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Multi-objective spatial optimization to balance trade-offs between farmland bird diversity and potential agricultural net returns

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ABSTRACT

Global farmland biodiversity has declined rapidly in recent decades due to the homogenization of agricultural landscapes, including an increase in field sizes and decrease in woody features, such as hedgerows. Restructuring landscapes by (re)introducing woody features and decreasing field sizes can support biodiversity but at the cost of lower returns in farming. Striking a balance between biodiversity and agricultural net returns is increasingly pertinent. Here, we use spatial multi-objective optimization to allocate woody features and adapt average field sizes at the landscape scale to assess the trade-off between biodiversity, measured as the occurrence of farmland birds, and potential net returns from crop production. Our results suggest that, compared to the current landscape configuration, both agricultural net returns and biodiversity can be simultaneously increased. Restructuring only 5% of the landscape can improve bird abundance by 2% and generate about €2 million in agricultural net returns. We show that increases in farmland bird diversity are highly dependent on the location and on farmers' willingness to accept negative impacts on agricultural net returns. Our spatially explicit approach supports spatially targeted land use planning that can strike a better balance between the economic objectives of farmers and the societal desire to conserve biodiversity.

1. Introduction

Agricultural landscapes have profoundly changed over recent decades, particularly in Europe and the United States, including the spatial separation of animal husbandry and arable farming, the reduced diversity of arable crops, and the disappearance of seminatural habitats. Land consolidation has reduced field margins, including grass strips, hedgerows, and ditches, which provide important refuge for biodiversity (Hartvigsen, 2014). The more coarse-grained landscapes feature a lower diversity of crop types, fewer field edges, and larger fields (Clough et al., 2020). Moreover, rising pesticide use and more homogenous crop rotations have reduced insect prey (Geiger et al., 2010). The result of this transformation of agriculture is a drastic decline in farmland biodiversity (Clough et al., 2020; Kleijn et al., 2008). The best data are available for birds, showing dramatic declines in farmland species, much stronger

than in any other group of birds (Burns et al., 2021; Inger et al., 2015; Noack et al., 2021; Stanton et al., 2018).

Larger field sizes with more homogenous cropping structures tend to increase the per-hectare profitability of farming because these reduce the time and fuel needed for mechanized field operations, such as sowing, tillage, input application, and harvesting per unit area (Batáry et al., 2017; Jeanneret et al., 2021; Kirchweger et al., 2020). More homogenous crop production leads to gains from specialization in terms of knowledge, intermediate inputs, and machinery (Noack and Larsen, 2019). Introducing more landscape elements into homogenous farming operations would reduce the total farmed area and be associated with higher operating costs and thus lower net returns from farming (Latruffe and Piet, 2014).

It is hence important to quantify the trade-offs between decreasing field sizes and increasing non-productive landscape elements with the

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lower returns of such more biodiversity-friendly farming (Clough et al., 2020; Rosa-Schleich et al., 2019). A concept that researchers often apply to balance these trade-offs is eco-efficiency, which implies producing more output at constant environmental costs or the same output at lower environmental costs (Kuusmanen and Kortelainen, 2005; Soliman and Djanibekov, 2020). Quantifications of eco-efficiency are usually implemented at the farm level and typically rely on frontier approaches that link economic and environmental models (Soliman and Djanibekov, 2020).

Multi-objective optimization can help to shed light on the production–conservation trade-offs. Such approaches simultaneously consider the multiple, often competing, demands for safeguarding biodiversity and ensuring agricultural returns (Strauch et al., 2019). Multi-objective spatial optimization has helped to pinpoint locations where trade-offs, such as between biodiversity, crop yields, and carbon stocks, are low in order to identify eco-efficient solutions (Kaim et al., 2021; Law et al., 2021; Polasky et al., 2008). This can be achieved with spatial optimization algorithms that rely on exact approaches, such as linear programming (Law et al., 2017, 2021), or on heuristic approaches, such as genetic algorithms (Cao et al., 2014; Kaim et al., 2021; Strauch et al., 2019; Verhagen et al., 2018). The resulting Pareto or efficiency frontiers allow for characterizing inefficiencies and assessing trade-offs between the competing objectives in a quantitative manner. Moreover, these methods permit identifying land use configurations that provide optimal solutions to mitigate the trade-offs (Law et al., 2021). Modeling results can also enable comparing the difference in observed land use with the optimized land use solutions.

We developed a landscape-scale, multi-objective optimization approach to assess the trade-offs between agriculture and farmland bird diversity in the federal state of Brandenburg, Germany. As decision variables, we used four types of agricultural landscapes based on average field sizes and the proportion of small woody features (hereinafter “woody features”). We maximized two objectives: farmland bird diversity and potential net returns from arable farming. We used a linear integer programming approach that allocates different agricultural landscape types to current agricultural landscapes in order to maximize biodiversity and simultaneously achieve a target for net returns from crop production. We approximated potential net returns at the plot and farm levels with field-level land use data. We used production-specific cost accounting to quantify the net returns. Our biodiversity metric is a composite based on species distribution models (SDMs) and relative abundance for a set of farmland birds.

Our overarching aim was to identify potential landscape configurations that balance trade-offs between farmland bird diversity and potential agricultural net returns. To achieve this aim, we addressed the following research questions:

1. What are the impacts of different field sizes and different proportions of woody features on farmland bird biodiversity and on agricultural net returns?
2. Where in our study region can agricultural net returns be increased or farmland bird biodiversity be enhanced or both?

2. Methods

2.1. Study region

Our study region is the federal state of Brandenburg in former East Germany. The average farm size in Brandenburg is 242 ha and the average field size is 12 ha. The removal of hedgerows was part of the agricultural intensification and farm collectivization that was implemented in East Germany from 1953 to 1960 (Batáry et al., 2017). As in many other post-socialist regions, large-scale agricultural structures persisted after the German reunification in 1990, while land ownership remained fragmented as a result of the restitution of land to its historical owners (Hartvigsen, 2014; Noack et al., 2021). Brandenburg’s

agricultural landscape is characterized by increasingly homogenous land use and the intensification of production, both of which are arguably associated with a decrease in biodiversity (Langgemach and Ryslavý, 2010). These trends continue despite the European Union’s (EU) support for sustainable land management practices within the Common Agricultural Policy (CAP) (Wolff et al., 2021). Brandenburg covers 29,479 km², of which about 10,400 km² were used as cropland in 2018, according to the Integrated Administration and Control System (IACS).

2.2. Data

We used plot-level data on agricultural parameters from the EU IACS for the years 2017, 2018, and 2019. We extracted spatial vector data to derive cropland area, field sizes, crops grown, average distances of all fields of a farm relative to each other, and whether a farm was managed for organic or conventional agriculture. To quantify woody features, we used remote sensing-based crop-type maps with a spatial resolution of 10 m by Blickensdörfer et al. (2022). These maps contain a woody features class from which we derived the proportions of all kinds of woody features (e.g., tree groups, hedgerows, small woods) in the agricultural landscapes for the three years (Blickensdörfer et al., 2022). Blickensdörfer et al., 2022 trained their algorithm on, among other reference data, a small woody feature high resolution layer (EEA, 2019) and to avoid confusion with forest, they used an agricultural land cover layer to mask out all non-agricultural land. We also used data on soil quality estimations from cadastral data, which capture the natural yield capacity of all cropland (Schmitz and Müller, 2020). Furthermore, we used data from the Common Breeding Bird Monitoring Scheme of Germany (CBBS) (Kamp et al., 2021) and the citizen science platform eBird.org (Sullivan et al., 2009) to assess the avian biodiversity (see below and supporting online material, Appendix A1–A1.6).

2.3. Landscape map

To create a map of agricultural land use, we used IACS (year 2018) and the woody features layer (classified as woody features in at least two of the three years from 2017 to 2019). We used rasterized IACS data to derive the cropland class and finally assigned the woody features class; that is, we then reclassified some of the cropland as woody features.

The resulting land cover classes were cropland, grassland, and woody features, spatially aggregated to a 1-km² resolution to match the spatial resolution of the bird sampling data. We reclassified all agricultural landscapes according to the proportion of woody features and average field size derived from IACS using K-means clustering. We identified the following types of agricultural landscapes (Fig. 1): high average field sizes and few woody features (“large fields, few woody features”), small-to-medium average field sizes and few woody features (“small fields, few woody features”), small-to-medium average field sizes and moderate woody features (“small fields, moderate woody features”), and low average field sizes and many woody features (“small fields, many woody features”). We refer to the resulting map, which serves as the baseline, as the initial landscape map in 2018.

2.4. Farmland bird biodiversity

We used a set of 22 common farmland birds (see A1, A1.5 and A1.6) to represent biodiversity; as birds are well studied, high-quality monitoring data are available, and they are good indicator species due to their location at the top of the food chain (Fraixedas et al., 2020). We used data from the CBBS (Kamp et al., 2021). In this scheme, which began in 2005, volunteer observers survey breeding birds annually on up to 1800 plots across Germany. Plots were selected randomly stratified, with the stratification representing the main ecoregions and habitats of Germany. All bird species are counted along a route of three kilometers, dissecting each survey plot. Counts are repeated four times between March 15 and



Fig. 1. Different types of agricultural landscapes: left: Scatterplot showing woody features vs. average field size for the four different clusters; images on the right-hand side represent the different landscape types: large fields, few woody features (1); small fields, few woody features (2); small average fields, average woody features (3); small fields, many woody features (4).

June 15, and the raw data are later combined into territories per plot. As the richness unit, we used the number of farmland bird species recorded per plot (see Appendix A1 for a justification of the selection) across all considered years and as abundance measures the number of territories per farmland bird species reported per plot and year (Kamp et al., 2021). We filtered the bird data for the years 2017, 2018, and 2019 (to match them to the spatial land use data; see above) and for the approximately 200 survey plots situated in Brandenburg.

Our farmland bird diversity metric (hereinafter referred to as “biodiversity metric” or “biodiversity”) employs SDMs and the relative abundance per species and agricultural landscape, both derived separately. We fitted the SDMs to a set of predictor variables and data from the CBBS and the citizen science platform eBird (Sullivan et al., 2009). We included observations of farmland bird presence for the years 2017 and 2018 and filtered the eBird data following Johnston et al. (2021): We included only expert-approved observations with no more than five hours of observation time, no more than 10 observers, and no more than five kilometers effort distance. In addition, we selected only protocols of the “Travelling” or “Stationary” type. Further, we spatially thinned the complete bird observation points consisting of CBBS and eBird data to avoid patterns of spatial autocorrelation. Aiming to have a maximum of one observation per grid cell, we chose a thinning parameter of one kilometer for our 500×500 -meter grid cells. We used Maxent (Phillips et al., 2017) as implemented in Wallace (Kass et al., 2018; Torres et al., 2020), which yielded probability maps of species occurrence. The set of relevant predictor variables included annual precipitation, precipitation of the wettest month, the maximum temperature of the warmest month (Fick and Hijmans, 2017), distance to urban area, distance to water, distance to forest, elevation, slope, and distance to protected areas as well as distance to solar plants and wind parks (see A1.1, A1.2, and A1.3 for a more detailed explanation).

We additionally calculated the relative abundance per species and for all four landscapes based on the CBBS data. We took the mean abundance per bird species and landscape type and divided it by the maximum mean abundance value per bird type and landscape type. The relative abundance values range between zero and one, where one is the species’ most preferred habitat and zero is the least preferred (see A1.4 and A1.5).

The biodiversity metric, used in the objective function, employs both

relative abundance and potential presence (from the SDM), whereas potential presence is multiplied by the relative abundance of the respective species and landscape, as allocated by the optimization algorithm. The resulting values are aggregated relative abundance values for the set of 22 farmland birds. The theoretical maximum is 22 for a single landscape, which would be achievable if all bird species could exist in a given location, and the preferred habitat of all bird species was allocated. Hence, the theoretical maximum cannot be achieved as our species have different habitat preferences. Applying this objective function to the current landscape configuration or a solution results in a farmland bird diversity map (see A1.3).

2.5. Potential net returns

We estimated the net returns per square kilometer with an online tool for farmers provided by the “Agricultural Advisory Board for Engineering and Building” (Batáry et al., 2017; Kirchweger et al., 2020; Kuratorium für Technik und Bauwesen in der Landwirtschaft e. V. (KTBL), n.d.). This online tool allowed us to calculate net returns for the main crop types based on input variables such as crop type, machinery, field size, fertility and soil type, distance to the farm, fertilizer inputs, and tillage practice. The tool also permits the separation of organic and conventional farming, which affects the yields and costs and therefore potential net returns. Within the tool, the assumed market price for each crop is multiplied by the expected yields, resulting in the total revenue in euro per hectare. From this, the expected direct costs for fuel, fertilizer, pesticides, and insurance payments as well as expected variable costs (e. g., for machinery) are subtracted. The net returns are obtained by subtracting the fixed costs from the total revenue per crop and hectare. We used the tool for the 14 main crop types in the study region, which in total represent about 90% of the cropland area (see A2). For the other 10% of crop types, we assumed average values obtained by grouping the data by organic or conventional, field size, a combination of yield and soil type, mechanization, and distance to the farm in the calculation of the average operating net returns per group.

We calculated the potential net returns for each agricultural landscape and each potential transition of that landscape (Fig. 2). In total, we obtained four potential net return values for each agricultural landscape. We achieved this by adapting the average field size for each transition

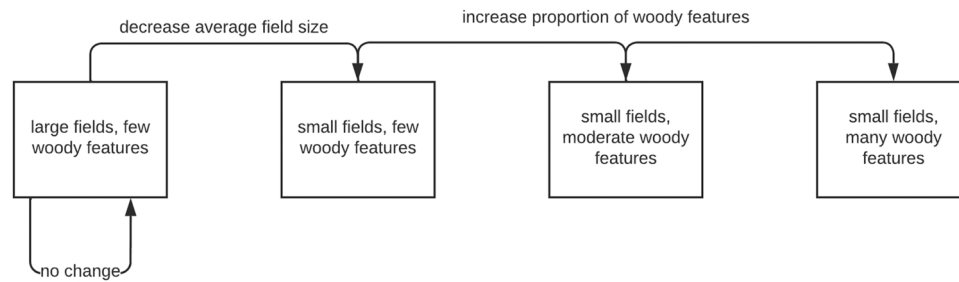


Fig. 2. Example of the transition of “large fields, few woody features” to “small fields, many woody features”; arrows depict the process of transition, and the different states appear in rectangles.

and changing the overall agricultural area in a cell caused by planting woody features in or removing them from agricultural land. We did this for the years 2017, 2018, and 2019 and calculated the average values to depict crop rotations to some extent. We refer to these as potential net returns because of assumptions about management practices, such as regarding the amount of direct costs, insurance payments, and fertilizer and pesticide application. More details about the calculation of potential net returns can be found in the Appendix (A2).

2.6. Optimization

2.6.1. Analysis framework

We used the four possible landscape types as *decision variables*, two *objective functions* (farmland bird biodiversity and potential agricultural net returns for crop production) and several *constraints*, as detailed below. The underlying idea was that it is possible to change field sizes and the proportion of woody features in a landscape (1 × 1 km) and that these changes affect farmland bird biodiversity and potential net returns. Our optimization framework yielded solutions maximizing both objective functions. The resulting optimal landscape configurations allowed us to analyze trade-offs between both objective functions. We also implemented two different scenarios that mainly differ by the specific constraints we set (see below). We used a linear programming approach following Law et al. (2021) and implemented it in Python 3.8 and Gurobi 9.5 (Optimization, 2020). A more detailed workflow with a mathematical description of the model appears in the Appendix (A3).

2.6.2. Decision variables and objective functions

Decision variables allocate cells into one of the four agricultural landscapes (Fig. 1). Each of these resulting agricultural landscapes provides spatially variable benefits for biodiversity and agricultural net returns. We assumed that the other landscape types (forest, grassland, urban, water, and other) remain stable during the optimization.

To allocate a new agricultural landscape to a pixel, we used our objective functions to calculate the effect of changing the overall amount of agricultural land or changing the field size in a landscape. One possible transition pathway, for instance, is the conversion from “large fields, few woody features” to “small fields, many woody features,” implying that an increase in the proportion of woody features denotes a decrease in the total farmed area and field size (Fig. 1). These changes, in turn, affect the objective functions and, hence, impact biodiversity and potential net returns. We maximized biodiversity while *gradually degrading* the agricultural net return target (the target constraint), starting with the maximum possible agricultural net return target for the respective scenario. We obtained the maximum net returns target by running the optimization once without the biodiversity objective while satisfying all constraints. We obtained the Pareto frontier by summing the outcomes for all cells and each objective.

2.6.3. Constraints

We set several constraints to limit the result to feasible solutions (Cao, 2018; Law et al., 2021; Strauch et al., 2019). We introduced single

species constraints limiting the maximum decline of the total relative abundance; this can be specified for each species individually. The constraint specifies minimum relative abundance values per species in comparison to the initial situation. For example, a 30% minimum species abundance constrains the decline of a single species to no more than 30% compared to the initial landscape map. Another constraint limits the overall number of transitions in comparison to the initial landscape map. Limiting the number of transitions permits identifying the most important areas of change and finding solutions with minimal change and maximal benefit. Another constraint guarantees the allocation of only one landscape type to a pixel. We used these constraints to implement and compare two different scenarios, described in the following section.

2.7. Scenarios

We compared two scenarios with assumptions about the maximum number of possible transitions and different constraints on the species target.

The “**No constraints**” scenario demonstrates an “optimal” landscape without any transition constraints and no constraints to limit the decline of bird species. In this scenario, all agricultural landscapes could transition to another agricultural landscape type (see Fig. 2).

The “**Small input, big gain**” scenario optimizes for farmland bird biodiversity and potential agricultural net returns under constraints. This scenario shows by how much biodiversity and potential net returns can be increased with a small number of possible transitions. This scenario therefore depicts areas that are suitable for achieving the greatest effect. We limited the maximum number of possible transitions to 5% of the total agricultural area (95% of all agricultural landscapes need to remain stable) as it is not realistic to reorganize all agricultural landscapes in Brandenburg. We also constrained the maximum species decline to 30% compared to the initial value for each species. In this way, we avoided some species being outvoted by other species with different habitat needs (Butsic et al., 2020).

2.8. Frontier and spatial analysis

After running the optimization, we calculated the sum of potential net returns and the biodiversity metric using our objective functions for each solution of both scenarios and for the initial landscape map. To get the average farmland bird diversity per agricultural landscape, we divided the overall value by the number of agricultural landscapes for visualization.

Each solution represents a landscape map, which represents the optimum in each iteration subject to all constraints and the objectives. We visualized the results in a scatterplot, where the optimized solutions form the Pareto frontier, and the initial landscape map is a point within the possibility space. We analyzed the Pareto frontier for the two scenarios and compared the initial landscape map with optimal solutions. The distance of the initial landscape map to the Pareto frontier represents potential Pareto improvements. The shape of the frontier visualizes

trade-offs between our objectives and reveals the potential impact on the agricultural net returns and biodiversity of the respective solutions.

Each solution represents a landscape map, which we used to map changes in the agricultural landscapes relative to the initial landscape map. We also created change maps for the biodiversity metric and for the potential net returns. This facilitated identifying areas with significant change and the predominant type of change. We then analyzed the spatial patterns of selected solutions to reveal regions that offer potential for the improvement of biodiversity and agricultural net returns. The results suggest the locations and types of desired transitions to more biodiverse landscapes with little loss in net returns.

3. Results

3.1. Frontier analysis

Our spatial optimization analysis reveals the option space for potential net returns and bird biodiversity for changing the proportion of woody features and average field sizes in agricultural landscapes (all results are accessible at <https://spopt.geographie.hu-berlin.de/>). The agricultural net return ranges between €260 million and €284 million, and the biodiversity indicator ranges between 4.51 and 6.03. Compared to the initial landscape (with a biodiversity value of 5.2), it would be an improvement of about 12% for the maximum biodiversity solution and a deterioration of 17% for the minimum biodiversity solution. Maximum biodiversity would reduce potential net returns from 266€ million to €260 million, which translates to a decrease of about 2%, while maximum potential agricultural net returns would increase by 6% from €266 million to €284million.

The Pareto-improved options (blue rectangle in Fig. 3) represent solutions where a dimension can be improved without losing in the other dimension. The distance from the initial landscape map, which appears in the lower left-hand corner of the rectangle, to the efficient solutions on the Pareto frontier is about €13 million and 0.62 biodiversity units. For the extreme points on both ends of the frontier, the optimization allocated mainly the “large fields, few woody features” class to the most pixels for the maximum agriculture solution and “small fields, moderate woody features” to the most pixels for the maximum biodiversity solution (Fig. 4 A).

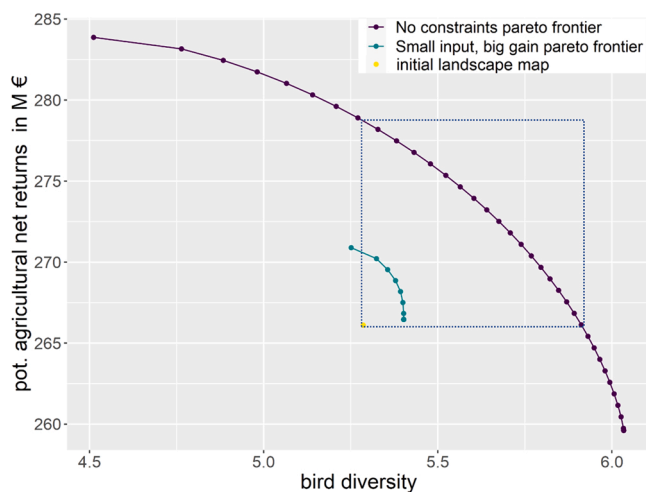


Fig. 3. Pareto frontiers for the two scenarios in purple and teal as well as a point for the initial landscape map. Each point on the frontier is a different solution, and each solution is an optimized landscape map. Purple is the Pareto frontier for the scenario without constraints on transitions and species (Scenario 1); teal is the frontier for the scenario with 95% stable agricultural landscapes and 30% maximum decline per species (Scenario 2). The blue rectangle shows all Pareto-improved options, where solutions that balance trade-offs can be found on the Pareto frontier.

The “small fields, many woody features” class is irrelevant in most solutions except some small shares in the maximum potential net returns solution (Fig. 4 A). The share of the “small fields, moderate woody features” class is continuously increasing as is the share of “small fields, few woody features,” which initially increases at the cost of the “large fields, few woody features” class and then decreases. We refer to the solution with the maximum potential net returns and lowest biodiversity as the maximum potential net returns solution and the solution on the other end of the frontier as the maximum biodiversity solution.

For the “Small input, big gain” scenario, the fundamental shape of the frontier remains similar to the shape of the “No constraints” scenario (purple curve and teal curve in Fig. 3). The option space for the “Small input, big gain” scenario is substantially smaller compared to the “No constraints” scenario because 95% of all agricultural landscapes were constrained to remain stable. The potential agricultural net return ranges between €266 and €271 million, and the biodiversity metric ranges between 5.25 and 5.4. Nevertheless, permitting 5% of the agricultural area in Brandenburg to transition into another land use category can lead to a more optimal landscape configuration for biodiversity and agriculture. Fig. 4 B shows that the “small fields, moderate woody features” class increases steadily, whereas from solution 5 on, there is no change until solution 20. Interestingly, the “small fields, many woody features” class plays a more prominent role compared to the “No constraints” scenario.

3.2. Spatial analysis

Applying the objective functions to the optimized landscape maps permitted mapping the expected effects on potential agricultural net return, on avian biodiversity, and on the difference between the initial and optimized landscape maps. For the maximum potential agricultural net return solution, the biodiversity metric decreases most drastically in the Northeast and in the East (Fig. 5C). We can also observe big gains in potential agricultural net returns in the Northwest and Southeast (Fig. 5A). Interestingly, the largest increases in potential agricultural net returns do not always coincide with the largest losses of farmland bird biodiversity, which can be seen in Fig. 5A and C in the Northwest, for instance. For the maximum biodiversity solution, the potential net returns decrease almost everywhere (Fig. 5B). Regions with the biggest gains of farmland bird biodiversity (Fig. 5D) coincide with the biggest losses of biodiversity in plot C in Fig. 6.

The “Small input, big gain” scenario shows that the maximum potential agricultural net return solution gains are rather scattered, with some clusters in the Southeast (Fig. 6A). Negative impacts on biodiversity are mainly observable in the Northeast and Southeast (Fig. 6C). Interestingly, gains in potential agricultural net returns are more frequently observed than losses in biodiversity, possibly indicating some win-win opportunities (e.g., Fig. 6B). The biggest gains in biodiversity are observable in the East, Northeast, and Northwest (Fig. 6D). The most important transition for the maximum potential net returns solution is any class transitioning to the “large fields, few woody features” class.

The most important change classes for the maximum biodiversity solution are transitions from the “large fields, few woody features” class to the “small fields, moderate woody features” class in the Northeast and East and transitions from the “small fields, many woody features” class to the “small fields, moderate woody features” class in the other regions. Larger losses in potential agricultural net returns are observable only in the Northeast and East but not in the Northwest.

An intermediate solution for the “Small input, big gain” scenario can be found within the blue rectangle on the teal frontier (Fig. 3). We arbitrarily chose solution 5 (Fig. 4 B). It balances gains in biodiversity and potential agricultural production, and the most frequent change classes are (a) transitions from “small fields, many woody features” to “small fields, moderate woody features” and (b) from “large fields, few woody features” to “small fields, moderate woody features.” The total expected gain in biodiversity is 0.1 (i.e., 2%), on average, of aggregated

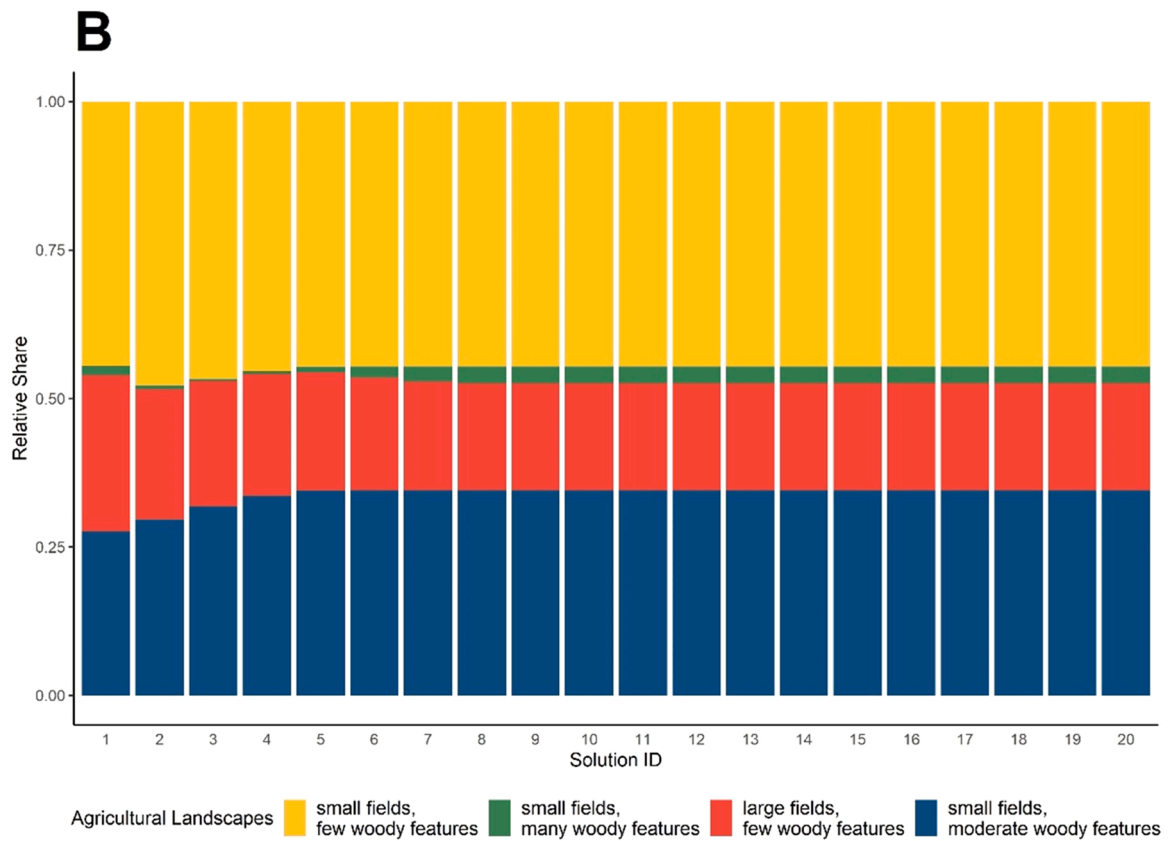
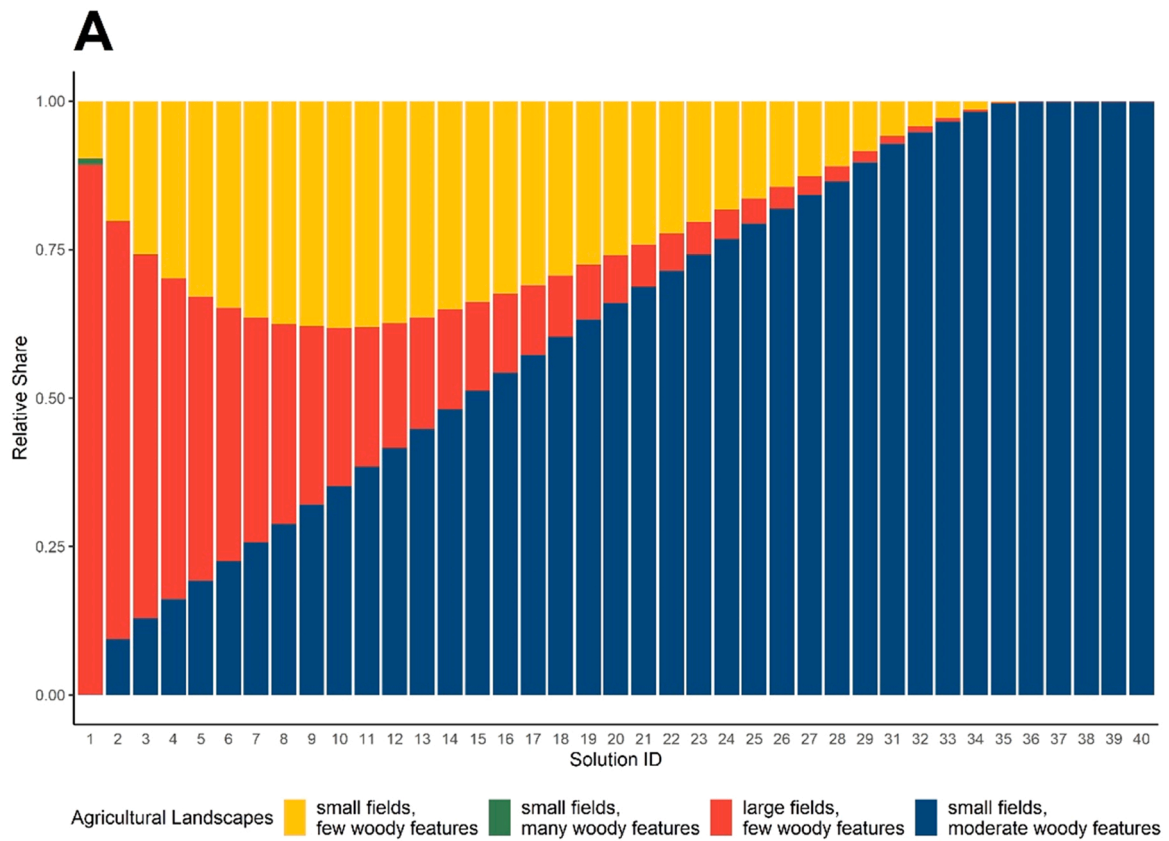


Fig. 4. A: Relative shares for agricultural land in the “No constraints” scenario. Solution 1 is the maximum agricultural production solution; solution 40 is the maximum biodiversity solution. B: Relative shares of agricultural land for the “Small input, big gain” scenario. Solution 1 is the maximum agricultural production solution; solution 20 is the maximum biodiversity solution.

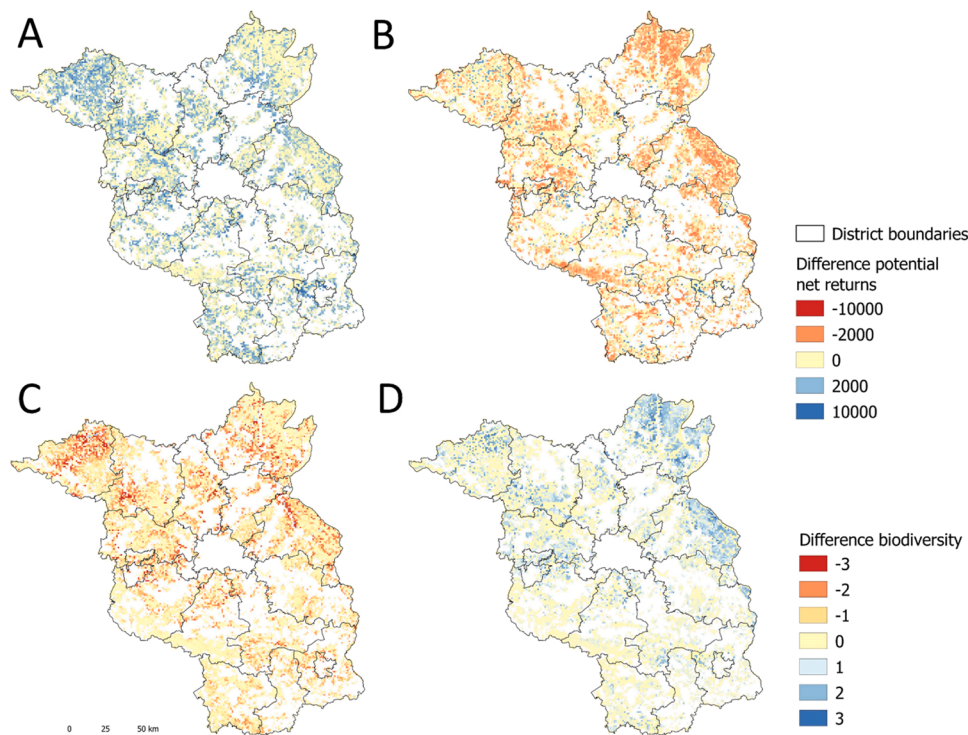


Fig. 5. Difference in the potential agricultural net returns (panels A and B) and the biodiversity metric (panels C and D) in comparison to the baseline landscape map for both endpoints of the Pareto frontier of the “No constraints” scenario. One endpoint is the maximum potential net returns solution, the other is the maximum biodiversity metric solution. A: Difference of potential net returns for the maximum net returns solution; B: Difference of potential net returns for the maximum biodiversity solution; C: Difference of the biodiversity metric for the maximum net returns solution; D: Difference of the biodiversity metric for the maximum biodiversity solution.

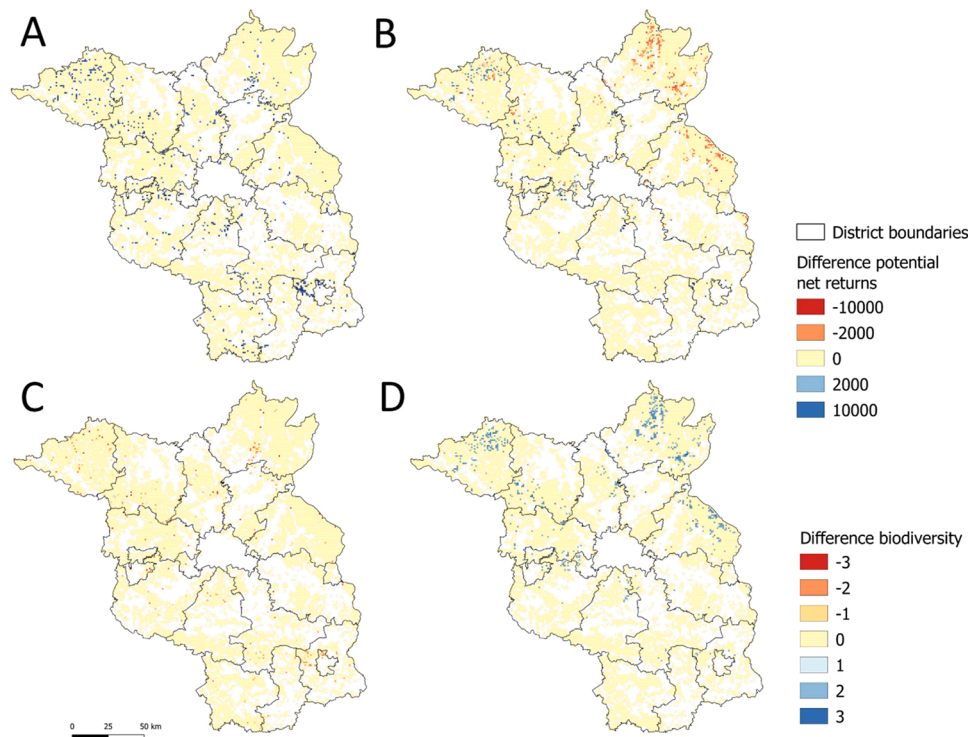


Fig. 6. Difference in potential agricultural net returns and the biodiversity metric in comparison to the baseline landscape map for both endpoints of the Pareto frontier of “Small input, big gain.” One endpoint is the maximum potential net returns solution, the other is the maximum biodiversity metric solution. A: Difference of potential net returns for the maximum net returns solution; B: Difference of potential net returns for the maximum biodiversity solution; C: Difference of the biodiversity metric for the maximum net returns solution; D: Difference of the biodiversity metric for the maximum biodiversity solution.

relative abundance per agricultural landscape and a total increase of about €2 million (0.7%) of potential agricultural net returns. Gains in biodiversity are observable for all pixels that transitioned, while gains in potential net returns are observable for all pixels except those that transitioned from “large fields, few woody features” to “small fields, moderate woody features.”

4. Discussion

We quantified the impacts of allocating different field sizes and proportions of woody features on farmland biodiversity and on potential agricultural net returns. We used a multi-objective spatial optimization approach that maximized farmland bird diversity while iteratively decreasing an agricultural net returns target. Our results show that the

current landscape configuration is not optimal and that both potential agricultural net returns and biodiversity can be simultaneously increased.

The shape of the Pareto frontier for the “**No constraints**” scenario reveals that trade-offs differ in magnitude between the individual solutions (Fig. 3). We found that small increases in potential net returns (+6%) would lead to an overall much higher loss of avian biodiversity (−17%), which is in line with Jeanneret et al. (2021), who found that an overall agricultural production increase leads to a much higher loss of species. The “**Small input, big gain**” scenario aimed to deliver more desirable solutions, where constraints reduce the option space compared to the “No constraints” scenario. Solutions that achieve high landscape-level multifunctionality can be found within the rectangle (Fig. 3). These Pareto-improved solutions are more desirable because they allow improvement without deteriorating one dimension in relation to the initial landscape map. In the middle of that frontier are solutions that are efficient and that balance trade-offs, which we deem desirable (Law et al., 2021). With this reduced option space, we can expect an average improvement of 0.1 (i.e., 2%) of aggregated relative bird abundance per agricultural landscape and an increase of about €2 million in potential agricultural net returns for the entire region, which is a comparably large difference considering that only 5% of the landscapes transitioned. This is in line with Concepción et al. (2020), who found that most of the positive effects of woody features on bird diversity come with small changes in the landscape and then saturate with further increases. In general, our results show that changing the proportion of woody features in the landscape and changing average field sizes might be an effective strategy to increase or reverse some of the recent losses of avian farmland biodiversity. This is consistent with Sirami et al. (2019), who found that decreasing field size is an effective measure to increase multitrophic diversity in agricultural landscapes when seminatural cover is low. Moreover, this implies that not just birds would benefit from decreased field sizes. Furthermore, we show that bird biodiversity would further decline with increasing field sizes and decreasing woody features, which aligns with Clough et al. (2020), Jeanneret et al. (2021), and Kirchweger et al. (2020), who found that increasing field sizes and decreasing seminatural cover lead to decreasing biodiversity.

An interesting finding is that in order to achieve maximum biodiversity, the optimization does not allocate the maximum proportion but only some woody features. For the “**No constraints**” scenario, the “small fields, many woody features” class is removed for almost all solutions (see Fig. 4 A). This is because our biodiversity metric is a composite metric of 22 farmland birds, which all have different habitat needs. While the yellowhammer, for instance, relies on a certain proportion of woody features in the agricultural landscape, the European skylark avoids hedges (Loretto et al., 2019; Whittingham et al., 2005). In the optimization process, we maximize the biodiversity metric to satisfy the needs of as many different bird species as possible. A good compromise for most species is the “small fields, moderate woody features” class although this implies that birds depending on woody features are outvoted by the majority of birds, which have different habitat requirements. This agrees with Concepción et al. (2020), who found that the positive effect of woody features on bird diversity levels off, which they explain with potential negative impacts of woody features on open land birds. One strategy to avoid this situation is to set species target constraints that limit a decrease in the relative abundance of certain bird species (Butsic et al., 2020). The “**Small input, big gain**” scenario, for instance, limits this decrease to 30% in relation to the initial value for each bird species, and, as a result, the “small fields, many woody features” class is not removed entirely in this scenario.

In our analysis, we assumed that introducing woody features and reducing field sizes has only negative impacts on potential agricultural net returns. However, introducing woody features to the landscape can also help in reducing wind erosion, creating a favorable microclimate, and controlling pests and diseases, leading to potential win-win

situations for farmers and bird diversity (Lajos et al., 2020; Torralba et al., 2016). Further, decreasing field sizes might improve pollination services, with potential benefits for farmers (Kirchweger et al., 2020).

Our second research question explored the location of measures (the transition of each of our four landscape types into another) to increase potential net returns or enhance biodiversity or both. We found that the biggest increases in our biodiversity indicator are possible in the Northeast and East of the study area, which are characterized by intensive agriculture, large field sizes, and low proportions of woody features in the landscape. Therefore, to increase biodiversity, the most common change class is from “large fields, few woody features” to “small fields, moderate woody features.” The Northeast of our study region is characterized by high overall bird diversity, which is in line with Gerlach et al. (2019) and might be related to the high share of protected areas in that region or to a high habitat diversity at the landscape scale. Due to the high occurrence probabilities for many bird species, this region would benefit from the introduction of woody features and a decrease in average field sizes (Fig. 6). The results also show that the biggest decreases in biodiversity can occur where we observed the biggest increases of biodiversity (Fig. 5 B and D). Interestingly, these areas do not coincide with areas where we would expect the biggest increases in potential agricultural net returns. The biggest increases in potential net returns are observable in regions where fields are comparably small, and the landscape contains many woody features, such as the Southeast. Counterintuitively, at the same time, biodiversity does not considerably decrease or even increases.

In general, we differentiate two types of win-win solutions, which together yield the potential of improvement in the Pareto frontier (Fig. 3). The first type is achieved for the entire study area. For instance, if one landscape transitions to the most biodiversity-friendly landscape and another to the landscape with the highest net returns, there can be gains in both biodiversity and potential net returns even if both landscapes lost individually in either biodiversity or potential net returns. These win-win solutions improve eco-efficiency. The other type of win-win can only be found when looking at individual agricultural landscapes (Fig. 5 B). In some cases, we found landscapes that transition from “small fields, many woody features” to “small fields, moderate woody features” and simultaneously increase biodiversity and potential net returns. However, these alleged win-win landscapes are partly due to our biodiversity indicator, which only includes farmland birds. While removing woody features will increase farmland bird biodiversity and increase potential net returns, it might lead to a decrease in woodland birds (Concepción et al., 2020). Second, our farmland bird biodiversity metric utilized spatially explicit distribution maps, and hence win-wins as well as trade-offs can differ substantially between locations depending on the set of species that can exist at a given location. Thus, win-wins and trade-offs depend on the spatial scale as well as on the location (Meyfroidt et al., 2022). The frontiers that we generate are possibility frontiers, and even though these solutions are possible, they may not be desirable. What is desirable ultimately depends on societal choices about how to balance the trade-offs (DeFries et al., 2004).

Using linear programming instead of a heuristic approach enables exact optimal solutions instead of near optimal solutions. In addition, the processing time of our approach was much lower and the number of decision units higher than other multi-objective spatial optimization approaches, such as the Constrained Multi-objective Optimization of Land use Allocation (CoMOLA) (Kaim et al., 2021; Strauch et al., 2019; Verhagen et al., 2018). However, linear programming approaches are more restricted in the formulation of the optimization problem. Moreover, we derived only a few landscape types due to the limited bird sampling data. More bird sampling data would have permitted classes with economically more meaningful boundaries for average field sizes. Our biodiversity indicator also does not depict the habitat needs of other groups of birds, such as woodland birds, and restricts the solution space to landscapes that are optimal for farmland birds. Regarding the farmland birds, we also assessed only common farmland birds as the

monitoring data currently available do not cover rarer species (e.g., Montagu's Harrier *Circus pygargus* and Great Bustard *Otis tarda*), and these species are also poorly represented in the eBird dataset. However, common farmland birds are the group of birds that have been declining the most in Germany (Kamp et al., 2021), therefore our approach considers landscape management for a bird species group with one of the highest conservation priorities in Germany. Several assumptions constrain the objective function for potential net returns, such as for farm management, market prices for crops, and yields. This was necessary because data on input applications, such as the use of fertilizers and pesticides, and about crop-specific management decisions and mechanization are lacking. In general, the estimation of the potential net returns assumes optimal farm management, which does not exist in reality. Additionally, we did not consider the costs of introducing woody features to the landscape, which is an important factor in the decisions of farmers. Finally, we were also unable to consider uncertainty as the optimization problem soon becomes too complex to solve. Yet both the SDMs and the agricultural net return calculation introduce uncertainty into our results.

5. Conclusions and outlook

We have successfully revealed trade-offs and potential synergies between biodiversity and potential net returns for the current landscape configuration. We show that increasing the proportion of woody features and reducing field sizes can be an effective strategy to increase avian farmland biodiversity but that there is spatial variation as to where this would be most effective. We further demonstrate that we can improve biodiversity with minimal effort even without deteriorating overall potential net returns. Our work is relevant for all actors, such as farmers, society, and policymakers, who are interested in striking a better balance between the multiple demands on agricultural land by including potential net returns and farmland biodiversity. Our results could, for instance, help to inform stakeholders such as farmers associations as well as nature conservation organizations. Moreover, policymakers benefit from the holistic nature of our approach, and easily accessible and understandable results are available via our webtool (spopt.geographie.hu-berlin.de). The limitations of the approach, however, should always be kept in mind, and it might be necessary to develop new scenarios to explore new questions.

Our study would not have been possible without the Dachverband Deutscher Avifaunisten's (DDA) bird monitoring data and IACS. Having access to high-quality species monitoring data, such as that of the DDA's, and to detailed spatial data about agricultural land use was essential for our analysis. Future studies should consider uncertainty, though this would require additional data and imply increased processing time. Despite the limitations, our approach holds great potential, and researchers can use it in the future to answer many questions regarding trade-offs on farmland.

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.

Data availability

The data that has been used is confidential.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agee.2022.108316.

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