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# Sustainable Intensification Farming as an Enabler for Farm Eco-Efficiency?

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## Abstract
Sustainable Intensification (SI) practices offer adopters exploiting improvement potentials in environmental performance of farming, i.e. enhance ecosystem functionality, while maintaining productivity. This paper proposes a directional meta-frontier approach for measuring farms' eco-efficiency and respective improvement potentials in the direction of farms' ecological output for SI evaluation. We account for farms' selection processes into SI using a behavioural model and rely on a matched sample for adopters and non-adopters of agronomic SI practices from the northern German Plain. We conclude that the SI adopters determined the sample's system frontier and showed higher mean eco-efficiency, but that most farms in our sample did not fully exploit the improvement potentials in biodiversity as ecological outcome.

**Keywords** Sustainable intensification concept · Directional data envelopment analysis · Eco-efficiency · Environmental sustainability · Matching · Meta-frontier

**JEL Classification** Q12 · Q15 · Q57

## Abbreviations

| | |
|---|---|
| DEA | Data envelopment analysis |
| DDF | Directional distance function |
| MTR | Meta technology ratio |
| SI | Sustainable intensification |

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## 1 Introduction

Humanity faces the crucial challenges: increasing global food production and transitioning quickly to sustainable and climate-smart agricultural production systems (Sarkar et al. 2020) at limited and contested natural resources (Li et al. 2019; Popp et al. 2014). Intense traditional farming practices contribute to loss of biodiversity, greenhouse gas emissions and groundwater contamination (Conijn et al. 2018; Foley et al. 2011). Many of the ecological improvements in farming associated with low-input or organic production, cannot maintain productivity levels and may even cause land conversions (Smith et al. 2019).

Given that farms operate in the complex social-ecological system, i.e. farming extracts and markets ecosystem services and provides maintenance by interacting with the natural system (cf. McGinnis and Ostrom 2014), a number of crucial farm management and production decisions may have adverse effects on ecosystem functioning. Hence, the concept of Sustainable Intensification (hereafter SI) has been proposed to offset the adverse effects of agricultural production (Balaine et al. 2020; Baulcombe et al. 2009), and to sustain rural economies (Godfray and Garnett 2014). SI-based production systems have been developed to reduce environmental harm while maintaining yield levels (Pretty 2018), or foster yield growth in developing countries while preserving ecosystems (Pretty 1997; Schut and Giller 2020) and closing yield gaps (Ray et al. 2012). SI thus governs the socio-economic dimension of sustainability, while enhancing functionality of the natural ecosystem, i.e. the ecological dimension of sustainability (e.g., Gunton et al. 2016). Other conceptual definitions include aspects of the social dimension of sustainability explicitly, for instance cultural or ethical aspects (Garnett and Godfray 2012).

Practical evaluations of the outcomes of adopting SI measures on farm level are mainly based on field trial data (e.g., Paul et al. 2015; Townsend et al. 2016) or simulation-based approaches (e.g., Devkota et al. 2016; Mao et al. 2015; Scherer et al. 2018) and strongly focus on yield effects. Yet holistic approaches seem underrepresented. Few studies exist demonstrating that farms in developing and developed countries can improve their ecological and economic performance by adopting SI measures (e.g., Kassie et al. 2015). For European cases, Areal et al. (2018) or Gadanakis et al. (2015) assess SI with indicators to track economic and ecological farm outcomes but do not causally link the outcome indicators to the adoption of specific SI measures. Petersen and Snapp (2015) indicate that assessing SI is challenging as adopting and combining different agronomic measures may impact the production process in various ways. This may explain the continuing debate about which measure could achieve an improved balance between the economic and ecological sustainability of agricultural production. Mahon et al. (2018) even emphasise the need for concrete outcome specifications of SI, while acknowledging the processes of ecosystem maintenance and service extraction under the respective local natural system and governance settings.

In this paper we analyse agronomic examples of SI measures (e.g., wider crop rotations, reduced tillage, integrated pest management, and plant and/or site-specific technologies) and their potential offset environmental harm without sacrificing productivity (cf. Weltin et al. 2018 for an overview of SI measures). In order to evaluate the benefits of these different measures, we propose a meta frontier approach for measuring farms' eco-efficiency and respective improvement potentials. We use rich survey data for a sample of SI adopters and non-adopters throughout the northern German Plain, which is characterised by peatlands. We follow the fundamental SI definition which states that SI practices can improve the balance between the economic and ecological sustainability of agricultural production without reducing either (Dicks et al. 2019).

We base our evaluation on a utility maximization model, where farmers opt consciously for a SI technology, and on a two-output (economic and ecological) production model and a directional meta-frontier approach to measure eco-efficiency (cf. Beltrán-Esteve and Reig-Martínez 2014; O'Donnell et al. 2008). The production frontiers of SI technology and traditional farming technology are enveloped by an eco-efficient system frontier. We assume that the system frontier offers the highest possible outputs in either direction. A farm's eco-inefficiency in direction of the ecological output reflects the improvement potential in environmental performance, i.e. maintaining or enhancing the eco-system's functionality, at a given level of economic outcome (cf. Kuosmanen and Kortelainen 2005).

We hypothesize that adopting SI offers an eco-efficient reduction of farms' improvement potentials and farms provide more maintenance in the form of ecological output at no economic cost. Our analysis involves three aspects: we examine whether SI adopters determine the system frontier in the ecological output direction and refer to this as the *technology effect*. As a second aspect, we explore whether adopting the SI technology reduces farms' improvement potentials, i.e., the distances to the system frontier in the direction of the ecological output, and as a third aspect, we acknowledge that farms' performance in the chosen technology can impact the improvement potential and refer to this as the *performance effect*.

Given that farmers make production decisions based on utility maximization, observed differences in the environmental performance improvement potentials between the SI adopters and non-adopters can also relate to the structural differences of the two groups (e.g., natural and socio-economic conditions or environmental preferences). In line with Mayen et al. (2010), linking technology adoption decisions and eco-efficiency analysis is a pre-condition for identifying causal relationships. Therefore, following the theoretical behavioural framework of Chabé-Ferret and Subervie (2013), we assume a representative farmer will choose the SI technology, and the inputs and outputs that maximise utility and improve ecological and economic potentials. Figure 1 illustrates our research plan and the effects we investigate.

We believe this is the first paper to provide a meta-frontier approach for evaluating SI by comparing improvement potentials in the direction of ecological outputs. We contribute to the environmental economics literature by using a matching algorithm to generate a control sample that reduces potential bias and causally interprets the differences in eco-efficiency through SI measures. The proposed meta-frontier approach separates the differences in improvement potentials between the SI adopters and non-adopters into a *technology effect* and a *performance effect*.

The remainder of this paper is organized as follows. Section 2 introduces the analytical framework, theoretical background and hypotheses. Section 3 describes the empirical model specification, data, and study region. Section 4 presents the results. Section 5 discusses the results. Section 6 concludes and offers suggestions for future research.

## 2 Conceptual Approach

### 2.1 Eco-Efficiency Analysis for SI Evaluation

The eco-efficiency analysis used in this paper offers an instrument for measuring the capability of farms to produce goods at the least environmental harm (e.g., Chen and Delmas

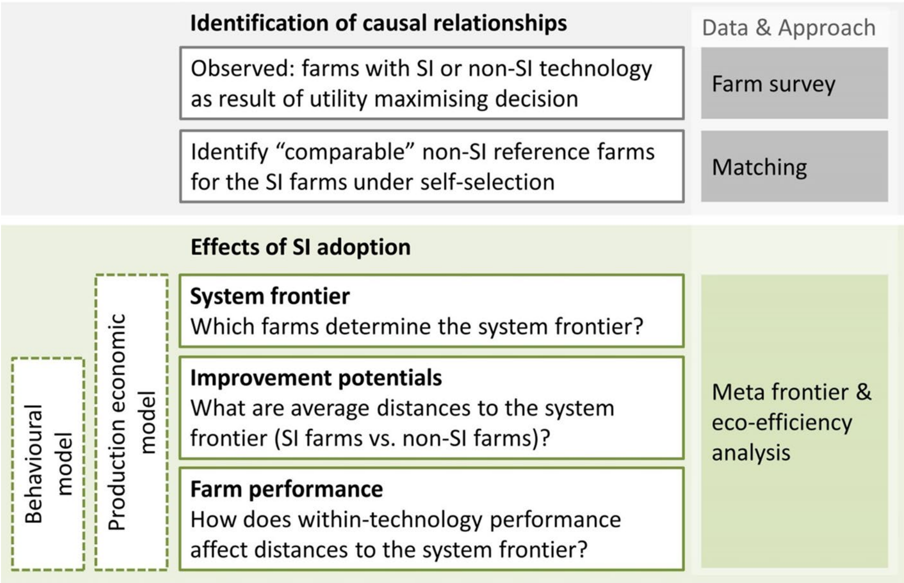



**Fig. 1** Research plan

2012; Halkos and Petrou 2019; Huppes and Ishikawa 2005). Typically, the production possibility frontier in a two-output model consists of an economic and environmental output dimension (see Sect. 2.2). Adopting and implementing SI measures successfully governs the two dimensions by mitigating or eliminating the undesirable environmental output and maintaining the economic production output, or vice versa. The eco-efficiency approach is thus preferable to using a single evaluation of indicators, such as a cost–benefit analysis of agricultural income before and after SI adoption (see Smith et al. 2017 for an overview).

In this paper farm-specific deviations from the production possibility frontier denote eco-inefficiencies. Farm-specific but directional eco-efficiency measures indicate respective inefficiencies in the ecological and economic output direction separately (Callens and Tyteca 1999; Picazo-Tadeo et al. 2012; Tyteca 1999), and the measured eco-inefficiency scores reflect farms' improvement potentials in the economic and ecological direction (Asmild et al. 2016).

Key for evaluating SI is the investigation to which extent farms exploit the respective improvement potentials. We follow the idea of sequential preferences by Asmild and Hougaard (2006), and presume that farm managers first aim at optimizing technical efficiency, that is, focus on optimizing in the economic output direction. Second, after meeting a certain economic threshold, and depending on their environmental preferences, they may improve the environmental output, along with SI adoption (see Sect. 2.3).

Our non-parametric directional approach based on Data Envelopment Analysis (DEA) relies on linear programming approaches to retrieve the production possibility frontier as the best practise frontier (Bogetoft and Otto 2011). Free of any distributional assumptions, the approach does not suffer from potential bias due to the functional form misspecification of the frontier. Farm-specific deviations from the best practise frontier in the ecological direction capture the ecological outcome improvement potentials without sacrificing economic performance (Zhou et al. 2018).

DEA approaches have been applied to eco-efficiency analyses of agricultural production, particularly for evaluating production systems that govern economic value creation at lower externalities, such as dairy farms' greenhouse gas emissions (e.g., Pérez Urdiales et al. 2016), environmental nutrient impacts (Iribarren et al. 2011), soil loss due to erosion (Eder et al. 2021), pesticide uses for olive production (Gómez-Limón et al. 2012; Picazo-Tadeo et al. 2012) and crop production (Bonfiglio et al. 2017). DEA approaches have been applied to production types related to policy support, such as participation in agri-environmental schemes (Picazo-Tadeo et al. 2011), sustainable coffee production certification (Ho et al. 2018), labour- versus capital-intensive farming systems (Grzelak et al. 2019), regional differences (Coluccia et al. 2020) and farm sizes (Stępień et al. 2021).

We base our analysis on the behavioural model of Chabé-Ferret and Subervie (2013) to frame the decision to adopt SI measures for causal identification of farms' respective improvement potentials. The model of was originally developed to identify (windfall) effects causally linked to participation in agri-environmental schemes in France; an issue that has been discussed for other regions (Arata and Sckokai 2016; Calvet et al. 2019), other policy measures, for instance decoupled payments (Esposti 2017a, b), and for other voluntary production choices such as organic farming (e.g., Cisilino et al. 2019). The behavioural model frames the role of environmental preferences while investigating farm level decisions to enter such policy schemes and has been mirrored in follow-up applications (Kuhfuss et al. 2016; Laukkanen and Nauges 2014; Mennig and Sauer 2020; Udagawa et al. 2014).

## 2.2 The Production Economic Model

We assume that a representative farm $i$ produces output vector $\boldsymbol{Y}$, with an economic $Y_{econ}$ and ecological dimension $Y_{ecol}$. We use agronomic SI measures to categorize the SI technology and the traditional farming technology with respective production technology sets $\Psi_j$ with $j = \{0;1\}$, where $j = 0$ indicates production without SI measures and $j = 1$ indicates the SI-adjusted production system. In both technology sets, farm $i$ chooses a variable input $X$ and on-farm labour $H$ to produce output $\boldsymbol{Y}$. Fixed inputs $\boldsymbol{I}$, such as human and physical capital, and unobserved factors $\boldsymbol{\varepsilon}$, such as land quality, weather conditions or managerial ability, enter the production possibility sets:

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

Following O'Donnell et al. (2008), the respective technologies, $\Psi_j$, determine a common production system frontier, $\Psi_m$, enveloping the SI and non-SI production possibility frontiers. The system production possibility frontier denotes the achievable production output for farms in a region, given the natural ecosystem and the governance settings. Figure 2 illustrates our production economic model.

The solid black line represents the system frontier $\Psi_m$ and the dashed lines represent the respective production possibility frontiers of the two technologies (SI, $\Psi_1$, versus traditional farming, $\Psi_0$). Farms producing on the system frontier $\Psi_m$ such as A in Fig. 2 fully exploit their improvement potentials in both directions (eco-efficient), whereas farms A' and A'' deviate and can improve in either direction against the overall system frontier (economic or ecological). Directional distances from these points measured against A give the degree of eco-inefficiency in the farm's ecological output direction for given economic outcome (e.g., Picazo-Tadeo et al. 2012). As we hypothesize that the SI technology determines the system frontier in ecological direction, A'', offers improvements in ecological direction

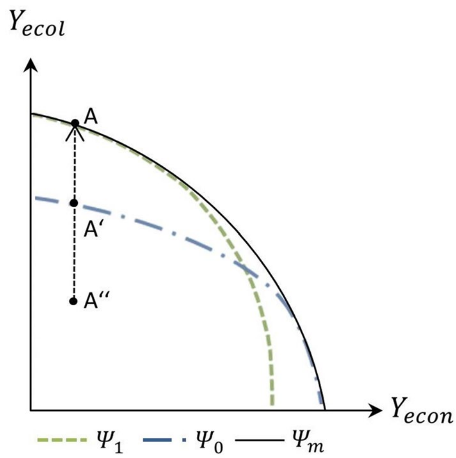



**Fig. 2** System frontier ($\Psi_m$) and the two group-specific frontiers, non-SI ($\Psi_0$) and SI ($\Psi_1$)

to A at the maximum under SI. If farms do not adopt SI and operate efficiently (A' in Fig. 2 on $\Psi_0$), they still have unexploited improvement potentials when compared to the system frontier (*technology effect*). In Fig. 2, such improvement potential in ecological direction is denoted by the directional distance between A' and A. While the distance A'' to A' suggests efficiency gains and efficient production when measured against the non-SI frontier, evaluated against the SI and the system frontier, inefficient.

Assuming that a farm producing efficiently under SI ($\Psi_1$) produces closer to the system frontier in an ecological direction than farms using traditional farming technology, leads to the following hypothesis:

**Hypothesis 1** *The SI frontier locates in the direction of the ecological output closer to the system frontier. Hence, SI adopters in this direction determine the system frontier.*

### 2.3 The Behavioural Model

We assume that the observed and measurable respective improvement potential of a farm, denoted as $\tilde{Y}_j$, results from two sequential decisions. First, the farm household's decision to adopt SI determines the possible improvement in the ecological direction by the respective group-specific frontier. Second, the farm household's decision regarding input allocation and intensity determines how eco-efficiently to operate with the chosen technology. Following Chabé-Ferret and Subervie (2013), we assume farms maximize utility as represented by utility function $U$, and evaluate optimized production input levels $X_j^*$ and on-farm labour time allocation $H_j^*$ for both technologies. Both $X_j^*$ and $H_j^*$ are functions of the exogenous variables, such as prices, consumption shifters, preferences and fixed inputs, as denoted by $g_j$ and $h_j$, respectively.

Presuming that sequential preferences guide the farm household's decision to adopt SI measures (cf. Asmild and Hougaard 2006), the SI farm aims to reduce the improvement potential in the ecological direction compared to their non-SI reference situation. We thus model their first stage decision-making such that the results from previous years and their experience enter the estimation of the reference improvement potential: $\tilde{Y}_0^* = \tilde{Y}_0\left(X_0^*, H_0^*\right)$.

The 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:

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

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

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

where utility $U$ depends on levels of consumption $C$, leisure $L$, variable input $X$, and on-farm labour hours $H$. Variable input $X$ and on-farm labour hours $H$ reflect the dependence of utility on the farm's preference for or rejection of certain input compositions. 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 $U$. Equation (3) above gives the transformation function in an explicit form regarding $Y_{econ}$ according to the implicit function theorem (e.g., Sauer and Wossink 2013), and Eq. (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 $w$. 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 given by:

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

and

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

When applying SI, the farm's input allocation is guided such that the improvement potential in the ecological direction, $\tilde{Y}_1$, does not exceed the optimized improvement potential of the reference situation, $\tilde{Y}_0^*$. This provides an additional voluntary constraint to the utility maximization problem. The constraint becomes applicable when the farm adopts SI ($D = 1$), where the reference improvement potential enters as a constant:

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

The voluntary constraint of Eq. (8) enters the first-order conditions:

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

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

where $\lambda$ denotes the respective Lagrangian multiplier.

Therefore, the optimized input choices under SI 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 improvement potential under SI. If the constraint is binding ($\lambda \neq 0$), the farm will adjust $X$ and $H$ but may be compensated by increases in utility, whereas if the constraint is not binding ($\lambda = 0$), the farm has no costs in terms of the constrained use of $X$ and $H$ when applying SI. Optimized input and labour allocation under SI are given by:

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

and

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

We note that if the farm's expected improvement potential under SI, $\tilde{Y}_1^*$, remains insufficiently large enough to increase utility compared to $\tilde{Y}_0^*$ according to the environmental preferences, the farm will not adopt ($D = 0$) and Eq. (8) becomes irrelevant.

We use the farm's decision outcome to measure the respective improvement potential $\tilde{Y}_j$ as shown in Fig. 2. The farm decides on SI based on the indirect utilities, $V_1$ and $V_0$. Indirect utilities depend on the same variables as $\tilde{Y}_1^*$ and $\tilde{Y}_0^*$. The implementation of SI may, however, induce search, implementation or information cost denoted by $V$. Cost $V$ potentially varies with education and experience and reduces indirect utility when choosing SI. The farm will adopt SI ($D = 1$) when the expected increase in indirect utility outweighs the cost of adoption:

$$D = \mathbf{1}\left[E\left[V_1 - V_0|\boldsymbol{Z}\right] - V \geq 0\right]], \tag{13}$$

where $\boldsymbol{Z}$ denotes the determinants of the adoption decision. The determinants may coincide with the determinants of input choices, such as environmental preferences, consumption shifters or fixed inputs. Since the adopters and non-adopters may systematically differ regarding their environmental preferences, we need to ensure comparability between the two groups before we assess the observed improvement potentials.

Thus far, we have assumed eco-efficient production under the respective technology. In the short-run, however, inefficiencies within the chosen technology may occur and farms may tolerate the adjustment costs of technology adoption in terms of output reductions (Ang and Oude Lansink 2017), although ignoring the possible inefficiencies of SI adopters would bias the retrieved improvement potentials (*performance effect*). For instance, a fully efficient non-SI farm could have a lower improvement potential compared to a weakly efficient SI-farm. Figure 3 illustrates two examples of non-SI reference situations.

If farm A could achieve A'', the improvement potential turns to zero, otherwise farm A may only be able to reduce the improvement potential up to a point A', which is also achievable in the non-SI technology, due to eco-inefficiencies within the SI technology. Farm B is eco-efficient within the non-SI technology but could exhibit eco-inefficiencies in the SI technology that prevent moving to a point B' that reduces the improvement potential. Assuming that performance B''' under SI corresponding to the ecological output level of A' could even increase farm B's improvement potential leads to the following hypotheses.

**Hypothesis 2a** *At the mean, for the same economic outcome, SI adopters produce at a lower ecological improvement potential than comparable non-adopters.*

**Hypothesis 2b** *If SI adopters have a low within-technology performance in the chosen technology and comparable non-adopters have a high within-technology performance, the non-adopters have lower improvement potential than the adopters in some cases.*

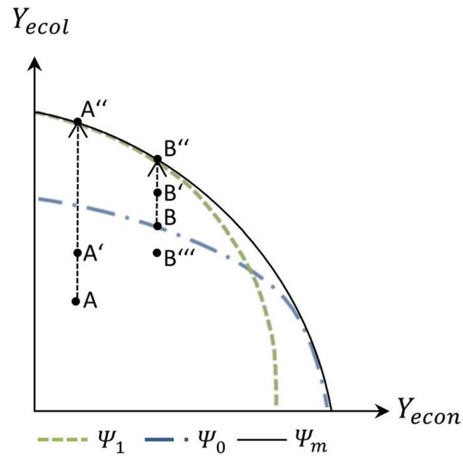



**Fig. 3** Improvement potentials for different reference situations of farms A and B. SI adoption may shift farm production to A′ and B′ with reductions in improvement potential. B‴ represents a situation when eco-inefficiencies in the SI technology increase the improvement potential compared to B

## 3 Data and Empirical Approach

### 3.1 Study Area, SI Measures, SI-Related Outcomes and Summary Statistics

Our study area is the northern German Plain characterised by abundant peatlands and lowland farming systems. These areas are classified as high-priority intervention areas in the European Common Agriculture Policy framework to protect carbon-rich soils and require adapting farming practices to meet Germany's climate protection and biodiversity goals (TEEB 2015) and EU's climate protection goals (European Commission 2020).

We use data from a survey of farming practices conducted between February and June 2017 for farms in the federal states of Brandenburg, Mecklenburg Western Pomerania, Saxony-Anhalt, Lower Saxony and Schleswig Holstein (for brevity, the full questionnaire is provided with the supplementary material). For the survey, farms in Brandenburg, Mecklenburg, and Western Pomerania were recruited in areas with at least 20% peatland area and 1000 ha of peatlands in total, and with more than 5000 ha of peatlands in total, based on postal code. Additional respondents were recruited via farmers' associations in all five federal states. From the 464 observations in the spatial expansion, we used the 410 farms for which we observed adoption decisions for SI measures, and excluded 26 farms below 5 ha, for a total of 384 farms. Figure 4 illustrates the study area.

The set-up and data, including sampling choices, selected SI measures and outcome definitions may affect the location of the eco-efficient frontier, and thus sensitivity respective improvement potentials (cf. Areal et al. 2018; Gadanakis and Areal 2018). Therefore, our approach contains a robustness analysis. We exclude the additional recruitments in in the first robustness scenario.

This evaluation study targets at investigating the contribution of agronomic SI measures in improving farms' eco-efficiency, and therefore, regionally relevant agronomic SI measures have to be identified. Following Dicks et al. (2019) and Firbank et al. (2013), we support our choice by stakeholder opinions. Thus, prior to conducting our survey, we invited farmers, representatives of environmental protection agencies, and local administrators, to a workshop in the Rhinluch in Brandenburg, explaining the research and to select our SI measures. Given the study region's urgencies to meet climate-protection and biodiversity goals by SI, our ecological outcome measures focus on on-farm and

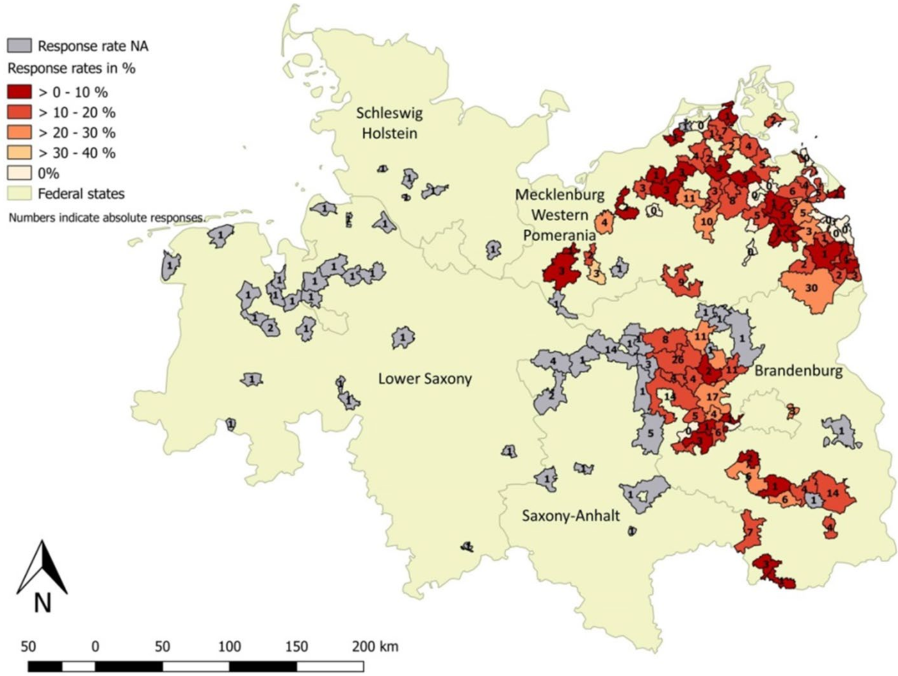



**Fig. 4** Map of the spatial expansion of the sample and response rates in North German Plain (based on Weltin and Zasada (2018). Note: 22 farms that did not give postal codes are excluded

on-land diversity, and we selected six agronomic SI measures with potential contributions to biodiversity and thus ecosystem functionality of grassland and arable farming: (1) reduced tillage, (2) intercropping, (3) growing legumes, (4) integrated pest management, (5) grazing, and (6) extensive use of grassland. While in this study we focus on the economic and ecological sustainability dimensions, SI measures discussed in the workshop also governed social aspects (see Weltin et al. 2021).

To specify the ecological output dimension in the eco-efficiency model, $Y_{ecol}$, we primarily focus on farm, farmland and crop diversity. We rely on several indicators classified as indirect or related to farmland use and management that correlate with biodiversity (cf. Bockstaller et al. 2011). Since landscape simplification is a strong predictor for losses in species richness and thus ecosystem functionality (Dainese et al. 2019), we follow a more holistic approach by Gibson et al. (2007) and consider farm-level heterogeneity between different landscape elements (on-farm diversity) and the diversity within each land use type (on-land diversity). We assign equal weight to both aspects of diversity in the final ecological output indicator (cf. Gan et al. 2017). For robustness scenarios 2 and 3, we vary the weighting scheme by assigning a higher weight of 80 percent to one diversity aspect. Table 1 reports the calculations of the indicators.

We use the Simpson diversity index to indicate on-farm diversity on cropped and non-cropped area, i.e. share of arable land, extensive grassland, and other grassland (cf. Van Eck and Koomen 2008). For non-cropped land, we observe the presence but not the amount of fallow land and flower or buffer strips. Acknowledging their high value for

**Table 1** Environmental output indicators and calculations

| Output indicators | Calculations |
|---|---|
| *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<br>$a_{i,norm.} = \frac{a_i}{1-\frac{1}{k}}$ normalises $a_i$ to the interval [0;1] |
| Presence of fallow $b_i$ | Indicator is 1if 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 | $\frac{1}{2}a_{i,norm.} + \frac{1}{4} b_i + \frac{1}{4}c_i$ |
| *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 | $\frac{\text{arable land}_i}{\text{UAA}_i} d_i + \frac{\text{total grassland}_i}{\text{UAA}_i} \frac{1}{3}\left(e_i + f_i + g_i\right)$ |

All indicators are in the interval [0;1]

biodiversity (Herbst et al. 2017; Weibull et al. 2003), we assign them 50% of the weight in the overall indicator for on-farm diversity.

For on-land diversity, we measure the biodiversity in arable land by the number of different crops grown within a year (Matson et al. 1997). For grassland we use three indicators: we include the share of permanent grassland to total grassland. The indicator captures the carbon sink function of grassland (Barnes and Poole 2012). We use farms' shares of permanent pasture that exceed regional averages to capture a biodiversity surplus extending the indicator of Areal et al. (2012). We use the third grassland indicator for the abundance of peatlands extensively managed or in conditions close to nature, with a high impact on carbon capture and biodiversity (TEEB 2015). We weight the three grassland indicators equally. We weight the indicators for arable and grassland by the respective share of each land-use type on the farm in the composite indicator for on-land diversity to reflect the heterogeneity of farm types in the sample. To account for potential farm-type effects, in the fourth robustness scenario, we exclude fully specialised farms that operate either only on arable land or only on pastures. Figure 5 maps the distribution of peat- and wetland areas in the studied region and the main land use types.

We consider economic outputs and ecological outputs without modelling all inputs in the production process. We use the agricultural area as input for deriving the improvement potentials for farms of comparable size. To specify the economic output dimension in the eco-efficiency model, $Y_{econ}$, we rely on a farm profit indicator provided on an

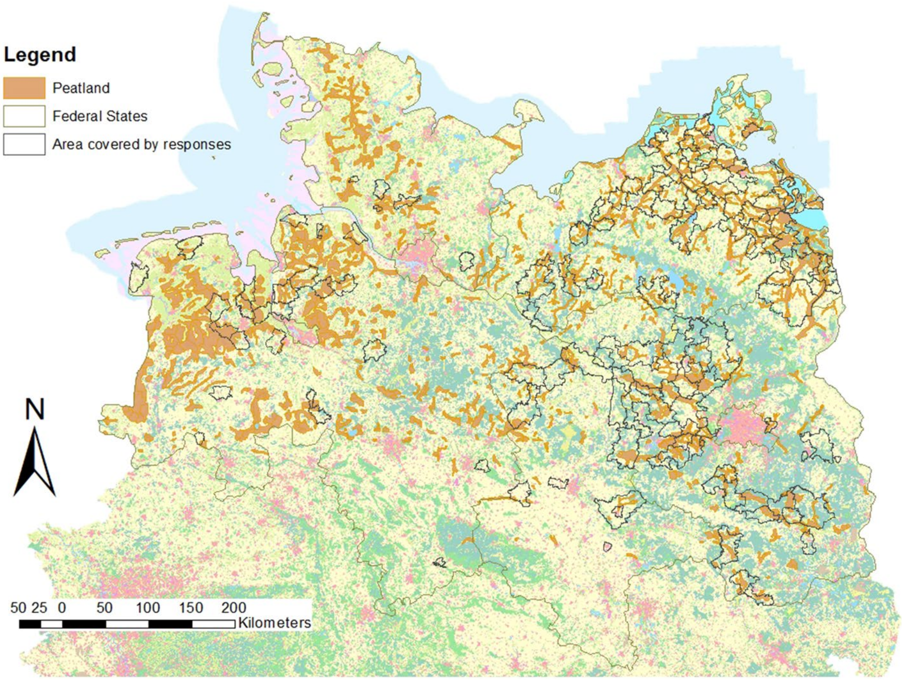



**Fig. 5** Map of main land use types and peatland areas in study region. Note: Land use visualistions based on CORINE Land Cover—10 ha (see http://sg.geodatenzentrum.de/wms_clc10_2012); red denotes artificial surfaces, yellow denotes agricultural areas, and green denotes forest and seminatural areas (for details see https://land.copernicus.eu/pan-european/corine-land-cover/clc-2012?tab=mapview)

ordinal scale with twelve categories and acknowledge its limitations compared to direct measures, such as agricultural income and associated risk (Smith et al. 2017).[1]

Our modelling relies on a binary distinction between SI and non-SI technology so we need to define a cut-off value that distinguishes SI adopters from non-adopters. If we assume that SI measures best exploit their benefits via combinations (Benton et al. 2003; Kassie et al. 2015), we need an SI adopter to apply at least two SI measures. We use the median number of adopted measures in our sample, that is three measures, to avoid potentially overestimating the performance of SI adopters. In our robustness analysis, we define further scenarios with cut-offs at two and four measures, respectively.

[1] The 12 categories are: 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€; and 12. more than 250,000€. For Category 1 we merge profit and loss because most of the farmers recruited for pre-testing refused to answer the survey question.

**Table 2** Summary statistics for SI and non-SI farms before matching

| Variables | SI farms | | | Non-SI farms | | |
|---|---|---|---|---|---|---|
| | N | Mean | SD | N | Mean | SD |
| Used agricultural area [ha]* | 217 | 638.90 | 763.33 | 166 | 141.99 | 277.33 |
| Business type [1 = full-time; 0 = part-time]* | 216 | 0.79 | 0.41 | 165 | 0.43 | 0.49 |
| Organic farming [1 = yes; 0 = no] | 216 | 0.19 | 0.40 | 164 | 0.21 | 0.41 |
| Specialisation arable farming [1 = yes; 0 = no][a*] | 217 | 0.37 | 0.48 | 164 | 0.25 | 0.43 |
| Labour intensity [workforce/ha UAA][b]* | 209 | 0.03 | 0.05 | 149 | 0.08 | 0.11 |
| Use of extension services [1; 5][c]* | 211 | 3.00 | 1.16 | 163 | 2.52 | 1.31 |
| Formal agricultural education [1 = yes; 0 = no]* | 209 | 0.79 | 0.41 | 160 | 0.63 | 0.48 |
| Highest educational degree [1; 3][d]* | 209 | 2.41 | 0.85 | 163 | 2.17 | 0.92 |
| Farming experience [years] | 209 | 27.97 | 12.44 | 158 | 26.65 | 14.53 |
| Regional attachment [1; 10][e] | 209 | 8.88 | 1.93 | 161 | 9.00 | 1.74 |
| Environmental awareness [1; 10][e] | 207 | 7.10 | 2.59 | 159 | 6.97 | 2.68 |
| Entrepreneurial attitude [1; 10][e]* | 206 | 6.62 | 2.01 | 153 | 5.25 | 2.26 |
| Economic output: profit indicator [1; 12]* | 188 | 5.16 | 3.97 | 152 | 3.17 | 2.95 |
| Ecological output indicator [0; 1]* | 211 | 0.46 | 0.13 | 160 | 0.34 | 0.13 |

*Wilcoxon rank sum test for differences between groups has a $p$ value $< 0.05$

[a]According to farmer's self-assessment

[b]Workforce below 1 person set as 1

[c]1 = never; 2 = sometimes; 3 = occasionally; 4 = often; 5 = very often

[d]1 = lower secondary or intermediate education or no degree; 2 = high school degree; 3 = university degree

[e]Farmers' responses to self-assessment questions; degree of agreement scale: 1 = fully disagree to 10 = fully agree

We characterise farmers by their responses to the survey questions and exclude 43 observations with missing values for a total of 265 observations.[2] Table 2 lists the characteristics of the SI and non-SI farms and the summary statistics.

The table indicates that SI farms are more likely to be full-time operations, operate at larger scale, their farmers are more highly educated (e.g., agricultural degree), and use agricultural extension services more often compared to non-SI farmers. SI farmers also have a stronger affinity for regional entrepreneurship. Differences in the unconditional means of variables self-indicated environmental awareness and regional attachment, however, are small.

### 3.2 Efficiency Model Specification and Matching Approach

We use a meta-frontier approach to measure the eco-efficiency scores to the system frontier and within-technology performance to the group-specific frontiers. Therefore, we rely on directional distance function (DDF) for measuring eco-inefficiency in either direction. We

[2] The questionnaire includes five self-assessments: environmental awareness; regional attachment; and attempts to adopt innovations, assume business risks, and contribute to regional economic development. The latter three form the variable regional entrepreneurship. Factor analysis supports the separation of the five self-assessments into three distinct constructs (for brevity, see supplementary material, Sect. 1).

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

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

For within-technology performance, $\Psi_j$ in Eq. (14) replaces $\Psi_m$. Symbol $\beta_{ecol,j}$ represents 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, which is the farm's 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 farm's distance to the system frontier if the farm produces on its group-specific frontier (Gómez-Limón et al. 2012). An MTR of 1 implies that the group-specific frontier coincides with the meta-frontier and offers to assess the *technology effect* of SI. Similarly, we calculate the farm's eco-efficiency in the economic direction by setting the direction vector to $g_y\left(0, Y_{econ}\right)$.

We use directional non-parametric DEA and opt for a full disposable hull technology to obtain the most cautious estimates of the respective improvement potentials. Since DEA results are sensitive to outliers with regard to inputs and outputs (Bogetoft and Kromann 2018), we use the minimum covariance determinant estimator for outlier control (Rousseeuw and Driessen (1999). We estimate robust Mahalanobis distances to assess the distance between an observation and the centre of the data (cf. supplementary material Sect. 2 for details). We observe land, profit and biodiversity indicators for 325 observations and eliminate 17 outliers. We use the R packages *Benchmarking* and *Robustbase.*

The SI adopters may differ in their farm(er) characteristics from the non-adopters as well, so that a comparison of the observed improvement potentials will not suffice to identify the causal differences. As sub-sample homogeneity is a precondition for the causal interpretation of outcomes when selectivity issues prevail (Bogetoft and Kromann 2018), we combine the eco-efficiency analysis with a matching approach. Using observed farm(er) characteristics $\boldsymbol{Z}$ as covariates, the matching approach offers generating a counterfactual control group with the characteristics that resembles the group of SI adopters. Comparing the eco-efficiency of SI adopters and these estimated counterfactual group of non-adopters offers a causal link of eco-efficiency and SI. We use kernel density matching based on Mahalanobis distances, offering more robust results in smaller samples (Zhao 2004), and the Epanachnikov kernel function. Kernel matching allows us to assign several control observations to each SI adopter, thus reducing the variance of the estimation. We determine the bandwidth of the estimator 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 the matched controls.

For the matching covariates $\boldsymbol{Z}$, we select farmers' education and experience, farm characteristics (full-time operation, specialisation in arable and organic farming), labour intensity to reflect the intensity of the farming operation., and use of advisory services offering knowledge input for the farm business. As farmers' environmental preferences and sustainability attitudes have proven relevant (e.g., Hansson et al. 2018; Jongeneel et al. 2008) and our survey remains limited, we additionally consider farmers' self-assessments for regional attachment, environmental awareness, and entrepreneurial attitude. Due to missing values, we exclude 43 observations (cf. Table A1 in Appendix A for descriptive statistics before matching).

**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 | SD | Mean | SD |
| Meta-technology ratio (MTR)[1] | 0.99 | 0.02 | 0.86 | 0.13 |
| Eco-efficiency to system frontier/improvement potential[a] | 0.75 | 0.17 | 0.63 | 0.10 |
| Eco-efficiency to group-specific frontier/within-technology performance[b] | 0.76 | 0.17 | 0.74 | 0.15 |
| | 149 | | 149 | |

[a]Wilcoxon rank-sum test for differences between SI and non-SI farms has a $p$ value < 0.01

[b]Wilcoxon rank-sum test has a $p$ value < 0.1

# 4 Results

To increase the precision of the estimates, we exclude the eight SI farms and 16 non-SI farms out of common support (cf. Lechner and Strittmatter 2017). The final sample with achieved covariate balance (all standardized differences are below 0.25 (cf. Stuart 2010) for DEA consists of 149 SI farms and their matched control non-SI farms. On average, an SI adopter has 11.49 control observations as matches (see Appendix Table B1 for the standardized differences and group means before and after matching).

The results in Table 3 lend support to our three hypotheses (also see in the supplementary material Table 3.1 for the respective results of the robustness scenarios).

## 4.1 System Frontier and Technology Effect

The meta-technology ratio that captures the eco-efficiency to the system frontier is 0.99 on average and is equal to 1 for 78 SI farms. In other words, if all SI farms were eco-efficient to their group-specific frontier, they would also be or nearly be eco-efficient to the system frontier. An average MTR of nearly 1 with a small variance (max. 0.05) for adopters is a consistent pattern across the robustness scenarios. The average MTR is 0.86 for non-SI farms, where only 26 have an MTR of 1. The MTR range for non-adopters in the robustness check is between 0.77 and 0.93. We use the distributions of the eco-efficiency scores to test the differences in the location of the frontiers. 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 non-SI farms ($D = 0.42$; $p = 0.00$), but cannot reject them for SI farms ($D = 0.07$; $p = 0.89$). The results lend support to hypothesis 1 (*The SI frontier locates in the direction of the ecological output closer to the system frontier. Hence, SI adopters in this direction determine the system frontier.*).

## 4.2 Performance Effect

Table 3 above also shows that SI farms are on average more eco-efficient to the system frontier (0.75) than matched control non-SI farms (0.63), or a difference of 0.12 score points. The result is consistent with similar differences for all scenarios of the

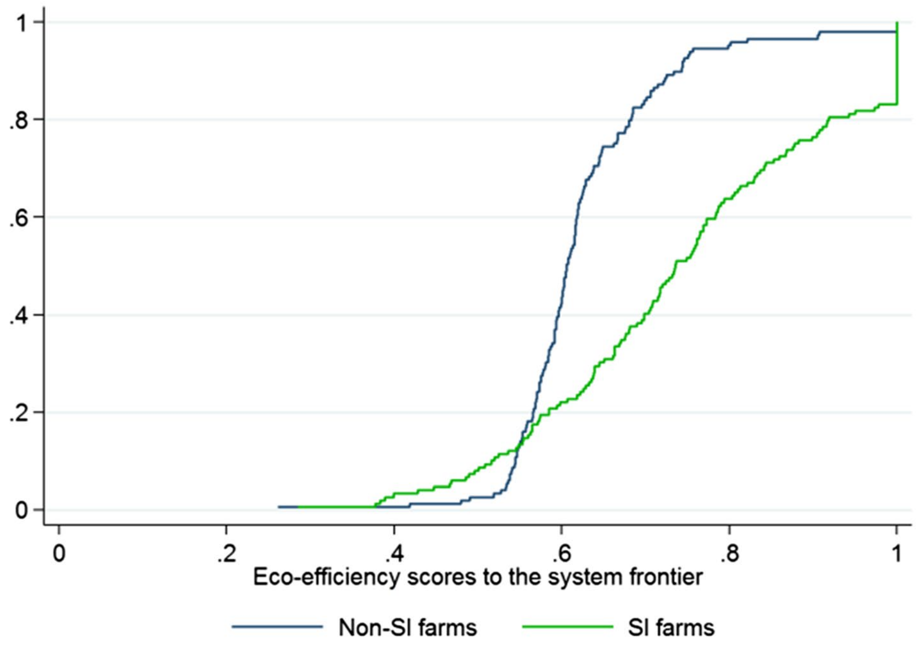



**Fig. 6** Empirical cumulative distribution of eco-efficiency scores to the system frontier for SI and non-SI farms

robustness analysis except for raising the weight of on-land diversity in the ecological outcome indicator (i.e., adopters are still more eco-efficient but the gap narrows to 0.04 score points; lowering the SI cut-off to the adoption of at least two SI measures yields the maximal difference of 0.14 score points). The results lend support to hypothesis 2a (*At the mean, for the same economic outcome, SI adopters produce at a lower ecological improvement potential than comparable non-adopters.)*. SI farms also have a higher mean eco-efficiency score to the system frontier in the direction of the economic output (0.57) than without SI (0.37) (see Appendix Table B2).

Despite the on average higher eco-efficiency scores of SI farms, the empirical cumulative distribution of eco-efficiency scores in Fig. 6 shows a heterogeneous distribution of the respective eco-efficiency scores, although SI measures offer a higher potential to produce on the system frontier. Only 25 SI adopters and three non-adopters produce on the system frontier. Comparing distributions shows similar patterns to those in Fig. 6 (see supplementary material Supp. Figures 3.1a–g).

For SI farms, Fig. 7a shows that the empirical cumulative distribution of eco-efficiency scores in the ecological direction of SI farms to their group-specific frontier is very close to the distribution of scores to the system frontier with an average distance of 0.76. 66% of SI farms could improve their within-technology performance. For non-SI farms, Fig. 7b shows a divergence of empirical cumulative distributions of distances to group-specific frontier and system frontier. Non-SI farms' average eco-efficiency score regarding the group-specific frontier is 0.74. The robustness analysis yields within-technology performance scores between 0.63 and 0.84 for adopters and 0.48 and 0.81 for non-adopters, respectively.

Figure 8 shows the effect of heterogeneity in within-technology performance on improvement potentials. For SI farms, 70% have a higher eco-efficiency score to the system frontier than their respective matched control non-SI farms. The increase in eco-efficiency is on average 0.22. Figure 8 also shows that 29% of SI farms have a lower eco-efficiency score than their matched control farms. The decrease in eco-efficiency is on average 0.12.

The results lend support to hypothesis 2b *(If SI adopters have a low within-technology performance in the chosen technology and comparable non-adopters have a high within-technology performance, the non-adopters have lower improvement potential than the adopters in some cases.).*

## 5 Discussion

Our aim was to evaluate agronomic SI in regional conditions characterised by peatlands at the farm level by using an eco-efficiency analysis. We relied on core SI definitions stating that the adoption of SI technology improved the balance between the economic and ecological sustainability of agricultural production without reducing either, and assumed that farms in our case study opt consciously for the SI technology. To account for farms' selection process into SI, we combined a behavioural model with a matching approach.

Based on the Mahalanobis distance matching, the sampled SI and non-SI farms are comparable with regard to socio-economic and farm-specific characteristics and the measures that captured behavioural factors (see Appendix Table B1). These measures, however, rest on self-assessments and thus remain limited in interpretation. While differences in mean regional attachment were minor before matching, SI farms indicated a slightly higher entrepreneurial attitude (6.62 versus 5.25, see Table 1), whereas environmental awareness indicated small differences in mean (7.10 versus 6.97). These numbers imply unimportant differences in farmers' self-perception between the unmatched groups, but could also be skewed by farmers' responses to the questionnaire (i.e., only environmentally aware farmers responded or they responded by intention socially desirable), or by farmers' homogenous awareness of the natural ecosystem in the study region. We note that the potential for bias could further limit investigating the behavioural factors for SI adoption (Weltin et al. 2021).

Results of the directional DEA meta-frontier showed that few farms could be eco-efficient to the system frontier without adopting SI. Hence, SI adopters mainly determined the system frontier and a *technology effect* of SI was clearly evident. This is in line with our argumentation of hypothesis 1 that SI farms could produce higher environmental output without sacrificing economic output when they took full advantage of the SI technology.

This suggests the following: in the short run, possible reductions in improvement potentials by SI farms were offered by the outward shift of the SI frontier (closer to the system frontier) compared to the non-SI frontier (see Fig. 2). For the majority of the sampled SI farms, adopting SI could in fact reduce the environmental improvement potential compared to their matched control references (i.e., eco-inefficiency in the ecological direction measured against the system frontier). This finding was in line with other studies on the effects of agronomic SI adoption on ecological output, such as diversity gains (Redlich et al. 2020).

SI farms produced 75% at the mean of the potentially possible ecological output, keeping land and economic output constant whereas non-SI farms produced 63% at the mean. This lends support to hypothesis 2a. Also, a *performance effect* of SI was evident,

**Fig. 7** **a** Empirical cumulative distribution of eco-efficiency scores to the system and group-specific frontier for SI farms. **b** Empirical cumulative distribution of eco-efficiency scores to the system and group-specific frontier for non-SI farms ▶

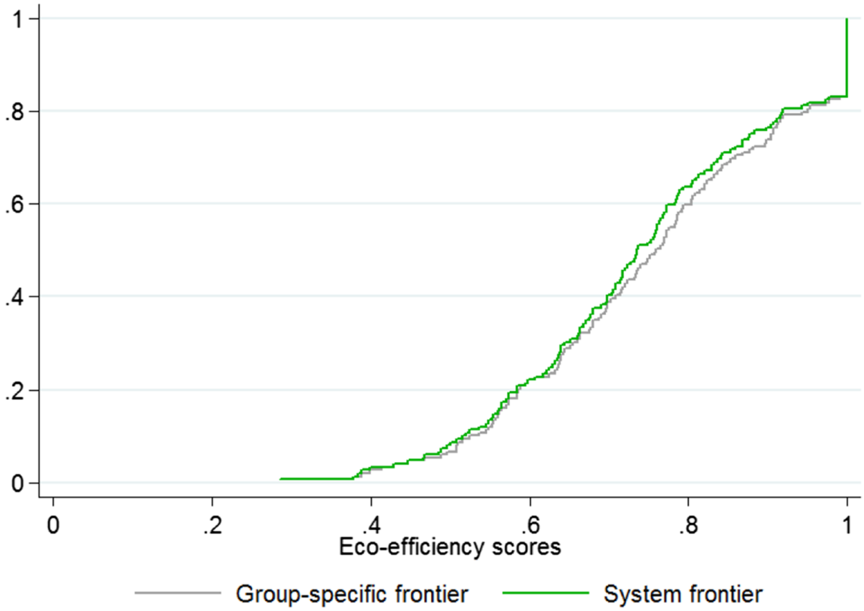
i.e., eco-inefficiencies within the SI technology could impede the SI technology's positive effects, lending support to hypothesis 2b. For non-SI farms, improvement potentials resulted from a mixture of inefficiencies to the group-specific frontier and the fact that non-SI technology did not allow reaching the system frontier in most cases.

The almost perfect overlap of the system frontier and group-specific frontier of SI adopters in ecological direction was consistent across all scenarios of the robustness analysis. To some extent, the cut-off value of adopted SI measures, sampling or farm-type heterogeneity influenced eco-efficiency scores but our general observations on technology and performance effects did not.

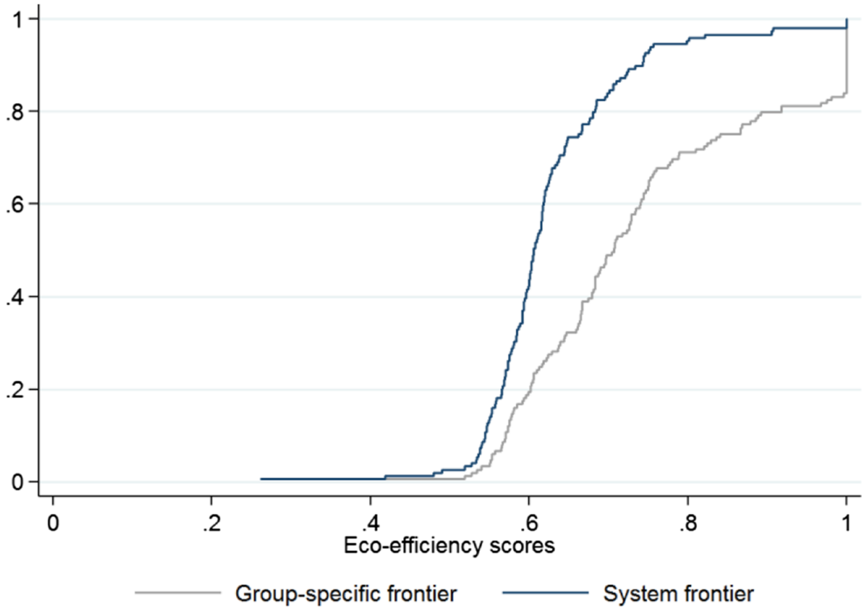
Results also lend support to our assumption of sequential preferences (i.e., farm managers could prioritize to become more efficient in an economic direction prior to adopting SI measures and improving in the ecological direction). It is possible that our assumption explained why non-SI farms with traditional farming technology and rather high eco-efficiency scores in the environmental direction did not adopt SI, or that intentional inefficiencies (Hansson et al. 2018) explained SI farms' larger distance to the frontier in an economic direction than in an ecological direction. After meeting a certain threshold in economic direction, SI farmers could have prioritised ecological outcome above economic efficiency gains when including non-financial values according to their environmental preferences in their utility function. Perhaps eco-inefficiency in the economic direction represented an adjustment or learning cost as farmers reduced ecological improvement potential with new technologies (Ang and Oude Lansink 2017).

In summary, our results empirically supported the core concept of SI that ecological improvement is possible without compromising economic outcomes. The heterogeneous distribution of the eco-efficiency scores is consistent with previous research on multidimensional performance assessments (e.g., Sidhoum et al. 2019). We suggest that the heterogeneity and increasing improvement potential for some SI adopters may be attributed to insufficient understanding of complex SI production systems (Kassam et al. 2011), and that biodiversity effects may only be obtained over time (Gabriel et al. 2013). High complexity and delayed visibility of ecological and/or economic benefits may also prohibit adopting SI technologies that improve ecological and economic outcomes in the short run (Dessart et al. 2019; Yeboah et al. 2015).

We note the following limitations of our research. The use of matching acknowledges the SI selection processes and ensures comparability between adopters and non-adopters, but the observational data and availability of measures for the behavioural factors were limited. We hope to address these shortcomings in future research with a more comprehensive investigation of the dispositional, cognitive, and social factors (Dessart et al. 2019), farmers' opinions of SI and traditional technology, their understanding of the potential advantages and risks of adoption, and their knowledge of the region's natural ecosystem, and governance system (e.g., Stupak et al. 2019). Encouraging large-scale adoption of SI and sustainable farming requires understanding of origins of eco-inefficiencies and overall performance effects in economic and ecological direction. Addressing climate protection goals further requires monitoring and coordinating activities at landscape scale given the correlation of eco-functionality with diversity in land use and management (Prestele and




**(a)** *Empirical cumulative distribution of eco-efficiency scores to the system and group-specific frontier for SI farms.*




**(b)** *Empirical cumulative distribution of eco-efficiency scores to the system and group-specific frontier for non-SI farms.*

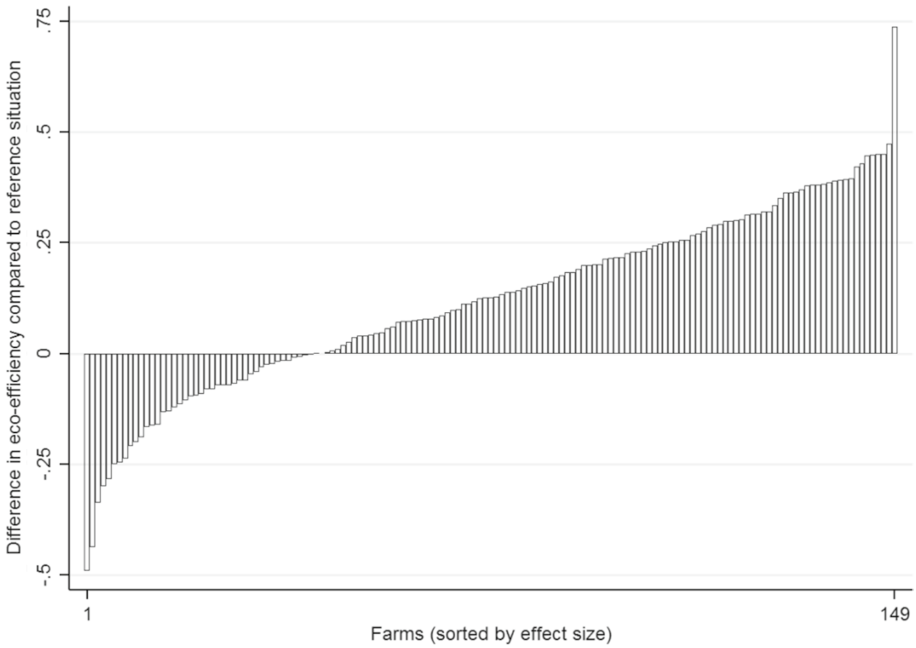



**Fig. 8** Difference in eco-efficiency to the system frontier for SI farms compared to their matched control non-SI farms

Verburg 2020). Larger field size and large-scale management will necessarily require more research staff and analysts.

Selecting the sustainability dimensions and SI measures could have introduced bias. While some studies take a system-perspective when analysing SI (cf. Mahon et al. 2018), we rely on agronomic SI measures governing the economic and ecological sustainability dimension only and ignored social, cultural or ethical aspects of SI as proposed by the broad SI concept (cf. Garnett and Godfray 2012). It is also possible that these aspects were not raised in our workshop to design the survey questionnaire. Our perspective allows us to identify the channels contributing to the heterogeneity in improvement potentials but may underestimate cross-effects from SI measures originally proposed to improve the social dimension of sustainability, for instance. Despite the robustness of our results to different specifications of SI adoption and outcome indicators, another limitation is the biodiversity measure by proxy indicators based on survey data at the farm level. We can only measure exact outputs on the farm, and comprehensive ecological indicator sets and appropriate weights are difficult to develop. Reliable region and country scale data and consistent definitions and applications of sustainability indicators could facilitate analysis at EU scale, where enhancing the Farm Accountancy Data Network could offer a starting point (Kelly et al. 2018). Too fine a regional perspective, particularly for heterogeneous regions, however, may limit generalization and transferability of the results to different agroecological, cultural and policy systems.

Our study's narrow regional focus on EU's high-priority intervention areas to protect carbon-rich soils however bears the advantage to analyse effects of contextual SI adoption from a microstructural perspective for a region largely shaped by peatland areas as potential carbon sinks (Busse et al. 2019; Häfner and Piorr 2020). Our approach and the results are thus argued to be transferable to comparable peatland regions under the same policy framework (Buschmann et al. 2020). We further suggest that our research will benefit investigations of regionally contextual farming measures that aim to overcome trade-offs in the objective function (e.g., building on the work of Kassie et al. (2015)).

Some authors also criticize the SI concept by not precluding specific measures to qualify for the concept "[…] *to improve efficiency within existing market, production and land use constraints."* (Franks 2014, p. 73). Even though SI can act as an enabler for reaching eco-efficiency it may also contribute to a *status-quo bias* in not seeking a system change (Petersen and Snapp 2015). Thus "smart" combinations various productions systems, including organic production, eco-intensified systems such as agroforestry (Mosquera-Losada et al. 2018) or ecological modernized systems relying on circular systems (Rocchi et al. 2020), have been proposed (Meemken and Qaim 2018). SI production systems could be a baseline to build such combinations on. This is left for future research.

Our results have policy implications. Policies to support farmers in increasing their production efficiency should accompany support of technology adoption, for instance by trainings and organized field days to offer exchange platforms (Hüttel et al. 2020), e.g. these might reduce operational complexity and thus support learning about efficient use of SI practises. Besides fostering process improvements, we suggest a policy mix targeting the ecological outcome dimension directly. Remuneration of potentially foregone returns from altering the production process, e.g. by input reduction as in agri-environmental programs of the EU, has been shown to be less effective (e.g., Brown et al. 2021; Uehleke et al. 2022). Also, in our study participation in such programs seems not generally associated with SI adoption: 35% of sampled SI adopters do not participate in such programs, where only 15% receive remuneration from such programs for adoption of at least three SI measures, i.e. the cut-off used in this study. Thus, result-based agri-environmental support that rewards farmers for achieving ecological improvements could complement the policy mix (e.g., Burton and Schwarz 2013; Russi et al. 2016). Large-scale adoption of these schemes could further foster pro-environmental behaviour, reinforce SI and scheme adoption decisions, and increase overall environmental performance of farming (Pe'er et al. 2020).

## 6 Conclusion

In this paper, we proposed directional meta-frontier approach combined with matching to assess selected agronomic SI measures for improving ecological outcomes in agricultural land use. Connecting the theoretical behavioural framework of Chabé-Ferret and Subervie (2013) with a production economic framework, we accounted for farmers' selection processes to either rely on traditional farming practises or adopt SI technology. Eco-efficiency scores to the system frontier estimated by directional DEA, captured farms' ecological improvement potential. Matching ensured comparability of SI adopters and non-adopters, and to link the differences in eco-efficiencies to SI adoption. Survey data on farms in the northern German Plain was combined with information from stakeholder workshops used to determine context-specific SI measures and a composite indicator for biodiversity as an ecological outcome. SI farms had higher eco-efficiency scores to the system frontier compared to farms staying with traditional farming at mean. The relatively low within-technology performance of many however hampered full environmental improvement. In fact, there was only a small probability of reaching the system frontier without adopting SI. Future research should examine farmers' characteristics and preferences in order to better compare the differences in eco-efficiency scores. We believe that our research, although confined to a small area, is also applicable to climate and sustainable policy-making at region, country, and EU levels. To facilitate exploiting full ecological improvement potentials, we suggest smart mixes of policy measures including result-based support to offer incentives for large scale SI adoption and for improving within-technology efficiency.

# Appendix

## A Details on sampling and additional descriptive statistics

**Table A1** Descriptive statistics of matching variables for the observations used in Data Envelopment Analysis

| Variables | SI farms | | Non-SI farms | |
|---|---|---|---|---|
| | Mean | Std. Dev | Mean | Std. Dev |
| Used agricultural area [ha] | 603.40 | 686.50 | 169.60 | 285.98 |
| Profit character [1 = full-time; 0 = part-time] | 0.81 | 0.81 | 0.49 | 0.50 |
| Organic farming [1 = yes; 0 = no] | 0.20 | 0.40 | 0.24 | 0.43 |
| Specialisation arable farming [1 = yes; 0 = no][a] | 0.39 | 0.49 | 0.28 | 0.45 |
| Labour intensity [workforce/ha UAA][b] | 0.03 | 0.05 | 0.07 | 0.08 |
| Use of extension services [1;5][c] | 3.04 | 1.16 | 2.69 | 1.36 |
| Formal agricultural education [1 = yes; 0 = no] | 0.80 | 0.39 | 0.70 | 0.46 |
| Highest educational degree [1; 3][d] | 2.45 | 0.84 | 2.21 | 0.93 |
| Farming experience [years] | 27.12 | 12.51 | 26.86 | 13.50 |
| Regional attachment [1; 10][e] | 8.77 | 1.97 | 8.95 | 1.76 |
| Environmental awareness [1; 10][e] | 7.13 | 2.56 | 7.07 | 2.56 |
| Entrepreneurial attitude [1; 10][e] | 6.68 | 1.94 | 5.37 | 2.25 |
| Economic output: profit indicator [1; 12] | 5.69 | 3.92 | 3.17 | 2.73 |
| Ecological output indicator [0; 1] | 0.44 | 0.12 | 0.36 | 0.11 |
| N | 157 | | 108 | |

[a] According to farmer's self-assessment.

[b] Workforce less than 1 is set as 1.

[c] 1 = never; 2 = sometimes; 3 = occasionally; 4 = often; 5 = very often

[d] 1 = lower secondary or intermediate education or no degree; 2 = high school degree; 3 = university degree

[e] Self-assessment responses indicating degree of agreement: 1 = fully disagree to 0 = fully agree

## B Additional results

**Table B1** 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] | 0.81 | 0.49 | 0.70 | 0.82 | 0.78 | 0.10 | 0.5 | 0.32 |
| Organic farming [1 = yes; 0 = no] | 0.20 | 0.24 | – 0.09 | 0.19 | 0.18 | 0.01 | 0.38 | 0.36 |
| Specialisation arable farming [1 = yes; 0 = no][a] | 0.39 | 0.28 | 0.23 | 0.39 | 0.39 | 0.01 | 0.5 | 0.19 |
| Labour intensity [workforce/ha UAA][b] | 0.03 | 0.07 | – 0.63 | 0.02 | 0.03 | – 0.11 | 0.09 | 0.16 |
| Use of extension services [1;5][c] | 3.04 | 2.69 | 0.28 | 3.02 | 3.18 | – 0.12 | 3.5 | 2.25 |
| Formal agricultural education [1 = yes; 0 = no] | 0.80 | 0.70 | 0.23 | 0.81 | 0.83 | – 0.03 | 0.63 | 0.38 |
| Highest educational degree [1;3][d] | 2.45 | 2.21 | 0.27 | 2.44 | 2.47 | – 0.03 | 2.62 | 1.88 |
| Farming experience [years] | 27.12 | 26.86 | 0.02 | 27.30 | 27.43 | – 0.01 | 23.75 | 27.56 |
| Regional attachment [1;10][e] | 8.77 | 8.95 | – 0.10 | 9.01 | 9.09 | – 0.04 | 4.38 | 7.75 |
| Environmental awareness [1;10][e] | 7.13 | 7.07 | 0.02 | 7.23 | 7.16 | 0.03 | 5.25 | 6.94 |
| Entrepreneurial attitude [1;10][e] | 6.68 | 5.37 | 0.62 | 6.74 | 6.42 | 0.16 | 5.5 | 4.10 |
| N | 157 | 108 | | 149 | 149 | | 8 | 16 |

[a]According to farmer's self-assess

[b]Workforce below 1 person set as 1

[c]1 = never; 2 = sometimes; 3 = occasionally; 4 = often; 5 = very often

[d]1 = lower secondary or intermediate education or no degree; 2 = high school degree; 3 = university degree

[e]Self-assessment questions for which respondents indicated the degree of agreement on a scale from 1 = fully disagree to 0 = fully agree

**Table B2** Descriptive statistics of matching variables for the observations used in Data Envelopment Analysis

| | SI farms | | Non-SI farms | |
|---|---|---|---|---|
| | Mean | Std. dev | Mean | Std. dev |
| Meta-technology ratio | 0.99 | 0.08 | 0.57 | 0.16 |
| Eco-efficiency to system frontier/improvement potential | 0.57 | 0.33 | 0.37 | 0.16 |
| Eco-efficiency to group-specific frontier /within-technology performance | 0.58 | 0.33 | 0.66 | 0.23 |
| N | 149 | | 149 | |

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

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## References

Ang F, Oude Lansink A (2017) Decomposing dynamic profit inefficiency of Belgian dairy farms. Europ Rev Agric Econ 45(1):81–99

Arata L, Sckokai P (2016) The impact of agri-environmental schemes on farm performance in five EU member states: a DID-matching approach. Land Econ 92(1):167–186

Areal FJ, Tiffin R, Balcombe KG (2012) Provision of environmental output within a multi-output distance function approach. Ecolog Econ 78:47–54

Areal FJ, Jones PJ, Mortimer SR, Wilson P (2018) Measuring sustainable intensification: combining composite indicators and efficiency analysis to account for positive externalities in cereal production. Land Use Policy 75:314–326

Asmild M, Hougaard JL (2006) Economic versus environmental improvement potentials of Danish pig farms. Agric Econ 35(2):171–181

Asmild M, Baležentis T, Hougaard JL (2016) Multi-directional program efficiency: the case of Lithuanian family farms. J Productiv Anal 45(1):23–33

Balaine L, Dillon EJ, Läpple D, Lynch J (2020) Can technology help achieve sustainable intensification? Evidence from milk recording on Irish dairy farms. Land Use Policy 92:104437

Barnes AP, Poole CEZ (2012) Applying the concept of sustainable intensification to Scottish Agriculture. Paper presented at the 86th Annual Conference of the Agricultural Economics Society, University of Warwick, United Kingdom, 16–18 April

Baulcombe D, Crute I, Davies B, Dunwell J, Gale M et al (2009) Reaping the benefits: Science and the sustainable intensification of global agriculture, vol RS Policy document 11/09. The Royal Society, London

Beltrán-Esteve M, Reig-Martínez E (2014) Comparing conventional and organic citrus grower efficiency in Spain. Agric Syst 129:115–123

Benton TG, Vickery JA, Wilson JD (2003) Farmland biodiversity: is habitat heterogeneity the key? Trends Ecol Evol 18(4):182–188

Bockstaller C, Lasserre-Joulin F, Slezack-Deschaumes S, Piutti S, Villerd J, Amiaud B, Plantureux S (2011) Assessing biodiversity in arable farmland by means of indicators: an overview. Oléagineux Corps Gras Lipides 18(3):137–144

Bogetoft P, Kromann L (2018) Evaluating treatment effects using data envelopment analysis on matched samples: an analysis of electronic information sharing and firm performance. Eur J Oper Res 270(1):302–313

Bogetoft P, Otto L (2011) Benchmarking with DEA, SFA, and R, vol 157. Springer, New York

Bonfiglio A, Arzeni A, Bodini A (2017) Assessing eco-efficiency of arable farms in rural areas. Agric Syst 151:114–125

Brown C, Kovacs E, Herzon I, Villamayor-Tomas S, Albizua A et al (2021) Simplistic understandings of farmer motivations could undermine the environmental potential of the common agricultural policy. Land Use Policy 101:105136

Burton RJ, Schwarz G (2013) Result-oriented agri-environmental schemes in Europe and their potential for promoting behavioural change. Land Use Policy 30(1):628–641

Buschmann C, Röder N, Berglund K, Berglund Ö, Lærke PE et al (2020) Perspectives on agriculturally used drained peat soils: Comparison of the socioeconomic and ecological business environments of six European regions. Land Use Policy 90:104181

Busse M, Heitepriem N, Siebert R (2019) The acceptability of land pools for the sustainable revalorisation of wetland meadows in the Spreewald Region. Ger Sustain 11(15):4056

Callens I, Tyteca D (1999) Towards indicators of sustainable development for firms: a productive efficiency perspective. Ecolog Econ 28(1):41–53

Calvet C, Le Coent P, Napoleone C, Quétier F (2019) Challenges of achieving biodiversity offset outcomes through agri-environmental schemes: evidence from an empirical study in Southern France. Ecolog Econ 163:113–125

Chabé-Ferret S, Subervie J (2013) How much green for the buck? Estimating additional and windfall effects of French agro-environmental schemes by DID-matching. J Environ Econ Manag 65(1):12–27

Chen C-M, Delmas MA (2012) Measuring eco-inefficiency: a new frontier approach. Oper Res 60(5):1064–1079

Cisilino F, Bodini A, Zanoli A (2019) Rural development programs' impact on environment: an ex-post evaluation of organic faming. Land Use Policy 85:454–462

Coluccia B, Valente D, Fusco G, De Leo F, Porrini D (2020) Assessing agricultural eco-efficiency in Italian Regions. Ecol Ind 116:106483

European Commission (2020) Future of the common agricultural policy. https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/future-cap_en. Accessed 6 Aug 2020

Conijn J, Bindraban P, Schröder J, Jongschaap R (2018) Can our global food system meet food demand within planetary boundaries? Agric Ecosyst Environ 251:244–256

Dainese M, Martin EA, Aizen M, Albrecht M, Bartomeus I et al (2019) A global synthesis reveals biodiversity-mediated benefits for crop production. bioRxiv:554170

Dessart FJ, Barreiro-Hurlé J, van Bavel R (2019) Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. Europ Rev Agric Econ 46(3):417–471

Destatis (2018) Bodennutzung der Betriebe. Struktur der Bodennutzung

Devkota KP, McDonald AJ, Khadka L, Khadka A, Paudel G, Devkota M (2016) Fertilizers, hybrids, and the sustainable intensification of maize systems in the rainfed mid-hills of Nepal. Eur J Agron 80:154–167

Dicks LV, Rose DC, Ang F, Aston S, Birch ANE et al (2019) What agricultural practices are most likely to deliver "sustainable intensification" in the UK? Food Energy Secur 8(1):1–15

Eder A, Salhofer K, Scheichel E (2021) Land tenure, soil conservation, and farm performance: an eco-efficiency analysis of Austrian crop farms. Ecolog Econ 180:106861

Esposti R (2017a) The empirics of decoupling: Alternative estimation approaches of the farm-level production response. Europ Rev Agric Econ 44(3):499–537

Esposti R (2017b) The heterogeneous farm-level impact of the 2005 CAP-first pillar reform: a multivalued treatment effect estimation. Agric Econ 48(3):373–386

Firbank LG, Elliott J, Drake B, Cao Y, Gooday R (2013) Evidence of sustainable intensification among British farms. Agric Ecosyst Environ 173:58–65
Foley JA, Ramankutty N, Brauman KA, Cassidy ES, Gerber JS et al (2011) Solutions for a cultivated planet. Nature 478(7369):337–342
Franks JR (2014) Sustainable intensification: a UK perspective. Food Pol 47:71–80
Gabriel D, Sait SM, Kunin WE, Benton TG (2013) Food production vs. biodiversity: comparing organic and conventional agriculture. J Appl Ecol 50(2):355–364
Gadanakis Y, Bennett R, Park J, Areal FJ (2015) Evaluating the sustainable intensification of arable farms. J Environ Manag 150:288–298
Gadanakis Y, Areal FJ (2018) Accounting for rainfall and the length of growing season in technical efficiency analysis. Oper Res 1–26
Gan X, Fernandez IC, Guo J, Wilson M, Zhao Y, Zhou B, Wu J (2017) When to use what: methods for weighting and aggregating sustainability indicators. Ecol Ind 81:491–502
Garnett T, Godfray HCJ (2012) Sustainable intensification in agriculture. Navigating a course through competing food system priorities. Food Climate Research Network and the Oxford Martin Programme on the Future of Food, University of Oxford, UK, Oxford
Gibson R, Pearce S, Morris R, Symondson WOC, Memmott J (2007) Plant diversity and land use under organic and conventional agriculture: a whole-farm approach. J Appl Ecol 44(4):792–803
Godfray HCJ, Garnett T (2014) Food security and sustainable intensification. Philos Trans R Soc B Biol Sci 369(1639)
Gómez-Limón JA, Picazo-Tadeo AJ, Reig-Martínez E (2012) Eco-efficiency assessment of olive farms in Andalusia. Land Use Policy 29(2):395–406
Grzelak A, Guth M, Matuszczak A, Czyżewski B, Brelik A (2019) Approaching the environmental sustainable value in agriculture: how factor endowments foster the eco-efficiency. J Clean Prod 241:118304
Gunton RM, Firbank LG, Inman A, Winter DM (2016) How scalable is sustainable intensification? Nat Plants 2:16065
Häfner K, Piorr A (2020) Farmers' perception of co-ordinating institutions in agri-environmental measures—the example of peatland management for the provision of public goods on a landscape scale. Land Use Policy 104947
Halkos G, Petrou KN (2019) Treating undesirable outputs in DEA: a critical review. Econ Anal Pol 62:97–104
Hansson H, Manevska-Tasevska G, Asmild M (2018) Rationalising inefficiency in agricultural production—the case of Swedish dairy agriculture. Europ Rev Agric Econ 1–24
Herbst C, Arnold-Schwandner S, Meiners T, Peters MK, Rothenwöhrer C et al (2017) Direct and indirect effects of agricultural intensification on a host-parasitoid system on the ribwort plantain (*Plantago lanceolata* L.) in a landscape context. Landsc Ecol 32(10):2015–2028
Ho TQ, Hoang V-N, Wilson C, Nguyen T-T (2018) Eco-efficiency analysis of sustainability-certified coffee production in Vietnam. J Clean Prod 183:251–260
Huppes G, Ishikawa M (2005) A framework for quantified eco-efficiency analysis. J Ind Ecol 9(4):25–41
Hüttel S, Leuchten M-T, Leyer M (2020) The importance of social norm on adopting sustainable digital fertilisation methods. Org Environ 1086026620929074
Iribarren D, Hospido A, Moreira MT, Feijoo G (2011) Benchmarking environmental and operational parameters through eco-efficiency criteria for dairy farms. Sci Total Environ 409(10):1786–1798
Jongeneel RA, Polman NB, Slangen LH (2008) Why are Dutch farmers going multifunctional? Land Use Policy 25(1):81–94
Kassam A, Friedrich T, Shaxson F, Reeves T, Pretty J, de Moraes Sá JC (2011) Production systems for sustainable intensification. Schwerpunkt Technikfolgenabschätzung 20(2):38–45
Kassie M, Teklewold H, Marenya P, Jaleta M, Erenstein O (2015) Production risks and food security under alternative technology choices in Malawi: application of a multinomial endogenous switching regression. J Agric Econ 66(3):640–659
Kelly E, Latruffe L, Desjeux Y, Ryan M, Uthes S et al (2018) Sustainability indicators for improved assessment of the effects of agricultural policy across the EU: is FADN the answer? Ecol Ind 89:903–911
Kuhfuss L, Préget R, Thoyer S, Hanley N, Le Coent P, Désolé M (2016) Nudges, social norms, and permanence in agri-environmental schemes. Land Econ 92(4):641–655
Kuosmanen T, Kortelainen M (2005) Measuring eco-efficiency of production with data envelopment analysis. J Ind Ecol 9(4):59–72
Laukkanen M, Nauges C (2014) Evaluating greening farm policies: a structural model for assessing agri-environmental subsidies. Land Econ 90(3):458–481

Lechner M, Strittmatter A (2017) Practical procedures to deal with common support problems in matching estimation. Econom Rev 1–15
Li M, Fu Q, Singh VP, Ji Y, Liu D, Zhang C, Li T (2019) An optimal modelling approach for managing agricultural water-energy-food nexus under uncertainty. Sci Total Environ 651:1416–1434
Mahon N, Crute I, Di Bonito M, Simmons E, Islam MM (2018) Towards a broad-based and holistic framework of Sustainable Intensification indicators. Land Use Policy 77:576–597
Mao LL, Zhang LZ, Zhang SP, Evers JB, van der Werf W et al (2015) Resource use efficiency, ecological intensification and sustainability of intercropping systems. J Integr Agric 14(8):1542–1550
Matson PA, Parton WJ, Power A, Swift M (1997) Agricultural intensification and ecosystem properties. Science 277(5325):504–509
Mayen CD, Balagtas JV, Alexander CE (2010) Technology adoption and technical efficiency: organic and conventional dairy farms in the United States. Am J Agric Econ 92(1):181–195
McGinnis MD, Ostrom E (2014) Social-ecological system framework: initial changes and continuing challenges. Ecol Soc 19(2):30
Meemken E-M, Qaim M (2018) Organic agriculture, food security, and the environment. Annu Rev Res Econ 10:39–63
Mennig P, Sauer J (2020) The impact of agri-environment schemes on farm productivity: a DID-matching approach. Europ Rev Agric Econ 47(3):1045–1093
Mosquera-Losada M, Santiago-Freijanes J, Rois-Díaz M, Moreno G, Den Herder M et al (2018) Agroforestry in Europe: a land management policy tool to combat climate change. Land Use Policy 78:603–613
O'Donnell CJ, Rao DP, Battese GE (2008) Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empir Econ 34(2):231–255
Paul BK, Vanlauwe B, Hoogmoed M, Hurisso TT, Ndabamenye T et al (2015) Exclusion of soil macrofauna did not affect soil quality but increased crop yields in a sub-humid tropical maize-based system. Agric Ecosyst Environ 208:75–85
Pe'er G, Bonn A, Bruelheide H, Dieker P, Eisenhauer N et al (2020) Action needed for the EU Common Agricultural Policy to address sustainability challenges. People Nat 2(2):305–316
Pérez Urdiales M, Lansink AO, Wall A (2016) Eco-efficiency among dairy farmers: the importance of socio-economic characteristics and farmer attitudes. Environ Resour Econ 64(4):559–574
Petersen B, Snapp S (2015) What is sustainable intensification? Views from experts. Land Use Policy 46:1–10
Picazo-Tadeo AJ, Gómez-Limón JA, Reig-Martínez E (2011) Assessing farming eco-efficiency: a data envelopment analysis approach. J Environ Manag 92(4):1154–1164
Picazo-Tadeo AJ, Beltrán-Esteve M, Gómez-Limón JA (2012) Assessing eco-efficiency with directional distance functions. Eur J Oper Res 220(3):798–809
Popp J, Lakner Z, Harangi-Rákos M, Fári M (2014) The effect of bioenergy expansion: Food, energy, and environment. Renew Sustain Energy Rev 32:559–578
Prestele R, Verburg PH (2020) The overlooked spatial dimension of climate-smart agriculture. Glob Change Biol 26(3):1045–1054
Pretty J (1997) The sustainable intensification of agriculture. Nat Res Forum 21(4):247–256
Pretty J (2018) Intensification for redesigned and sustainable agricultural systems. Science 362(6417):1–7
Ray DK, Ramankutty N, Mueller ND, West PC, Foley JA (2012) Recent patterns of crop yield growth and stagnation. Nat Commun 3:1–7
Redlich S, Martin EA, Steffan-Dewenter I (2020) Sustainable landscape, soil and crop management practices enhance biodiversity and yield in conventional cereal systems. J Appl Ecol
Rocchi L, Boggia A, Paolotti L (2020) Sustainable agricultural systems: A bibliometrics analysis of ecological modernization approach. Sustainability 12(22):1–16
Rousseeuw PJ, Driessen KV (1999) A fast algorithm for the minimum covariance determinant estimator. Technometrics 41(3):212–223
Russi D, Margue H, Oppermann R, Keenleyside C (2016) Result-based agri-environment measures: Market-based instruments, incentives or rewards? The case of Baden-Württemberg. Land Use Policy 54:69–77
Sarkar D, Kar SK, Chattopadhyay A, Rakshit A, Tripathi VK, Dubey PK, Abhilash PC (2020) Low input sustainable agriculture: a viable climate-smart option for boosting food production in a warming world. Ecol Ind 115:106412
Sauer J, Wossink A (2013) Marketed outputs and non-marketed ecosystem services: the evaluation of marginal costs. Europ Rev Agric Econ 40(4):573–603
Scherer L, Verburg P, Schulp C (2018) Opportunities for sustainable intensification in European agriculture. Glob Environ Change 48:43–55

Schut AG, Giller KE (2020) Sustainable intensification of agriculture in Africa. Front Agric Sci Eng 7(4):371–375
Sidhoum AA, Serra T, Latruffe L (2019) Measuring sustainability efficiency at farm level: a data envelopment analysis approach. Europ Rev Agric Econ 1–16
Smith A, Snapp S, Chikowo R, Thorne P, Bekunda M, Glover J (2017) Measuring sustainable intensification in smallholder agroecosystems: a review. Glob Food Sec 12:127–138
Smith LG, Kirk GJ, Jones PJ, Williams AG (2019) The greenhouse gas impacts of converting food production in England and Wales to organic methods. Nat Commun 10(1):1–10
Stępień S, Czyżewski B, Sapa A, Borychowski M, Poczta W, Poczta-Wajda A (2021) Eco-efficiency of small-scale farming in Poland and its institutional drivers. J Clean Prod 279:123721
Stuart EA (2010) Matching methods for causal inference: a review and a look forward. Stat Sci 25(1):1–21
Stupak N, Sanders J, Heinrich B (2019) The role of farmers' understanding of nature in shaping their uptake of nature protection measures. Ecolog Econ 157:301–311
TEEB (2015) Naturkapital und Klimapolitik–Synergien und Konflikte. Technische Universität Berlin, Helmholtz-Zentrum für Umweltforschung—UFZ
Townsend TJ, Ramsden SJ, Wilson P (2016) How do we cultivate in England? Tillage practices in crop production systems. Soil Use Manag 32(1):106–117
Tyteca D (1999) Sustainability indicators at the firm level: pollution and resource efficiency as a necessary condition toward sustainability. J Ind Ecol 2(4):61–77
Udagawa C, Hodge I, Reader M (2014) Farm level costs of Agri-environment measures: the impact of entry level stewardship on cereal farm incomes. J Agric Econ 65(1):212–233
Uehleke R, Petrick M, Hüttel S (2022) Evaluations of agri-environmental schemes based on observational farm data: The importance of covariate selection. Land Use Policy 114:105950
Van Eck JR, Koomen E (2008) Characterising urban concentration and land-use diversity in simulations of future land use. Ann Reg Sci 42(1):123–140
Weibull A-C, Östman Ö, Granqvist Å (2003) Species richness in agroecosystems: the effect of landscape, habitat and farm management. Biodivers Conserv 12(7):1335–1355
Weltin M, Zasda I, Schulp CJE, Scherer LA, Moreno Perez O et al (2018) Conceptualising fields of action for sustainable intensification—a systematic literature review and application to regional case studies. Agric Ecosyst Environ 257:68–80
Weltin M, Zasada I, Hüttel S (2021) Relevance of portfolio effects in adopting sustainable farming practices. J Clean Prod 313:127809
Weltin M, Zasada I (2018) Adopting and combining strategies of sustainable intensification. An analysis of interdependencies in farmers' decision making. Paper presented at the International Association of Agricultural Economists (IAAE) 2018 Conference, Vancouver, British Columbia, July 28–August 2, 2018
Yeboah FK, Lupi F, Kaplowitz MD (2015) Agricultural landowners' willingness to participate in a filter strip program for watershed protection. Land Use Policy 49:75–85
Zhao Z (2004) Using matching to estimate treatment effects: data requirements, matching metrics, and Monte Carlo evidence. Rev Econ Stat 86(1):91–107
Zhou H, Yang Y, Chen Y, Zhu J (2018) Data envelopment analysis application in sustainability: The origins, development and future directions. Eur J Oper Res 264(1):1–16