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Spatially-explicit biodiversity models help unpack the varying effectiveness of Agri-Environment Measures

Abstract

Agri-Environment Measures (AEM) are the primary policy tools under the European Union's Common Agricultural Policy to combat farmland biodiversity loss, yet their effectiveness is highly variable. This synthesis paper summarizes findings of a doctoral thesis investigating drivers of variation in modelled biodiversity responses to AEM: (1) the use of different land-use intensity (LUI) metrics, (2) the types of AEM and their species-specific scale of effect, (3) landscape structural complexity across different regions. First, virtual species (i.e. species with known species-environment relationships) were used to explore how using alternative LUI metrics in biodiversity models influences the estimated species-AEM relationships. Second, bird observations for the Mulde River Basin in Germany were used to model farmland bird responses to different AEM across scales. These relationships varied across species and AEM type, but were generally strongest at the landscape level as compared to locally. Lastly, landscape-moderated effects of AEM on red-backed shrike (*Lanius collurio*) occurrences were analyzed across three study regions in Germany, Spain and Czechia. Positive shrike-AEM associations were stronger in structurally simple compared to complex landscapes, but this effect was inconsistent across regions. These findings exemplify species-, scale- and landscape-dependent AEM effects, and support AEM's spatial targeting and regional tailoring.

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1 Introduction

Nearly half of the European Union (EU)'s land is covered by agroecosystems, defined as "communities of plants and animals interacting with their physical and chemical environments that have been modified by people to produce food, feed, fibre, energy and other products for human consumption and processing" (Maes et al., 2020). Agroecosystems provide important habitats for a variety of plant and animal species, many of which have adapted to and coevolved with traditional farming practices (Lomba et al., 2015). However, the mechanisation of agriculture and the development of synthetic fertilisers and pesticides led to a rapid industrialisation and intensification of agriculture during the 19th century (Emmerson et al., 2016; van Zanten et al., 2014). These developments changed European agroecosystems dramatically, as landscapes were gradually homogenised and semi-natural habitats were lost, posing a serious and still ongoing threat to farmland biodiversity (Emmerson et al., 2016; Rigal et al., 2023).

The Common Agricultural Policy (CAP) of the EU included environmental protection amongst farmers' obligations in 1992, and currently features the preservation of landscapes and biodiversity amongst its objectives (European Council, 2025; EC, 2024). With each CAP reform, different policy tools were developed to address these goals, among them Agri-Environmental Schemes (AES, also known as Agri-Environment and Climate Schemes), Ecological Focus Areas (EFA) and organic farming. AES are voluntary contracts that compensate farmers for income foregone deriving from the adoption of environmentally-friendly practices (Emmerson et al., 2016). Examples include measures aimed at reducing the application of synthetic fertilisers and pesticides, lowering ploughing and mowing intensity, and protecting species-rich grasslands and landscape features, such as hedges and field trees. Similar to AES, EFA entailed subsidies for farms with > 15 ha of cropland, which, under the 2014-2022 CAP, were required to set aside 5% of their land for landscape features or for field-wide measures like fallows, cover crops and nitrogen-fixing crops (Pe'er et al., 2017). EFA were discontinued in the current CAP (2023-2027) and replaced by eco-schemes, for which participation is voluntary (EC, 2023a). Organic farming, a farming method aimed at reducing environmental impacts of agriculture by using organic fertilisers and pesticides instead of synthetic ones, is also subsidised by the EU through the rural development commitments of the CAP (EC, 2023b). AES, EFA and organic farming thus have similar environmental objectives, and in this paper they will be referred to collectively as Agri-Environment Measures (AEM).

With about "35% of funds […] allocated to measures to support climate, biodiversity, environment and animal welfare", and 25% of the direct payments' budget allocated to eco-schemes in the current CAP (EC, 2023a), the EU expenditure towards AEM is significant. Yet their effectiveness for biodiversity conservation is recurrently questioned (Gamero et al., 2017; Pe'er et al., 2020, 2022), and a systematic monitoring and evaluation of AEM outcomes is lacking, also due to data gaps on biodiversity and on land-use/land-management practices across the EU (Alliance Environnement, 2020). Much of our knowledge on the biodiversity benefits of AEM thus derives from a fragmented landscape of individual studies, which found varying support for their ecological (cost) effectiveness (Ansell et al., 2016; Batáry et al., 2015; Concepción & Díaz, 2019; Daskalova et al., 2019; Kleijn & Sutherland, 2003; Reif et al., 2024). A wide range of factors appear to moderate AEM effectiveness; among them are the type of intervention (e.g. productive vs. non-productive measures; Pe'er et al., 2017; and action-based vs. result-based measures; Hagemann et al., 2025), its temporal duration (Staggenborg & Anthes, 2022), its ecological contrast (in terms of resources provided compared to the surrounding habitat; Marja et al., 2019), the amount of AEM area and its location (Sharps et al., 2023), the landscape and regional contexts (Tscharntke et al., 2012). Understanding the combined, intertwined effects of these factors on AEM efficacy is challenging, especially given the limitations in the availability and accessibility of biodiversity and land-use/land-management data across the EU.

This paper synthesises the doctoral thesis by Roilo (2024a), which investigated sources of variation in the modelled effectiveness of AEM for biodiversity conservation (Figure 1). Specifically, the following research questions were addressed: (1) How does

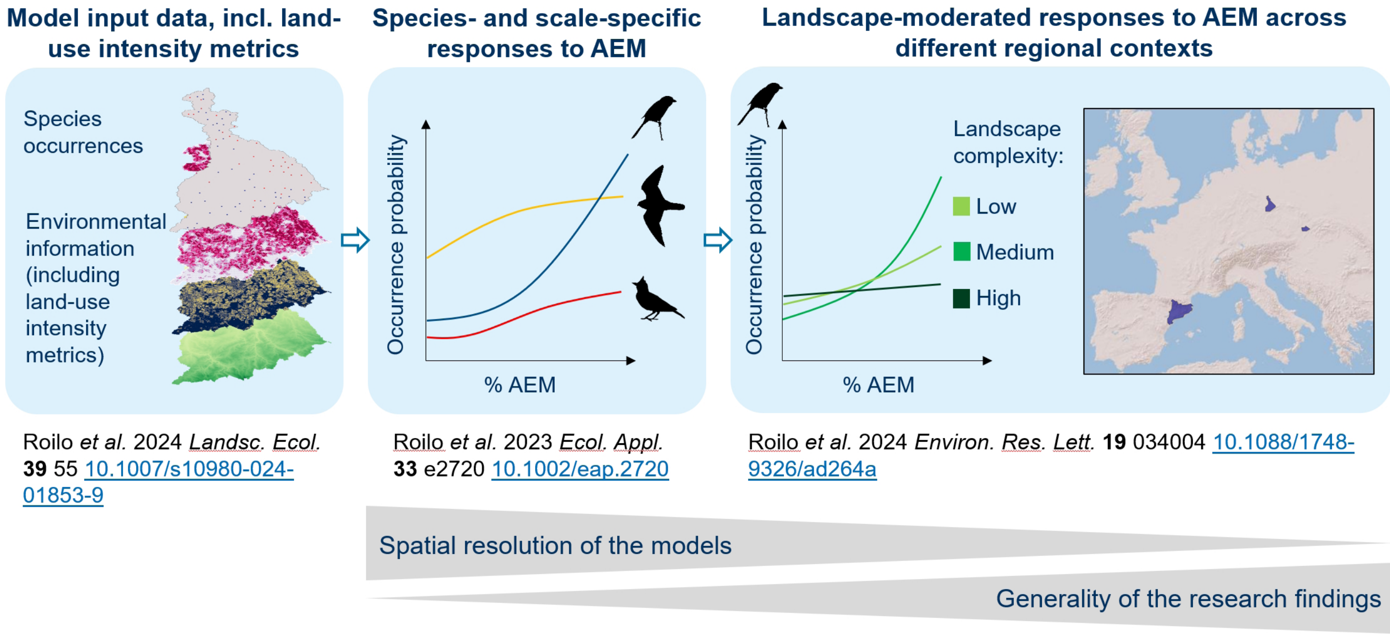

Figure 1. Sources of variation in modelled biodiversity responses to AEM explored in the publications referenced below each box and synthesised in this manuscript. AEM, Agri-Environment Measures. Adapted from Roilo, 2024a.

the use of different land-use intensity (LUI) metrics impact the modelled biodiversity responses to AEM in spatially-explicit models? (2) How do biodiversity responses to AEM vary across different species, types of AEM and spatial scales?, and (3) How does structural complexity of the surrounding landscape moderate these responses, and is this affected by regional context? Answering such questions is crucial to advance ecological modelling for policy impact assessment, and to deepen our understanding of what moderates AEM benefits for biodiversity, and how to maximise these gains.

2 Research approach and methods

This research focused on three study regions in Europe: the Mulde River Basin (5,814 km^2) in Germany, Catalonia (32,106 km^2) in Spain and South Moravia (2,089 km^2) in Czechia. The regions differ significantly in climate, topography, and agricultural systems, with cropland being the predominant land cover in the Mulde River Basin and South Moravia, while Catalonia features a mix of cropland, fruit orchards and grassland. Grasslands are abundant in the mountainous areas of all three regions. For these regions, I collated field-level data on land use and AEM adoption from the Integrated Administration and Control System (IACS), geospatial data describing climate, topography and land cover (for details, see Roilo et al., 2023; Roilo, Paulus, et al., 2024; Roilo, Spake, et al., 2024). Additionally, I used virtual species and pre-collected bird occurrence data to investigate drivers of variation in modelled biodiversity responses to AEM, as specified in the following sections.

2.1 Quantifying agricultural land-use intensity to inform spatial biodiversity models

When developing spatial biodiversity models for impact assessment in agricultural lands, one crucial step is the spatially-explicit quantification of LUI. This is challenging as LUI is a multifaceted phenomenon for which multiple definitions exist. In this work, LUI is defined as “the degree of adoption of land management practices enabling yield increases from a given area of agricultural land” (Kehoe et al., 2015). Often, detailed field-level information on land management practices is not available nor accessible, which hinders LUI quantification. Ecological modellers have to rely on different proxies of LUI, which can lead to variable and sometimes contrasting outcomes in their modelled biodiversity-LUI relationships. To quantify how the choice of different metrics, and of their spatial aggregation unit, affects LUI quantification at species occurrence points and

Table 1. Land-use intensity (LUI) metrics computed in this study and their units of measure, alongside the utilized input data and calculation details. All proportions (%) were calculated on the total grid-cell area. The "LUI dimension" column classifies each metric into one of the three dimensions of agricultural systems proposed by Firbank et al. (2008). Adapted from Roilo, Paulus, et al., (2024).

Metric (unit)	Abbreviation	Input data	Description and calculation	LUI dimension
Utilised agricultural area (%)	UAA	Integrated Administration and Control System (IACS) data (SMEKUL, 2020)	Proportion of utilised agricultural area (arable land, grassland, permanent cultures)	Land use
Arable land (%)	Arable	IACS data (SMEKUL, 2020)	Proportion of arable land cover	Land use
Arable land on UAA (%)	Arable_UAA	IACS data (SMEKUL, 2020)	Proportion of arable land on total UAA	Land use
Conventionally farmed UAA (%)	Conv_farm	IACS data (SMEKUL, 2020)	Proportion of conventionally farmed UAA (%UAA - %area under organic farming)	Land management
Intensively farmed UAA (%)	Intens_f	IACS data (SMEKUL, 2020)	Proportion of intensively farmed UAA (%UAA - %area under agri-environment schemes and ecological focus areas)	Land management
Nitrogen input (index from 1 to 3)	N_input	Land-use intensity raster by Temme and Verburg, 2011	The original raster, which had separate categories for arable and grassland pixels, was reclassified to three classes (1-3): low N input (<50 kg N/ha), medium (50-150 N kg/ha on arable land, >50 kg N/ha on grassland), and high (>150 kg N/ha on arable land). The weighted average per grid-cell was then calculated from the raster.	Land management
Agricultural land-use homogeneity (index)	ALU_homog	IACS data (SMEKUL, 2020)	Opposite of the Shannon Diversity Index (SDI) of agricultural land-use types (e.g. different crops and grassland types); all other non-agricultural land covers are considered as one "other" category	Landscape structure
Land-use/land cover homogeneity (index)	LULC_homog	Land cover raster by Preidl et al., 2020	Opposite of the SDI of LULC types based on the Preidl et al. raster, which includes 24 different LULC classes of which 18 are crops and permanent cultures	Landscape structure
Land cover homogeneity (index)	LC_homog	Land cover raster S2GLC by Malinowski et al., 2020	Opposite of the SDI of land-cover types based on the S2GLC raster, which includes 15 different land-cover classes (different crops are merged into the "cultivated areas" class)	Landscape structure
Field size (ha)	Field_size	IACS data (SMEKUL 2020)	Mean field size (in ha) of all fields whose centroids fall within a grid cell	Landscape structure

potentially propagates uncertainty in impact assessment biodiversity models (research question 1), I computed ten commonly used LUI metrics (Table 1) using the Mulde River Basin as study area. I quantified divergences in LUI values at point locations between the ten metrics and three grid types (square, hexagonal and Voronoi grids). The selected metrics (Table 1) were calculated using IACS data and geospatial information on land-use/land-cover and nitrogen input, and described different dimensions of LUI, namely land use, land management and landscape structure. I tested how the use of different LUI metrics affects inferences on species-environment relationships using three virtual species with varying habitat requirements (an arable land, a grassland, and a wetland species) with known response curves to specific LUI metrics. The virtual species occurrences were modelled in a Species Distribution Modelling (SDM) framework, a popular method in biodiversity conservation studies (Zurell et al., 2022). For more details on this work, see Roilo, Paulus, et al. (2024).

2.2 Modelling species- and scale-specific bird responses to AEM

To explore variations in AEM effects across species and AEM types, as well as across spatial scales (research questions 2), I used ensemble SDM to model the responses of 15 farmland bird species to five different groups of AEM in the Mulde River Basin (Roilo et al., 2023). The investigated AEM groups were buffer areas (strips or areas taken out of production and either left self-vegetated or sown with specific seed mixtures), cover crops (crops planted to cover the soil between the harvest and the sowing of main crops), extensive grassland management (i.e. with reduced grazing and/or mowing pressure, fertilizer and pesticide use), fallow land (land lying fallow for ≥1 year(s) without any management requirements; Ziv et al., 2021), and organic farming. The bird data consisted of bird occurrences collected from 2016 to 2019 with a spatial uncertainty ≤ 100 m, which were extracted from the Saxon Central Species Database (SMUL, 2025). The database is curated by the Saxon State Agency for Environment, Agriculture and Geology, and collates observations from a variety of standardised and opportunistic monitoring activities. The dataset was filtered to exclude non-breeding observations, duplicates, and incomplete or incorrect taxonomies. Pseudo-absences were generated using the target-group approach (i.e., using the presence points of other bird species in the dataset as pseudo-absences in the SDM of the target species), a popular method to reduce the influence of spatial biases in biodiversity dataset (Ranc et al., 2017).

Bird occurrences were related to environmental variables describing topography, distance from highways and from forest edges, land-use/land-cover, and AEM adoption (input data and processing are detailed in Roilo et al., 2023). To investigate the scale of effect, i.e. the spatial scale at which AEM and land-use/land-cover variables elicited the strongest modelled response, we computed these variables as the proportion of cover within circular buffers of varying radius (200, 500 and 1,000 m) around each bird presence/pseudo-absence point. To select the best scale for each variable, univariate linear models relating the species occurrence data with the given variable calculated at each of the three scales were fitted and ranked by their Akaike Information Criterion corrected for small sample size (AICc) score. The model with the lowest AICc score identified the scale at which the variable entered the model. Highly correlated (Spearman's $|R| \geq 0.7$) variables were excluded from the same model (further details and model codes are published in Roilo et al., 2023).

2.3 Evaluating landscape- and regional-level context dependency of AES relationships

The impact of landscape and regional contexts in AEM effectiveness (research question 3) was explored in Roilo, Spake, et al., (2024) by focusing on one type of AEM, namely grassland-based AES. I investigated how landscape complexity regulates AES effectiveness in protecting or creating habitat for the red-backed shrike (*Lanius collurio*), a carnivorous passerine emblematic of open farmlands in Europe. This analysis encompassed three study regions, i.e. the Mulde River Basin in Germany, Catalonia in Spain, and South Moravia in Czechia, within which individual SDM were fitted to model the shrike occurrence. This allowed to describe regional variations while also identifying common patterns on the efficacy of grassland-based AES across the three regions.

Generalised Linear Models were used to model red-backed shrike occurrence relative to land-use/land-cover (i.e. the proportion of area covered by AES, arable land, grassland, orchards, forests, shrubs), topographic (i.e. elevation) and climatic variables (i.e. maximum temperature and precipitation sum; see Roilo, Spake, et al., 2024 for details). To investigate potential interactive effects of structural (i.e. proportion of shrubs cover, SHRUBS) and compositional (i.e. Shannon diversity index of land cover types, LANDDIV) landscape complexity on AES effects, two interactive terms were included in the model structure:

shrike_occurrence ~ AES + ARABLE + GRASS + ORCHARD + FOREST + SHRUBS + LANDDIV + TMAX + PRECIP + ELEVATION + AES:SHRUBS + AES:LANDDIV

Rigorous model diagnostics were performed to ensure that the model assumptions, also pertaining to the unbiased estimation of interactive effects among variables, were met. The output models were used to produce maps of the probability of shrike occurrence under the 2019 AES adoption levels (i.e. the AES cover as reported in 2019 IACS data) as well as a hypothetical scenario in which all permanent grassland fields are converted to AES. The arithmetic difference between the two scenarios' projections produced an "effect map" (Spake et al., 2019), which visualises the change in occurrence probability of the shrike following the conversion of all grassland to AES.

3 Key findings

3.1 Improving land-use intensity quantification for spatially-explicit biodiversity models

The ten LUI metrics calculated for the Mulde River Basin revealed large spatial variations in LUI hot- and coldspots across metrics as well as across different grid types (i.e. square, hexagonal and Voronoi grid) used as spatial aggregation unit (Roilo, Paulus, et

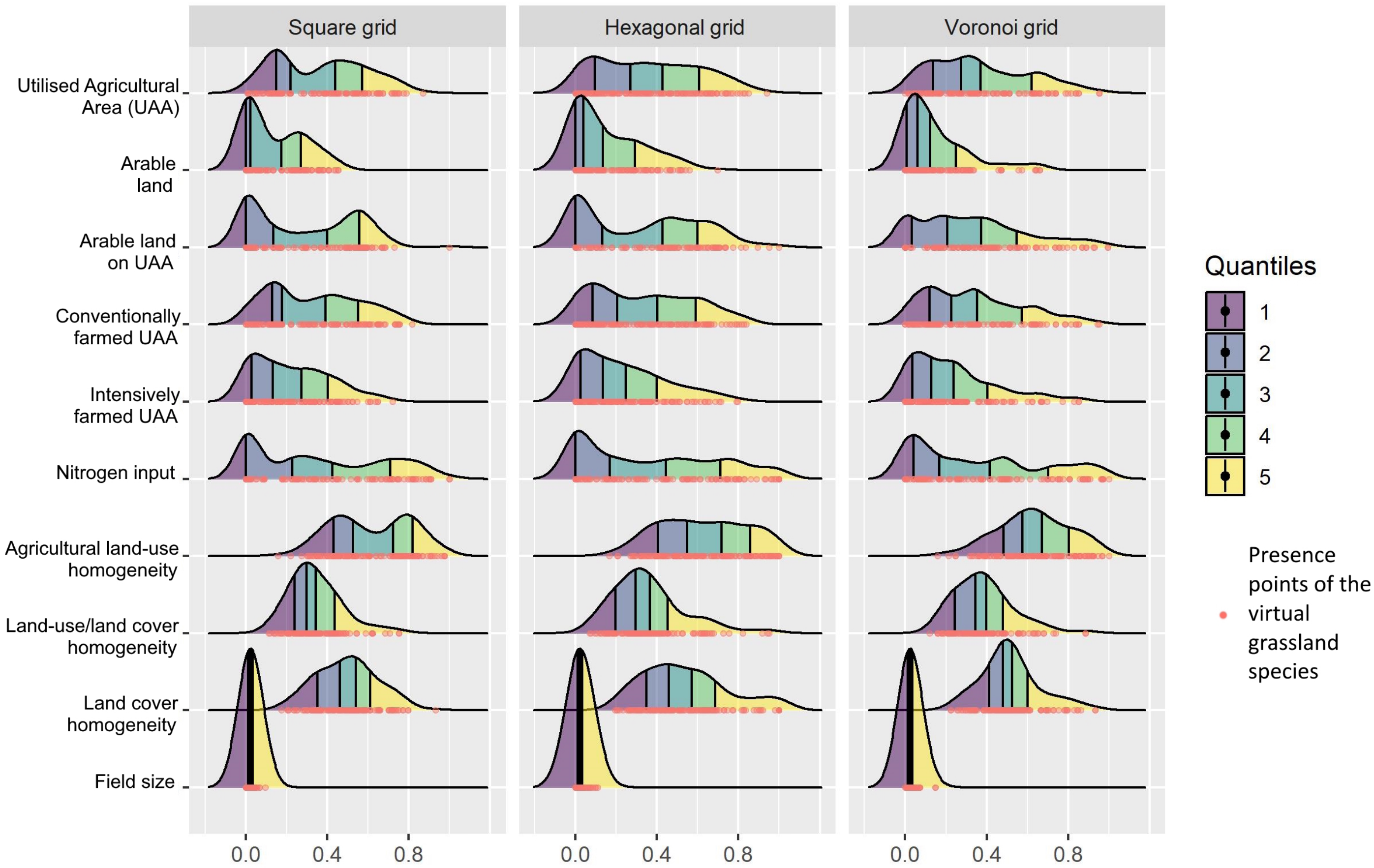

Figure 2. Density distributions of the land-use intensity (LUI) metrics extracted at the 99 presence points of the virtual grassland species, shown by grid type. The x-axis indicates the value of each metric (with higher values indicating higher LUI); the y-axis indicates the density (frequency) of data points along the LUI gradient. All metrics were scaled between 0 and 1 to ease cross-metric comparisons. Different colours represent the different quantiles in the distribution of the sampled values. True sampled values are shown as red dots along the x-axis and fall within the value range [0,1], while the estimated density distribution may exceed these range limits. Adapted from Roilo, Paulus, et al. (2024).

al., 2024). Such differences were observable in the variations in density distributions of the LUI values extracted at the presence points of the virtual species (Figure 2). For example, the virtual species locations fall within the lower end of the values' range for LUI metrics such as field size and arable land. On the other hand, they are in the upper half of the range of values of agricultural land-use homogeneity, and are fairly evenly spread across the range of nitrogen input. Cross-grid comparisons of the same metric reveal similar discrepancies, as there are noticeable differences in the density distributions for metrics such as arable land on UAA, and in agricultural land-use homogeneity depending on the spatial aggregation unit used (Figure 2). These findings show that inferences on species-LUI relationships can dramatically change depending on the LUI metric and on the type of grid used. These variations also affect the modelled relationships of the species to other covariables, including AEM-related ones in impact assessment models. The SDM of the virtual species occurrence detailed in Roilo, Paulus, et al., (2024) further prove this point, as the predefined species-AEM relationships characterising the environmental niches of two out of three virtual species remained undetected in models that omitted certain LUI dimensions.

3.2 Species- and scale-dependent responses to AEM

The ensemble SDM of 15 farmland bird species in the Mulde River Basin in Germany performed well overall, with mean Area Under the receiver operating characteristic Curve (AUC) ≥ 0.8, and specificity and sensitivity both ≥ 0.74 for all models (Roilo et al., 2023). The importance scores of different envi-

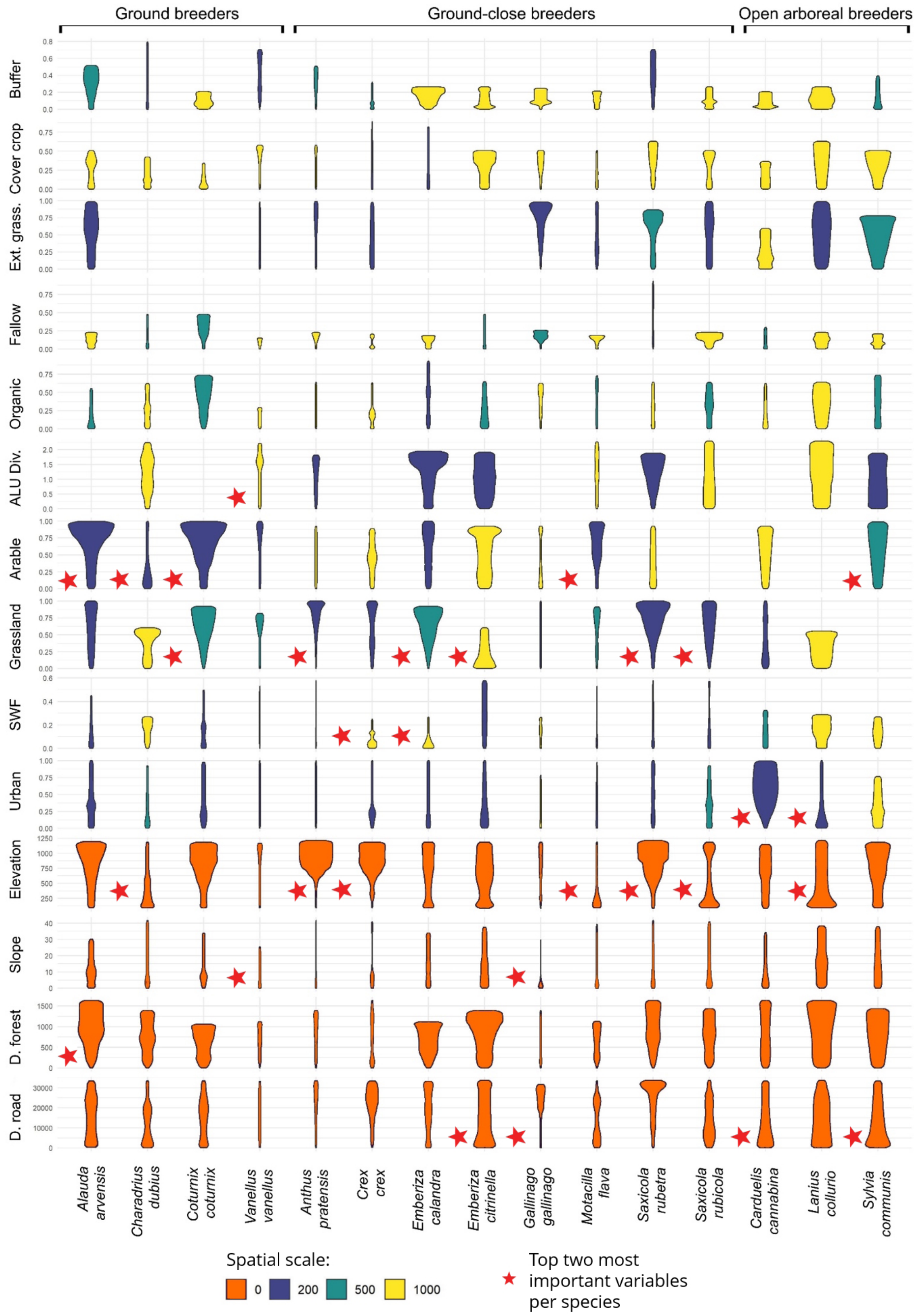

Figure 3. Effects of explanatory variables on breeding habitat suitability of 15 farmland bird species. The range of each variable is shown on the y-axis, and the width of each violin plot corresponds to the habitat suitability for the given species (e.g., increasing proportions of arable land correlate positively with habitat suitability for *A. arvensis* and negatively for *C. dubius*). Red stars mark the two most important variables in each species' model. Variable importance scores for all variables and species can be consulted in Roilo et al. (2023). The color code of each violin plot reflects the spatial scale, that is, the radius (in meters) of the circular window used for variable calculation. ALU, agricultural land use; D. forest, distance from forest edge; D. road, distance from highways; SWF, small woody features. Adapted from Roilo et al. (2023).

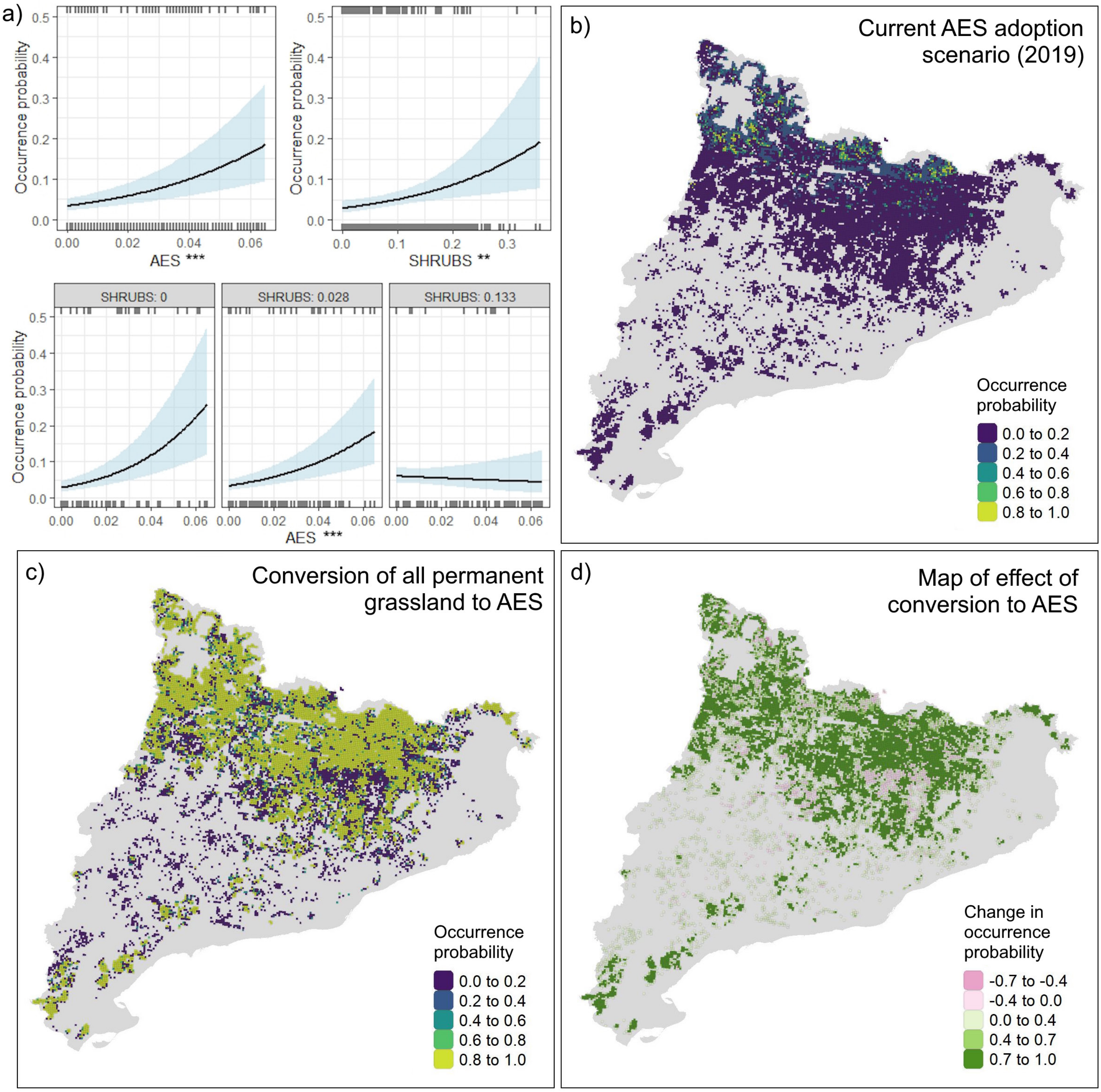

Figure 4. Panel a) Conditional plots displaying the effect of AES, SHRUBS and their interaction term on the occurrence probability of the red-backed shrike in the best model for Catalonia. Relationships were graphed for each predictor with all other covariates held at their medians. To visualise interactive effects of SHRUBS with AES, plots describing the effect of AES on occurrence probability were produced for the 10th, 50th and 90th percentiles of the value distributions. Shading shows average estimated standard errors. Ticks on the upper and lower border of the plots represent data points. Asterisks indicate whether predictors are significant at the 0.01 (**), or 0.001 (***) levels. Panels b-d) Predictions of occurrence probability of the red-backed shrike in Catalonia under the current, as of 2019, AES adoption (b), if all permanent grassland was converted to AES (c), and the change in occurrence probability after conversion to AES (d). Only grid cells with at least 1 ha of grassland and with an elevation between 200 and 2,000 m a.s.l. are displayed. Adapted from Roilo, Spake, et al. (2024).

ronmental variables differed greatly across species, but were consistently low for the five AEM-related variables quantifying the percent cover of buffer strips, cover crops, extensive grassland, fallow land, and organic farming, as compared to other variables. In fact, the most important variables across all modelled species were elevation and grassland cover (Figure 3). This shows that topography and land cover are strong drivers of bird distributions, while AEM adoption has a more marginal, though not necessarily negligible, effect. This is in line with previous research reporting beneficial effects, but still insufficient or too variable to stop farmland birds' decline (Concepción & Díaz, 2019; Gamero et al., 2017).

Bird relationships to AEM were mostly positive, especially in the case of extensive grassland, fallow land and buffer areas, while responses to cover crops and organic farming were more variable (Figure 3; Roilo et al., 2023). Indeed, non-productive AEM typically achieve biodiversity goals more effectively than productive options (Pe'er et al., 2017; Staggenborg & Anthes, 2022). The observed interspecies variations in their association with AEM were expected, based on the different ecologies of species, but they are important for regional landscape planning. In fact, since no single intervention will be equally beneficial across the species community (Żmihorski et al., 2016), interspecies trade-offs are likely to arise in alternative AEM adoption scenarios (Topping et al., 2019).

The multi-scale modelling approach revealed that most AEM had the strongest modelled effect at the landscape level, with the exception of extensive grassland, whose scale of effect was finer (200 m, Figure 3; Roilo et al., 2023). These findings support the idea that landscape-scale diversification supports farmland biodiversity through the provision of multiple, complementary resources (Tscharntke et al., 2021).

3.3 Landscape-moderated responses to AEM and cross-regional comparisons

The analysis of red-backed shrike relationships with the AES extensive grassland in the Mulde River Basin, Catalonia and South Moravia showed that shrike occurrence was positively correlated with AES area in all three regions. In the model for the Mulde River Basin, a Gaussian process spline term had to be added to correct the high spatial autocorrelation in the model residuals. This spline, due to its flexible and non-linear nature, explained much of the variation in the data, contributing to a relatively high adjusted R^2 (0.58) for the best model, compared to the Catalan (adj. R^2 = 0.20) and South Moravian (adj. R^2 = 0.07) top-ranking models. In Catalonia and South Moravia, but not in the Mulde River Basin, the interaction term between the percent cover of AES and that of small woody features (SHRUBS) was included in the 1st and in the 12th-ranked models respectively, presenting evidence for a landscape-moderated effect of AES. This effect was strongest in the Catalan model, where the interaction term was also highly significant (p-value <0.001).

The conditional plots of the variables describing AES and SHRUBS, as well as their interaction, in the Catalan model showed that AES is more effective in structurally simpler landscapes (i.e. with a lower shrubs cover), whereas its response curve flattens out in landscapes with increasing shrubs cover (Figure 4a). These effects reflect also in the projections of shrike habitat suitability in the alternative AES adoption scenarios. Indeed, the hypothetical scenario in which all permanent grassland is converted to AES (Figure 4c) shows a large increase in shrike occurrence probability across Catalonia, when compared to the status quo (Figure 4b). However, the map of effect of the conversion to AES reveals that the change in modelled shrike occurrence is not always positive (Figure 4d), due to the landscape-moderated effect of AES, which varies across grid-cells depending on the amount of shrubs cover. These findings highlight that the spatial targeting of AES is crucial in determining how effective the intervention will be. Moreover, these results elucidate that, even when focusing on a single species, regional variations in species-AES relationships exist.

4 Conclusions and outlook

In this synthesis paper, different sources of variation in modelled biodiversity responses to AEM were explored (Figure 1), unveiling important insights for ecological modellers, practitioners and policymakers. First, this research addressed methodological sources of variation in modelled AEM effects, i.e. potential biases in model inferences arising from a narrow or one-dimensional representation of LUI (Figure 2; Roilo, Paulus, et al., 2024). Consequently, I make suggestions for a more inclusive and realistic quantification of LUI, encompassing different dimensions (i.e. land use, land management and landscape structure), and for a thoughtful selection of spatial aggregation unit in spatially-explicit models. Additional best practices must be followed to ensure a robust quantification of species-AEM relationships, which are exemplified in the SDM trained on empirical bird data from the three study regions (Roilo et al., 2023; Roilo, Spake, et al., 2024). These practices include careful dataset filtering to meet minimum quality standards in the input data, accounting and correcting for spatial sampling bias in biodiversity data, inspection of model residuals and quantification of their spatial autocorrelation, and testing the validity of assumptions underlying multiplicative interaction models. Moreover, acknowledging the limitations of the used models (e.g. the fact that correlative SDM do not inherently reveal causal relationships) is a crucial part of model interpretation and assessment (Roilo, 2024a). Finally, open-source data and model codes can help advance biodiversity modelling, by allowing the scientific community to reuse, adapt and improve existing modelling frameworks for future applications. For these reasons, all model codes described in this paper are openly available (Roilo, 2022, 2024b).

The SDM trained on empirical bird data showed that there is no unique and simple solution to halt the decline of farmland biodiversity through AEM. Indeed, my findings showed that species' responses to AEM vary across species, AEM types, spatial scales (Figure 3), and across gradients in landscape complexity as well as between regions (Figure 4). Thus, policy-makers must set clear conservation goals, ideally at the regional or landscape level, so that region-specific context-dependent factors can be accounted for. Regional-level landscape planning is meaningful also to better navigate trade-offs between biodiversity conservation and other ecosystem services, including food production, based on detailed local knowledge on resource needs and biodiversity patterns (Jungandreas et al., 2022). Importantly, farmers' attitudes are crucial for the success of AEM, which depends also on their adoption rates and correct implementation (Bartkowski et al., 2023). Regional variations in farmers' values and behaviour and in farm typologies, all of which are influenced by contextual factors, need consideration when adapting AEM policies to local needs (Alarcón-Segura et al., 2023; Paulus et al., 2022; Václavík et al., 2024).

Future research to assess and improve AEM outcomes would greatly benefit from an increased accessibility to existing EU data on agricultural land use and land management. A valuable effort in this sense is exemplified by the project Europe-LAND, which has been working to collate and harmonize IACS data for 27 European countries, making them openly available whenever possible (Jänicke et al., 2024). Technological advances in environmental monitoring, thanks to novel remote sensing techniques and improved sensors, enable the collection of data at higher spatio-temporal resolution (European Space Agency, 2024). Such data can be used to map agricultural practices such as mowing intensity (Lange et al., 2022). Remote sensing, and specifically Light Detection and Ranging data, are also increasingly used to collect biodiversity data, with successful applications including the automatic detection of wild flowering species (Barrasso et al., 2024) and the detection of roe deer fawns (Cukor et al., 2019) in croplands. Biodiversity monitoring is also being revolutionized by novel or improved monitoring tools like camera traps (Roilo, Hofmeester, et al., 2024), ecoacoustic monitoring devices (Cord et al., 2025), and bio-loggers (Williams et al., 2020), all bearing great potential for their use in farmland habitats. Such high-resolution data on the environment and on the species that inhabit it will provide both challenges and opportunities for the development of more robust biodiversity models for policy impact assessment.

5 About this work

This work is a synthesis of the cumulative dissertation for the degree of Doctor of Natural Sciences (Dr. rer. nat.) titled "Modelling impacts of agricultural practices on biodiversity in Europe", which was submitted to the Faculty of Environmental Sciences at the Dresden University of Technology in 2024. The dissertation builds upon three published articles, whose results are summarized in this manuscript. This synthesis thus presents (adapted) extracts from the dissertation and the published articles therein.

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Declaration of Competing Interest

The author declares no competing interest.

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