ECO-EFFICIENCY OF AGRICULTURAL LANDSCAPES– INSIGHTS FROM NORTH RHINE-WESTPHALIA, GERMANY

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Eco-efficiency of Agricultural Landscapes – Insights from North Rhine-Westphalia, Germany

Abstract

We analyze ecological improvement potentials of agricultural landscapes in North Rhine-Westphalia, Germany. Using an eco-efficiency approach, we model agricultural landscapes at a 20km² hexagonal grid. Ecological output is captured by indicators based on agricultural land cover data from the Integrated Administration and Control System. We derive measures for landscape configuration and composition including a Shannon crop diversity index, edge density, grassland shares, ecological focus areas, and landscape elements. We approximate economic output potential using local standard farmland values. Ecological improvement potentials are measured against a non-convex frontier estimated with the non-parametric, robust order-m estimator. We find overall high eco-efficiency of the agricultural landscapes; yet for the given economic output potential, landscapes could improve in the ecological direction. We detect spatially concentrated improvement potentials for single ecological indicators. Our results underline that eco-efficiency requires coordination at the landscape scale where directional improvement potentials can help designing locally adapted strategies.

Keywords: agricultural landscapes, eco-efficiency, ecological improvement potentials, IACS data, spatial patterns

1 Introduction

The transition to a low-carbon, bio-based and circular economy is seen as an important step towards a more sustainable future, creating, however, new demands and challenges for agricultural production systems. In fact, increased demand for fuel, fiber and food means increasing ecosystem service extraction (Popp *et al.*, 2014).

Farms operate in the complex social-ecological system, i.e., farming means extracting and marketing ecosystem services food, fiber and fuel, and providing maintenance by interacting with the natural system (cf. McGinnis and Ostrom, 2014; Meyfroidt *et al.*, 2022). That is, core land use and management decisions by farms can have adverse effects on ecosystem functioning.

Currently, widespread intense and large-scale agricultural production systems substantially contribute to biodiversity losses and land degradation by creating homogenous agricultural landscapes with larger field sizes (Qiu *et al.*, 2015; Sklenicka *et al.*, 2014). Also, groundwater contamination from nutrient leaching, for instance, induced by intense fertilization and cover-free periods, and other adverse impacts on water cycle functioning harm the ecosystem's functionality (Chaplin-Kramer *et al.*, 2019). Thus, transforming agricultural production systems towards more sustainable ones must be part of the transition toward a bio-based circular economy.

The structure of agricultural landscapes plays thereby an important role as the composition and configuration determine the local ecosystem's functionality and thus the respective production potential. Well documented is that agricultural landscapes of multifunctional composition with diverse types of land cover and use can support and stabilize ecosystem service provision (Meyfroidt *et al.*, 2022). For instance, an improved habitat provision for natural enemies of pests offers more robust crop production (Redlich, Martin and Steffan-Dewenter, 2021; Zhang *et al.*, 2018). Also water and nutrient cycling, soil formation and retention may improve with improvement potentials for fertilizer and nutrient efficiency (Bethwell *et al.*, 2021; Weibull, 2003). In addition, sustainable designs of multifunctional agricultural landscapes incorporate land rehabilitation, food security, and biodiversity conservation, as well as climate change mitigation and adaptation (Scherr, Shames and Friedman, 2012).

Economic pressure, but also agricultural policy trends with low adoption rates of agri-environmental programs have induced trends toward homogenous landscapes (Baylis *et al.*, 2016). Sustainable farming practices or systems mainly targeting at improving ecosystem functionality, for instance, wider crop rotations or organic farming, offer the potential to counteract these trends but often cannot maintain yield levels (Meemken and Qaim, 2018) or even may cause land conversion (García *et al.*, 2020). However, the functionality of the ecosystem serves as a base of production and ecosystem withdrawal (Bennett *et al.*, 2015). Thus, overcoming the perceived trade-off between supporting ecosystem functionality at the expense of productivity becomes inevitable (Pretty, 2018).

Ecosystem service provision capacities and functionality of landscapes remain hard to assess, challenging the evaluation of suggested practices for overcoming these trade-offs (Wolff *et al.*, 2021; Cord *et al.*, 2017). Various indicators have been discussed, for instance, agricultural yield levels have been used as productivity indicators (Bethwell *et al.*, 2021; Kanter *et al.*, 2018), while quantitative landscape metrics have been used to describe a landscape's structure (Uuemaa, Mander and Marja, 2013). These metrics or indicators capture well single dimensions of the complex ecosystem and its functionality but seem limited given the multi-dimensional nature of ecosystem service provision of the social-ecological system (Bethwell *et al.*, 2021).

In this paper, we target at addressing this gap and propose a combined view of economic and ecological output generating potentials to assess agricultural landscapes' potential for ecosystem service provision using an eco-efficiency approach. We aim to evaluate agricultural landscapes in the German Federal State of North-Rhine Westphalia (western Germany) by quantifying their ecological improvement potential while acknowledging the respective economic output potential using the eco-efficiency score, i.e., the distance of observed output of the location towards the highest one in the sample (best-practice). We argue that the eco-efficiency approach is superior to single indicators by linking impacts of economic performance on the environment (Caiado *et al.*, 2017; Mickwitz *et al.*, 2006; Chen and Delmas, 2012) and offers systematic monitoring for policy makers at the regional scale (Mickwitz *et al.*, 2006). Typically, eco-efficiency approaches have been applied to measure improvement potentials at the decision-makers level, for instance, to measure farms' improvement potentials in the economic and ecological output (Asmild and Hougaard, 2006; Asmild, Baležentis and Hougaard, 2016). This approach, however, has rarely been applied for meso-economic level of analysis, the perspective we take in this paper. For instance, in Italy, agricultural landscapes with high economic production and nature conservation regions could be identified (Coluccia *et al.*, 2020). For the European Union regions with low labor and high capital intensity, lower improvement potentials (higher eco-efficiency) could be identified (Grzelak *et al.*, 2019). However, no distinction in which direction the improvement potentials are higher was offered.

2 Methodology

2.1 Eco-efficiency framework

We base our analysis on the eco-efficiency framework by Schmidheiny and Zorraquin (1998), further developed by Kuosmanen (2005) and Kuosmanen and Kortelainen (2005). We focus on the ecosystem function perspective with agricultural landscapes maximizing ecosystem functions for given economic value added.

We consider land use and land management decisions by a social planner at the landscape level. These decisions concern agricultural economic output ($y_{econ} \in \mathbb{R}^K$) and ecosystem functions ($y_{ecol} \in \mathbb{R}^L$) for given agricultural land ($x \in \mathbb{R}$). The provision of these outputs is assumed to be costly in the sense that an increase in one dimension may cause a loss in the another. The production possibility set describing the set of all feasible combinations of economic outputs and ecosystem functions that can be provided given the land input is defined as $\Psi = \{(x, y_{ecol}, y_{econ}) | (y_{econ}, y_{ecol})\ can\ be\ produced\ with\ \mathrm{x}\}$.

The actual level of ecosystem functions provided may, however, vary between agricultural landscapes for identical levels of economic output. Further, ecological outputs are not marketed, non-excludable (access with zero marginal costs), and may offer rival benefits. Thus, supply and demand may not be at welfare-maximizing levels (Romstad, 2008). In short, agricultural landscapes may not achieve Pareto-optimal levels of economic output and ecosystem functions but may rather indicate some degree of improvement potential (inefficiency).

We focus on improvement potentials in terms of ecosystem functions and following Kuosmanen and Kortelainen (2005), we classify a unit as eco-efficient if is not possible to increase any ecosystem function without decreasing economic outputs or increasing any other ecosystem function. Thereby, we treat all ecological outputs with the same weight and impose no valuation on the single ecological outputs.

Figure 1 illustrates our concept for two ecosystem functions $y_{ecol,1}$ and $y_{ecol,2}$. The best-practice frontier provides attainable combinations of these ecosystem functions for a given level of y_{econ}. If the level of provided ecosystem functions is below frontier levels, improvement potentials exist and various paths to achieve the frontier may be feasible.

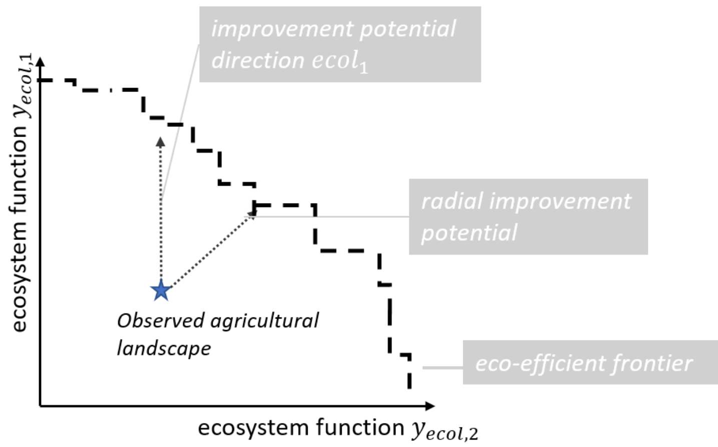

Figure 1: Joint generation of ecological and economic outputs and ecological improvement potentials

We measure these improvement potentials using the distance to the frontier in the direction of ecosystem functions using the directional distance function (DDF) introduced by Chambers, Chung and Färe (1996). For unit i, directional improvement potentials β_i are

$$\beta_i(y_{ecol}, y_{econ}|d) = \sup\{\beta_i > 0 | (y_{ecol} + \beta_i d, y_{econ}) \in \Psi\}, \quad (1)$$

where $d \in R^L$ is a pre-specified directional vector, and β measures the distance to the frontier along the path defined by d (Daraio and Simar, 2014).

We consider two settings indicated in **Figure** 1: First, setting $d = y_{ecol}$, we consider the simultaneous and proportional increase of all ecosystem functions corresponding to the radial approach by Farrell (1957). That is, with a fixed ratio of provided ecosystem functions, their levels are increased until a landscape is located on the frontier. Second, we consider the distance to the frontier in the direction of each ecosystem functions separately. Thus, we set $d_l > 0$ for ecosystem function l, and zero otherwise. For instance, the directional distance for ecosystem function $l = 1$ is derived using $d = (d_1 > 0,0,0, \dots, d_L = 0)$ without altering the provision of other ecosystem functions or economic outputs. (i.e., the vertical improvement in Figure 1).

2.2 Study area

The Federal state of North-Rhine Westphalia is particularly suitable for our analysis as it is characterized by a substantial share of high-intensity managed agricultural land (approx. 43% of the total land), heterogeneous farm and size structures, bioenergy production, and lignite mining areas (Landwirtschaftskammer Nordrhein-Westfalen, 2020). Trends of increasing farm sizes go along with changes in the landscape configuration through the increased scale of the operation (Noack *et al.*, 2021). Thereby, large farms are associated with large fields and reduced crop diversity, and therefore with lower amounts of edge habitat relative to the crop area with demonstrably negative effects on biodiversity (Samberg *et al.*, 2016; Fahrig *et al.*, 2015; Batáry *et al.*, 2017). With the lignite phase-out, the respective regions became priority regions towards a transformation to a sustainable, low-carbon and circular bioeconomy (Stark *et al.*, 2021; MKW NRW, 2012). These landscapes were, however, created after the mining process with the aim of renaturation at high production potentials. Whether these high productivity agricultural landscapes are as ecologically efficient as other regions in the same state under the same governance structures remains and is tackled in the spatial pattern analysis omitted from this conference paper for brevity.

2.3 Indicator selection and calculation

To identify locally adapted ecological improvement potentials, we use a 20 km² hexagonal grid to represent the landscape level as shown in Figure 2. Unlike potential units of analysis following administrative borders, e.g., municipalities, that vary in size and form, a hexagonal grid provides a smooth surface and have therefore been used in landscape analyses (Birch, Oom and Beecham, 2007; Wolff *et al.*, 2021).

We consider two different data sources: ecological output indicators are based on the 2019 Integrated Administration and Control System (IACS). IACS is based on the farmers' reported crop choices used to determine the annual direct EU CAP payments and provides spatially explicit information on agricultural land use on a plot level including ecological focus areas. Economic output potential of agricultural landscapes is approximated using local standard farmland values (BORIS, *Bodenrichtwertinformationssystem*). Standard land values are determined by local land valuation committees for grassland and arable land, and other land use types based on transactions in the same area in the two years prior to the reporting year. Transaction prices are corrected for transaction-specific particularities, e.g., markdowns/markups for soil conditions.

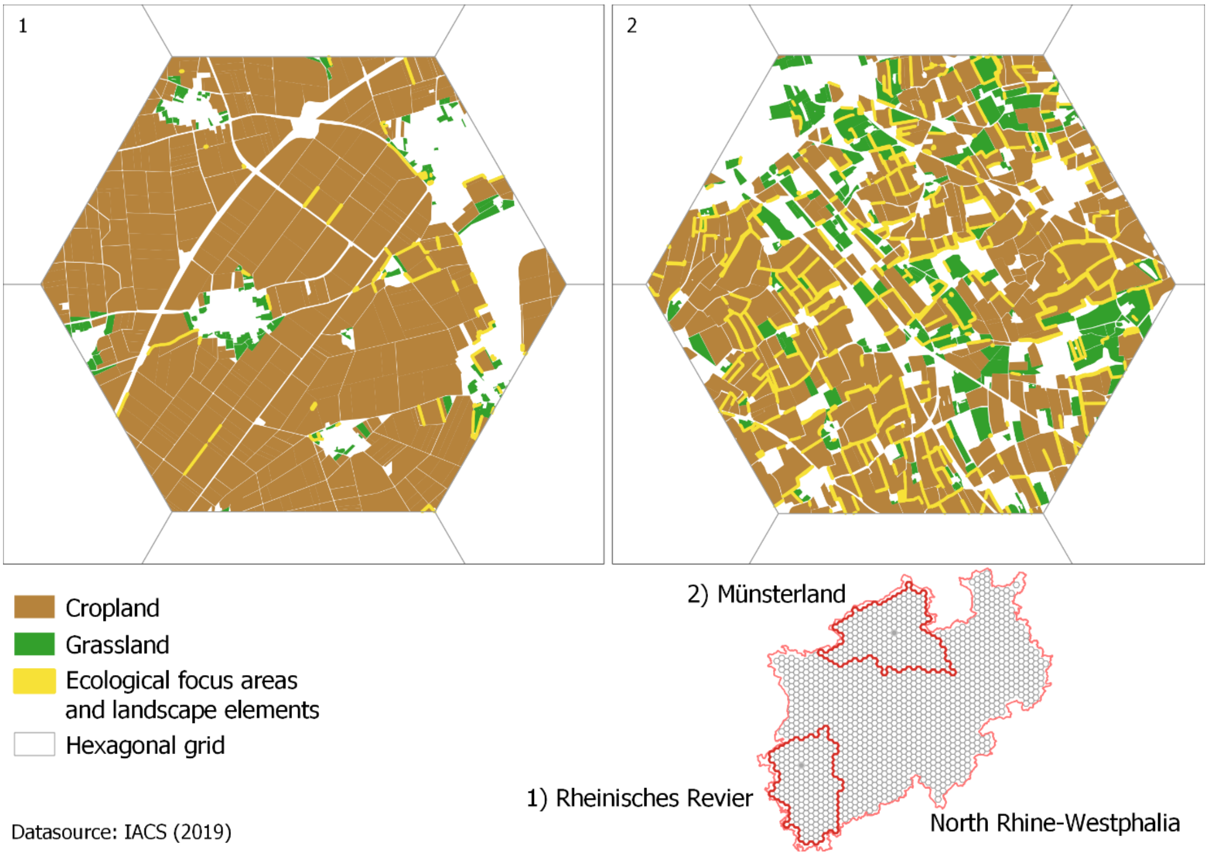

Figure 2: Samples of the distribution of cropland, grassland and ecological focus areas and landscape elements within a hexagon for the 1) Rheinische Revier and 2) Münsterland

Economic output

To approximate the economic output potential of an agricultural landscape, we follow the Ricardian modeling framework introduced by Mendelson, Nordhaus and Shaw (1994) and rely on the value of the land of the analyzed landscapes as an economic output indicator. Following Mendelson, Nordhaus and Shaw (1994), we argue that land values represent the expected present value of future returns of land use including the full range of potential adaptations to changing climate conditions. Therefore, land values account for today's economic outputs and future economic output potentials.

We rely on standard land values derived by local land valuation committees for land value zones, which are compact and granular areas with homogenous agronomic and market-microstructural characteristics. Land values are observed for 4,527 land value zones (average size: 9 km^2). For each hexagon, we calculate the weighted average standard land value with weights corresponding to the shares of the respective land use types (arable, grassland).

Land values are suitable for our cross-sectional analysis as they are less sensitive to shocks and to transaction specificities, such as buyer/seller-specific search costs and market power considerations (Balmann *et al.*, 2021). Land values may, however, be sensitive to off-farm influences and non-agricultural factors, e.g., land development options (Ortiz-Bobea, 2020). We therefore exclude hexagons with low levels of agricultural land use (<5%) or with land values suggesting reflecting option values for potential rezoning from the analysis.

Ecosystem function indicators

Within the eco-efficiency framework, economic output is combined with ecosystem functions a landscape can provide. Agricultural landscapes are human-environment systems where the provision of ecosystem functioning rely on the modification and management of the ecosystem (Bethwell *et al.*, 2021). Such agro-ecosystems are managed ecosystems where multiple actors, primarily farmers, interact which can lead to positive or negative environmental impacts (Petz and van Oudenhoven, 2012; Zhang *et al.*, 2007). Using multiple indicators, we want to approximate ecosystem functioning by incorporating landscape metrics as proxies for landscape composition and configuration. Composition thereby describes number and proportion of land cover/use types in or of a landscape, whereas configuration describes the spatial arrangement of land cover/use types (Fahrig et al., 2011). Landscape metrics consider landscape patterns and have been successfully used to as indicators for landscape functions (Uuemaa, Mander and Marja, 2013). These can include habitat functions (biodiversity, habitats), landscape regulating functions (fire control, microclimate control, etc.), and information functions (landscape aesthetics).

We consider four agro-ecological indicators at the landscape level indicating agricultural landscape composition (SDI, share of grassland, share of EFAs) and configuration (edge density), summarized as agricultural landscape heterogeneity. A heterogeneous landscape structure can benefit, for example, species richness (Fahrig *et al.*, 2011) and increased yields (Burchfield, Nelson and Spangler, 2019) at the same time. In general, a multifunctional agricultural landscape can provide multiple ecosystem functions (Bennett *et al.*, 2015).

Shannon Diversity Index (SDI)

The SDI measures agrobiodiversity and compositional heterogeneity (Fahrig *et al.*, 2011; Uthes, Kelly and König, 2020). We consider land uses with 210 crop types, 5 variations of grassland and 29 semi-natural habitats, i.e., it incorporates the whole agricultural landscape and the total utilized agricultural area (UAA). The SDI reflects richness and abundance calculated as

$$SDI = -\sum_{i=1}^{n} p_i \ln p_i$$

where p_i= share [%] of agricultural land use type/land use type and usage i in utilized agricultural area. Thus, higher values of the SDI correspond to richer crop diversity.

Grassland share

Grasslands provide a broad range of ecosystem functions, such as filter or retention functions, carbon storage, habitat provision, maintaining biodiversity, and recreational services (Schwieder *et al.*, 2022). Grassland is potentially used more extensively compared to intensively farmed cropland (Barraquand and Martinet, 2011). In contrast to high-diversity grasslands, intensively farmed grasslands are characterized by increasing grazing pressure and mowing frequency, use of fertilizers and herbicides, and reseeding after plowing (Batáry, Matthiesen and Tscharntke, 2010). However, the IACS data does not include specifications on management practices for grassland. To represent the difference in the ecological value of grassland compared to cropland, we use the grassland share of the agricultural area.

Edge density

Edges of crop- and grassland plots serve as contact surfaces between agricultural (plot-to-plot edges) and other neighboring land uses (plot outline edges) and can be beneficial to habitat diversity, e.g., pollinator abundance (Tscharntke *et al.*, 2021). Thus, higher edge density serves as an indicator of greater landscape heterogeneity (Uthes, Kelly and König, 2020). Edge density is related to plot size and shape and increases with higher shape complexity of a polygon. In addition, higher edge densities are known to enhance yields (Martin *et al.*, 2019). High edge densities support shorter travel distances and/or greater resource complementation between habitats and crops for different species (Martin *et al.*, 2019). We calculate the edge density as kilometers per agricultural hectares (cropland and grassland only) derived from individual plot edges. Thereby, plot-to-plot edge lengths is counted only once to avoid overestimation.

Share of ecological focus areas

Ecological focus areas (EFAs) serve as semi-natural habitat and increase landscape heterogeneity. They include linear or patchy landscape elements, such as hedges and woody or herbaceous patches. They provide shelter and shadow to a variety of animals, can influence the micro-climate, and provide some protection against wind erosion (Uthes, Kelly and König, 2020; Tscharntke *et al.*, 2021). In addition, EFAs work as connective elements in the landscape, providing corridors for movement or islands of breeding and nesting to species (Burel and Baudry, 2005). We consider all landscape elements and selected EFAs, including fallow land and plots taken out of production as semi-natural. We calculate the share of EFAs per total UAA using weighted area values with weights corresponding to their ecological value according to the CAP Greening framework (German Federal Environment Agency, 2014).

2.4 Empirical implementation

Frontier estimation

Estimating the DDF (eq. 1) requires knowledge about the frontier, i.e., the upper boundary of the production possibility set Ψ, which is unfortunately unknown and needs to be estimated. To estimate simultaneously the efficient frontier and the landscapes' improvement potentials, we use the fully non-parametric, robust order-m estimator introduced by Cazals, Florens and Simar (2002) extended by Simar and Vanhems (2012) to the directional distance approach.

The idea is to estimate the frontier out of observed data by enveloping observed combinations of (y_{ecol}, y_{econ}). In contrast to full frontier approaches, such as DEA or FDH, order-m is a partial frontier estimator and estimates the expected optimal output level achieved by m randomly drawn peers. As a result, the estimated frontier may not necessarily envelope all observations but allows levels of (y_{ecol}, y_{econ}) with a low probability to be located beyond the frontier.

Cazals, Florens and Simar (2002) estimate this expected optimal level using a Monte-Carlo procedure, in which the DDF for observation i is derived using a bootstrap procedure with B $(b = 1, \dots, B)$ frontier estimations. For each b, m observations with higher levels of economic output than observation i are drawn with replacement. The maximum possible expansion of ecosystem functions for i is calculated relative to this sample. Averaging over the B replication provides i's value of the DDF. For details, we refer to Daraio and Simar (2014).

The order-m estimator brings several advantages making it particularly appealing for our analysis: first, no pre-specified functional form is required to model the relationship between economic outputs and ecosystem functions at landscape level, for which otherwise a theoretical basis would be missing. Second, the estimator has a reduced sensitivity against outliers as points are allowed to be located outside the frontier (Simar and Vanhems, 2012). Third, order-m allows a non-convex production possibility set, which has been suggested for ecosystem functions (see Ruijs *et al.*, 2013; Tschirhart, 2012) and may also arise due to the use of ratio-measures (Olesen, Petersen and Podinovski, 2015, 2022), as in our application.

The empirical implementation relies on the approach by Daraio, Simar and Wilson (2020), who derive a numerically stable approach to obtain exact directional distance estimates. Following Daraio, Simar and Wilson (2020), we estimate the model for $m = \{50, 75, 100, \dots, 5000\}$ and select $m = 3500$ as the share of superefficient observations is stable for higher values of m. We set $d = y_{ecol}$ to obtain the distance as a proportional increase in the direction of all outputs, and $d_l = y_{ecol,l}$ to estimate ecosystem function-specific improvement potentials.

Spatial pattern analysis

[Omitted for brevity]

Data treatment and descriptive statistics

Our initial dataset of 1,531 hexagons covers around 90% of the study region. Considering only cells with at least 5% under agricultural land removes 70 hexagons with less than 100 ha of cropland or grassland. Another hexagon is removed as an outlier due to its extremely high land value likely reflecting option values for potential rezoning.

The resulting dataset contains 1,460 observations, covering 85.6% of the state's area. The dataset shows substantial variation across our study region, with land values varying between around 10 and 110 thousand €/ha (see Table 1). We note a bimodal distribution of land values with hexagons clustered around 20 and 75 thousand Euro per hectare, respectively, where the former cluster is located in particular in the more mountainous south-eastern part of the state. This division is also visible in the other indicators: whereas the south-east is predominantly characterized by high grassland shares and higher edge densities, the western and the northern part of the state show higher shares of cropland and higher crop diversity. Concerning EFAs, we observe a strong variation across the state with some small focus areas in the south-west, north, and north-east.

Table 1: Descriptive statistics

N=1,460	Unit	Mean	Med.	SD	Q1	Q99	CV
Economic output							
Land values	€/ha	50,601	52,409	26,597	11,956	108,058	0.526
Ecosystem function indicators							
Shannon diversity	Index	2.790	3.070	0.689	1.096	3.650	0.247
Grassland share	%	36.763	23.763	30.557	1.356	99.916	0.831
Edge density	100 Km/ha	25.744	25.000	6.478	14.000	46.410	0.252
EFAs	Weighted % of UAA	2.657	2.342	1.733	0.280	7.960	0.625

3 Results and discussion

3.1 Ecological improvement potentials

Estimates of the order-*m* distance functions are summarized in Table 2. The upper part of Table 2 shows the estimates transformed into Shephard efficiency scores to indicate the degree in percentages to which the units have achieved the frontier. The lower part summarizes the improvement potentials in units of the indicators. Thus, higher values in the upper half indicate that a region is providing higher levels of ecosystem functions for a given level of economic output, whereas higher values in the lower half indicate higher improvement potentials.

Results for the radial efficiency scores indicate that the units can increase all ecosystem functions indicators simultaneously by around 6% on average (mean: 0.94) while keeping economic output levels constant. Thus, ecosystem function provision seems to be close to optimal levels on average. Results suggest, however, substantial variation between the units as improvement potentials of 10% or more is indicated for a quarter of the units, whereas around 10% of the units are located beyond the frontier (see maps in Figure 3).

We note that radial measures indicate high efficiency if an observation performs well in at least one ecosystem function indicator dimension. Thus, units with a very high grassland share obtain high radial efficiency scores, whereas units with a low share indicate a substantially higher variation in the efficiency measure. In turn, as the grassland share is inversely related to the SDI, efficiency scores are rather high for low SDI values and have a higher variation for high SDI values.

For the directional efficiency measures, where the improvement potentials are determined by improving each indicator separately, results show substantially higher improvement potentials (see maps 2 to 5 in Figure 3). The lowest average improvement potentials are indicated for the Shannon diversity index and edge density, where indicators could be improved by 29 to 40% on average.

Results indicate that the analyzed units could increase their respective grassland share on average by more than 50%, corresponding to an increase of around 34% percentage points, keeping all ecosystem function indicators and the economic output constant. While the highest variation in the efficiency scores is found for the EFAs, the actual improvement potentials show substantially less variability. This results from the high skewness of the indicator and few units with substantially higher values in this dimension dominate the frontier.

Table 2: Descriptive statistics of radial and directional efficiency scores

	Mean	Median	SD	Q1	Q99	CV
Radial efficiency score	0.937	0.958	0.066	0.765	1.005	0.07
Directional efficiency scores (%)						
Shannon diversity	0.712	0.780	0.193	0.263	0.979	0.271
Grassland share	0.475	0.415	0.289	0.027	1.000	0.608
Edge density	0.604	0.600	0.147	0.322	0.967	0.243
EFAs	0.272	0.218	0.204	0.022	0.995	0.752
Directional improvement potentials in units of the indicators						
Shannon diversity (index points)	1.172	0.886	0.822	0.080	3.068	0.701
Grassland share (%)	35.53	32.554	23.345	0.000	86.706	0.657
Edge density (100 km/ha)	18.469	17.994	9.607	1.000	36.837	0.520
EFAs (% of UAA)	8.240	8.845	3.323	0.031	12.806	0.403

3.2 Spatial patterns

[Spatial pattern analysis and illustration with sample regions omitted for brevity]

3.3 Discussion

We find an overall high eco-efficiency in the agricultural landscapes in North Rhine-Westphalia with efficiency scores above 85% for 90% of the observations. That is, for the given level of economic outputs, all ecological output indicators could increase simultaneously by around 15% on average. Despite the overall high average, results suggest substantial and spatially concentrated improvement potentials for single ecological outputs.

We find high improvement potential for EFAs, whereby particularly landscape elements like hedges play an important role in habitat provision for different species (Tscharntke *et al.*, 2021). Between single ecological dimensions, various co-benefits exist. For example, if the amount of EFAs is increased through the establishment of hedges at field edges, the edge length, i.e., density is increased as well as the agricultural landscape diversity. Increasing crop diversity can be achieved through dividing plots and thus decreasing plot size which goes along with increasing edge length. Thereby, more edges provide the potential for implementing landscape elements such as hedges and marginal (flower) strips for increasing semi-natural habitat. Overall, meeting the different improvement potentials in one or more directions is likely to increase landscape heterogeneity which can be beneficial for several ecosystem functions including increased yields and habitat provision (Burchfield, Nelson and Spangler, 2019; Tscharntke *et al.*, 2021). In addition, we identify potential conflicts within the ecological dimension. For instance, a low improvement potential for the share of grassland relates to the high improvement potential of the share of EFAs.

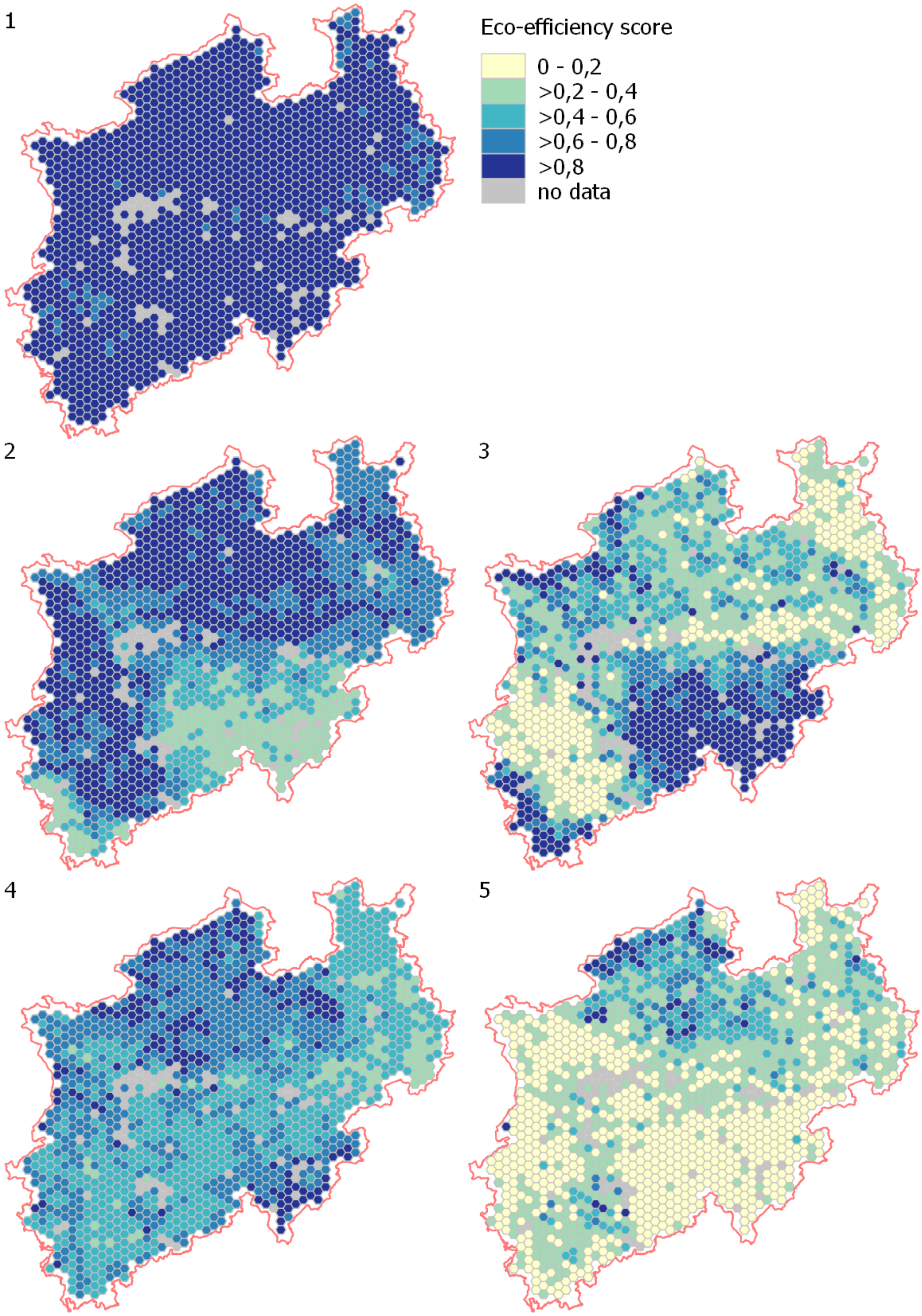

Figure 3: Maps of eco-efficiency scores for 1) radial efficiency score 2) SDI, 3) grassland share, 4) edge density and 5) share of EFAs

We note that eco-efficiency does not imply sustainability (Mickwitz *et al.*, 2006; Kuosmanen, 2005). Both sustainable development and eco-efficiency are concepts introduced from outside to the local policy context. To implement these concepts, they would have to be interpreted and introduced into the local decision-making process (Mickwitz *et al.*, 2006). The assessment on the landscape level thereby calls for collective management of single actors (e.g., farmers). Sustainable development is one of the key purposes of the Common Agricultural Policy (CAP) within the European Union (EU) but targets farmers as decision-makers and farms as operating units instead of landscapes as spatial units.

We also note the following limitations of our study. First, ecosystem function indicators are limited in their informative value. For example, IACS data provides no information on the management intensity of grassland albeit extensively manage grasslands potentially provides higher ecological value (Barraquand and Martinet, 2011; Schwieder *et al.*, 2022). The SDI lacks information on the spatial distribution of agricultural plots and presents the total extent of each category (Dušek and Popelková, 2017; Fjellstad *et al.*, 2001). Thereby, it depends on the overall share of agriculture and number of crops within a hexagon. Spatial crop species diversity strongly increases with the sample size (i.e., the share of agriculture within a hexagon) (Merlos and Hijmans, 2020; Kindt and Coe, 2005). Second, our empirical approach identifies only improvement potentials relative to a best practice frontier determined by the sample and therefore likely underestimate the true improvement potentials. Lastly, while our analysis does not require any ex-ante assumptions concerning a weighting of different ecological output indicators, the resulting equal weighting of the different indicators may not reflect the actual contribution to ecosystem functionality.

4 Conclusions

This paper aimed to quantify the ecological improvement potential of agricultural landscapes while acknowledging the respective economic output potential using an eco-efficiency analysis approach. Taking this combined view of economic and ecological dimensions of the ecosystem's functions potential offers a more holistic view given the complexities of the social-ecological system.

Results indicate overall high average eco-efficiency of agricultural landscapes in the study region. However, substantial improvement potentials are present in single ecological dimensions. Spatial clustering of improvement potentials underlines that coordination at the landscape scale is necessary to derive locally adapted strategies account for to natural landscape conditions to target such improvement potentials. The proposed eco-efficiency is scalable and may serve as a basis to derive and monitor such policies.

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