Journal of Environmental Management 393 (2025) 126939

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Minimizing trade-offs in agricultural landscapes through optimal spatial allocation of agri-environmental practices

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ABSTRACT

The implementation of agri-environmental practices (AEPs) is a key strategy to reach biodiversity and environmental objectives in agricultural landscapes, but their widespread application is often hampered by perceived trade-offs with crop production. However, the extent of these trade-offs remains poorly understood and has rarely been quantified in real-world case studies.

Hence, our aim was to analyze trade-offs between crop yield, water quality and farmland biodiversity using an optimization approach for the spatial allocation of AEPs for a catchment in Eastern Germany. Potential AEPs were selected based on a co design approach with local stakeholders (stakeholder-based scenario) and were complemented by additional AEPs to reach current EU policies targets (policy-based scenarios). Consequences for crop production and environmental objectives were evaluated through spatially-explicit crop, water and biodiversity models. Contrary to common perception, we found that crop losses required to increase environmental objectives were marginal (maximum loss of 1.1% in the stakeholder based scenario). The implementation of AEPs even led to win-win outcomes for crop production and environmental objectives in over 20% of the Pareto-optimal solutions as compared to the status quo. These win-win outcomes resulted merely from biophysical effects as positive biodiversity feedbacks to agriculture were not included in our model. Spatial optimization of AEPs allocation was key to mediating trade-offs across scenarios, highlighting the large potential of spatially explicit approaches for the management of agricultural landscapes.

1. Introduction

The simplification and management intensification that has characterized agricultural landscapes in industrial nations since the mid-20th century has increased agricultural productivity but is also associated with high environmental costs (Campbell et al., 2017). These costs are reflected in environmental changes such as the loss of fertile soils and decreasing water quality, as well as ecosystems degradation and resulting loss in ecosystem functions (Dainese et al., 2019). As a consequence, agricultural landscapes are becoming more vulnerable, e.g. to droughts, floods, pest outbreaks and to the overall risk of yield instability (IPCC et al., 2022; Zhao et al., 2017), which can negatively affect agricultural production itself.

An often promoted strategy to mitigate these environmental challenges and their negative socio-ecological impacts is to reconsider the current structure of agricultural landscapes (Landis, 2017; Sietz et al., 2022). Such a redesign should encompass an increase in landscape complexity and a reduction in land use intensity (Batáry et al., 2020; Garibaldi et al., 2023; Landis, 2017). The implementation of agri-environmental practices (from here on abbreviated as AEPs) addresses both goals. Many AEPs are supported by agri-environmental payments, both in Europe (Hasler et al., 2022) and in other countries (e.g. Baylis et al. (2022); Pannell and Rogers (2022)). We here use the term AEPs to denote the actual practices, such as establishment of hedgerows, riparian buffer, fallow land, reduced tillage and cover crops, regardless of whether they are subsidized. AEPs have different impacts on biodiversity and ecosystem services supply (Bullock et al., 2021). For instance, fallow land is expected to favor farmland biodiversity (Pe’er et al., 2017), riparian buffers to reduce water pollution (Baaken, 2022; Möckel et al., 2024; Williams et al., 2023) and cover crops to reduce soil

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https://doi.org/10.1016/j.jenvman.2025.126939
Received 1 April 2025; Received in revised form 7 August 2025; Accepted 8 August 2025
Available online 14 August 2025

erosion (Williams et al., 2023).

The implementation of AEPs, however, is often perceived to lead to trade-offs with agricultural production, as they are usually linked to reductions in chemicals input and decreases in cultivated area. If certain targets of implementation need to be reached, for example at the European Union level to comply with overarching policy objectives (e.g. the Farm to Fork strategy) or to be able to access subsidies (e.g. Good Agricultural and Environmental Conditions (GAEC) under the current Common Agricultural Policy (CAP) enhanced conditionality), this perception can even be stronger.

As a response, farmers tend to implement AEPs in less productive or already complex landscapes, following economic and management reasons (i.e. lower opportunity costs, already difficult mechanization processes) (Alarcón-Segura et al., 2023; Bartkowski et al., 2023; Paulus et al., 2022), which in turn are often less effective in improving environmental aspects. Instead, optimal spatial allocations of AEPs within agricultural landscapes would allow maximizing ecological effects, while minimizing trade-offs, or even obtaining win-win situations between the considered objectives (Ekroos et al., 2014).

Multi-objective optimization techniques can support the identification of such optimal spatial allocation. They have been used in multiple land use studies to analyze trade-off situations and provide Pareto-optimal solutions (Kaim et al., 2018). Pareto-optimal solutions are defined as land-use configurations for which no single optimization goal can be increased without simultaneously decreasing one or more of the other goals (Coello et al., 2007). Studies on multi-objective optimization have been conducted to address specific environmental and climatic problems (e.g. eutrophication (Rodríguez-Gallego et al., 2019), water scarcity (Farrokhzadeh et al., 2020)) or to foster agricultural adaptation to climate change (Klein et al., 2013). Various studies also included biodiversity indicators (e.g. habitat suitability, species richness, functional diversity) as an objective, although only few are working with real landscapes (Kaim et al., 2021; Reith et al., 2022; Verhagen et al., 2018; Witing et al., 2022).

In this study, we present a spatially explicit, multi-objective optimization approach to evaluate the potential for maximizing crop yield, water quality regulation and farmland biodiversity through the implementation of AEPs for the agricultural landscape of the Schwarzer Schöps river basin, Germany. Potential AEPs were selected based on a co-design approach with local stakeholders (*stakeholder-based* scenario) and were complemented by additional AEPs to comply with current EU policies targets, particularly those related to reducing fertilizer input and having a minimum share of non-productive areas within a farm's arable land (*policy-based* scenarios). As proxies for modelling biodiversity potential, we used a set of indicators novel to optimization approaches, including an index for probability of connectivity, which estimates the connectivity between semi-natural habitat (SNH) patches in the entire catchment, and an index for habitat quality, which estimates the negative spill-over effects of nitrogen from neighboring fields. Specifically, we aimed to (i) quantify the losses in agricultural production, compared to the current management, when environmental objectives are increased; (ii) identify possible hotspots for AEPs implementation; and (iii) analyze how the results change when AEPs implementation needs to comply with EU targets.

2. Material and methods

2.1. Analysis workflow

We used the Schwarzer Schöps river basin in Saxony (Germany) as an example of an intensively used and simplified agricultural landscape in which to implement AEPs. We performed a multi-objective optimization for indicators of crop yield, water quality regulation and farmland biodiversity potential (represented by habitat connectivity and habitat quality). Our goal was to simultaneously:

i. Maximize habitat connectivity index;
ii. Maximize habitat quality index;
iii. Minimize phosphorus load at the catchment outlet;
iv. Minimize losses in agricultural production.

The interest was in increasing farmland biodiversity both from a conservation point of view and for its potential to supply different agriculture-enhancing ecosystem services (e.g. pollination, nutrient cycling). As the water bodies in the case study often suffer from phosphorus pollution, the interest was also in decreasing the phosphorus load into the main reservoir, thereby improving water quality regulation.

Each of the considered objectives corresponds to the output of a particular spatially-explicit biophysical or ecological model, each of which was determined by a fixed set of input variables as well as varying sets of AEPs (Fig. 1). We refer to each set of implemented AEPs and their specific spatial allocation as a land-use configuration (Fig. 1). The considered AEPs in this study (see Table S3.1 for details) included the implementation of landscape elements (hedgerows, riparian buffers, grassed waterways, and retention ponds) as well as changes in agricultural practices (reduced tillage in combination with winter cover crops and fallow land). Using the multi-objective optimization tool CoMOLA (Constrained Multi-objective Optimization of Land-use Allocation) (Strauch et al., 2019) we identified specific land-use configurations that resulted in the optimization of our four objectives.

2.2. Multi-objective optimization

CoMOLA is based on the NSGA-2 genetic algorithm (Deb et al., 2002). It starts an optimization process by first creating a randomly generated set of land-use configurations. For each of these configurations, model outputs are computed for all four optimization objectives. The genetic algorithm then applies a Pareto ranking (i.e. non-dominated sorting) to identify the land-use configurations that performed well with respect to optimization objectives. Based on these rankings, the algorithm generates new land-use configurations by '*recombining*' previously well performing configurations (Strauch and Schürz, 2024). In this way, multiple '*offspring*' configurations are produced forming a new '*generation*' for which model outputs are computed. The entire procedure was repeated for 200 generations using a population size of 100 individuals, resulting in 20,100 model simulations (see section 1.1 in Supplementary Information for additional details on the configurations of the optimization algorithm and accompanying sensitivity analyses).

2.3. Biophysical models

In our approach, we relied on three distinct biophysical models (Fig. 1). These were (i) the Soil and Water Assessment tool (SWAT+), (ii) a habitat connectivity model and (iii) a habitat quality model.

2.3.1. SWAT+: modelling water quality regulation and agricultural production

SWAT is a conceptual, continuous-time watershed model developed to assess the impact of land management on water supplies and nonpoint source pollution (Arnold et al., 1998). Recently, improvements have been incorporated into the updated SWAT + version (Bieger et al., 2017), e.g. a better representation of water routing and thus connectivity between land and water objects (Bieger et al., 2019; White et al., 2022). In our simulations, we further improved model resolution for water routing by applying the contiguous object connectivity approach - COCOA (Schürz et al., 2022). COCOA allows a site-specific assessment of the effectiveness of different AEPs within a catchment (Piniewski et al., 2024) and provides the basis for optimizing the spatial allocation of AEPs at the landscape scale (Strauch and Schürz, 2024). We calibrated our model against observed annual crop yield, daily runoff and 4–6 weekly sediment and phosphorus loads at the catchment outlet for the period 2009 to 2020 (Piniewski et al. (2024), see also section 2.1 in

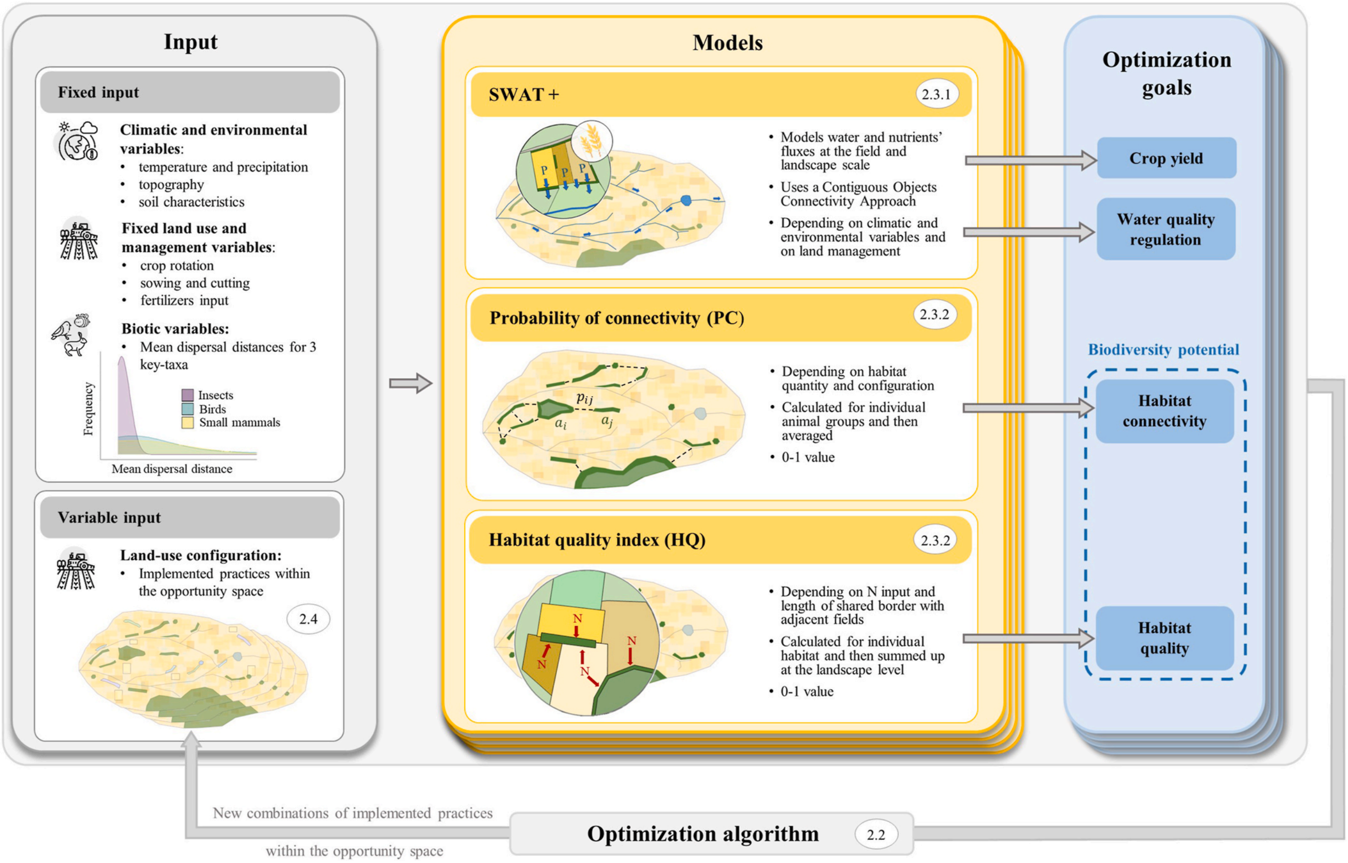

Fig. 1. Overview of the multi-objective optimization approach applied in the study. Four optimization goals were modelled based on three coupled models based on fixed input variables and land-use configurations that were derived from an opportunity space and varied across model runs. Each step is explained in detail in the methods sections (see sections' numbers in the white ellipses).

Supplementary Material). The main outputs used in our optimization procedure were (i) annual *phosphorus load* in the Schwarzer Schöps river at the catchment outlet, which was used as indicator of water quality and (ii) the average annual sum of *crop yield* in the whole catchment area, which was measured in grain units, reflecting the produced nutritional value and used to standardize the harvested biomass across crop types.

2.3.2. Biodiversity modelling

The lack of available data (e.g. management-dependent species observations, pesticide use) and the complexity of biodiversity dynamics (Hillebrand and Matthiessen, 2009; Tscharntke et al., 2012) prevented modelling of responses of biodiversity to changes in AEPs. Instead, we considered landscape structure (habitat connectivity model) and land-use effects on biodiversity (habitat quality model) to simulate a biodiversity potential that could be realized if other conditions were also favorable.

2.3.2.1. Habitat connectivity. Our evaluation of habitat connectivity was based on the *probability of connectivity* (PC) index (Saura and Pascual-Hortal, 2007), which is widely used in the analyses of ecological habitat networks (Hashemi and Darabi, 2022; Keeley et al., 2021). PC values represent the connectivity of suitable habitats in an entire landscape and are based on computing dispersal probabilities (p_{ij}) between individual habitat patches following the formula

$$PC = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} a_i a_j p_{ij}^{*}}{A_L^2} \tag{1}$$

where i and j stand for two of the n habitat patches in the landscape, a represents the size of an individual habitat patch and A_L is the total area of the landscape (Fig. 1).

In our approach, we focused on ecotones between arable land and SNH. SNH in our study included both AEPs and others SNH, e.g. field margins, small forest patches and also the edges of larger natural habitats within a 12.5 m buffer zone around each agricultural field. This buffer allowed us to account for the known decrease of the abundance of farmland species in core forest and other natural areas (Lacasella et al., 2015). Non-permanent SNH (e.g. annual fallow) was considered habitat in the respective year due to its importance for farmland biodiversity (Pe'er et al., 2017). To account for non-permanency, we adjusted the habitat size a by multiplying it by the proportion of time the patch was not used for agricultural production.

Dispersal probabilities were calculated using a decreasing exponential function (Equihua et al., 2024), based on the formula

$$p_{ij} = e^{-kd_{ij}} \tag{2}$$

where d_{ij} represents the edge-to-edge Euclidian distances between two habitat patches and k is chosen so that the function matches a desired probability distance value. We assigned a 50 % dispersal probability when d_{ij} was equal to the mean dispersal distance of a species of interest.

Mean dispersal distances, defined as the average distance an individual travels during a dispersal event, which varies by taxon and functional group, can significantly impact PC values (Wang et al., 2021). To account for this, we used a multi-species approach simulating mean dispersal distances in insects, birds and small mammals, chosen for their ecological role in agricultural landscapes (German National Academy of Sciences Leopoldina acatech, 2020). We retrieved literature values of mean dispersal distance for 43 insect, 67 bird and 30 small mammal species from databases or published studies (section 2.2 in Supplementary Material for details). Based on these data, we established distributions for the mean dispersal distance of each of the three taxonomic groups (Figure S2.4). We then divided the distributions of each taxonomic group into ten equal parts using the decile values, resulting in 27 mean dispersal distances (i.e. three times 9 decile values). PC values were calculated for each of these 27 mean dispersal distances, which were then combined into a single mean PC value for a given land-use configuration. This single value groups all considered species, but it also accounts for both intra- and inter-group variability in dispersal abilities.

PC can range from 0 (no habitat patches present in the considered landscape or all habitat patches further away than mean dispersal distance) to 1 (one habitat patch covering the considered landscape).

2.3.2.2. Habitat quality. Our habitat quality index (HQ) is based on the estimation of negative spill-over effects of nitrogen from neighboring fields and is computed for a given habitat patch *j* as

$$HQ_j = 1 - \sum_{f=1}^{s} \left(\frac{F_f L_{fj}}{L_j} \right) \tag{3}$$

where *f* stands for one of s fields adjacent to habitat patch *j*, *F* represents the nitrogen fertilization amount of a field, L_j is the total edge length (i.e. perimeter) of habitat patch j and L_{fj} stands for the length of the edge that is shared by a field and the natural habitat patch j (Fig. 1). *F* values are results of management simulations within SWAT+ (see section 2.3.1) and were min-max normalized between 0 (no nitrogen input) and 1 (maximum modelled nitrogen input in the catchment).

Based on the *HQ* values of individual habitat patches, we computed the HQ_{tot} value for the entire case study area as

$$HQ_{tot} = \frac{\sum_{j=1}^{n} HQ_j}{N} \frac{\sum_{j=1}^{n} a_j}{A_L} \tag{4}$$

Where *N* stands for the number of habitat patches in the landscape. The second term of formula 4 was included to ensure that a transformation of an agricultural field into a low-quality habitat patch does not reduce HQ_{tot}.

We computed HQ for the same set of SNH considered in the habitat connectivity index, with the only differences that fallow land was not included for HQ. This differentiation was implemented based on the assumption that short-term fallows will be only suitable habitat for a relatively small subset of species. Hence, its exclusion represents a conservative approach to avoid potential inflation of HQ_{tot} values. However, fallow land still positively impacted the HQ of neighboring habitat patches as fallow land is not fertilized and hence their implementation reduced nutrient spill-over to natural habitat patches. HQ can range from 0 to 1, with 0 indicating low and 1 indicating high habitat quality, respectively.

2.4. Model case study catchment and the establishment of possible land-use configurations

The modelling and optimization approach described above was applied to the case study catchment of the Schwarzer Schöps river basin, focusing specifically on the upper part up to its discharge into the

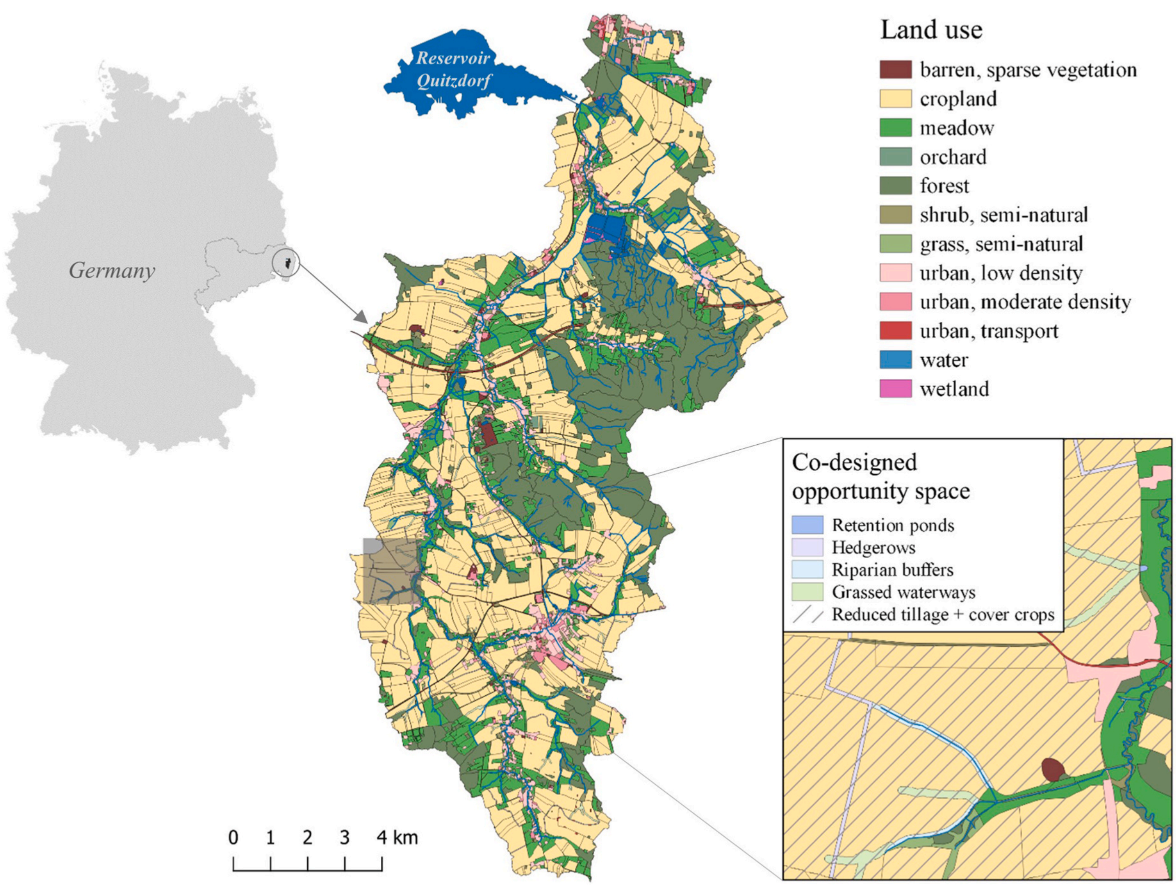

Fig. 2. Case study catchment. Case study area, the Schwarzer Schöps river basin in Eastern Germany (the grey outline shows the federal state of Saxony). Land cover classes are displayed by colors in the central map of the catchment. The inset map provides an example of the co-designed opportunity space, which indicates the categories and spatial allocation of AEPs that were considered as feasible in the stakeholder consultation process.

Quitzdorf reservoir (Fig. 2). Located in eastern Germany, in the federal state of Saxony, the catchment measures about 136 km^2, and it is dominated by agricultural land (54 % cropland and 20 % grassland), with winter wheat, winter rapeseed, winter barley and maize silage as main crops. The agricultural landscape is characterized by intensive management and low structural complexity (e.g., large field sizes, SNH limited to 7.5 % of the total area).

High land use intensity has been associated with several environmental challenges, such as (i) high phosphorus pollution and blue-green algae blooms in the Quitzdorf reservoir, which plays an important role for nature conservation and recreational activities in the region, (ii) increased surface runoff, contributing to recent flooding and (ii) increased soil erosion (Routschek et al., 2014) leading to lower soil moisture and drought resistance with implications for crop yield stability in the area.

2.4.1. Co-designed opportunity space

The AEPs to be implemented in the case study area and their specific implementation location were co-designed together with a network of local stakeholders representing different interest groups in the case study area, such as agricultural production, environmental protection and water body management, and different levels of decision making, from the field (i.e. farm advisors) to the regional level (i.e. federal state offices) (Van den Brink et al., 2021).

The co-designed opportunity space was defined in a two-step process. In the first step, we proposed 13 AEP categories and local stakeholders were asked to prioritize them based on their relevance and potential to address the environmental issues identified in the case study area. Six of these (see Table S3.1) were selected for the next step, as they were considered most relevant for the optimization objectives, as well as feasible for modeling (Marval et al., 2022). In the second step, potential implementation sites for the practices (Fig. 2) were discussed together with the stakeholders (Krzeminska and Monaco (2022) – Annex 4). The identification of these potential implementation sites was based on a high-resolution land-use map (see Fig. 2 and section 3.2 in Supplementary Material for more details). For each AEP category, we proposed relevant datasets (e.g. existing maps recommended by state agencies or from previous modeling projects) and spatial rules (e.g. topographic or biophysical rules) for mapping potential sites (see section 3.3 of the Supplementary Material). We then asked local stakeholders to confirm their agreement with these suggestions. In cases of disagreement, alternative approaches were discussed. Final decisions also took into account 'soft criteria', such as the presence of nearby SNH and the logistic of farm operations (e.g. driving around a hedgerow) after implementing an AEP.

This stakeholder consultation resulted in a co-designed opportunity space encompassing a total of 302 possible implementation sites for the six AEP categories (spread over 804 land-use polygons; see section 3.4 in Supplementary Material for details), which served as input for our modelling approach (Fig. 1). In each model run, a different combination of these 302 features (land-use configuration) was implemented and tested.

2.4.2. Policy-based scenarios

We complemented the stakeholder-based scenario with three additional optimization runs (Fig. 3), reflecting policy scenarios with more ambitious environmental and biodiversity conservation goals.

i. 20 % reduction in fertilizer input as aimed for by the EU Farm to Fork Strategy (European Union, 2020), though not yet reflected in specific regulations or incentives;
ii. Minimum proportion of non-productive areas and features within a farm's arable land of 4 %, as was originally set by the GAEC 8 in the current CAP (2023–2027) (European Union, 2023). This requirement has been on and off during the development of the CAP, although maintaining non-productive areas has been shown to have positive impacts on biodiversity (Pe'er et al., 2017);
iii. Combination of i and ii.

For each of these policy-based scenarios, we prepared new input data to run the optimization procedure. For the *reduced fertilization* scenario, we reduced the nutrient inputs by 20 % every time that a fertilization procedure occurred. For the *fallow land* scenario, we expanded the co-designed opportunity space to achieve a 4 % proportion of non-productive areas at the farm level. While the 20 % reduction in fertilization was mandatory for all fields, fallow land acts as a new AEP category that can (but is not required to) be implemented. For all the compliant farms (i.e. farms with arable land >10 ha or farms with permanent grassland <75 % (Reiter et al., 2024)) we selected fields that could be converted to fallow land in order to reach the set threshold of 4

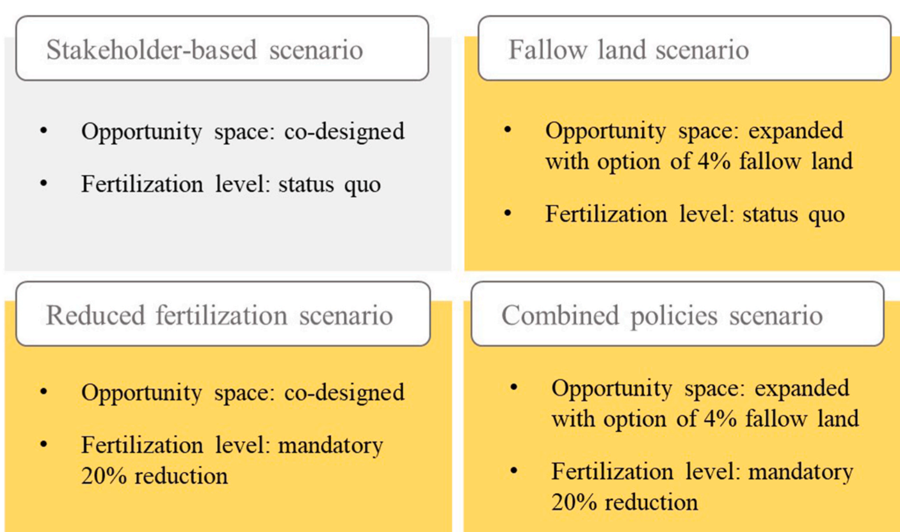

Fig. 3. The four possible scenarios considered in the analyses. The scenarios included the stakeholder-based scenario in grey and policy-based scenarios in yellow. The expanded opportunity space that was used in two of the policy-based scenarios includes, in addition to the co-designed opportunity space, new sites for the implementation of fallow land. These act as new AEPs that can (but are not required to) be implemented, as opposite to the 20 % reduction in fertilization level, which is mandatory. Each scenario represents a separate optimization run that encompassed the analysis of over 20,000 land-use configurations.

% non-productive areas within a farm's arable land. This selection was based on the field size and the soil quality rating (SQR) for cropland (see Table S3.2), assuming that farmers prefer to take land out of production where the soil quality is lower, as shown by Paulus et al. (2022) and Alarcón-Segura et al. (2023) for a case study area in another part of Saxony. Multiple smaller fields were also preferred over a few larger fields, assuming that this would help optimize farm logistics. We selected 41 fields that could be converted to fallow land, which we added to the list of 302 possible implementable AEPs when running the optimization. For the *combined policies* scenario, we included both policy-based management changes.

2.5. Analysis of optimization results

2.5.1. Analysis of the pareto frontier

The result of the multi-objective optimization is a set of Pareto-optimal solutions. As for each of the solutions we know the values of the four considered objectives, this allowed us to plot them in a four-dimensional space and to analyze the resultant Pareto frontier. We analyzed the shape and range (i.e. the difference between the minimum and maximum modelled values reached by each objective) of the Pareto frontier. We performed this analysis first considering all four objectives together and then all possible pairs of objectives. Shape and range of the Pareto frontiers were analyzed for the results of the stakeholder-based scenario as well as for the policy-based scenarios.

2.5.2. Frequency analysis

For each AEP we calculated its polygon-wise frequency of implementation among all optimal solutions, and then grouped them by AEP category in order to calculate the mean frequency of implementation. We also mapped the frequency of implementation for each land-use polygon, assuming that high frequencies indicate hotspots for AEPs

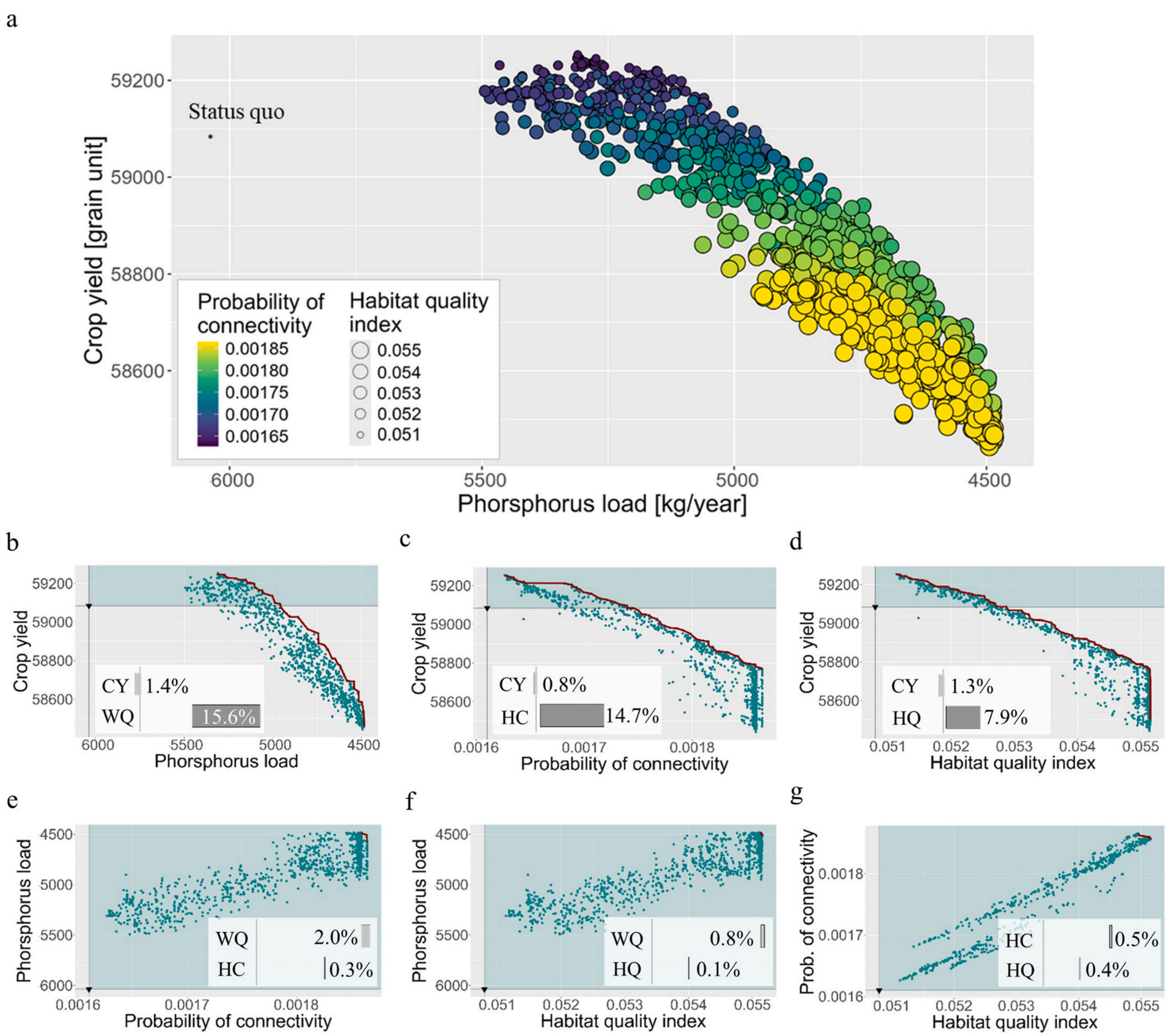

Fig. 4. Four-dimensional Pareto frontier for the stakeholder-based scenario. (a) Four-dimensional Pareto frontier considering all objectives and (b–g) plots of the same Pareto-optimal solutions for pairwise comparisons of the objectives. In plots b-g the colored area represents the area for win-win solutions, which are defined as improvement compared to the status quo management (black triangle). The red line represents the two-dimensional Pareto frontier in pairwise comparison of objectives. Bar charts in b-g show the range of modelled values (percentages) in the two-dimensional Pareto frontiers, calculated as the variation between the minimum and maximum values among Pareto-optimal solutions. The ranges are then plotted relative to the status quo (vertical line). Abbreviations stand for: CY = crop yield, WQ = water quality regulation, HC = habitat connectivity and HQ = habitat quality.

implementation. The frequency analysis was also performed for 13 clusters of Pareto-optimal solutions (Figure S4.2), which were identified along the Pareto frontier grouping solutions with similar objectives' values (section 4.1. of Supplementary Information).

2.6. Software used for models and analyses

All analyses were performed in R version 4.3 (R Core Team, 2023). We used the R package *Makurhini* (Godínez-Gómez, 2020) to calculate PC. We used the packages *sf* (Pebesma, 2018) and *tidyverse* (Wickham et al., 2019) to calculate for all SNH patches their area and the temporal persistence weight in the habitat connectivity model, to calculate HQ and for the frequency analysis. The package *stat* (R Core Team, 2020) was used for the cluster analysis.

3. Results

3.1. Stakeholder-based scenario

3.1.1. Trade-offs between crop yield and environmental objectives

In our stakeholder-based scenario, multi-objective optimization resulted in 1070 Pareto-optimal solutions (Fig. 4). The shape of the Pareto frontier indicated clear trade-offs between crop yield and each of the other objectives (water quality regulation, habitat connectivity and habitat quality). The range of the modelled values indicated a potential reduction in phosphorus loads of 18.4 % (1009.8 kg/year) and a potential increase in habitat connectivity of 14.7 % and habitat quality of 7.9 %, respectively. These variations were even greater when compared to the status quo values (i.e. 25.7 %, 15.8 % and 8.6 %, respectively). On the other hand, we observed a variation between the minimum and maximum values of crop yield of only 1.4 % (809.6 grain units). Of this, 1.1 % corresponded to a decrease in crop yield compared to the status quo, while 0.3 % corresponded to an increase.

The Pareto frontier also showed that 23.8 % of the total solutions were win-win solutions, i.e., solutions where the environmental objectives increased while crop yield remained constant or even increased as well (compared to the status quo). An in-depth evaluation of the solutions with the highest crop yield increase revealed that most of the fields with increased crop yield correlated with a reduced drought stress compared to the status quo (Figure S5.1). Without compromising current crop yields, the maximum increases in environmental objectives compared to the status quo could be of 17.9 % for water quality regulation, 8.1 % for habitat connectivity and 4.1 % for habitat quality.

Further, we found synergies among the multiple environmental objectives considered in this study (Fig. 4e–g). Maximum values of all three objectives were achieved when agricultural production was at its minimum (i.e., bottom-right of the Pareto frontier). However, slight trade-offs between the environmental objectives were also observed at intermediate values of agricultural production, with higher values of water quality regulation corresponding to suboptimal values of habitat connectivity and quality and vice versa (Fig. 4e and f).

Trade-offs with habitat connectivity, which are strongly dependent on assumed dispersal abilities of considered species, changed in strength when different taxonomic groups were considered individually (Figure S5.2). For example, the range of modelled values indicated a possible 10 % increase in habitat connectivity for insects (below the values of the grouped index) and a 15.5 % increase for both birds and small mammals. Compared to the status quo, the maximum increases in environmental objectives could be of 11 % for water quality regulation, 16.6 % for habitat connectivity and 16.9 % for habitat quality.

3.1.2. Implementation frequency of AEPs

Different categories of AEPs showed different patterns in their implementation frequency. Hedgerows, riparian buffers and grassed waterways showed the highest implementation frequency. Out of these AEPs, over 60 % were implemented on average across the 1070 Pareto-optimal solutions (Fig. 5a). Retention ponds and reduced tillage combined with cover crops had instead a lower average frequency of implementation (respectively 42.5 % and 52 %). Independently of this, for all AEP categories, some individual AEPs showed a high frequency of implementation. For instance, there were three specific retention ponds that were implemented over 80 % of the time, or there were grassed waterways and fields with reduced tillage implemented almost 100 % of the time (Fig. 5a).

When mapped, the frequency of implementation of individual AEPs also allowed us to highlight their optimal allocation and therefore possible hotspots for landscape redesign (darker polygons in Fig. 5b). For instance, from the map we could identify 12 site-specific AEPs with an implementation frequency of 100 % (dark red polygons).

The frequency of implementation of AEPs changed along the Pareto frontier, generally increasing with higher values of the environmental objectives (Figure S5.3). For instance, the mean frequency of implementation of hedgerows, riparian buffers and grassed waterways was always below 30 % when crop yield was similar to the status quo and water quality regulation and biodiversity potential were slightly increased (cluster 1). It was always above 85 % when all the environmental objectives were – simultaneously - at their maximum values (cluster 13). Similarly, for most of the clusters (1–11), the average frequency of reduced tillage combined with cover crops ranged between 43 and 54 %. Clusters 12 and 13 contained solutions with the highest implementation rates, 61 and 75 % respectively.

3.2. Policy-based scenarios

Trade-offs between crop yield and the environmental objectives were also observed in the policy-based scenarios. The range of the modelled values and differences from the stakeholder-based scenario varied depending on the considered scenario (Fig. 6).

In the reduced fertilization scenario, the maximum value for water quality regulation increased by an additional 5.5 percentage points compared to the maximum value of the stakeholder-based scenario. The maximum value for habitat quality also increased an additional 3 percentage points, while the values for habitat connectivity remained similar. The entire range of values for crop yield decreased by about 4 percentage points compared to the stakeholder-based scenario. Therefore, no win-win solutions were possible compared to the status quo values.

In the fallow land scenario, maximum values for habitat connectivity increased by an additional 6 percentage points compared to the maximum value of the stakeholder-based scenario, while habitat quality values increased by less than 1 percentage point. Crop yield values decreased by less than 1 percentage point compared to the stakeholder-based scenario. Compared to the status quo values, crop yield also increased slightly (0.2 percentage points) and win-win solutions were possible (18.5 % of the total solutions). For these, the maximum increase in environmental objectives from the status quo was 16.2 percentage points for water quality regulation, 7.2 for habitat connectivity and 2.9 for habitat quality.

In the combined policies scenario, the individual effects of reduced fertilization and fallow land added up to a reduction in crop yield values of about 5 percentage points. Water quality, habitat connectivity and habitat quality values increased by 4, 5, and 4 percentage points, respectively, compared to the stakeholder-based scenario.

In all policy-based scenarios, AEPs had a similar average implementation frequency and distribution as in the stakeholder-based scenario (Figure S5.4). In both the scenarios including the implementation of fallow land, around 15 out of the 41 possible fallow land (36.2 % and 37.1 % respectively) were implemented on average across the Pareto-optimal solutions (Figure S5.4 and Figure S5.5).

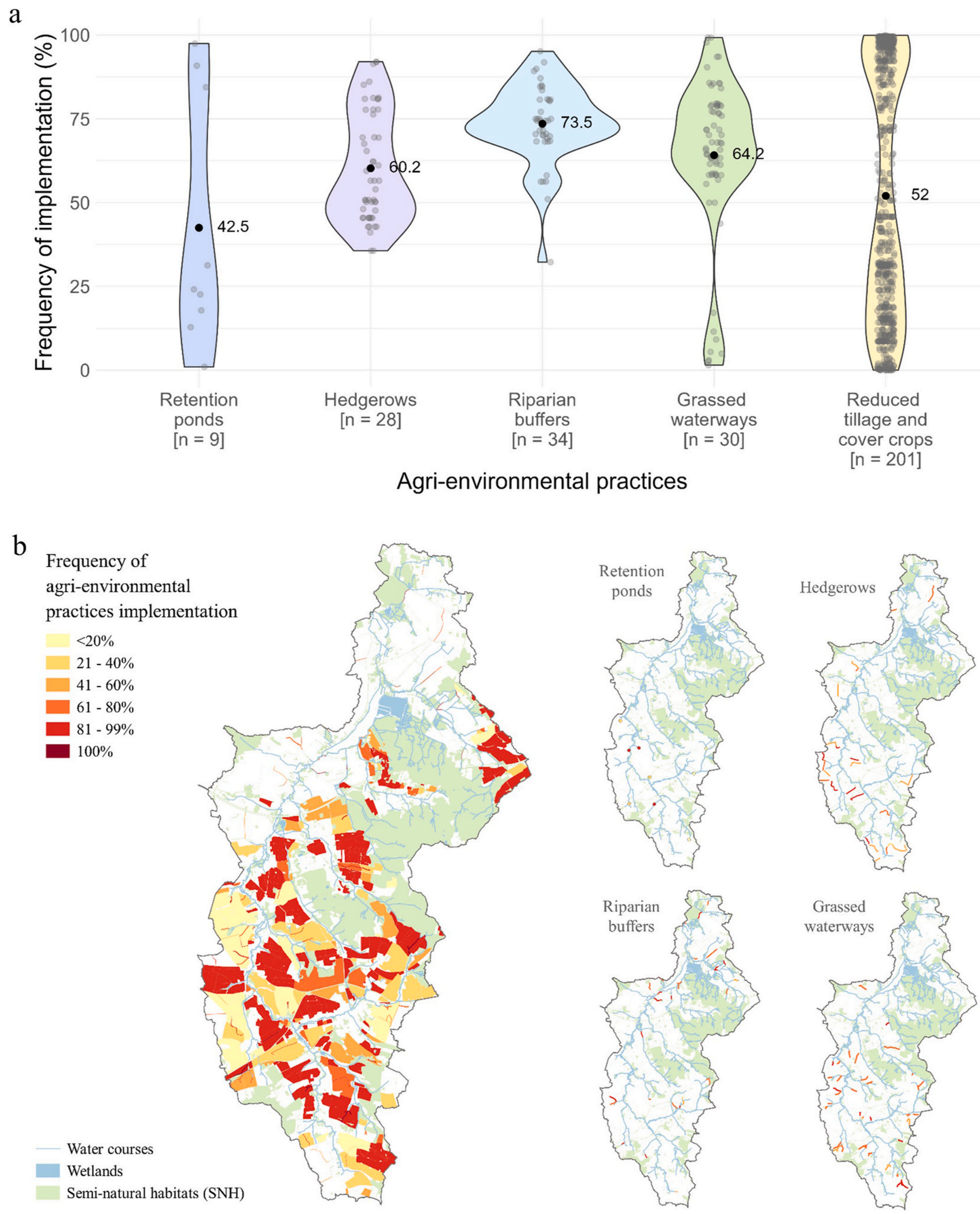

Fig. 5. Implementation frequency of AEPs. (a) Implementation frequencies for different categories of AEPs across all Pareto-optimal solutions. The number in parenthesis under each AEP category indicates the number of sites that were chosen for each category in the co-design process of the opportunity space. (b) Mapped frequency of AEPs implementation. The big map shows all the considered AEPs together, while the four small maps focus respectively on retention ponds, hedgerows, riparian buffers and grassed waterways.

4. Discussion

4.1. Marginal yield losses when improving environmental objectives

The results of all multi-objective optimization runs showed that implementing AEPs lead to improved performance in environmental objectives, although the AEP categories differed in their relative efficacy of targeting the environmental objectives as also found by Bullock et al. (2021) in their farm-scale experimental study. In two out of the four tested scenarios, pareto-optimal solutions contained a large number of win-win solutions, showing that improvements in environmental objectives can be achieved while maintaining or even slightly increasing agricultural production. When production losses occurred, they were always smaller in relative terms than the corresponding increases in environmental objectives. Yield reductions were around 1.1 % for the stakeholder-based scenario, while in the scenarios with reduced fertilization they were around 4.5 %. This result is in line with those reported by Williams et al. (2023), i.e., that a 2–10 % loss in crop yield is expected as effect of a 20 % reduction in N fertilizer use. However, also in the scenarios with reduced fertilization yield, losses were smaller than the increases in environmental objectives.

It is important to highlight that such marginal yield losses occurred over the spectrum of implementable AEPs that we investigated, while more ambitious environmental targets might intensify trade-offs. Moreover, a full analysis of the impacts on agricultural production would require translating the identified yield effects into overall

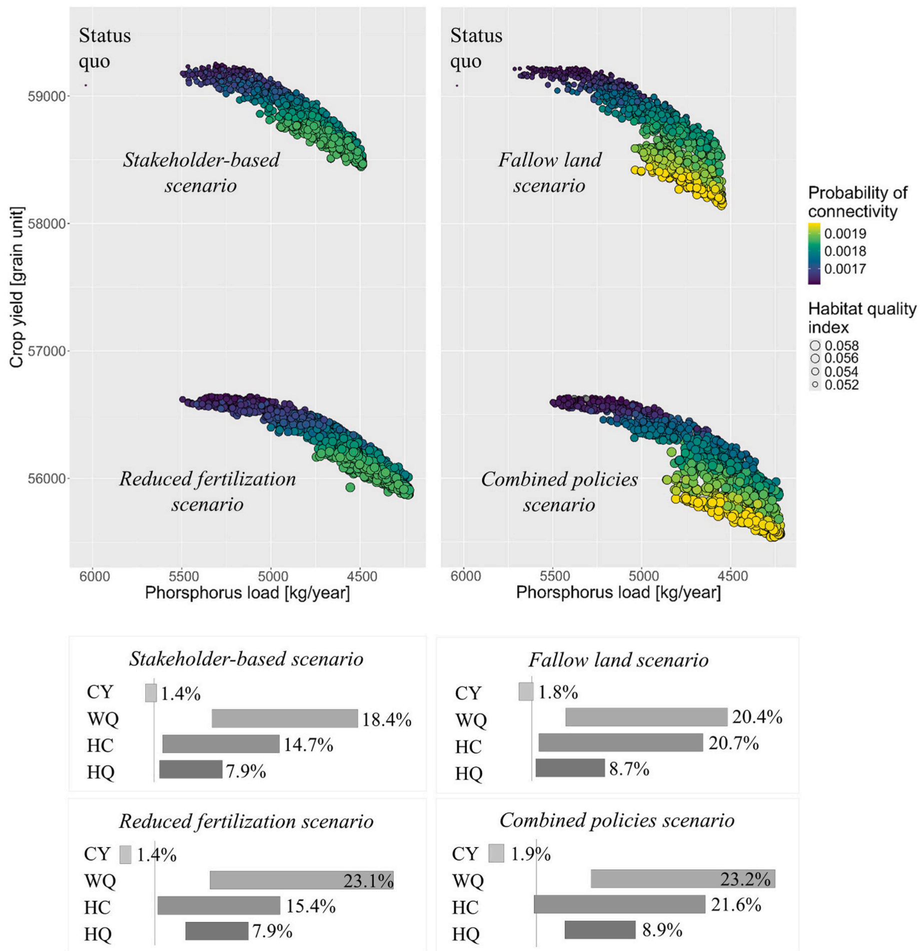

Fig. 6. Four-dimensional Pareto frontiers for all four considered scenarios. To avoid an overlap between Pareto-optimal solutions of different scenarios, the fallow land scenario and the combined policies scenario were plotted separately from the other two scenarios. Color and size scales are consistent across all scenarios. The bar charts show for each scenario the range of modelled values (percentage), calculated as the variation between the minimum and maximum values among Pareto-optimal solutions. The ranges are then plotted relative to the status quo (vertical line). Abbreviations stand for: CY = crop yield, WQ = water quality regulation, HC = habitat connectivity and HQ = habitat quality.

changes in farm income. For instance, farm income also depends on the costs of implementation and maintenance when implementing AEPs as well as the potential increased effort (e.g. of driving around hedgerows), with the associated higher fuel and labor costs. Such an analysis was beyond the scope of our study, but we acknowledge the importance of these additional considerations.

4.2. Efficient land management as driver for win-win solutions

Our results on the win-win solutions are consistent with those of other studies (Jones et al., 2023; Magrach et al., 2023) that showed how the adoption of biodiversity-friendly practices or diversification of agricultural practices can be synergistic with increases in crop yield (relative to the status quo). Such results are often related to positive feedbacks of biodiversity on agricultural production (e.g., through pollination or natural pest control). In our case, such feedbacks were not included in the modelling approach, but we acknowledge that they can be substantial, although sometimes high biodiversity can also provide disservices to agriculture (see e.g. Daelemans et al. (2023); Vogel et al. (2023)).

In our case, the results were mainly related to a more efficient land management when implementing the proposed practices, in line with Teillard et al. (2017). The win-win solutions had a lower number of implemented AEPs compared to solutions in other regions of the Pareto frontier, but they were placed in the right location. The areas taken out of production in these solutions were often characterized by low productivity (e.g. thalwegs with high risk of soil erosion and water logging in the case of grassed waterways). If reduced tillage was implemented in the right areas, helping to maintain soil moisture levels during the growing season by increasing infiltration and water-holding capacity, crop yields could even be increased.

4.3. The benefits of spatial optimization

Also outside the win-win solutions, the results of our study showed that the key to minimize trade-offs is to have a mix of different AEPs that are optimally allocated in the case study area, as also shown by Ekroos et al. (2014) and Verhagen et al. (2018). For instance, well-placed hedgerows connecting existing SNH can result in a substantial improvement in habitat connectivity without losing large amounts of cultivated area (Wesemeyer et al., 2023). Similarly, well-placed riparian buffers and grassed waterways can reduce surface runoff and increase nutrient retention, thereby improving water quality regulation (Kreig et al., 2019; Rao et al., 2009).

The produced maps of frequency of implementation (Fig. 5b and Figure S5.5) can serve as an important tool for identifying the locations where the implementation of AEPs will maximize the delivery of environmental objectives while reducing trade-offs with agricultural production. Implementing AEPs in low-frequency polygons is only necessary if environmental values have to be maximized at the expense of reduced crop yields. In contrast, implementing AEPs in high-frequency areas alone will likely result in a significant improvement in environmental objectives with little to no yield loss and potentially higher yields compared to the status quo.

For the policy-based scenarios, such maps (Figure S5.5) also highlighted that not all the proposed fallows were implemented with the same frequency. Generally, setting a minimum threshold of non-productive area for all farms would certainly increase the biodiversity potential, but this would not be the best solution for reducing trade-offs between multiple objectives. The spatial allocation of such practices plays an important role in maximizing their effectiveness and reducing trade-offs, and should therefore be considered in policy design (Tscharntke et al., 2005).

4.4. Stakeholders' preferences to prioritize among objectives

Although the environmental objectives are mainly synergistic, maximum values of all of them were only achieved when crop yield was at its minimum. Otherwise, we observed slight trade-offs between water quality regulation on one hand and habitat connectivity and quality on the other hand. Specific practices and their spatial allocation influenced regulating ecosystem services and biodiversity conservation differently, leading to situations different from the often-expected win-win (Ziv et al., 2018).

All this has important management implications, as reducing yield losses and potential trade-offs between regulating ecosystem services and conserving biodiversity requires careful decisions about which AEPs to implement and about their spatial allocation. Ultimately, it is all about prioritizing among objectives, which should be done jointly with stakeholders (Kaim et al., 2020) or using preference data (Kaim et al., 2021). In our approach, stakeholders were involved in the beginning in generating the co-designed opportunity space. A further step, not included in this analysis, would be to bring the results of the multi-objective optimization back to them (Strauch and Wittekind, 2025). The frequency maps, for instance, would be a great tool for the communication of the optimization results.

4.5. Potential for further improving environmental objectives

The co-designed opportunity space is in itself an important result of the deliberative process among stakeholders, and the optimization results showed that the currently proposed AEPs may enable improved environmental outcomes for the case study area. However, a more ambitious AEPs implementation could allow for a further increase as shown by our policy scenarios. For instance in our case study region, the current land use is characterized by 7.5 % of SNH; less than 1 % is added if all the structural elements are implemented, and with these additional habitat patches the landscape still remains quite fragmented. At the same time, we have seen that the identified maximum improvements in environmental objectives were achieved at the expense of a marginal reduction in crop yield. This may leave a certain margin for further implementation of AEPs to further improve the environmental objectives without significantly impacting crop yield. However, considering overall changes in farm income caused by AEPs implementation would be necessary for a full analysis of how implementing more AEPs would impact on agricultural production.

4.6. Strengths and limitations of the modelling approach

Modelling the impact of agriculture on biodiversity is generally very challenging, because this is affected by a multiplicity of factors, both at the local and landscape scale, many of which are deeply interconnected. Burian et al. (2024), for instance, have attempted to untangle some of these relationships, but only conceptually. Different taxa also react differently to these drivers, making taxa-adapted models necessary (see e.g. Bonato et al. (2023); Martin et al. (2019)). Even if models were available, many data are often not available (e.g. no data on pesticides application was available for our case study area), limiting the ability to capture the full set of drivers and therefore to more comprehensively model biodiversity potential.

Despite all these challenges, our approach allowed us to take into account two major mechanisms that drive biodiversity in agricultural landscapes (i.e. the connectivity among semi-natural habitat and the negative spillover effect from cultivated to semi-natural land). Additionally, the multi-group and multi-species approach that we used for calculating habitat connectivity also allowed us to consider the variability with which taxa respond to this driver.

Unlike the indicators used for agricultural production and water quality regulation, we acknowledge that the indicators of biodiversity potential are rather abstract and less tangible. In fact, while phosphorus load and crop yield have clear physical meaning (i.e. phosphorous load is measured in kg/ha/year and crop yield is measured in grain units), biodiversity indicators lack a direct physical correlate, such as the number of individuals or species that can move in the landscape with a specific value of habitat connectivity. Additionally, biodiversity potential indicators are context-dependent, making them less comparable to indicators calculated in another landscape unless all assumptions are maintained. Nevertheless, both biodiversity indicators directly respond to the implementation of new AEPs by showing the direction and magnitude of change in habitat connectivity and habitat quality, thus working perfectly for the trade-offs analysis that we performed.

Due to the lack of data, a precise parameterization of the SWAT + model was also challenging, especially with respect to sediment and phosphorus processes. As a result, the impact on soil erosion and thus particulate phosphorus loss might be overestimated, while the impact on dissolved phosphorus loss, which often increases with conservation measures (Bechmann et al., 2005), might be underestimated (Flaten et al., 2024). This might explain why the implementation of fallow land in the policy-based scenarios did not have a substantial impact on water quality, even though fallow land is characterized by the absence of fertilization and includes a permanent vegetation cover. Another reason could be that fallow land, as opposed to the other AEPs could not be allocated on erosion-prone land in our study.

4.7. Management and policy implications

The results of our multi-objectives optimization approach may have various implications for management and policy. The land-use configurations associated with the Pareto-optimal solutions may serve as detailed spatial plans for redesigning agricultural landscapes to address the challenges raised by stakeholders during the workshops. Outside of the study design, the results of our multi-objective optimization could support a landscape redesign aimed at achieving policies' targets. Indeed, different EU directives and regulations target the same objectives that we considered in our analysis. For instance, the Water Framework Directive aims to achieve a "good status" for the EU water bodies (European Parliament and Council of the European Union, 2000). The Nature Restoration Regulation, instead, aims to restore habitats (including farmland) from a poor to good condition and enhance species-focused connectivity (European Parliament and Council of the European Union, 2024). Both legal acts require the creation of management plans (i.e. River Basin Management Plans, National Restoration Plans), in which local authorities must identify priority measures and their locations. The optimal land-use configurations resulting from multi-objective optimization exercises could therefore form the basis for drawing such management plans. Still, the optimization itself disregards institutional, economic and social constraints. Hence, the implications for management and policy are rather indirect and partial.

The results of our study could also support the redesign or spatial targeting of economic subsidies so that they only cover the most environmentally efficient AEPs, ensuring that the right AEPs are placed where they will be most effective. In Saxony and other German federal states, this is partly already achieved through the establishment of so-called *Kulissen*, which define zones that are eligible for specific subsidies. These zones are defined based on general spatial and environmental criteria (e.g. soil types, hydrology or conservation status). Implementing specific measures in these zones is expected to deliver **certain ecological benefits.** Our method could improve the definition of these zones. In our study, in fact, optimal allocations of AEPs that deliver higher environmental values were identified through spatially explicit models, after testing over 20,000 different land-use configurations.

5. Conclusion

Agricultural landscapes are very often perceived as characterized by trade-offs between different objectives, especially in the context of implementing AEPs. In this study, we performed a multi-objective optimization between crop yield, water quality regulation and biodiversity potential for the case study of the Schwarzer Schöps river basin. Our aim was to better understand modelled trade-offs between the considered objectives.

Our results suggest the possibility that production losses are not a limiting factor for implementing AEPs, as we observed only marginal losses in crop production linked to increased environmental objectives. In order to reduce trade-offs between crop production and environmental objectives, it was important to implement a mix of different AEPs that are optimally allocated in the case study area. Especially for win-win solutions, it was crucial to have a low number of implemented AEP, but placed in the right location. Well-placed reduced tillage, in particular, could reduce water-related stress on crops, leading to increased yield compared to the status quo.

Our study showed how biophysical and ecological modeling approaches combined with a multi-objective optimization of AEPs implementation can provide valuable support for redesigning agricultural landscapes. The application of these spatial planning tools demonstrates the importance of thoughtfully allocating AEPs and related subsidies, highlighting the potential to deviate from “one size fits all” policy approaches and to allow more flexibility for local decision-making.

CRediT authorship contribution statement

Marta Bonato: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Alfred Burian:** Writing – review & editing, Methodology, Conceptualization. **Juliàn A. Equihua:** Writing – review & editing, Methodology, Conceptualization. **Anna F. Cord:** Writing – review & editing, Supervision, Conceptualization. **Bartosz Bartkowski:** Writing – review & editing, Supervision, Conceptualization. **Michael Strauch:** Writing – review & editing, Validation, Supervision, Software, Resources, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to thank the other colleagues working on the German case study of the OPTAIN project (https://www.optain.eu/, grant no. 862756): Martin Volk, Felix Witing, Christoph Schürz, for the help with the land-use map, the SWAT + modelling and the exchange with the network of local stakeholders. This work was carried out within the framework of the INTERCEDE (Interactions of Farmland Biodiversity and Agricultural Ecosystem Services under Climate Change) PhD consortium at the Helmholtz Centre for Environmental Research (UFZ). AFC was supported by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany’s Excellence Strategy – EXC 2070–390732324.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.126939.

Data availability

The R software used for modelling and for the analysis of the multi-objective optimization results can be found at: https://github.com/mrtbonato/optiscape and can be cited with this DOI: https://doi.org/10.5281/zenodo.15739236. The code for the used multi-objective optimization tool (CoMOLA) can be found at: https://github.com/michstrauch/CoMOLA.

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