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Erstveröffentlichung in / First published in:

Ecological applications. 2023. 33(1). Wiley. ISSN: 1939-5582.

DOI: https://doi.org/10.1002/eap.2720

Received: 8 November 2021 | Revised: 7 April 2022 | Accepted: 27 June 2022

DOI: 10.1002/eap.2720

ARTICLE

ECOLOGICAL APPLICATIONS
ECOLOGICAL SOCIETY OF AMERICA

Landscape-level heterogeneity of agri-environment measures improves habitat suitability for farmland birds

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Funding information
European Union, Grant/Award Number: 817501; Ministry of Education, Youth and Sports of the Czech Republic, Grant/Award Number: CZ.02.1.01/0.0/0.0/16_019/0000797

Handling Editor: Claudio Gratton

Abstract

Agri-environment schemes (AESs), ecological focus areas (EFAs), and organic farming are the main tools of the common agricultural policy (CAP) to counteract the dramatic decline of farmland biodiversity in Europe. However, their effectiveness is repeatedly doubted because it seems to vary when measured at the field-versus-landscape level and to depend on the regional environmental and land-use context. Understanding the heterogeneity of their effectiveness is thus crucial to developing management recommendations that maximize their efficacy. Using ensemble species distribution models and spatially explicit field-level information on crops grown, farming practice (organic/conventional), and applied AES/EFA from the Integrated Administration and Control System, we investigated the contributions of five groups of measures (buffer areas, cover crops, extensive grassland management, fallow land, and organic farming) to habitat suitability for 15 farmland bird species in the Mulde River Basin, Germany. We used a multiscale approach to identify the scale of effect of the selected measures. Using simulated land-use scenarios, we further examined how breeding habitat suitability would change if the measures were completely removed and if their adoption by farmers increased to meet conservation-informed targets. Buffer areas, fallow land, and extensive grassland were beneficial measures for most species, but cover crops and organic farming had contrasting effects across species. While different measures acted at different spatial scales, our results highlight the importance of land-use management at the landscape level—at which most measures had the strongest effect. We found that the current level of adoption of the measures delivers only modest gains in breeding habitat suitability. However, habitat suitability improved for the majority of species when the implementation of the measures was increased, suggesting that they could be effective conservation tools if higher adoption levels were reached. The heterogeneity of responses across species and spatial scales indicated that a mix of different measures, applied widely across the agricultural landscape, would likely maximize the benefits for biodiversity. This can only be achieved if the measures in the future CAP will be cooperatively designed in a regionally targeted way to improve their attractiveness for farmers and widen their uptake.

KEYWORDS

agriculture, agri-environment schemes, biodiversity conservation, breeding habitat, ecological focus areas, land use, multiscale, organic farming, scale of effect, species distribution model

INTRODUCTION

With nearly half of the total European Union's (EU) land area covered by agroecosystems, a large share of biodiversity in the old continent relies on farmland (Batáry et al., 2015). Hence, maintaining agroecosystems in good condition is of pivotal importance for biodiversity conservation in Europe. However, land-use intensification and the loss of traditional types of management in agricultural landscapes led to a rapid and widespread decline in farmland biodiversity across many taxa in recent decades (Batáry et al., 2015).

Two main tools within the current EU common agricultural policy (CAP) are specifically designed to better protect biodiversity, habitats, landscapes, and ecosystem services and to contribute to climate change mitigation and adaptation: ecological focus areas (EFAs) and agri-environment schemes (AESs) (Pe'er et al., 2014). EFAs are funded under Pillar I of the CAP as part of greening measures. To obtain EFA subsidies, farmholders with arable areas exceeding 15 ha must dedicate 5% of their land to ecologically beneficial elements, like terraces, hedges, or ponds, but also fallow land, nitrogen-fixing crops, and cover crops (Pe'er et al., 2017). AESs are funded under Pillar II as voluntary contracts with farmers who receive a payment for implementing measures aimed at preserving biodiversity, cultural landscapes, and permanent grasslands and reducing nutrient emissions from farmland to water (Batáry et al., 2015). Organic farming, which is also supported under Pillar II, has similar objectives and promotes a more sustainable and more wildlife-friendly agriculture by not using mineral fertilizers and synthetic pesticides (BMEL, 2021; Gabriel et al., 2010).

EFAs, AESs, and organic farming account for a consistent share of the total CAP expenditure, but their effectiveness is regularly questioned (Pe'er et al., 2014, 2020). The greening measures have been described as largely ineffective because some of the most widely implemented EFA schemes, such as cover crops and nitrogen-fixing crops, are also the least beneficial in ecological terms (Pe'er et al., 2017). Similarly, although some studies found AESs to be beneficial for farmland biodiversity (Batáry et al., 2015; Zingg et al., 2019), many more have shown only marginal effects (Gamero et al., 2017; Kleijn et al., 2006) or no effect at all (Daskalova et al., 2019; Zmihorski et al., 2016). The benefits of organic farming for biodiversity are also often debated because the responses and their effect sizes are highly variable across taxonomic and functional groups and landscape context (Gabriel et al., 2010; Tscharntke et al., 2021; Tuck et al., 2014). In this study, we focus on EFAs, AESs, and organic farming and refer to them as AEMs henceforth.

The effectiveness of AEMs depends on the landscape structure and context, as biodiversity responses are often stronger when the measures are applied in intensively managed regions and simplified or homogenized landscapes (Marja et al., 2019). Spatial scale is another important modulator of the effect of different land uses: Although management at the field and farm level significantly influences within-farm biodiversity (Stoeckli et al., 2017), certain species and taxa seem to benefit from AEMs only if they are widely implemented across the agricultural landscape (Gabriel et al., 2010).

Despite the growing body of work on the relationship between AEM effectiveness and landscape structure across scales, the majority of studies so far have been conducted at the farm level (Daskalova et al., 2019; Gabriel et al., 2010; Stoeckli et al., 2017) or at the level of monitoring units or plots (Concepción & Díaz, 2019; Zingg et al., 2019; but see Walker et al., 2018). To capture the effect of gradients in land-use intensity and landscape structure, research at the broader regional scale is necessary (Batáry et al., 2015). Hence, the spatial heterogeneity of AEM efficacy remains largely unexplained, and relating spatial data on changes in field-level management, grassland conversion rates, and land-use intensity to biodiversity trends was recently highlighted as a top research priority (Daskalova et al., 2019; Kamp et al., 2021). Assessing the scale of effect of AEMs at the local and landscape level is thus crucial to determine the optimal scale of management and to estimate the minimum area of an AEM to produce significant outcomes (Gabriel et al., 2010; Spake et al., 2019).

Birds are often regarded as ecological indicators, as their presence is strongly linked to such environmental characteristics as landscape features, marginal vegetation, insect abundance, and anthropogenic disturbance

(Benítez-López et al., 2010; Morelli et al., 2014). Moreover, birds rank among the best-monitored taxonomic groups in Europe, making them ideal candidates for studying the impacts of different land-use management practices across countries and environmental gradients (Engler et al., 2017; Kamp et al., 2021). Here, we used ensemble species distribution models (SDMs) (Araújo & New, 2007) to link farmland bird occurrences to environmental conditions and land-cover/land-use information. We examined the association between 15 farmland bird species and five groups of AEMs, namely, buffer areas, cover crops, extensive grassland management, fallow land, and organic farming, in the Mulde River Basin, a traditionally agricultural region in Saxony, Germany. We used spatially explicit field-level information on land-use management derived from the Integrated Administration and Control System (IACS) of Saxony (InVeKoS Sachsen; SMEKUL, 2020), as well as geospatial information on topography, anthropogenic disturbance, and land cover. IACS is a yearly updated database supporting the administration of direct payments for European farmers and holds precise information on size and geometry of each agricultural field, the type of crop grown, the farming practice (organic vs. conventional), and the implemented AESs and EFAs in each year (Santos et al., 2021). Moreover, since drivers of species distributions act at varying spatial scales (Fournier et al., 2017; Spake et al., 2019), we investigated the scale of effect of the different measures and land-cover types by applying a multiscale modeling framework in which the optimal scale for each covariate is selected empirically (McGarigal et al., 2016). Specifically, we aimed to answer the following questions:

1. Which landscape and land-use factors are the strongest drivers of farmland bird distribution in the Mulde River Basin, Germany?
2. What is the effect of the selected AEMs (i.e., buffer areas, cover crops, extensive grassland management, fallow land, and organic farming) on habitat suitability for farmland birds? At which spatial scale are they most effective?
3. How would habitat suitability for the 15 farmland bird species change if AEMs were absent and if their implementation was increased to meet conservation-informed targets?

METHODS

Study area

The Mulde River Basin (Figure 1) is located in the western part of the federal state of Saxony, Germany, and covers an area of 5814 km^2, spanning from the Pleistocene lowlands in the north to the Ore Mountains in the south, with elevation ranging from 24 to 1214 m above sea level (asl) (Staatsbetrieb Geobasisinformation und Vermessung Sachsen, 2016). The climate is predominantly continental, with a total annual precipitation between 570 and 1260 mm and mean annual temperatures ranging between 7.4°C and 14.1°C (Deutscher Wetterdienst, www.dwd.de). The Mulde River Basin is partly characterized by fertile soils rich in loess deposits, making them highly suitable for intensive arable farming. Thirty-eight percent of the study area is covered by cropland, and another 13% of the area is dedicated to mowing pastures and meadows. The study area is representative of traditional agricultural regions in Central Europe. Land-use changes, like soil sealing, and conflicts related to increased bioenergy production and intensification are regarded as the main threats to biodiversity and ecosystem services in the region (Ziv et al., 2020).

Bird occurrence data

The data set provided by the Saxon State Agency for Environment, Agriculture and Geology consists of georeferenced bird observations collected from 2016 to 2019 with a spatial uncertainty ≤100 m, compiled in the Saxon Central Species Database (Zentrale Artdatenbank, www.natur.sachsen.de/zentrale-artdatenbank-zena-sachsen-6905.html). This database comprises observations from standardized monitoring projects (e.g., breeding bird monitoring, Natura2000 monitoring; 55% of the data), monitoring activities of special interest groups and nongovernmental organizations (NGOs) (36%), and opportunistic observations (9%); the data entries are checked and harmonized by the state agency staff before being uploaded in the Central Species Database. The diverse source of the data entails biases in the monitoring effort, which is higher in protected areas and close to cities, and in the species ratio, with rare species being monitored more intensively. We here focused on farmland bird species and selected those breeding in (wet) grassland, arable land, and fallow areas (Blischke, 2017; Busch et al., 2019). We filtered the data set to retain only observations for which the breeding status was categorized as possible, probable or confirmed, and included in the analysis only those farmland species with a minimum of 40 presence points. To avoid pseudo-replicates, observations that fell in the same environmental raster cell (20-m resolution) were removed, even if they occurred in different years (as some environmental variables, like elevation and slope, were kept constant across the 4 years), in which case the most recent observation was retained. Species selection and data set filtering are described in detail in the Overview,

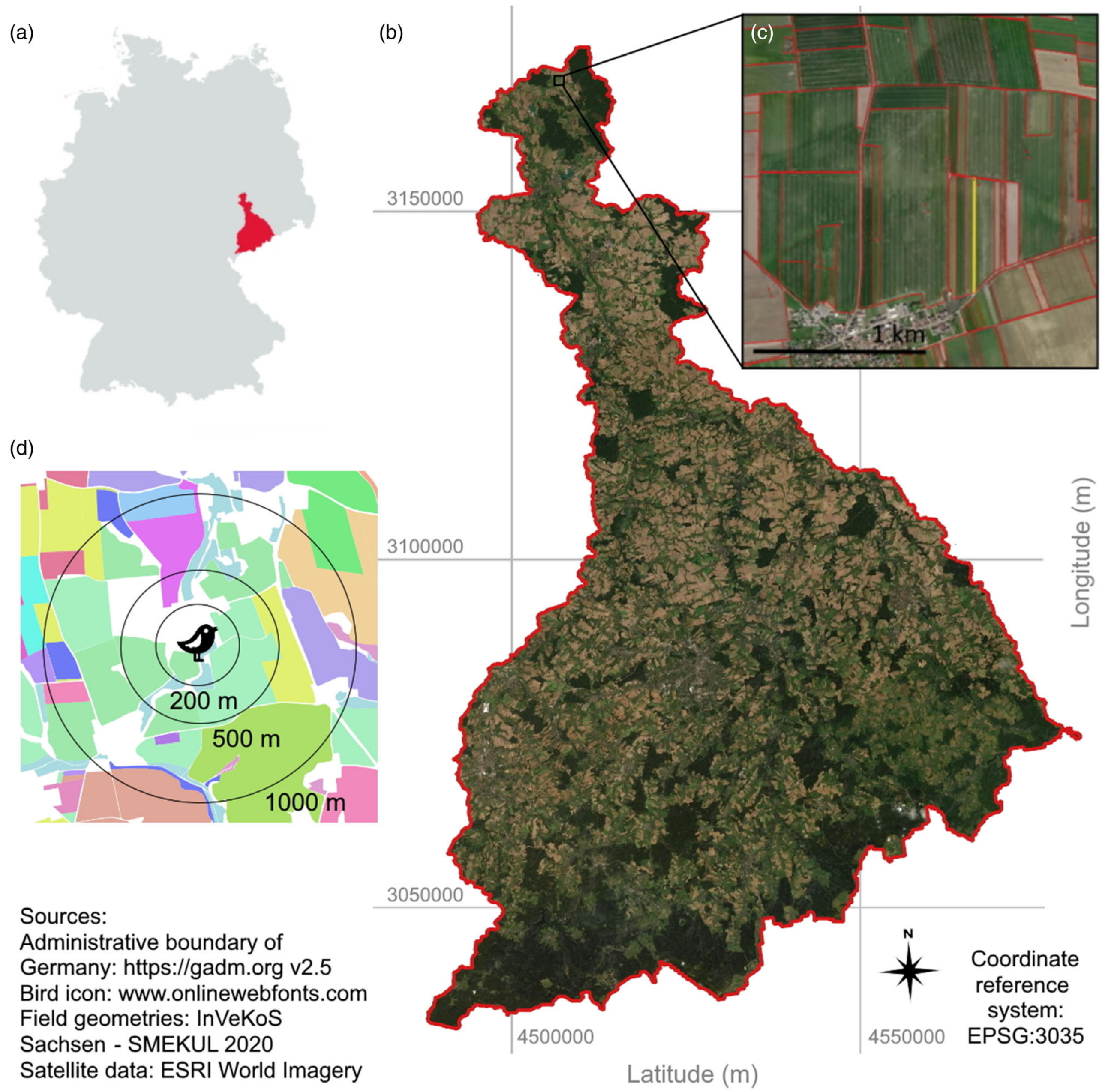


FIGURE 1 Study area and multiscale land-cover/land-use variable calculation design. (a) Location of the Mulde River Basin in Germany. (b) Aerial image of the basin. (c) Inset showing Integrated Administration and Control System data, with field boundaries shown in red and linear ecological focus areas in yellow. (d) Exemplary design of multiscale land-cover/land-use variable calculation using circular windows of different radii around each bird presence/absence point.

Data, Model, Assessment and Prediction (ODMAP) protocol (Zurell et al., 2020) in Appendix S1. The final list consisted of 15 species (Table 1). As absence points, we used randomly selected presence points of other (farmland and nonfarmland) bird species in the data set, with a minimum distance to all presence points of 500 m. This is a common approach to control for unequal monitoring effort and reduce the influence of spatially biased samples, for example, toward more accessible or protected areas (Ranc et al., 2017), as well as for ensuring an adequate environmental distance between presence and absence points (Iturbide et al., 2015). We set the number of absence points at 10 times that of presence points for each species, an average value among those recommended for different algorithms (Barbet-Massin et al., 2012). For *Lanius collurio*, the most abundant species in our data set, we used all observations of other birds as absence points, resulting in a presence/absence ratio of 0.4.

TABLE 1 List of species included in the analyses and number of presence points used for modeling after filtering. Information on nest type is from Storchová and Hořák (2018): ground = on ground directly; ground-close = nest in tussock very close to ground but not directly on ground, hidden in surrounding vegetation; open arboreal = cup in bush, tree, on cliff ledge.

Species	Common name	Presence points	Nest type
Alauda arvensis	Eurasian skylark	79	Ground
Anthus pratensis	Meadow pipit	299	Ground-close
Carduelis cannabina	Common linnet	55	Open arboreal
Charadrius dubius	Little ringed plover	96	Ground
Coturnix coturnix	Common quail	63	Ground
Crex crex	Corncrake	84	Ground-close
Emberiza calandra	Corn bunting	90	Ground-close
Emberiza citrinella	Yellowhammer	164	Ground-close
Gallinago gallinago	Common snipe	63	Ground-close
Lanius collurio	Red-backed shrike	988	Open arboreal
Motacilla flava	Blue-headed yellow wagtail	92	Ground-close
Saxicola rubetra	Whinchat	411	Ground-close
Saxicola rubicola	European stonechat	205	Ground-close
Sylvia communis	Common whitethroat	106	Open arboreal
Vanellus vanellus	Northern lapwing	41	Ground

Variable selection and calculation

Explanatory variables were chosen to reflect environmental and habitat conditions likely to impact farmland birds' distributions at the field and landscape levels (Table 2). Climatic predictors, for example, multiannual total precipitation and minimum and maximum temperatures, were initially included in the models, but, due to their high correlation ($|r| > 0.7$) with elevation and their coarser spatial resolution (1 km), we ultimately excluded them, thereby using elevation in the models. Detailed information on the preparation of the environmental layers is provided in the ODMAP protocol (Appendix S1).

Elevation, slope, and distances from highways and forest edges were extracted directly from the corresponding raster layers at the location of each presence/absence point. We computed the proportion of different land-cover/land-use types within a circular window around each presence/absence point, using 200-, 500-, and 1000-m radii, respectively (Figure 1d). The first two approximate territory size and mean foraging movement distances of farmland birds (Söderström & Pärt, 2000), whereas the largest buffer captures landscape-scale effects (Martin et al., 2020). Agricultural land-use diversity (ALU div.) was calculated within each circular window using the Shannon's diversity index

$$\mathrm{SDI} \quad \Sigma p_i \times \ln(p_i) \tag{1}$$

where p_i is the relative proportion of agricultural land-use type i. Land-use types included different types of crops, grassland uses (e.g., meadows, mowing pastures), and AEM information. We matched the bird presence/absence points of each year to the corresponding IACS information for the calculation of the land-use and AEM-related variables; whereas topography, distance metrics, and land-cover layers remained constant across the 4 years. Information on the AEM schemes that constitute the five groups is given in Appendix S2. To select the best scale for each variable and exclude highly correlated variables from the same model, we fitted univariate linear models with binomial distribution for each explanatory variable and ranked them by their Akaike information criterion corrected for small sample size (AIC_c) score. For each species, we then selected the best set of uncorrelated variables (i.e., with Spearman's correlation coefficient <0.7) with the lowest AIC_c score (Bellamy et al., 2020; McGarigal et al., 2016). All calculations were carried out in R version 4.0.2 (R Core Team, 2020), using the packages sf (Pebesma, 2018), raster, and terra (Hijmans et al., 2020, 2021), and the R codes are available in Zenodo (Roilo, 2022).

Modeling approach

For each of the 15 species, we applied an ensemble modeling approach to minimize the prediction

TABLE 2 Explanatory variables used in species distribution models, sources of original data, and ecological importance for farmland birds.

Group	Variable (units)	Data source (original resolution)	Ecological importance (references)
Topography	Elevation (m)	DGM20, Staatsbetrieb Geobasisinformation und Vermessung Sachsen (20 m)	Habitat and climatic differences, proxy for temperature (Morelli et al., 2014; Stoeckli et al., 2017)
	Slope (°)	DGM20, Staatsbetrieb Geobasisinformation und Vermessung Sachsen (20 m)	Nesting suitability for ground-breeding species (Morelli et al., 2014)
Distance metrics	Distance from forest edge (m)	Copernicus High Resolution Layer Forest type 2015 (20 m)	Edge avoidance from ground-breeding species (Besnard et al., 2016)
	Distance from highways (m)	OpenStreetMap 2020 (shapefile)	Avoidance of traffic noise (Benítez-López et al., 2010)
Land cover/use	Agricultural land-use diversity (Shannon's index)	IACS 2016–2019 (shapefile)	Landscape heterogeneity and structural diversity (Wilson et al., 2017; Zellweger-Fischer et al., 2018)
	Arable land (%)	IACS 2016–2019 (shapefile)	Feeding and breeding habitat (Concepción & Díaz, 2019; Wilson et al., 2017)
	Grassland cover (%)	Copernicus High Resolution Layer Grassland status map 2015 (20 m)	Feeding and breeding habitat for grassland species (Morelli et al., 2014)
	Small woody features (SWF) cover (%)	Copernicus High Resolution Layer Small Woody Features 2015 (5 m)	Nesting sites for open-arboreal breeders; avoidance by open ground breeders; proxy for landscape elements (Morelli et al., 2014; Wilson et al., 2017)
	Urban cover (%)	Adaptable pixel-based compositing and classification land cover map 2016 (Preidl et al., 2020) (20 m)	Anthropogenic disturbance, soil sealing (Morelli et al., 2014; Zingg et al., 2019)
AEM	Buffer areas (%)	IACS 2016–2019 (shapefile)	Seminatural habitat, breeding and feeding habitat (Perkins et al., 2002; Zellweger-Fischer et al., 2018)
	Cover crops (%)	IACS 2016–2019 (shapefile)	Feeding opportunities due to higher invertebrate abundance (Concepción & Díaz, 2019; Stoeckli et al., 2017)
	Extensive grassland management (%)	IACS 2016–2019 (shapefile)	Breeding habitat for grassland-breeding species; feeding opportunities (Stoeckli et al., 2017; Zellweger-Fischer et al., 2018)
	Fallow land (%)	IACS 2016–2019 (shapefile)	Breeding habitat for ground-breeding species; feeding opportunities (Concepción & Díaz, 2019)
	Organic farming (%)	IACS 2016–2019 (shapefile)	Beneficial effects of lower pesticide use and higher invertebrate abundance (Gabriel et al., 2010; Tuck et al., 2014)

Abbreviations: AEM, agri-environment measure; IACS, Integrated Administration and Control System.

uncertainty arising from single algorithm models (Araújo & New, 2007). We used five modeling algorithms, namely, generalized linear models, generalized additive models, random forest, generalized boosting models, and maximum entropy, as implemented in the biomod2 package version 3.4.6 (Thuiller et al., 2019). Model settings for each algorithm are described in the ODMAP protocol (Appendix S1). We fitted 10 repetitions for each model by randomly subdividing the data set into 70% training data and 30% testing data. Each model run was evaluated via cross-validation. We used the area under the receiver operating characteristics curve (AUC), the true skill statistic (TSS), specificity, and sensitivity as evaluation metrics (Fletcher & Fortin, 2018). To obtain a relevant combination of unbiased (i.e., with fair accuracy) models, only models with AUC $\geq$ 0.7 were retained, and the ensemble model was constructed by computing the weighted (by AUC scores) average of all remaining models (Hao et al., 2019). Spatial autocorrelation in the model residuals was assessed with spline correlograms using the ncf package (Bjornstad, 2020). Variable importance scores, obtained using the get_variable_importance() function in the biomod2 package, were normalized, so that the sum of the importance scores of all variables in a model equalled 100. The variable response plots were built with the response.plot2() function of the same package, and the SD was calculated across the 10 model runs.

Projection of models to simulated AEM scenarios

We calculated the mean AUC for each algorithm across the 10 model runs and fitted full models (trained on the full data set) only for the algorithms with mean AUC ≥ 0.7. The ensemble prediction map of breeding habitat suitability was then calculated as weighted (by AUC scores) average of the single algorithm model predictions using the weighted.mean() function of the raster package (Hijmans et al., 2020). We projected the models into three simulated scenarios: (1) the current scenario (CURR), based on the IACS data of 2019; (2) a scenario without AEM (NOAE), in which the proportions of buffer areas, cover crops, extensive grassland management, fallow land, and organic farming were set to zero across the entire study region; and (3) a conservation-informed scenario (CONS), in which the proportion of AEMs was increased to meet the average values recommended by conservation experts in Germany (Oppermann et al., 2020). In the CONS scenario, the percentage of agricultural land under organic farming was increased from 6.9% (in year 2019) to 20%, according to the 20% organic farming target set by the German Federal Government (BMEL, 2021). The proportion of buffer areas on cropland was increased from 1.9% to 12.5% and that of fallow land from 1.1% on total agricultural land (grassland and cropland) to 12.5%. Extensive grassland management, which covered 28.7% of all permanent grasslands in 2019, was increased to 50%. The specific spatial allocation of additional AEMs on individual fields was carried out randomly but respected the cropland and permanent grassland distribution of 2019, that is, there was no conversion between cropland and grassland or vice versa. The proportion and distribution of cover crops was left unchanged because they were not described as a highly beneficial measure for farmland birds by Oppermann et al. (2020). For each land-cover/land-use variable, we calculated three raster layers at a 20-m resolution (one for each of the three considered spatial scales) in which each raster cell value corresponded to the proportion of the given land-cover/land-use type within circular windows with radii of 200, 500, and 1000 m. This process was repeated for all three scenarios, and the resulting rasters served as inputs for the model projections.

RESULTS

Main drivers of farmland bird distribution

All models performed well, with mean AUC ≥0.8 and mean TSS ≥0.49 for all species, indicating a good predictive performance of the models (Appendix S1: Table S1). Sensitivity and specificity were ≥0.74, showing that the models correctly classified both presences and absences. For some species, spatial autocorrelation in the model residuals was detected with relatively low magnitude (maximum correlation <0.5 for all species) and at short distances compared to the entire distance range of our data set (Appendix S1: Figure S1). Overall, we deemed this level of autocorrelation acceptable, as subsampling the data set would likely have larger deleterious effects of prediction accuracy (Thibaud et al., 2014). Only two pairs of variables (grassland and extensive grassland management, arable land and agricultural land-use diversity) were highly correlated in certain species data sets, leading to a lower number of explanatory variables in their models. Variable importance scores varied greatly across species and variables, but in general topographic, distance metrics, and land-cover/land-use variables had higher importance than the AEM-related variables (Figure 2). In fact, none of the AEM variables was among the two most important variables in any model (Appendix S1: Table S1). Across all species and spatial scales (200, 500, and 1000 m), extensive grassland management was the AEM variable with the highest average importance (4.2), whereas cover crops had the lowest (1.4). For ground breeders, the proportion of arable land at the local scale (i.e., 200 m) was a consistently important variable. For ground-close breeders, the proportion of grassland and elevation were the main drivers of habitat suitability. Finally, for open arboreal species, urban cover and distance from highways had the highest variable importance.

Effects of environmental variables and AEM at different spatial scales

While distance from forest edges and slope had consistent effects (positive and negative, respectively) on habitat suitability for all birds, all other variables had heterogeneous

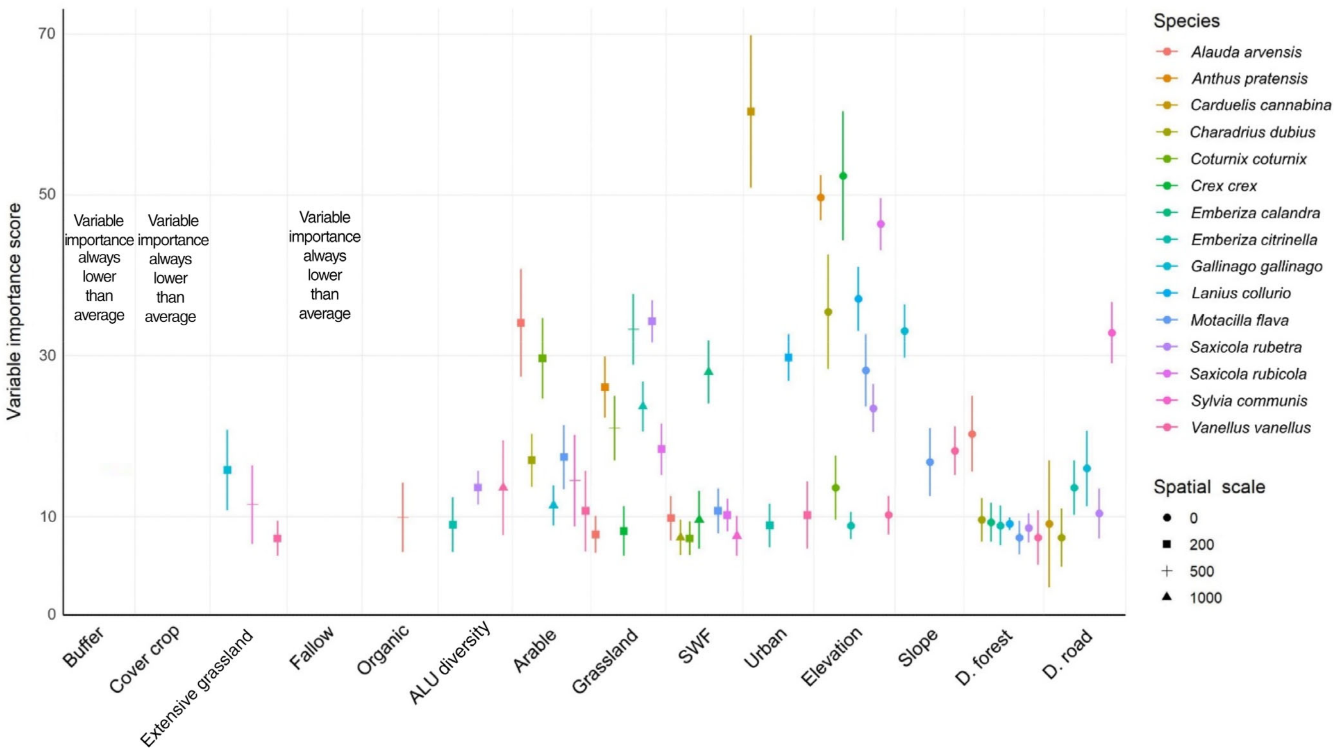
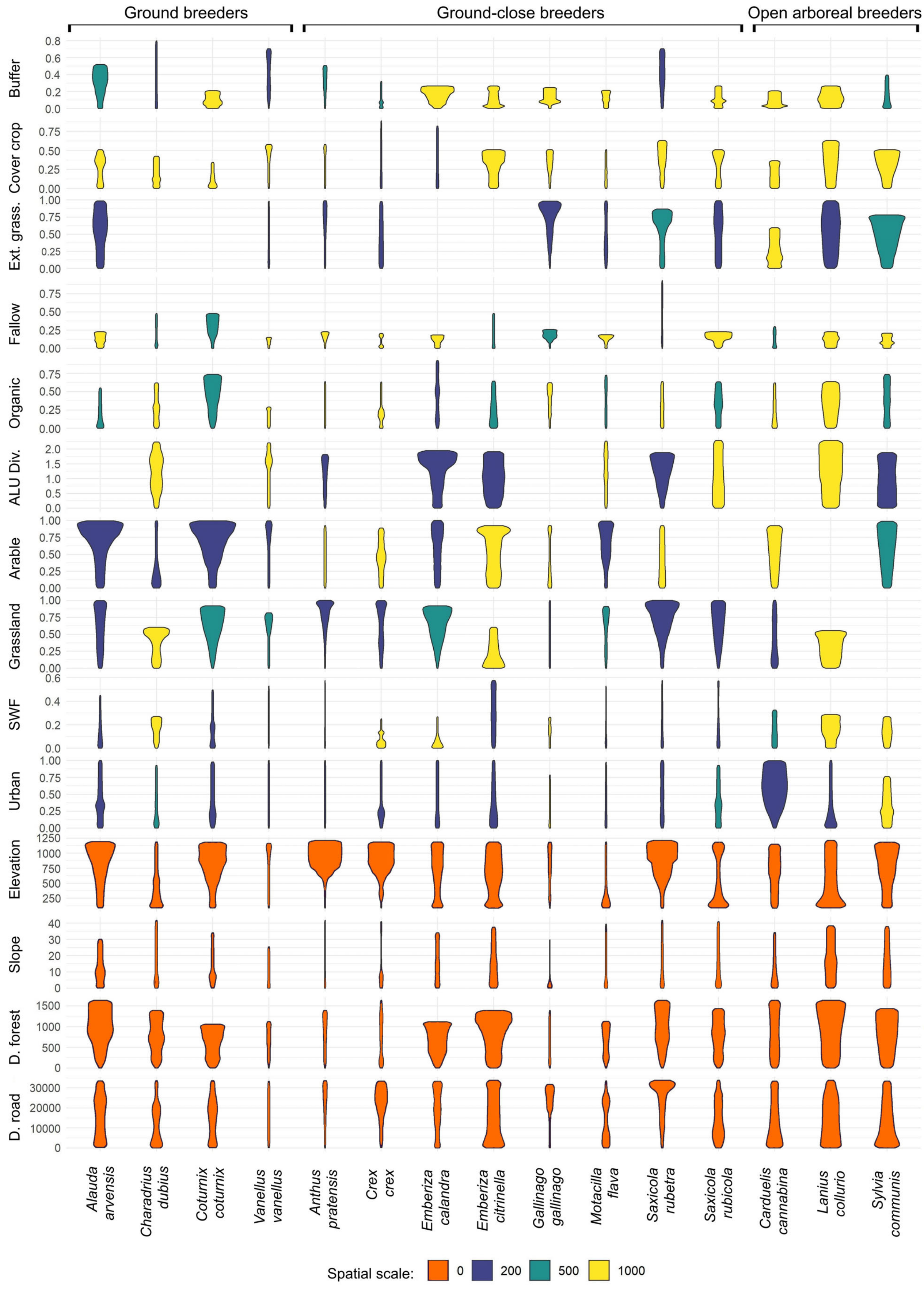


FIGURE 2 Mean (±SD) variable importance scores across the 10 ensemble model runs. Only variables with a mean importance score >7.14 (=100/14, the average importance value in a model with 14 variables) are shown. The shape of the dot indicates the spatial scale at which the variable was calculated. All variable importance scores are reported in Appendix S1: Table S1. ALU, agricultural land use; D. forest, distance from forest edge; D. road, distance from highways; SWF, small woody features.

effects across species (Figure 3). Focusing on the AEMs, buffer areas and fallow land were beneficial for the majority of modeled species, though their effects were often nonlinear (Figure 3 and Appendix S3). Extensive grassland management was always positively related to habitat suitability, with the exception of *C. crex* (mild negative effect), *M. flava*, and *C. cannabina* (nonlinear responses). Cover crops and organic farming showed more diverging outcomes across species, with positive, negative, or negligible effects. Regarding the scale of effect of the land-cover/land-use variables, arable land, grassland, extensive grassland management, and urban cover were often better predictors at the local scale (200 or 500 m). Small woody features cover and agricultural land-use diversity were selected both at the local (200 m) and the landscape scale (1000 m), depending on the species. All AEMs, with the exception of extensive grassland management, had the strongest effect at the landscape scale for the majority of species (Figure 3).

Habitat suitability change in simulated AEM scenarios

Compared to the current conditions (CURR scenario), breeding habitat suitability remained stable or decreased for most species when AEMs were stripped away (NOAE scenario), although for some species (*A. arvensis*, *C. cannabina*, *C. dubius*, *C. crex*, *E. citrinella*, *S. communis*) we observed the opposite trend (Figure 4). These same species showed a decrease in habitat suitability in the CONS scenario with increased AEM implementation. For *A. arvensis*, *C. cannabina*, *C. crex*, and *E. citrinella* this was caused by an increase in organic farming, which was negatively correlated with their occurrences (Figure 3). Higher proportions of fallow land negatively impacted the projected habitat suitability of *C. cannabina*, *C. dubius*, and *E. citrinella*, and the increase in buffer areas similarly affected *C. cannabina*, *C. crex*, *E. citrinella*, and *S. communis*. A larger proportion of extensive grassland was also partly responsible for the decrease in habitat suitability of *C. cannabina* in the CONS scenario. Altogether the increase of AEMs led to a noticeable decrease in breeding habitat for four species, namely, *A. arvensis*, *C. cannabina*, *E. citrinella*, and *S. communis*, milder negative effects were detected for *C. dubius* and *C. crex*. For all of the other nine species, the CONS scenario led to an increase in habitat suitability, which was especially evident for *A. pratensis*, *E. calandra*, *G. gallinago*, *L. collurio*, *S. rubicola*, and *V. vanellus*.



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DISCUSSION

Effects of environmental variables and AEM on farmland bird habitat across spatial scales

Model performance was good for all modeled species, indicating that unstructured biodiversity data sets from multiple sources, if appropriately cleaned, could be used to build informative models. We found that topography, distance from forest edges and from highways, and land cover/use are the main drivers of farmland bird distribution in our study area. These factors define the general limits to farmland bird breeding habitat, whereas current AEM adoption had overall beneficial but weak effects on modeled habitat suitability. Here we focused on habitat suitability rather than bird abundance, which may respond more strongly to AEMs, but our findings were in agreement with other studies in Europe, showing mild positive effects of AEMs on farmland bird populations, which are likely insufficient to stop their decline (Concepción & Díaz, 2019; Daskalova et al., 2019; Gamero et al., 2017). Indeed, habitat loss through agricultural intensification and homogenization of the landscape are believed to be the main threats to farmland birds' subsistence (Kamp et al., 2021). Our study aimed at assessing the contribution of AEMs to farmland birds' habitat conservation over a large agricultural region: Although the relationship between population size and area and quality of habitat is complex and species-specific, avian SDMs from presence/absence data were shown to correlate positively and significantly with population densities and abundances (Carrascal et al., 2015; Oliver et al., 2012). Moreover, despite the constantly growing availability of resources and methods for SDMs (Peterson et al., 2022), modeling and predicting spatial variation in abundances remains a challenging task, and extrapolated abundance predictions under changing environmental scenarios often have high uncertainty (Waldock et al., 2022). New methodological frameworks linking changes in area of habitat to species persistence have recently been developed (Durán et al., 2020). Such tools could be applied to our results to estimate the biodiversity impacts of future land-use changes.

Among the selected groups of measures, we expected fallow land and buffer areas to be the most effective ones for avian conservation (Concepción & Díaz, 2019; Pe'er et al., 2017; Perkins et al., 2002). Our results suggest that such extensively used areas constitute high-quality breeding habitat, especially for ground and ground-close breeders. Extensive grassland management was also positively related to habitat suitability, especially for open grassland breeders like *A. arvensis*, *G. gallinago*, *S. rubetra*, and *S. rubicola*, but also for species that breed in bushes and use grasslands as foraging habitat (e.g., *L. collurio* and *S. communis*). We expected cover crops and organic farming to hold higher insect abundance and, hence, to benefit invertebrate feeders (Stoeckli et al., 2017; Tuck et al., 2014), but we found no strong or consistent (across species) effect of these variables. Indeed, Oppermann et al. (2020) also did not identify cover crops as highly beneficial measures for farmland birds, with few exceptions, such as the gray partridge (*Perdix perdix*), which was not included in our analyses. This may depend on the temporal mismatch between cover crop application (typically in winter) and bird breeding season. The contrasting effects of organic farming across different species could reflect the fact that landscape characteristics (i.e., composition and configuration, landscape elements) override the benefits deriving from the organic management of the farms (Gabriel et al., 2010; Tscharntke et al., 2021). Moreover, in this study we modeled breeding habitat suitability, so that differential habitat use for breeding and feeding may camouflage any potential beneficial effects of organic farming and of other AEMs in our results. For example, some open arboreal breeders (*C. cannabina* and *S. communis*) showed negative associations with buffer areas, and habitat suitability of *C. cannabina* was also negatively related to extensive grassland and fallow land; these types of habitats are likely important feeding grounds for the species but are not selected as breeding territories.

Our multiscale modeling technique allowed us to explore the differential scale of the effects of AEMs across a large agricultural region. With the exception of extensive grassland management, all AEM groups had the strongest effect at the landscape scale, in accordance with the notion that landscape-scale diversification, providing access to multiple resources, is key to supporting farmland biodiversity (Tscharntke et al., 2021). These findings have important management implications, as widespread implementation of AEMs across the landscape can be

FIGURE 3 Effects of explanatory variables on breeding habitat suitability of 15 farmland bird species. The range of each variable is shown on the *y*-axis, and the width of each violin plot corresponds to the habitat suitability for the given species (e.g., increasing proportions of arable land correlate positively with habitat suitability for *A. arvensis* and negatively for *C. dubius*). The color code reflects the spatial scale, that is, the radius (in meters) of the circular window used for variable calculation. Variable response plots for all variables and species are available in Appendix S3. ALU, agricultural land use; D. forest, distance from forest edge; D. road, distance from highways; SWF, small woody features.

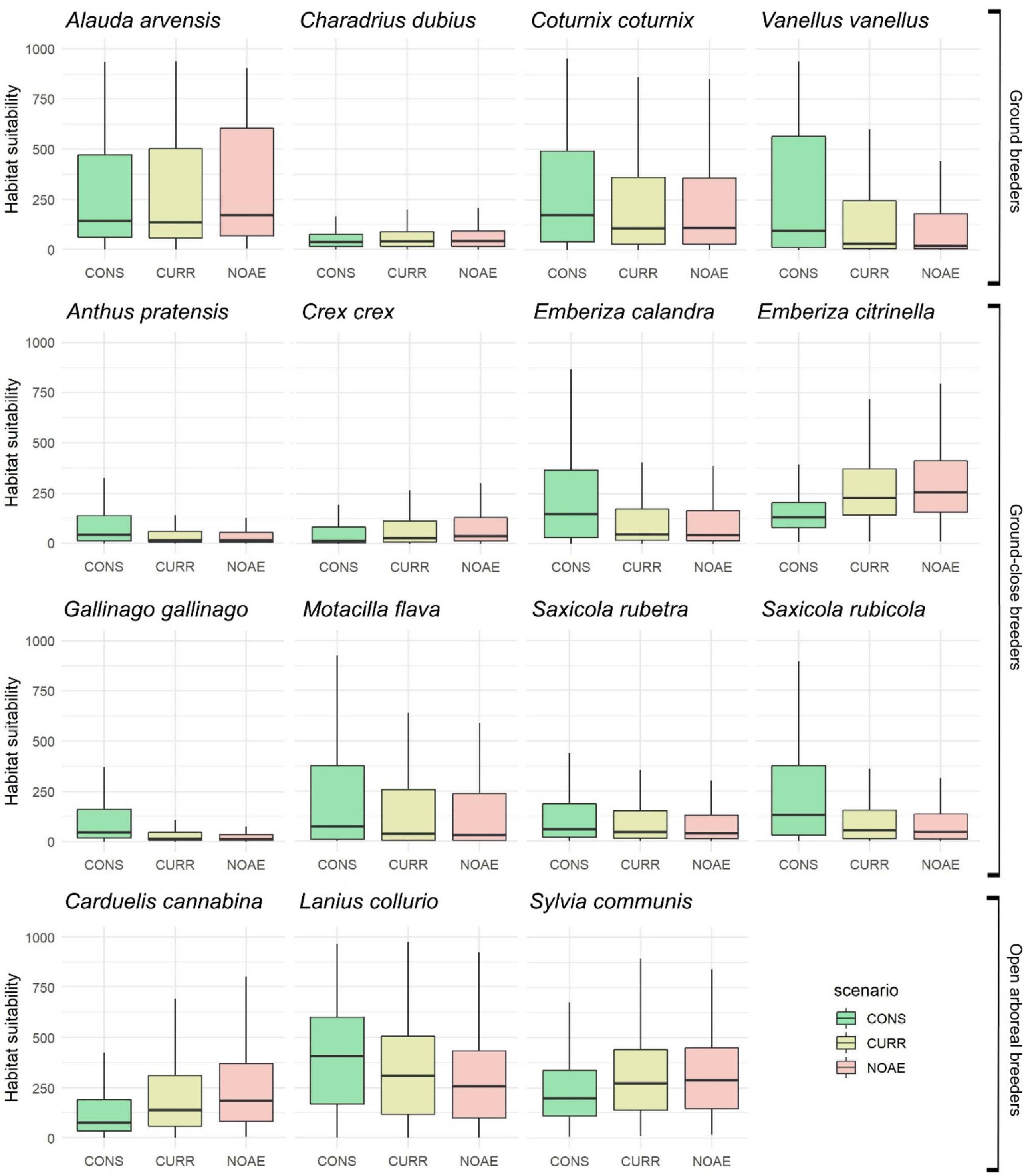

FIGURE 4 Comparison of modeled breeding habitat suitability (each 20 × 20 m raster pixel corresponds to one value) across the three scenarios (CONS, conservation-informed scenario with increased AEM; CURR, current conditions as of 2019; NOAE, no AEM scenario) in the Mulde River Basin, for each species. AEM, agri-environment measure; SWF, small woody features.

achieved only if their adoption by farmers is significantly increased. The future CAP should therefore aim at designing regionally targeted measures in collaboration with local stakeholders to maximize their attractiveness to farmers.

Change in habitat suitability across AEM scenarios

The removal of AEMs from the landscape did not have substantial effects on the modeled breeding habitat suitability of the 15 bird species considered here. Stronger differences, provoked by larger changes in AEM distribution, are discernible between the current (CURR) and the conservation-informed (CONS) scenario: Six species showed a decrease in habitat suitability, whereas for nine species it increased in the CONS scenario. The relatively small differences in habitat suitability between the CURR and the NOAE scenarios imply that the current level of AEM application is too low to significantly increase the suitable breeding area. However, the positive responses of most species to the CONS scenario indicate that AEMs can be valuable conservation tools if higher implementation goals are set (Concepción & Díaz, 2019; Gamero et al., 2017; Pe'er et al., 2014).

To project the models in the CONS scenario, the relationships between habitat suitability and AEM variables had to be extrapolated outside of the training data range. Although it is impossible to assess the adequacy of our predictions in this new scenario due to an obvious lack of data, other studies hindcasting the impacts of land-use changes on bird communities found SDM transferability to be good especially for species tied to agricultural lands (Regos et al., 2018). Nonetheless, we acknowledge that species–environment relationships can change as the availability of resource changes. For example, fallows and buffer areas, which in current land-use conditions cover a small percentage of our study area, may be selected for more strongly if they become more widespread. The assumption of constant relationships between species and environmental factors remains a caveat in SDMs (Jarnevich et al., 2015), and reliable projections of (changes in) species distributions in new environmental conditions can only derive from continued biodiversity monitoring over time and across regions.

For the design of the CONS scenario, the additional AEMs were randomly assigned across the study region, as our main goal was to assess the potential habitat gain deriving from increased AEM implementation across the landscape. A more ecologically tailored positioning of such measures using spatial optimization would surely further improve conservation outcomes, but this was beyond the scope of the study. Nonetheless, more realistic scenarios of future AEM allocation would need to take into account several other socioeconomic factors affecting farmers' decisions (Ziv et al., 2020).

CONCLUSIONS

We showed that AEMs are beneficial for farmland birds but that their current adoption level is too low to deliver significant improvements in breeding habitat suitability for the modeled species. We found land cover, topography, and distance to forest edges and highways to be the strongest drivers of farmland bird distributions; this supports our assertion that AEMs can be more effective if targeted more carefully. Different measures act at different spatial scales and have contrasting effects for different species; land management actors should therefore aim at implementing a diversified set of measures, thereby ensuring a varied mix of habitat types and resources for biodiversity, across the agricultural landscape. Altogether, our results support the plea for a more widespread AEM application through, for example, advanced environmental conditionality and the collaborative design of more regionally targeted, species-specific measures.

AUTHOR CONTRIBUTIONS

Stephanie Roilo and Anna F. Cord conceived the idea and designed the methodology. Stephanie Roilo designed the scenarios and implemented the models. Jan O. Engler helped with species and variable selection. Stephanie Roilo led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

ACKNOWLEDGMENTS

We wish to thank the Saxon State Agency for Environment, Agriculture and Geology (LfULG) for providing the bird data set from the Zentrale Artdatenbank Sachsen and the Saxon State Ministry for Energy, Climate Protection, Environment and Agriculture (SMEKUL) for providing the IACS data (InVeKoS Sachsen). We also thank the Centre for Information Services and High Performance Computing (ZIH) of the Technische Universität Dresden for generous allocation of computing resources. This work was supported by European Union's Horizon 2020 research and innovation program, grant agreement no. 817501 (BESTMAP), and by the "SustES – Adaptation strategies for sustainable ecosystem services and food security under adverse environmental conditions" project (CZ.02.1.01/0.0/0.0/16_019/0000797). Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The bird data set used in this study is owned by the Saxon State Agency for Environment, Agriculture and Geology, and the IACS data are owned by the Saxon State Ministry for Energy, Climate Protection, Environment and Agriculture. Both data sets hold sensitive information and thus cannot be made publicly available but can be requested from those agencies for research purposes. The novel R code (Roilo, 2022) used to run the species distribution models is available on Zenodo at https://doi.org/10.5281/zenodo.6761798.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Roilo, Stephanie, Jan O. Engler, Tomáš Václavík, and Anna F. Cord. 2023. "Landscape-Level Heterogeneity of Agri-Environment Measures Improves Habitat Suitability for Farmland Birds." *Ecological Applications* 33(1): e2720. https://doi.org/10.1002/eap.2720