendly peatland management (Häfner et al. 2017, Weltin et al. 2019). The data was collected in the federal states of Brandenburg, Mecklenburg Western Pomerania, Saxony-Anhalt, Lower Saxony and Schleswig Holstein from February to June 2017. In the first three states, we addressed 3,000 farmers by mail through the Ministries of Agriculture. We targeted postal code areas with at least 20 % peatland area and 1,000 ha of peatlands in total, and those with more than 5,000 ha of peatlands in total. The response rate was 13.5 %. Additional respondents were recruited via newsletters of farmers associations. The full sample contains 464 observations in the spatial expansion presented in the appendix (cf. Figure 5).

We investigate the following SI measures aimed at enhancing diversity:

(i) reduced tillage,
(ii) intercropping,
(iii) growing legumes,
(iv) integrated pest management,
(v) grazing, and
(vi) extensive use of grassland.

We base our selection of these agronomic measures on an extensive literature review of SI measures and discussions in a workshop with farmers and stakeholders in the Rhinluch region, situated in the area surveyed (Weltin et al. 2016). The SI measures develop their beneficial effects through combination (Kassie et al. 2015), as agricultural practices interact and influence diversity collectively (Benton et al. 2003). We, thus, define a farm as an adopter of SI when applying at least two measures. We observe the adoption decision for 410 farms in the sample. We exclude 26 farms that operate an agricultural area below 5 ha in order to focus on professional farming.

Regarding the extent of their business operation, SI farms are more likely to be full-time farms, operate a larger area and use professional extension services more frequently (Table 1). Farm managers adopting SI are better educated while their farming experience is similar to non-adopters. We further characterise farmers by self-assessment statements on their values and attitudes. These comprise farmers' propensities to act economically and socially sustainably in the long-run represented by the personal attachment to the region and by a regional entrepreneurship variable. The latter is composed of three aspects: the endeavours to adopt innovations, bear business risks and contribute to regional economic development. Farmers' awareness of contributing to environmental conservation objectives constitutes the third attitude. Factor analysis supports the separation of the five self-assessments into three distinct constructs. The SI farms show a stronger affinity than non-SI farms for the regional entrepreneurship variable. Differences in environmental awareness, however, are small. The full questionnaire can be found in Weltin et al. (2019).

Table 1. Descriptive statistics for SI and non-SI farms

	SI farms			Non SI farms		
Variables	N	Mean	Std. Dev	N	Mean	Std. Dev
Used agricultural area [ha]*	304	513.00	698.60	79	79.21	163.80
Profit character [1=full-time; 0=part-time]*	303	0.71	0.46	78	0.36	0.48
Organic farming [1=yes; 0=no]	303	0.20	0.40	77	0.19	0.40
Specialisation in arable farming [1=yes; 0=no]	304	0.34	0.47	77	0.25	0.43
Labour intensity [workforce/ha UAA][a]*	288	0.04	0.06	70	0.11	0.14
Use of extension services [1; 5][b]*	298	2.91	1.23	76	2.34	1.25
Formal agricultural education [1=yes; 0=no]*	295	0.77	0.42	74	0.57	0.50
Highest educational degree [1; 3][c] *	296	2.39	0.86	76	1.99	0.93
Farming experience [years]	295	27.62	13.03	72	26.50	14.77
Regional attachment [1; 10][d]	294	8.95	1.83	76	8.87	1.93
Environmental awareness [1; 10][d]	291	7.12	2.58	75	6.75	2.80
Entrepreneurial attitude [1; 10][d] *	288	6.34	2.13	71	4.82	2.21
Economic output: profit indicator [1; 12]	271	4.63	3.80	69	2.84	2.81
Ecological output indicator [0; 1]	295	0.44	0.13	76	0.30	0.19

* Wilcoxon rank sum test for differences between groups has a p-value < 0.05.
[a] Workforce below or equal to 1 person is summarized as 1.
[b] 1=never; 2=sometimes; 3=occasionally; 4=often; 5=very often
[c] 1=lower secondary or intermediate education or no degree; 2=high school degree; 3=university degree
[d] Self-assessment questions for which respondents indicated the degree of agreement on a scale from 1=fully disagree to 10=fully agree

We use the agricultural area as farm input in the eco-efficiency analysis to assess farms of comparable size. A farm profit indicator provided on an ordinal scale with twelve categories[2] measures the economic output dimension, Y_{econ}. We conceptually follow approaches from ecology and address diversity on two scales, measuring heterogeneity on the farm between different landscape elements (on-farm diversity) as well as the diversity within each land use type (on-land diversity) for the environmental output dimension, Y_{ecol}. We assign equal weight to both components in the indicator for ecological output. We ignore the heterogeneity on the landscape scale as a third layer of diversity because our dataset does not allow the spatial location of farms. Still, habitat heterogeneity on a smaller scale is associated with biodiversity in the farmed landscape (Benton et al. 2003) and ecological assessments also take place exclusively within the borders of the farm (Gibson et al. 2007). Other than ecological studies measuring richness and abundance of plants, insects or birds directly and mostly considering a limited number of farms, we have to rely on proxy measures that proved relevant in the

[2] Categories: 1 loss/smaller than 0 €; 2 up to 10,000 € ; 3 up to 20,000 € ; 4 up to 40,000 € ; 5 up to 60,000 € ; 6 up to 80,000 €; 7 up to 100,000 €; 8 up to 120,000 €; 9 up to 140,000 €; 10 up to 200,000 €; 11 up to 250,000 €; 12 more than 250,000 €.

literature. The final indicator is defined in the interval [0; 1]. We present details on the calculation of all components in Table 2.

Table 2. Components of the environmental output considered for the assessment of eco-efficiency

Indicator component	Calculation
On-farm diversity	
Normalised Simpson diversity index $a_{i,norm}$	$a_i = 1 - \sum_k p_{ik}^2$; p_{ik} share of land use type k on farm i; k includes arable land, permanent grassland and other grassland. $a_{i,norm.} = \frac{a_i}{1-\frac{1}{k}}$ normalises a_i to the interval [0;1].
Presence of fallow b_i	Indicator turns to 1 if fallow is present on farm i.
Presence of flower and buffer strips c_i	Indicator turns to 1 if flower or buffer strips are present on farm i.
Aggregated indicator on-farm diversity	$1/_2\, a_{i,norm.} + 1/_4\, b_i + 1/_4\, c_i$
On-land diversity	
Crop diversity in arable land d_i	Number of crops grown on farm i per year divided by the sample maximum.
Permanent grassland e_i	Share of permanent to total grassland on farm i.
Biodiversity surplus of permanent grassland f_i	$f_i = \frac{q_i - \overline{q}_{reg.size}}{1-\overline{q}_{reg.size}}$; q_i share of permanent pasture to UAA of farm i; $\overline{q}_{reg.size}$ average share of permanent pasture to UAA by federal state and farm size class retrieved from Destatis (2018). f_i is set to 0 if $\frac{q_i - \overline{q}_{reg.size}}{1-\overline{q}_{reg.size}} < 0$.
Extensively managed peatlands g_i	Share of near-natural or extensively managed peatland area to total peatland area on farm i.
Aggregated indicator on-land diversity	$\frac{\text{arable land}_i}{\text{UAA}_i} d_i + \frac{\text{total grassland}_i}{\text{UAA}_i} \frac{1}{3} (e_i + f_i + g_i)$

Farm level heterogeneity includes all types of cropped and non-cropped areas on the farm. We capture the shares of arable land, extensive grassland and other grassland by the Simpson diversity index (Van Eck and Koomen 2008). For non-cropped land, we only observe the presence, but not the amount of fallow land and flower or buffer strips. Acknowledging the high value of these semi-natural areas for biodiversity (Weibull et al. 2003, Herbst et al. 2017), we assign them 50 % of the weight in the overall indicator for on-farm diversity.

For on-land diversity, biodiversity in arable land is accounted for by the number of different crops grown on the farm within a year, describing the diversity planned by the farmer (Matson et al. 1997). For grassland, we follow Areal et al. (2012) and rely on the share of permanent pasture on the farm as a measure of biodiversity, but differentiate their approach further. We include the share of permanent grassland to total grassland. In addition to biodiversity, this indicator captures the carbon sink function of grassland (Barnes and Poole 2012). Additionally, we measure the biodiversity surplus in terms of how far shares of permanent pasture exceed regional averages. The third component is the abundance of peatlands extensively managed or in conditions close to nature, having both a high impact on carbon capture and biodiversity

(TEEB 2015). All three components are weighted equally. Sub-indicators for arable and grassland are weighted by the respective share of each land-use type on the farm in the indicator for on-land diversity.

3.2 Empirical model specification

The improvement potential observed, $\tilde{Y}_j$, corresponds to eco-inefficiency to the system frontier, thus, higher eco-efficiency scores imply a reduced improvement potential. We measure eco-efficiency scores to the system frontier and within-technology performance regarding the group-specific frontiers using a meta-frontier approach (e.g., Gómez-Limón et al. 2012). We are interested in the proportional increase of the ecological output dimension, while keeping economic output constant and staying in the respective production set Ψ_m or Ψ_j. Hence, we rely on directional distance functions (DDF) following Picazo-Tadeo et al. (2012).

We specify the DDF with outputs $\boldsymbol{Y} = (Y_{ecol}, Y_{econ})$, agricultural area input Q and define the direction vector $g_y(Y_{ecol}, 0)$:

$$\vec{D}_{ecol,j}(Q, \boldsymbol{Y};\ g_y) = Sup[\beta_{ecol,j}\colon (\boldsymbol{Y} + \beta_{ecol,j}\ g_y) \in \Psi_m] \tag{14}$$

For within-technology performance, Ψ_m is replaced by Ψ_j in equation (14). Symbol $\beta_{ecol,j}$ is the proportion by which Y_{ecol} could be increased to reach the respective frontier. The ratio $1/(1+\beta_{ecol,j})$ determines the fraction of the feasible output realized by the farm, that is, eco-efficiency in the interval $[0;1]$. The following relationship holds: eco-efficiency to the system frontier equals the meta-technology ratio (MTR) multiplied by group-specific eco-efficiency. The MTR is the distance of a farm to the system frontier after it has been augmented on its group-specific frontier (Gómez-Limón et al. 2012). A MTR of 1 implies that the group-specific frontier coincides with the meta-frontier and offers to assess the *technology effect* of SI. Eco-efficiency in the economic direction could be similarly calculated by setting the direction vector to $g_y(0, Y_{econ})$.

We refer to directional Data Envelopment Analysis (DEA) following Asmild and Hougaard (2006). The DEA approach is flexible, requires no functional form assumptions and allows the inclusion of both monetary and non-monetary inputs and outputs (Charnes et al. 1978). We opt for a full disposable hull technology to get the most cautious estimates of eco-inefficiency scores, that is, the respective improvement potentials. Since DEA results are known to be sensitive to outliers (Bogetoft and Kromann 2018), we refer to the minimum covariance determinant estimator by Rousseeuw and Driessen (1999) for outlier control in Y_{ecol}, Y_{econ} and land. We eliminate 17 outliers from 325 observations (for brevity, we present the full descriptive statistics in Table 4 in the appendix). We refer to the R packages *Benchmarking* and *Robustbase* for all steps.

While the eco-efficiency approach presented offers an estimate of the improvement potential of adopters and non-adopters, unobservable determinants of the voluntary SI adoption decision, such as preferences, may yet confound differences in the outcomes observed and, thus, give biased eco-inefficiency estimates. Likely adopters will differ in their farm(er) characteristics from non-adopters and contrasting the improvement potentials observed will not suffice to identify causal differences. Sub-sample homogeneity is a precondition for causal interpretation of outcomes when selectivity issues prevail (Bogetoft and Kromann 2018). Hence, we use a matching approach with farm(er) characteristics $\boldsymbol{Z}$ as covariates. This allows the generation of a control group that resembles the group of SI adopters in these core characteristics. Based on that, we compare the eco-efficiency of adopters with their respective counterfactual under non-SI.

Matching methods have been widely applied in efficiency studies to reduce differences between groups with stochastic frontier approaches (Mayen et al. 2010, Bravo-Ureta et al. 2012) and DEA (Bogetoft and Kromann 2018). We use kernel density matching based on Mahalanobis distances and the Epanachnikov kernel function. Mahalanobis distances deliver robust results in small samples (Zhao 2004). Kernel matching allows the assignment of several control observations to each SI adopter and reduces the variance of the estimation. The bandwidth of the estimator is determined by cross-validation to minimize the mean squared error regarding the averages of the covariates. We use the command *kmatch* in Stata14 and generate a sample of control observations from the weighted averages of matched controls.

The matching variables $\boldsymbol{Z}$ consist of farm characteristics, where we consider full-time operation, specialisation in arable and organic farming, and labour intensity to reflect the intensity of the farming operation and input use. The use of advisory services represents external knowledge input in the farm business. We focus on farming experience and education, both general and agricultural, among the farmers' characteristics. Both groups of variables have proven relevant in selection equations for farm management decisions or in two-stage eco-efficiency approaches (e.g., Gómez-Limón et al. 2012, Chabé-Ferret and Subervie 2013, Gadanakis et al. 2015, Pérez Urdiales et al. 2016). Farmers' preferences and sustainability attitudes represent the third indispensable component of decision-making (e.g., Jongeneel et al. 2008, Hansson et al. 2018). However, these we do not observe directly, and we use the self-assessments of respondents as proxies. Due to missing values, a further 43 observations have to be excluded (cf. Table 5 in the appendix for descriptive statistics of the final sample).

4 Results and discussion

The covariate balance indicates the comparability of SI farms and matched control farms. Standardized differences are mostly small and all below the rule-of-thumb value of 0.25 (Stuart 2010). On average, a SI adopter has 3.78 control observations as matches. Twenty-eight SI farms are out of common support and are dropped to increase the precision of estimates following Lechner and Strittmatter (2017). Three control observations are not used. For brevity, we summarize standardized differences and group means before and after matching in the appendix (Table 6). The final sample for DEA consists of 193 SI farms and just as many generated matched control farms. Table 3 summarizes the core results.

Table 3. Eco-efficiency scores in the direction of the ecological output for SI adopters and their matched controls

	SI farms		Non-SI farms	
	Mean	Std. dev.	Mean	Std. dev.
Meta-technology ratio (MTR)	1.00	0.00	0.77	0.13
Eco-efficiency to system frontier/ improvement potential	0.75	0.18	0.61	0.15
Eco-efficiency to group-specific frontier/ within-technology performance	0.75	0.18	0.80	0.14
N	193		193	

Note: Wilcoxon rank-sum test for differences between SI and non-SI farms has a p-value < 0.01 for all three measures.

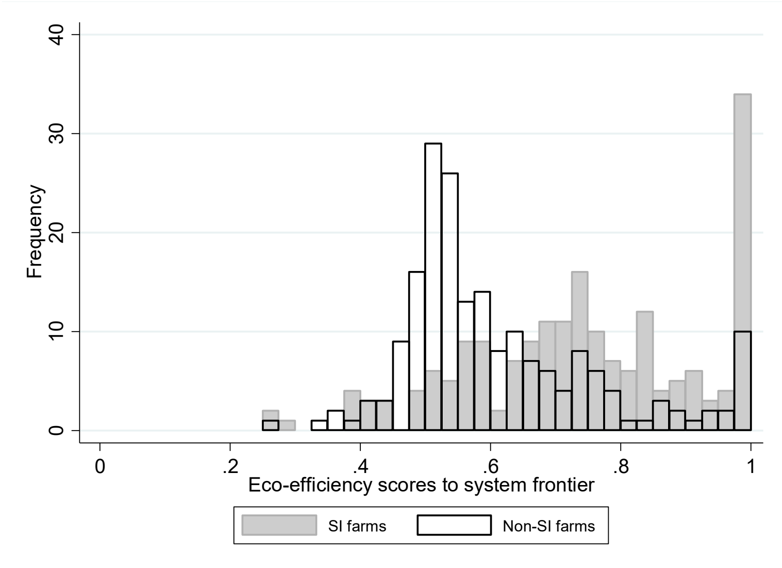
The results, firstly, reveal SI measures to be promising to reduce the environmental improvement potential measured as eco-inefficiencies in the ecological direction to the system frontier, where SI farms are, on average, more eco-efficient (0.75 versus 0.61 for matched control non-SI farms). Most importantly, the results indicate that SI farms determine mainly the system frontier (cf. *Hypothesis 1*): the MTR is equal to 1 for 64 % of SI farms and nearly 1 for the other 36 % (std. dev. 5.73e-08). That is, if all SI farms were fully efficient to their group-specific frontier, they would also be eco-efficient regarding the system frontier. By contrast, the average MTR of non-SI farms is 0.77, where only 20 of those have a MTR of 1. This, however, also means that some ways exist to be eco-efficient regarding the system frontier without adopting SI.

In this regard, we test the differences in the location of the frontiers based on the distributions of eco-efficiency scores. Based on a Kolmogoroff-Smirnov test, we reject the null hypotheses that the distributions of eco-efficiency scores to the group-specific frontier and system frontier are identical for the non-SI farms (D=0.65; p=0.00). We cannot not reject this hypothesis for the SI farms (D=0.01; p=1.00), that means the system and SI frontiers coincide. We, thus, find evidence for not rejecting *Hypothesis 1*, reinforcing the *technology effect* of SI.

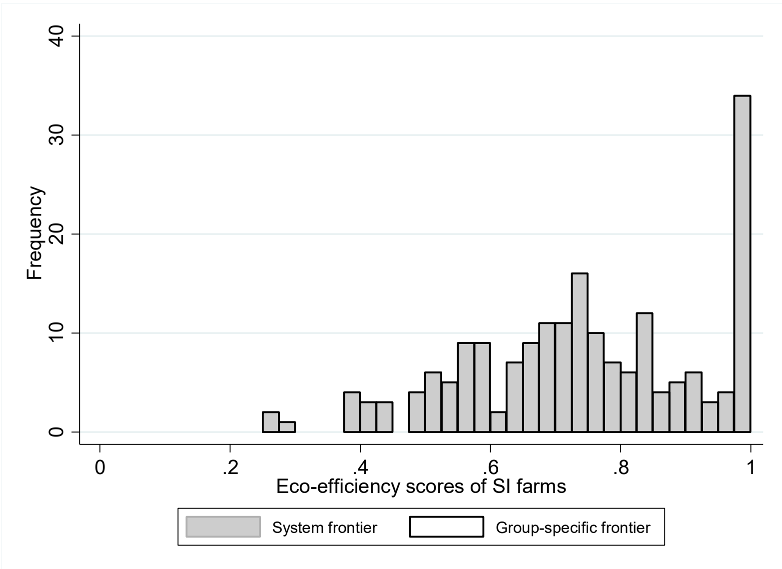
On average, SI is associated with a reduction of the ecological improvement potential corresponding to an increase in eco-efficiency to the system frontier (cf. *Hypothesis 2a*). The average difference in eco-efficiency compared to the non-SI reference situation is 0.13 score points, where SI farms produce 75 % and non-SI farms 61 % at the mean of the potentially possible ecological output, keeping land and the economic output constant.

Figure 3. Distribution of eco-efficiency scores

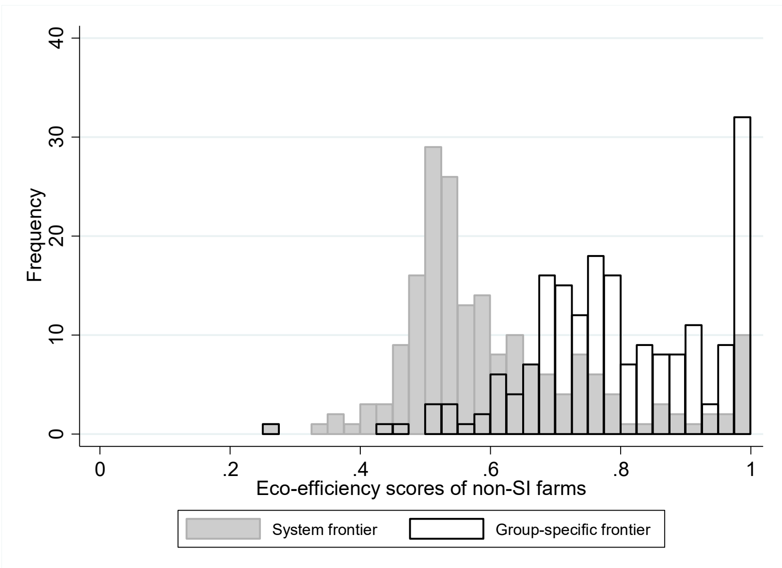
a. … to the system frontier for SI and non-SI farms



b. … for SI farms to the system and group-specific frontier



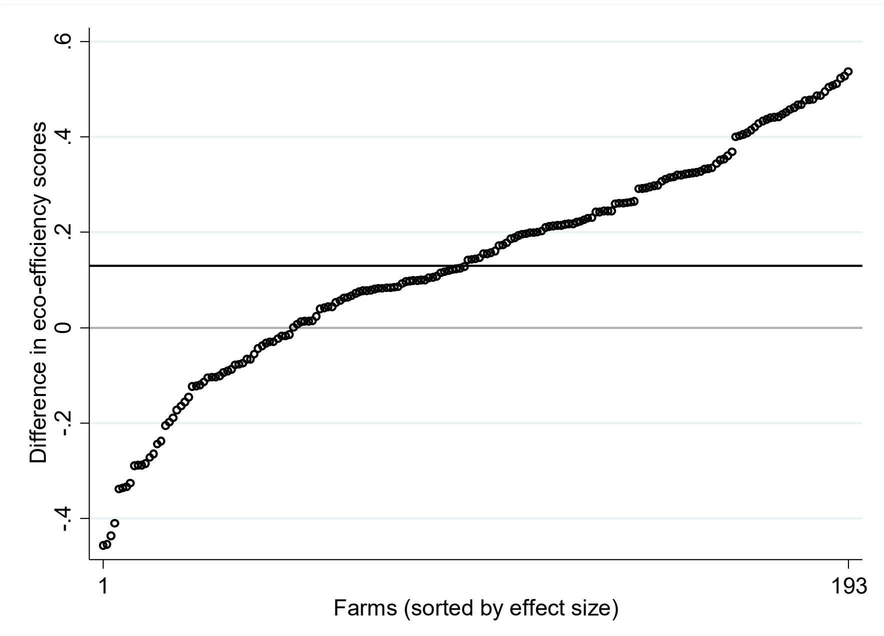
c. … for non-SI farms to the system and group-specific frontier



Due to the matching approach, in addition to average differences, we are able to compare the full distributions of eco-efficiency scores (cf. Bogetoft and Kromann 2018). As illustrated in Figure 3a, 31 SI adopters and 10 non-adopters produce on the system frontier. Respective eco-efficiency scores, however, are heterogeneously distributed, although SI measures offer a higher potential to produce on the system frontier. Deviations from the system frontier for SI farms stem exclusively from eco-inefficiencies within the group-specific technology. Regarding SI farms, 84 % could improve their within-technology performance. Eco-efficiency scores in the ecological direction of SI farms regarding their group-specific frontier are almost identical to their scores to the system frontier (cf. Figure 3b). Improvement potentials for non-SI farms result from a mixture of inefficiencies to the group-specific frontier and the fact that the non-SI technology mostly does not allow the system frontier to be reached. Their average eco-efficiency score regarding the group-specific frontier is 0.80 (cf. Figure 3c).

Within-technology performance sheds light on the distribution of changes in improvement potentials through SI. We compare the magnitude of differences in eco-efficiency observed to the system frontier for each adopter to the respective matched control farm (Figure 4). We find a gain in eco-efficiency compared to the matched control observation for 74 % of adopters. These farms move closer to the system frontier and reduce their improvement potential by adopting SI. Their gain is an average of 0.24 and can be as high as 0.54 score points. However, we observe that 25 % of farms for which eco-efficiency deteriorates up to a change of -0.45 and by -0.17 score points on average, that is, the improvement potential increases. Eco-inefficiencies within the SI technology for these farms impede possible reductions in improvement potentials offered by the outwards shift of the SI frontier, at least in the short-run (cf. *Hypothesis 2b*). Hence, we find evidence for the *performance effect* in improvement potentials.

Figure 4. Difference in eco-efficiency to the system frontier for SI farms compared to their matched controls.



Farms are sorted by the size of the effect. The black horizontal line indicates the average difference of 0.13 score points.

The heterogeneous distribution of eco-efficiency scores is consistent with previous research on multidimensional performance assessments (e.g., Sidhoum et al. 2019). Reasons for this heterogeneity and increasing improvement potentials for some SI adopters may lie in insufficient knowledge and experience on how to effectively apply and combine measures in the more complex SI production system (Kassam et al. 2011) or that biodiversity effects may only be realised in the long-run (Gabriel et al. 2013). Our results also provide some evidence for the existence of sequential preferences found by Asmild and Hougaard (2006). Farm managers may first need a certain degree of eco-efficiency in an economic direction before they consider switching to the SI technology that offers higher ecological output. The SI farms have a higher mean eco-efficiency score (0.54) than without SI (0.39) to the system frontier in the direction of the economic output (cf. Table 7 in the appendix). Rational inefficiencies (Hansson et al. 2018) offer a part of the explanation for a larger distance to the frontier in an economic direction than in an ecological direction. Farmers may rationally decide to prioritise the ecological outcome above economic efficiency gains at a certain level when non-financial values are included in their utility function (cf. section 2). We do not discuss eco-efficiency results in the economic direction in detail, as we cannot determine the sources of eco-inefficiencies based on the profit indicator.

Eco-inefficiencies in the economic direction may also represent adjustment cost for the farmer, when reducing the ecological improvement potential (Ang and Oude Lansink 2017). A detailed analysis of adjustment costs is beyond the scope of this paper and would require longitudinal data. As the investigated SI measures overlap with voluntary agri-environmental schemes of the European Union's Common Agricultural Policy, some compensation is available. However, financial support does not seem to be generally associated with SI adoption. Thirty-six per cent of SI adopters do not take support payments for their SI measures. Only 31 % of adopters receive payments for two or more SI measures, defined as the minimum for being considered a SI farm (cf. section 3.1). Resentments to accept monetary compensation through agri-environmental schemes may be related to the framing of the policy, perceived restrictions and control by the government (Burton and Schwarz 2013). Our findings are in line with behavioural economic results showing that farmers are willing to contribute to environmental protection even if this contribution is costly and not remunerated (cf. Thomas et al. 2019).

5 Concluding remarks

Proponents of sustainable intensification postulate the possible compromise as a solution for sufficient food production at high environmental standards. We investigate this promise of SI measures to contribute ceteris paribus to ecological sustainability in agricultural land-use. Based on the theoretical frame of Chabé-Ferret and Subervie (2013), farmers compare utility for choosing SI or not, and we model this choice altering the production possibility set. The distance of the farm's actual production to a potential output on the system frontier in the direction of the ecological output represents the farm's improvement potential. We disclose an intended reduction of this improvement potential by adopting SI although constrained by within-technology performance and sources of selectivity. The latter are met by a matching approach. Eco-efficiency scores to a meta-frontier estimated by directional DEA capture the improvement potential empirically. We use farm survey data from northern Germany and determine an indicator for biodiversity as an ecological outcome.

On average, SI farms exhibit higher eco-efficiency scores to the system frontier and, thus, a reduced improvement potential. The mean difference in eco-efficiency scores between SI farms and non-SI farms is 0.13 score points. However, a low within-technology performance of SI farms in some cases increases the improvement potential. Eighty-four per cent of SI farms are eco-inefficient to the overall system frontier. However, if adopters were eco-efficient within the SI technology, they would produce on the system frontier. Thus, the SI measures offer a way to reduce the improvement potential, but this is frequently not used to its full extent. The probability for being able to reach the system frontier without adopting SI is small.

Advancing from previous studies of eco-efficiency and SI, we show that farmers' characteristics and preferences need to be acknowledged to adequately compare differences in improvement potentials. Fostering pro-environmental behaviour or feelings of responsibility could reinforce adoption decisions and environmental performance as has also been advocated from a behavioural economics perspective. Longitudinal studies could be helpful to account for long-run economic planning, sequential preferences or longer time horizons to realize environmental effects. This could lead, in turn, to a robust basis for the design of incentives to ensure that environmentally promising measures lead to more environmentally beneficial behaviour.

As limitation to our study, SI measures are indicated in the data as being either present or not. The extent of their application is ignored and may contribute to the heterogeneity in improvement potentials observed. Additionally, the ecological output is assessed by proxy indicators derived from farm survey data. A trade-off exists in the number of observations and degree of detail of output measures. Exact outputs can only be measured directly on the farm (e.g., Picazo-Tadeo et al. 2011, Schulte et al. 2018). However, even in this case, the attempt to find a comprehensive indicator set and appropriate weights is challenging (Franks 2014). A large-scale consistent set of data and sustainability indicators would be needed for analysis beyond the regional or country scale. Kelly et al. (2018) suggest enhancing the Farm Accountancy Data Network in that regard for Europe.

As financial support neither necessarily implies adoption of SI measures nor a full reduction of the improvement potential, the current policy schemes for the uptake of measures might need expansion or rearrangement. Result-based support measures that reward farmers for achieving ecological improvements represent a currently discussed option, notably for promoting biodiversity (e.g., Burton and Schwarz 2013). A necessity would be to find reliable output indicators. In this regard, possibilities of digitisation for self-monitoring, for instance, via apps, to directly measure outcomes on farm are a promising angle of future research to reduce effort and transaction costs.

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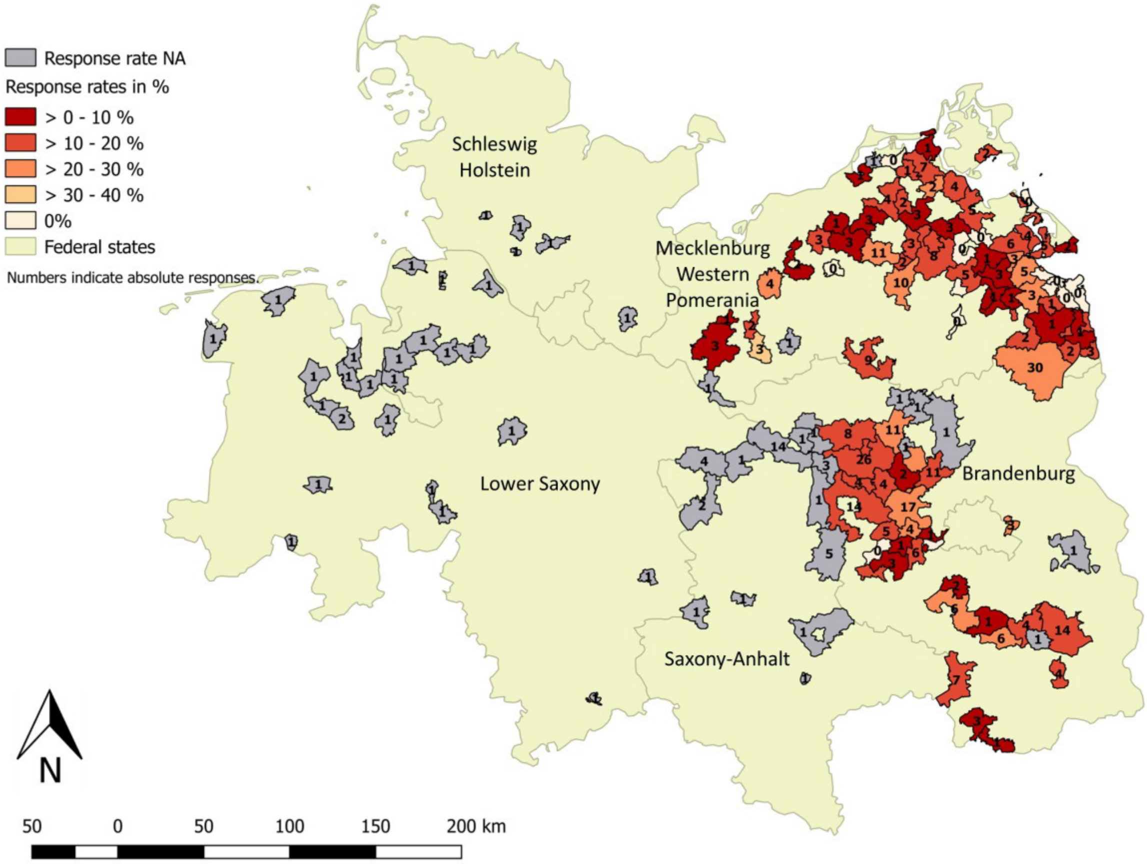
7 Appendix

7.1 Details on sampling and additional descriptive statistics

Figure 5. Map of the spatial expansion of the sample and response rates based on Weltin and Zasada (2018)



Note: 22 farms are excluded from the map as they did not provide their postal code.

Table 4. Outputs and input for eco-efficiency analysis (before and after outlier control)

	Before outlier control		After outlier control[a]	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Economic output: profit indicator [1; 12]	4.21	3.65	4.33	3.66
Ecological output indicator [0;1]	0.41	0.13	0.40	0.12
Input: Used agricultural area [ha]	447.52	682.17	383.17	575.61
Sustainable intensification [1=yes; 0=no]	0.81	0.40	0.80	0.40
N	325		308	

[a] An outlier is identified by a robust Mahalanobis distance larger than the cut-off value $sqrt(\chi^2_{99\%;3})$.

Table 5. Descriptive statistics of matching variables for the observations used in Data Envelopment Analysis

	SI farms		Non-SI farms	
Variables	Mean	Std. Dev	Mean	Std. Dev
Used agricultural area [ha]*	489.99	631.19	108.27	174.94
Profit character [1=full-time; 0=part-time]	0.73	0.45	0.43	0.50
Organic farming [1=yes; 0=no]	0.21	0.41	0.25	0.44
Specialisation arable farming [1=yes; 0=no]	0.37	0.48	0.27	0.45
Labour intensity [workforce/ha UAA]	0.04	0.07	0.05	0.07
Use of extension services [1;5][a]	3.00	1.23	2.36	1.24
Formal agricultural education [1=yes; 0=no]	0.78	0.41	0.66	0.48
Highest educational degree [1; 3][b]	2.42	0.85	2.02	0.98
Farming experience [years]	26.82	12.62	28.00	14.35
Regional attachment [1; 10][c]	8.88	1.89	8.68	1.90
Environmental awareness [1; 10][c]	7.20	2.51	6.66	2.79
Entrepreneurial attitude [1; 10][c]	6.39	2.10	4.93	2.07
Economic output: profit indicator [1; 12]	5.05	3.79	2.70	2.37
Ecological output indicator [0; 1]	0.43	0.12	0.34	0.09
N	221		44	

[a] 1=never; 2=sometimes; 3=occasionally; 4=often; 5=very often
[b] 1=lower secondary or intermediate education; 2=high school; 3=university degree
[c] Self-assessment questions for which respondents indicated the degree of agreement on a scale from 1=fully disagree to 10=fully agree

7.2 Additional results

Table 6. Means and standardised differences (std. diff.) of SI farms and non-SI farms before and after matching

	before matching			after matching				
				matched			unmatched	
	Mean SI=1	Mean SI=0	Std. diff.	Mean SI=1	Mean SI=0	Std. diff.	Mean SI=1	Mean SI=0
Profit character [1=full-time; 0=part-time]	0.73	0.43	0.63	0.76	0.70	0.13	0.50	0.33
Organic farming [1=yes; 0=no]	0.21	0.25	-0.09	0.19	0.17	0.05	0.39	0.00
Specialisation arable farming [1=yes; 0=no]	0.37	0.27	0.20	0.36	0.35	0.04	0.39	0.33
Labour intensity [workforce/ha UAA]	0.04	0.07	-0.39	0.03	0.03	-0.07	0.11	0.17
Use of extension services [1;5][a]	3.00	2.36	0.52	2.95	2.94	0.01	3.39	1.00
Formal agricultural education [1=yes; 0=no]	0.78	0.66	0.28	0.81	0.82	-0.01	0.57	0.33
Highest educational degree [1;3][b]	2.42	2.02	0.44	2.40	2.47	-0.08	2.57	1.67
Farming experience [years]	26.82	28.00	-0.09	26.78	26.93	-0.01	27.07	25.00
Regional attachment [1;10][c]	8.88	8.68	0.10	9.09	8.99	0.05	7.43	7.33
Environmental awareness [1;10][c]	7.20	6.66	0.20	7.21	7.21	0.00	7.14	4.67
Entrepreneurial attitude [1;10][c]	6.39	4.93	0.70	6.48	5.99	0.23	5.80	3.33
N	221	44		193	193		28	3

[a] 1=never; 2=sometimes; 3=occasionally; 4=often; 5=very often
[b] 1=lower secondary or intermediate education; 2=high school; 3=university degree
[c] Self-assessment questions for which respondents indicated the degree of agreement on a scale from 1=fully disagree to 10=fully agree

Table 7. Eco-efficiency scores in the direction of the economic output for SI adopters and their matched controls

	SI farms		Non-SI farms	
	Mean	Std. dev.	Mean	Std. dev.
Meta-technology ratio	0.98	0.11	0.59	0.17
Eco-efficiency to system frontier / improvement potential	0.54	0.34	0.39	0.20
Eco-efficiency to group-specific frontier / within-technology performance	0.56	0.34	0.65	0.24
N	193		193	

Note: Wilcoxon rank-sum test for differences between SI and non-SI farms has a p-value < 0.01 for all three measures.