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D5.1 Past-to-present EBV modelled datasets and status indicator for selected species in the Birds Directive

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EUROPABON

Past-to-present EBV modelled datasets and status indicator for selected species in the Birds Directive

31/12/2023

Lead beneficiary:

The Centre for Ecological Research and Forestry Applications (CREAF)

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Task number	**T5.1**
Institution leading task	**The Centre for Ecological Research and Forestry Applications (CREAF).** **With essential contributions from the European Bird Census Council, the Czech Society for Ornithology, the Swiss Ornithological Institute and the Catalan Ornithological Institute.**
Author(s)	**Sergi Herrando, Sara Fraixedas, Guillem Pocull, Dani Villero, Anna Gamero, David Martí, Verena Keller, Petr Voříšek, Alena Klvaňová, Gabriel Gargallo and Lluís Brotons**
EC project officer	**Laura Palomo-Rios**
Deliverable description	This deliverable shows, using farmland birds as a demonstrative case study, how the existing European network of bird monitoring schemes could be used to regularly update the distribution of terrestrial breeding birds across the whole of EU and neighbouring countries. In addition, it shows how changes in distribution could be assessed on frequent intervals suitable for informing on the achievement of EU environmental policy targets.
Keywords	**distribution, modelled maps, change, birds, farmland**

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List of acronyms

Acronym	Name
Ab	Abundance
AdaSTEM	Adaptive Spatio-Temporal Exploratory Model
ANN	Artificial Neural Network
AUC	Area Under the Curve
BMCC	Biodiversity Monitoring Coordination Centre
BRT	Boosted Regression Trees
CBD	Convention on Biological Diversity
CSO	Czech Society for Ornithology
DG ENV	Directorate General Environment
EBBA1	First European Breeding Bird Atlas
EBBA2	Second European Breeding Bird Atlas
EBCC	European Bird Census Council
EBP	EuroBird Portal
EBV	Essential Biodiversity Variable
EBBALF	European Breeding Bird Atlas Live Farmland
EEA	European Environment Agency
EESV	Essential Ecosystem Services Variable
ESA CCI	European Space Agency's Climate Change Initiative
ETRS	European Terrestrial Reference System
EU	European Union
FBI	Farmland Bird Indicator
FDA	Flexible Discriminant Analysis
GAM	Generalized Additive Models
GLM	Generalized Linear Models
HBW	Handbook of the Birds of the World
JRC	Joint Research Centre
LAEA	Lambert Azimuthal Equal-Area projection
LC	Land Cover
LPI	Living Planet Index
MARS	Multivariate Adaptive Regression Splines
MODIS	Moderate Resolution Imaging Spectroradiometer (NASA)

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MS	Member State
NA	Not Available (No Data)
NDVI	Normalized Difference Vegetation Index
NUTS	Nomenclature of territorial units for statistics
OCC	Site-Occupancy Models
OECD	Organisation for Economic Co-operation and Development
PECBMS	Pan-European Common Bird Monitoring Scheme
PET	Potential EvapoTranspiration
PO	Probability of Occurrence
RET	Real EvapoTranspiration
RF	Random Forests
SD	Standard Deviation
SDM	Species Distribution Models
SEBI	Streamlining European Biodiversity Indicators
SHDI	Shannon Habitat Diversity Index
SLD	Site-Level Database
SMOG	Spatial Modelling Group
TPS	Thin Plate Spline
TSS	True Skills Statistic
TVMP	Temporal Validation of Models’ Prediction
UNEP	United Nations Environment Programme
UTM	Universal Transverse Mercator
wEP	weighted Ensemble Prediction
Δwp	difference on weighted predictions

Executive summary

The present showcase attempts to demonstrate the capacities of the current network of bird monitoring coordinated by the European Bird Census Council (EBCC) to update bird species distributions of terrestrial birds on a regular and frequent basis. This EBV is very important for the reporting and evaluation of the Birds Directive, but also for other European Union (EU) policies, and as such it was ranked within the top 10 EBVs by national policy makers (Moersberger et al. 2022).

After preliminary discussions with stakeholders, the showcase was developed for farmland birds, which undoubtedly represent one of the groups of terrestrial birds of higher conservation concern. The EBCC promoted the case study among its partners and the project was named EBBA Live Farmland

(EBBALF). National coordinators from 35 countries participated in the project by providing standardised monitoring data for 50 farmland birds, expertise in validating data and outcomes, as well as deciding together with the EBCC steering committee on the final availability of the products. This data was used to develop the four aims of the project, which were: i) to evaluate capacities of the monitoring network to produce maps of observations at 50 x 50 km resolution, ii) to define gaps of monitoring data, iii) to update 10-km modelled maps and iv) to generate maps of change in distribution between the periods 2013–2017 and 2018–2022, roughly matching the Article 12 reporting periods of the Birds Directive.

The results of this study show that the existing network of bird monitoring could be used to update the breeding distributions of farmland birds at 10 x 10 km resolution by means of spatial distribution modelling techniques. This is the most important outcome of this showcase, which suggests that, at least for this group of species, the EBV distribution of terrestrial birds can be at regular intervals of 5 years. Modelling is essential as a procedure to update distributions since the comparison with the reference European Atlas (EBBA2; Keller et al. 2020) showed that maps based exclusively on monitoring data do not allow to generate observed distributions in a satisfactory manner, even at a coarse resolution of 50 x 50 km. Data gaps are identified, especially in south-east Europe, where further efforts to promote bird monitoring would be necessary. Robustly assessing changes in the probability of occurrence between consecutive periods of 5 years is more challenging than updating distributions. Our results indicate that this can also be assessed using monitoring data, although probably not for species with restricted distribution or mostly occurring in areas of low monitoring data such as in south-east Europe.

Preface

EuropaBON, along with a large community of stakeholders from various sectors (policy, NGO, academia, business, citizen science) across Europe, has worked on defining and specifying a list of priority Essential Biodiversity Variables (hereafter EBVs) to be measured across the continent (Deliverable 4.1; Moersberger et al. 2022) that could potentially allow tracking the progress of biodiversity-oriented policy instruments such as the European Biodiversity Strategy for 2030, the EU Strategy on Green Infrastructure, the Nature Restoration Law, the Habitats and Birds Directives or the Water Framework Directive. A list of 70 Essential Biodiversity Variables (Deliverable 4.1) have been developed to enable tracking the progress of these policy instruments by providing robust information on the changes in biodiversity. One of the top-ranked priority EBVs is the “Species distribution of terrestrial birds” which (as indicated by the title of this showcase) is very closely related to the reporting of the Birds Directive.

Birds are undoubtedly among the best-known biological groups and their distribution has received a lot of attention from ornithologists for decades. As of 2021, over 600 bird atlases projects have been implemented across 93 countries, with at least 380,000 participants worldwide (Pototsky and Cresswell 2023). In Europe, bird atlases have been developed at multiple scales, from the municipality to the continental level, but no agreement on standardized methods has been reached after decades of technical development (Gibbons et al. 2007). The situation varies substantially among EU countries, not only technically but also in other capacities (e.g., fieldwork coverage, coordination structure and data flow), and while some have already done three national atlases, others have none yet. In this

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context a pan-European approach has been revealed to be crucial to develop consistent knowledge about the distribution of terrestrial birds that can be extremely useful for research (Herrando et al. 2019). However, this has not been fully implemented yet to inform EU policies.

The Atlas of European Breeding Birds, coordinated by an association of ornithologists (the European Bird Census Council – EBCC), is one of the monitoring initiatives that has undergone significant improvements towards the distribution of terrestrial birds in recent years. The publication of the Second European Breeding Bird Atlas (EBBA2; Keller et al. 2020) constitutes the most up-to-date source of information on distribution and abundance of breeding birds across Europe and on the changes in distributions elapsed between the 1980s (when the First European Breeding Bird Atlas, EBBA1, was published) and the 2010s (30 years apart). However, despite this tremendous milestone for European ornithology, it has some limitations for its use in policy. Considering the characteristics of EBBA2, EuropaBON Deliverable 3.3 identified current monitoring bottlenecks for the development of the EBV "Species distribution of terrestrial birds" (Morán-Ordóñez et al. 2023; Fig. 1). As a result, there is an increasing interest in obtaining updated data on species' distributions and how they change through time more frequently, and in ensuring that this information is harmonised across Europe.

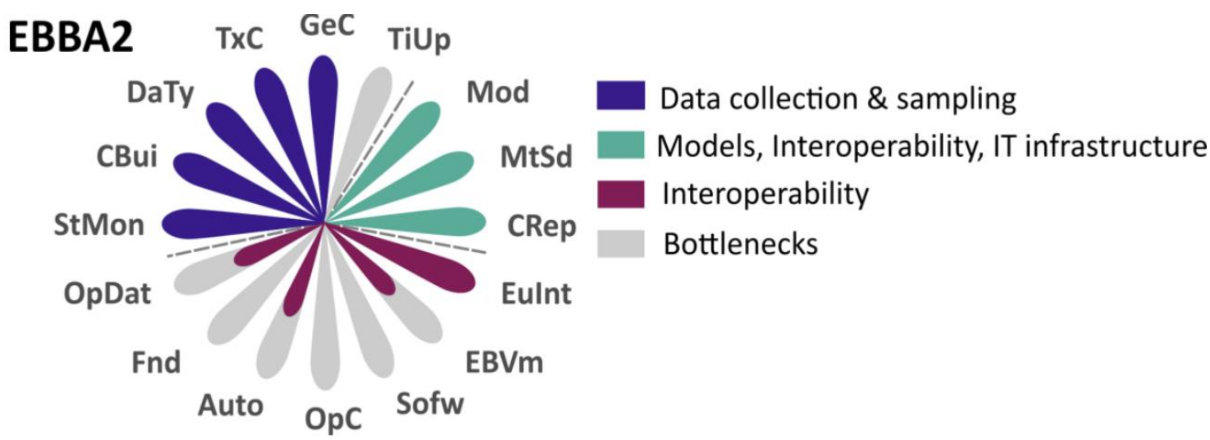

Figure 1. Possible bottlenecks in the generation of the EBV "Species distribution of terrestrial birds" from EBBA2 data according to Morán-Ordóñez et al. (2023): 1) it will be difficult to replicate the effort dedicated to EBBA2 with a frequency lower than five years for all species (Timely Update *TiUp* bottleneck); 2) only c. one third of the species were modelled at 10 x 10 km resolution (EBV match *EBVm* partial bottleneck); 3) species distribution models generated by the project were fitted using R (a priori, a non-user friendly software), and the code used to fit the models is not openly available (Open and reproducible code *OpC* and Software *Sofw* bottlenecks); 4) funding support ended with the publication of the Atlas, hindering the continuity of sampling programs in some countries/regions and data integration tasks (Funding *Fnd* bottleneck); 5) automatization of data flows from sampling plots to national coordinators was lacking (Automated data streams *Auto* partial bottleneck); and 6) the data generated in EBBA2 is available either openly accessible or upon request (Open Data *OpDat* partial bottleneck).

The bottlenecks identified in EuropaBON by Morán-Ordóñez et al. (2023) represented a reference point for the development of the EBBA Live concept, which seeks to improve the spatio-temporal resolution of current distribution maps developed by the EBCC. EBBA Live's main idea of updating data

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on breeding bird distributions on a more frequent basis was presented in the EBBA2 workshop in Lucerne (22nd EBCC conference). EBBA Live was seen, however, as a very ambitious project and an initial pilot project was needed to evaluate its feasibility and the interest in its outcomes. In this context, the EBBA2 coordination team, on behalf of the EBCC Board, proposed the development of a small project based on a subset of bird species using site-level data from the Pan-European Common Bird Monitoring Scheme (PECBMS). The group of farmland birds was proposed as a candidate for this project, given its overall decline and known interest for conservation. This pilot project, which we developed in the context of the EuropaBON WP 5.1, is called EBBA Live Farmland (EBBALF).

1. Introduction

1.1. State of the art in monitoring bird distributions across Europe

At present, two main processes are identified in EuropaBON WP3.1 to allow the generation of a bird species distribution EBV in Europe: 1) the Article 12 reporting of the Birds Directive and 2) the national/European atlases.

The Article 12 report is carried out every six years and contains information on status and trends of bird populations together with information on main pressures and threats. The report further contains information related to the impact of the Natura 2000 network and conservation measures. As clearly stated by its official website (https://www.eionet.europa.eu/etcs/etc-be/activities/reporting/article-12), an important component of the Article 12 report is a map of breeding distribution mapped using a 10 x 10 km grid. In addition to updated distribution, changes in bird species distribution both in the long-term (c. 1980s to present) and short-term (last 12 years) are also a substantial part of the report (Fig. 2). The next report, due in 2025, will cover the period 2019–2024. Unfortunately, according to the official website, figures shown by the reporting periods are not directly comparable due to changes in methods or variations in the amount and quality of data over time. This is not surprising because data on species distribution in Article 12 reports is far from being homogeneous across the EU (Fig. 3).

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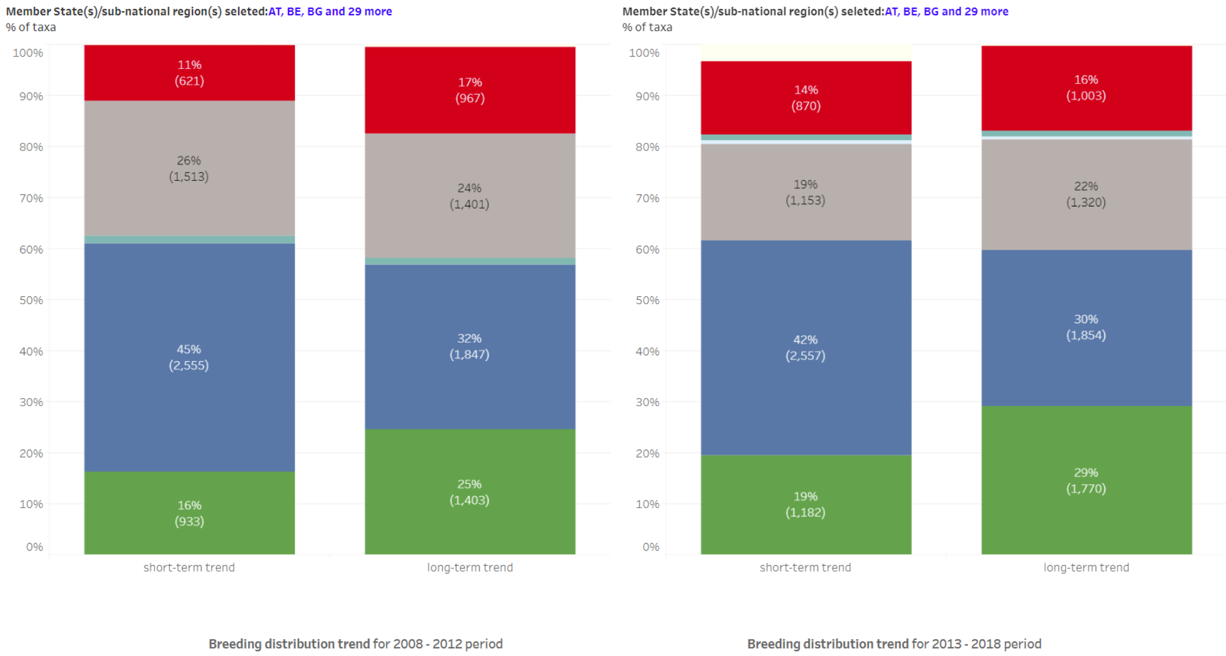

Figure 2. Proportion of breeding birds having reported increasing (green), stable (blue), unknown (grey) and decreasing (red) trends in distributions in the short- and long-term in the two last Article 12 reporting periods (2008–2012 and 2013–2018) based on data as reported from EU Member States (https://www.eea.europa.eu/themes/biodiversity/state-of-nature-in-the-eu/article-12-national-summary-dashboards-archived/breeding-population-and-distribution-trends).

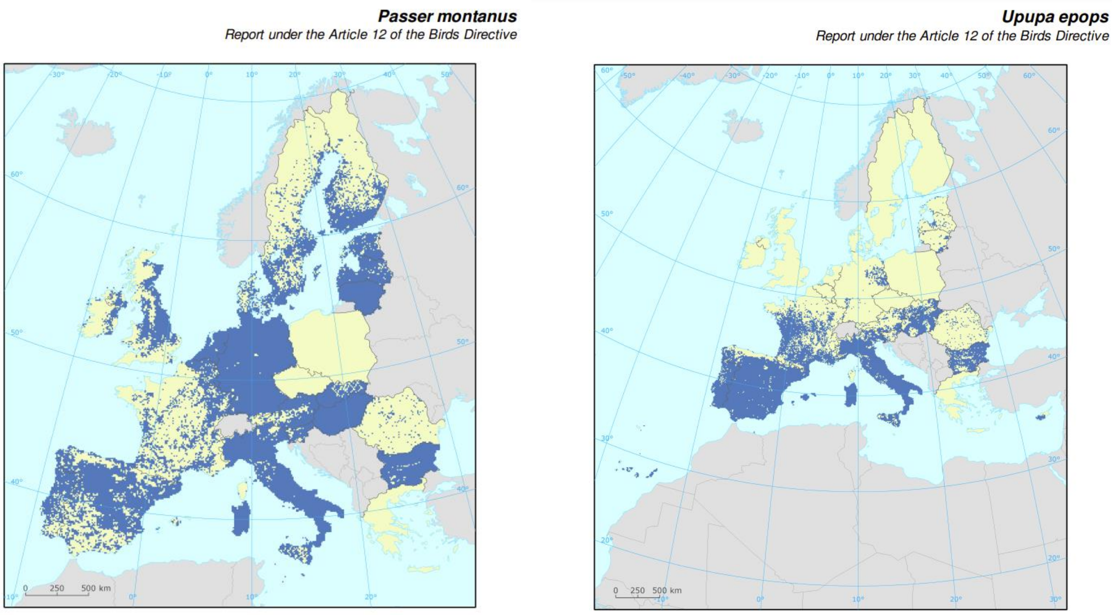

Figure 3. Examples of distribution for two farmland bird species (Eurasian Tree Sparrow *Passer montanus* (left), Common Hoopoe *Upupa epops* (right)) in the EU Article 12 reporting. Source: Report under the Article 12 of the Birds Directive for period 2008–2012.

National bird atlases are produced by national ornithological organisations, often with the support of national and subnational governments but with no direct linkage with EU policy (EBCC 2022). There is no harmonisation at a supranational scale since every country uses its own taxonomy, grid system,

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resolution, etc. National atlases are often repeated, typically after 15–25 years, and this allows to track temporal changes in bird distribution. However, the situation greatly varies among countries, and some have up to three editions while others have no atlas done so far (EBCC 2022). The publication of the European Breeding Bird Atlases (EBBA) coordinated by the EBCC allowed the generation of simultaneous and harmonised information of breeding bird distribution across European countries. EBBA2 and its online version (https://ebba2.info) represented a milestone for European ornithology and it currently constitutes the most updated source of information on distribution and abundance of breeding birds across Europe and on the changes in distributions. The time elapsed between EBBA1 (1980s) and EBBA2 (2010s) is c. 30 years.

EBBA2 is one of the biggest-ever citizen science projects focusing on mapping biodiversity (Keller et al. 2020). It standardised protocols and coordinated fieldwork in 48 European countries in an area of 11 M. km^2 between 2013 and 2017. The EBBA2 project collected information on the number of breeding birds of each species per atlas square of 50 x 50 km (50-km from here onwards), mapping breeding distributions for almost 600 species (both native and non-native) during 2013–2017. It is estimated that more than 120,000 fieldworkers have been involved in the data collection process (EBCC 2022). In parallel to the EU Commission, EBCC adopted the Handbook of the Birds of the World (HBW)-BirdLife species checklist for all its projects in 2017, including EBBA2, which should facilitate informing EU policy. Fieldwork for EBBA2 did not follow a common procedure in each country and the data sources varied among countries. Four main types of sources were identified: atlas data, monitoring data, casual observations and targeted EBBA2 surveys. Each country developed its own strategy to provide the data for EBBA2. This was seen as an advantage rather than a limitation because the different situations in each country could be considered. Nevertheless, this variety of data sources required common standards at the European level for a proper integration of the data. Two grid systems were used in EBBA2, depending on the type and purpose of each map. For breeding evidence, abundance and change maps, the 50-km Universal Transverse Mercator (UTM) grid that was used in EBBA1 was also selected for EBBA2. However, for the EBBA2 modelled maps (a novelty of the second atlas), the current European standard grid ETRS89-LAEA 10 x 10 km grid (10-km from here onwards) was employed. Birds are mobile species and can be observed far from the areas where they reproduce, e.g., as visitors during migration or during post-breeding dispersal. Standardised categories to determine whether a species is a possible (A), probable (B) or confirmed (C) breeder in the surveyed area were used for EBBA2. Depending on the characteristics of the observation in the field, it was assigned to a given atlas code, and the maximum atlas code recorded per 50-km square was used in EBBA2 to document the breeding evidence for that species in that square. Data from timed surveys was used to model the relative probability of occurrence of breeding birds in 10-km squares. Standardised data originated from any source that specified the time used to compile a complete list of observed breeding bird species. These data came from line transects or from combining several point counts. Based on a sample of timed surveys, probability of occurrence was modelled using eight different Species Distribution Modelling (SDM) techniques which included information on observed presence/absence of birds, environmental predictors, detection probability and spatial autocorrelation. As a final step, the modelled distribution was cropped to the broad patterns of a species range. Validation of the quality of the data was extremely important in EBBA2. Several online tools and protocols assisted national and European coordinators to check whether data (shown in preliminary maps and graphs) was consistent with previous knowledge on distribution and phenology or should be carefully revised (Keller et al. 2020; EBCC 2022).

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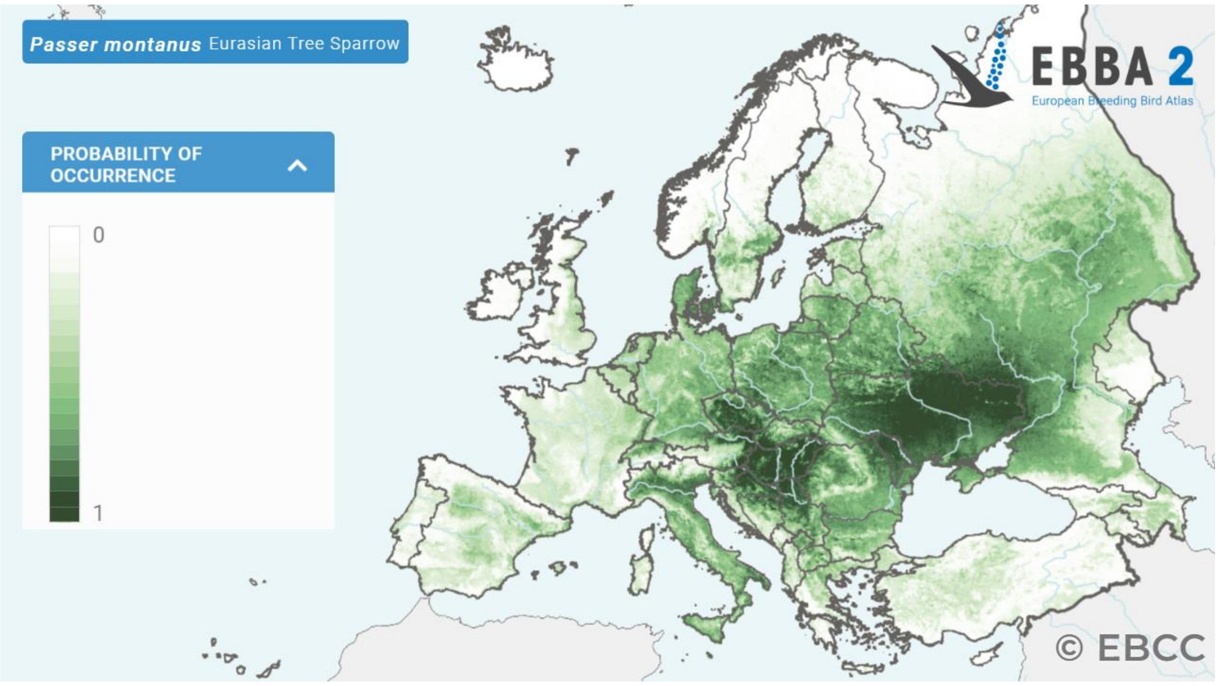
The huge effort conducted in EBBA2 allowed to determine the distribution at 50-km resolution of a total of 596 species, including 539 native species and 57 non-native species. Out of the 407 native species for which a change in 50-km distribution could be robustly assessed between the 1980s and 2010s, 187 showed an increase in distribution, 135 a decrease, and for 85 species distribution did not change or the trend was uncertain. By species ecological groups, the agricultural and grassland birds showed the largest distribution retraction (Keller et al. 2020). This is consistent with population declines in common farmland birds recorded in Europe because of agricultural intensification (Rigal et al. 2023) and justifies the focus of this showcase on farmland bird species.

EBBA2 did another large step forward in bird species distributions and generated for the first time 10-km modelled maps of probability of occurrence for the whole of Europe for a total of 222 species. Within the group of 84 bird species characteristic of agricultural and grassland habitats, a total of 52 had robustly evaluated 10-km modelled maps (Fig. 4). The 32 agricultural and grassland species for which these maps could not be built were mostly scarce or nocturnal species such as the Olive-tree Warbler *Hippolais olivetorum* or the Little Owl *Athene noctua*, respectively (Keller et al. 2020). One of the lessons learnt from EBBA2 is that modelling is a very robust tool, although it has clear limitations for species of restricted distribution or with low amounts of data. However, a visual comparison between 10-km distributions gathered in Article 12 reporting (Fig. 3) and EBBA2 (Fig. 4) shows the distinct quality of the final maps derived from these two processes. From our perspective, two key elements may help to understand these different results, and both are related to data flows and the degree of implication of stakeholders. First, in Article 12 reporting, all the information process is done by MS and no responsibility is taken at European level regarding the data flow. Therefore, Article 12 species' distribution maps simply merge the contributions from countries. Second, the role of ornithological organisations and ornithologists, usually the ones that have the best knowledge on species distribution, is not warranted in the process. In contrast, these elements were carefully taken into consideration in the process that resulted in EBBA2 maps.



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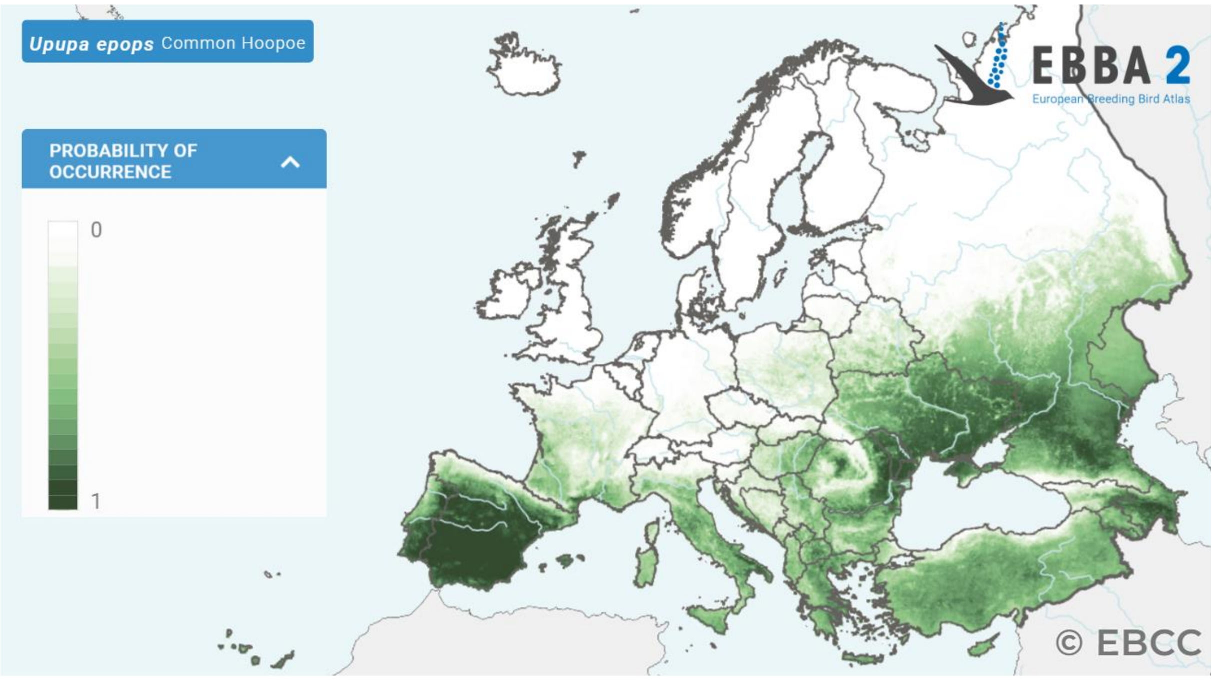

Figure 4. Examples of distribution for two farmland bird species (Eurasian Tree Sparrow *Passer montanus* (top), Common Hoopoe *Upupa epops* (bottom)) in EBBA2 (Keller et al. 2020; EBCC 2022).

1.2. Showcase goals

EBBA Live is the general name in which the idea of updating harmonised data on breeding bird distributions on a more frequent basis is further developed in EuropaBON WP5.1. under the concept European Breeding Bird Atlas Live Farmland (EBBALF). EBBALF provides the first attempt to generate an EBV on bird distributions across Europe since EBBA2 by developing maps of observed distributions for a set of farmland bird species at 50-km and modelling the probability of occurrence at 10-km scale, in this case for the period 2018–2022. In addition, EBBALF has developed maps of change in distribution between 2013–2017 (EBBA2 period) and 2018–2022. Importantly, this showcase is focussed on the use of common bird monitoring data compiled across Europe. The purpose of this specific data selection is to develop maps that reveal spatial patterns of change that maximise consistency with current knowledge on population trends of species at European level (www.pecbms.info). The products expected from EBBALF are a series of analyses and maps for European farmland birds, specifically: i) updated information on the observed species distribution at 50-km square resolution, ii) a gap analysis of the performance of the current coverage of bird monitoring data to update bird distributions, iii) updated 10-km modelled maps based on monitoring data for the period 2018–2022 covering the EBBALF study region, including an evaluation of model performance, and iv) maps of change in distribution between 2013–2017 and 2018–2022, including an evaluation of model performance. This project uses site-level monitoring data from the national common bird monitoring projects compiled at European level by the PECBMS project (Brlík et al. 2021; www.pecbms.info). This showcase should therefore allow us to evaluate the feasibility, robustness and interest of the stakeholders in the EBBA Live concept.

Conscious of the complexity of developing abundance maps based on counts from bird monitoring data at European scale (Brotons et al. 2005; Waldock et al. 2022), this first trial towards EBBA Live attempted to be less demanding in terms of integration of diverse abundance data across Europe.

Therefore, the showcase generated information on species occurrence rather than abundance data. However, the present deliverable includes an analysis on the relationship between the probability of occurrence (sum of occurrence probabilities resulting from EBBALF models at 10-km for the period 2013–2017) in each square of 50-km and EBBA2 abundance estimates (ANNEX V).

This showcase generated maps of breeding birds, i.e., maps showing the occurrence of the species while they are breeding. Many bird species perform seasonal short- or long-distance movements and mapping bird occurrence without taking this into consideration would produce maps that would be ecologically difficult to interpret, and so the information derived would be difficult to be used in conservation planning. Consequently, data used in EBBALF comes exclusively from breeding bird monitoring projects, in which non-breeding birds are excluded. Determining the breeding character of the observed birds is done by experienced fieldworkers that follow strict monitoring rules of interpretation of observations (Voříšek et al. 2008).

This showcase covers all EU27 countries, plus UK, Norway, Switzerland, Moldova and the Western Balkans. The farmland bird species included in this showcase consists of all species included in the Farmland Bird Indicator (FBI; www.eea.europa.eu/en/analysis/indicators/common-bird-index-in-europe) together with the rest of species categorised in EBBA2 as agricultural/grassland that occur in the study area (Fig. 5) according to EBBA2 (Keller et al. 2020).

2. Showcase participatory design

2.1. Stakeholders' engagement process

Methodology

EBBALF was led and managed by the EBCC and its partner organisations, in close cooperation with the EuropaBON stakeholders. The methodology used to develop the participation of the project stakeholders was based on the development of governance protocols on project aims, data sharing and output features that were based on EBCC proven governance.

The idea of developing a case study to attempt to update bird distributions in the context of the EuropaBON Birds Directive showcase was developed by the EBCC and discussed in the final EBBA2 workshop held in the XXII EBCC conference in Lucerne, Switzerland, in 4-8 April 2022. In that workshop there was a general agreement to develop the project as a continuation of EBBA2, following the EBBA2 governance principles developed and approved by national coordinators. In short, these principles state that national coordinators will share monitoring data to develop the project objectives and they will be included in the discussions on the product quality and use, including the potential publicity of project outputs. No printed publication was expected out of EBBALF, but an online portal for stakeholder's use had to be developed. As in EBBA2, the ownership of the raw data is retained at the national level, but the products (maps) are owned by the EBCC. The governance protocol was a key issue to mobilise tens of thousands of highly validated surveys from all participating countries, as well as a key element for the future implementation of products harmonised at the European level by national organisations. This is very important to mention because it opened the possibility of data

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providers to be also among the final users of EBBALF products, which strengthens their interest and involvement in the project.

After the project launch, a first meeting with the EBCC Board was held on 19/04/2022 to develop the project governance. Representatives of the EBCC Board, PECBMS and EBBA2 constituted a steering committee for the EBBALF project. The steering committee set up a project office to coordinate the stakeholder participation, data flow and modelling. This office was established at the research institution CREAF and its partner ornithological organisation, the Catalan Ornithological Institute (ICO). The project was assisted by modelers from the Spatial Modelling Group (SMOG) of the EBCC, who supervised the modelling framework of the project.

The essential role of product users was developed in the context of the EuropaBON. In addition to the alignment with the outcomes of other work packages, a series of meetings with stakeholders from the EU Commission were organized to determine the specific needs from the policy arena. In particular, discussions in the workshop in Troia, Portugal, in April 2023 revealed to be very important, among others, to effectively implement the complementary roles of Member States (MS) and the EU Commission.

Key stakeholders: users and data providers

EBBALF data providers are the organisations responsible for national bird monitoring across the EU and in neighbouring countries, which are coordinated by the EBCC, mostly in the context of the network of common bird monitoring data constituted through the PECBMS site-level data project (Fig. 5). A total of 50 organisations from 35 countries participated in the project (ANNEX I). The main users of the project outputs at European level are the Directorate-General for Environment (DG ENV), the Joint Research Centre (JRC) and the European Environment Agency (EEA).

Figure 5. Area and countries included in the EBBA Live Farmland project. See ANNEX I for a list of involved ornithological stakeholders per country.

Stakeholder representativeness and gaps

The stakeholder representativeness of data providers was very high (ANNEX I). From an ornithological perspective, only three countries within the study area, Malta, Albania and Kosovo, did not have any representative in the showcase. In the latter two cases, national coordinators from the Albanian Ornithological Society and the Ministry of Economy and Environment of Kosovo showed their interest in participating in the project but could not provide any monitoring data for this project. Malta is the only EU member that has no common bird monitoring scheme and could not provide any data for this showcase. However, the BirdLife partner in the country is about to launch a scheme of such characteristics, which suggests that the future implementation of the EBBA Live concept could also be developed with the country's participation. From the policy perspective, three institutions of the EU Commission, DG ENV, EEA and JRC participated in the process. No environmental agency from any MS or ministry has directly participated in the process of development of this showcase, but Biodiversa+ members have been informed on the project development.

2.2. Key inputs from stakeholders

Stakeholders from the EU Commission (JRC, EEA and DG Env) and from the EBCC (national coordinators and modellers) provided relevant input for the project development. The diverse nature and interests of this wide group of people and organisations is one the fundamental pillars of EBBALF.

The Joint Research Centre (JRC) provided key input in the meetings conducted in April 2022 and November 2022 by stressing the importance of focussing on farmland species in this showcase. At that moment, the Farmland Bird Index (FBI) was a key element in the discussions around the implementation of the proposed Nature Restoration Law, so that including these species in the proposal would be important for future assessments related to farmland bird distribution changes.

The European Environmental Agency (EEA) provided relevant input in terms of the harmonization of results. The experience of this institution on the Birds Directive and the Article 12 reporting was crucial to establish some of the priorities in terms of the showcase outputs. Of particular relevance was the need to build maps that were harmonised among countries, so that the European maps produced in EBBALF could complement the official maps reported by MS. It was also mentioned that consistency between the two scales should be maximised and thus the same data should be ideally used in MS reporting and in this showcase. In addition, these project partners highlighted the importance of generating information on change in a time frame that should be consistent with policy needs (e.g., updated every 6 years, as in the Article 12 reporting).

DG ENV also provided crucial input in the development of the project. They stressed the relevance of producing indicators to evaluate the achievement of EU environmental targets, such as agri-environmental schemes. Their input on the interpretation of results for practical reasons was very relevant, in particular the relationship between probability of occurrence and abundance. They also stressed the importance of including in the project or, whenever possible, a set of species for which special protection plans should be developed, such as game birds.

The network of national coordinators of common bird monitoring projects involved in PECBMS was absolutely essential for this showcase. Without their commitment and work, the project could not

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have been developed. On 10th February 2023, a meeting with them was organised. They agreed on the provision of data to the EBCC for the development of this EuropaBON case study but always under the condition that raw data would not be shared to third parties. The EBBALF project follows the same data policy of EBBA2, which in short is: 1) raw national data are owned by their providers (copyright is at national level), and 2) European aggregated data are owned by EBCC on behalf of its partners across Europe (copyright is at EBCC level). Following the agreement with national coordinators, modelled maps at national scale have not been developed and all outputs are made at European level. Apart from data and governance issues, a schedule of data revision was developed together with the principles and technical approach. National coordinators provided input on potential errors in data (e.g., pending revisions of non-breeding birds in the PECBMS site-level database).

The Spatial Modelling Group (SMOG) of the EBCC is composed of expert modellers of spatial distribution of birds. This group met in February 2022 and provided key input on technical aspects such as making validations at regional scale to identify where data are missing and whether validations are acceptable or not for parts of Europe. It also considered that despite the difficulties to find change in occurrence in such a short time interval, the difference between the two models (one per period) was the best approach to start (as done e.g., in the latest Swiss Breeding Bird Atlas; Knaus et al. 2018).

Finally, the EBBALF steering committee of the EBCC, as a dedicated group of the EBCC Board and leading partners from PECBMS, EBBA2 and EuroBirdPortal not only supervised the project development according to EBCC principles but also provided important insights. Among them, we could cite the need to include future data from all online data collection portals (Ornitho, eBird, BirdTrack, Observation.org etc) or the importance of keeping the consistency of change maps with PECBMS results by using the same set of data.

3. Policy targets

3.1. Reporting needs and data gaps

As indicated by its title, the Birds Directive is a clear umbrella for the development of this showcase. The data flowing to the reporting of the Birds Directive (2009/147/EC) does not systematically originate from standardized monitoring surveys. Expert opinion, for instance, is frequently used to assess the conservation status of specific species/habitats and it integrates a wide variety of species data that do not follow the same standard harmonization procedures in all MS. This is particularly relevant for the EBV "Species distribution of terrestrial birds", for which maps provided by national ministries and agencies do not always represent the actual species distribution but a series of observations gathered with different effort depending on the country or region.

Article 12 reporting of the Birds Directive is the official mechanism to compile information on the state of bird populations in the EU. Every six years MS are asked to provide, among others, information on the distribution of all bird species at 10-km scale in the 6-year reporting period using the official EU coordinate reference system and a common taxonomy, and statistics to evaluate the change in distribution. The next reporting period is 2019–2024 (https://cdr.eionet.europa.eu/help/birds_art12). MS compile the information based on available data, often based, at least partially, on data provided by national organisations involved in bird monitoring and atlas work. The amount and quality of the provided information greatly depend on countries' capacity (e.g., fieldwork coverage, coordination structure and data flow) and the final European distributions are not harmonised between countries and often even within countries.

The EuropaBON project has shown that bird species distributions are ranked to be the 9th top ranked EBV – Essential Ecosystem Services Variable (EESV) by national policy makers, while it is considered to be not properly monitored in the majority of EU countries (Moersberger et al. 2022). EuropaBON WP3.3 (Identification of current monitoring workflows and bottlenecks) reports the need of producing an EBV for Species distributions of all terrestrial birds at a spatial resolution of at least 10-km and a temporal frequency of 3–6 years.

Therefore, one of the remaining challenges is to harmonise data flows and integration at local and subnational levels to improve the quality of the resulting EBVs. In this sense, the current EBV generated in this showcase could eventually be compiled at different scales, such as a product of the national data aggregation in the Birds Directive reporting process or as an EBV produced at EU level for the EEA.

3.2. Cross-policy contributions

This showcase represents a demonstrative case study on how biodiversity monitoring data could be used to derive harmonised information on distribution across European MS. In this context, the procedures implemented here could be useful to build similar EBVs for non-bird species included in the reporting of the Article 17 of the Habitats Directive. The feasibility of the approach essentially depends on the quality of the monitoring data, and few groups have a comparable situation to that of birds. Undoubtedly, butterflies are one of them. The availability of Butterfly Monitoring Schemes and the complementary implementation of the standardised 15-min timed counts (Roy et al. 2020) could be a very useful source of information for this modelling approach. Other groups included in this Directive, such as mammals, amphibians or reptiles have much less standardised data and data flows.

The Nature Restoration Law is another key potential application for the EBVs flows described in this deliverable. More specifically, the possibility to account for spatial patterns of distribution change will allow the identification of areas with recent decreases in populations. One particular use of EBVs information would therefore be that of identification of priority areas for restoration as areas that have either more strongly lost species distributions or done so more recently. However, the identification of these areas does not allow to directly infer which have been the driving factors of these losses and the actions to be applied for their restoration. This will certainly require the integration of additional information and analyses to better understand the underlying causes of the observed change, and therefore recommend robustly informed conservation policies in the areas where the species have decreased or otherwise increased (suitable areas), depending on the case.

4. Essential Biodiversity Variables design and outputs

4.1. EBV design characteristics

EBV description

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EBV: Species Distributions Terrestrial Birds
Realm: Terrestrial
EBV class: Species Populations
EBV name: Species distributions of terrestrial birds
Definition: The presence/absence or probability of occurrence of each European terrestrial bird species within contiguous spatial units (grid squares) across the EU over time.
Metric: Binary presence/absence - Probability of occurrence
Spatial resolution unit: 1 × 1 km – 10-km
Temporal resolution unit: 3 or 6 years
Taxonomic/ ecosystem focus group: All terrestrial birds of the EU (taxonomy based on HBW and BirdLife Taxonomic Checklist, with a focus on those bird species that are officially recognized in the List of birds of the EU).

Extent and spatiotemporal resolution

EBBALF's first phase has focused on a subset of countries. Despite not all countries had reported data to the EBCC (as detailed in section 2), the entire study area utilized for the dataflow and workflow encompassed the following 39 countries: Albania, Andorra, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Irish Republic, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Moldova, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom.

The following countries, which were used in the EBBA2 Atlas, were excluded during this first phase of the EBBALF project: Armenia, Azerbaijan, Belarus, Georgia, Iceland, Kazakhstan, the European part of Russia, Turkey, and Ukraine.

EBBALF encompassed an extended area of 5,050,025 km^2, accounting for 45.6% of the total area covered by the EBBA2 Atlas (11,075,000 km^2).

The primary spatial resolution employed was the standard and official European Terrestrial Reference System (ETRS) 10-km grid. This grid system was utilized for the allocation of observation data to specific grid squares, the development of predictors, and the generation of modelled maps. The 10-km grid is projected in the Lambert Azimuthal Equal-Area (LAEA) projection and adheres to the cartesian reference frame ETRS89 (Keller et al. 2020). To achieve the goal of reducing strong biases caused by survey density, the same 50-km grid used in the EBBA2 Atlas was employed to thin data on highly sampled places (see data processing section in Keller et al. 2020).

In accordance with the suggestions developed in WP3.3, the birds showcase encompasses two 5-year periods: 1) the same period as in the EBBA2 Atlas, spanning from 2013 to 2017; and 2) the new period following the end of EBBA2 fieldwork, that is, 2018–2022. The latter time window is entirely included within the next EU Article 12 Birds Reporting period (2019–2024). Both periods relied on data collected during the designated birds breeding season, which occurs annually from April to July. Conversely, the development of the predictors consisted of an upscaling of the temporal resolution, transitioning from daily or monthly data to the mean values of the years within each respective period (more information can be found in the next section).

4.2. Input biodiversity data

Data

EBCC is the European-level integration node of three different integration initiatives: the European Breeding Bird Atlas – EBBA2, the EuroBirdPortal – EBP and the Pan-European Common Bird Monitoring Scheme – PECBMS. Although these integration initiatives are carried out by the same institution, data integration differs among them. Most of the data used for producing the EBBALF maps are based on bird monitoring data collected in the PECBMS site-level database (SLD).

PECBMS is a European-level integration initiative whose main goal is to collect and harmonize data from large-scale and long-term bird monitoring schemes in European countries to generate indicators of the general state of nature (Table 1). The common bird monitoring schemes that feed data to this initiative are mainly based on fieldwork of volunteers and follow a standardized methodology and formal design (Voříšek et al. 2008). Most of the monitoring schemes participating in this initiative started during the period 1980–1990. PECBMS integrates data from 34 national and sub-national integration nodes. The coordination unit of this initiative (European-level integration node) is the Czech Society for Ornithology (CSO). This coordination unit integrates data on species population trends of common birds reported by all the national and subnational nodes on an annual basis and calculates European-wide long-term trends of species populations (170 species), as well as a set of wild bird indicators (all common birds – 168 species, common farmland birds – 39 species, and common forest birds – 34 species).

The multi-species population indices (indicators) produced by PECBMS have been the main outputs used for various policy purposes. Our European common bird indicators are included among the Streamlining European Biodiversity Indicators (SEBI), EU common bird indicators are part of the Indicators of Sustainable Development of the EU, and the European FBI has been accepted as biodiversity indicator for EU's Structural Indicator. National versions of FBI have also been approved as the Regulation indicators in the EU's Rural Development Plans (Council Regulation, EU Commission No 1698/2005). The indicators produced by PECBMS have been used by other international institutions too, such as the Organisation for Economic Co-operation and Development (OECD), United Nations Environment Programme (UNEP), EEA, Secretariat of the Convention on Biological Diversity (CBD), or the European Court of Auditors among others. The indicators have also been included in the Living Planet Index (LPI). PECBMS also contributed to the latest EU indicators in relation to the last update of the European Red List of Birds, published in October 2021. PECBMS also constitutes a network of cooperation among organisations. As such, it provides a robust platform to periodically share and update knowledge on bird monitoring issues (from fieldwork design to statistical modelling) among its partners, which becomes of great value at national level to enhance the standardisation of multiple reporting tasks, such as that of the Birds Directive (Article 12 reporting).

The PECBMS SLD consists of annual breeding bird abundances at georeferenced census sites from 40 monitoring schemes (30 European countries). Generally, these are common bird monitoring schemes and a few specific monitoring schemes. It contains information from 30,790 monitoring sites and 451 species. PECBMS SLD is periodically updated by national coordinators on a voluntary basis (Table 1).

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A specific workshop with PECBMS SLD national coordinators was carried out on 19/05/2022 to discuss the project and reach agreement on data mobilization, validation, and product sharing. Countries that do not participate in the PECBMS project yet (Moldova, North Macedonia, Bosnia and Herzegovina, Serbia) provided available monitoring data for the study period. Only Malta, Albania and Kosovo could not provide any bird monitoring data (Fig. 6; ANNEX I). In this showcase we named PECBMS+ to the data used in this project, which is basically PECBMS data plus data from these few schemes that are not integrated in PECBMS yet (Table 1).

Table 1. Raw data features.

DATASET TITLE	PECBMS+ (*)
Raw data collection design	Raw data come from common bird monitoring projects. These projects use a variety of sampling methods (point counts, line transects and territory mapping) to record the abundance of breeding bird species in surveyed sites across European countries. Each country has its own spatial sampling design based on the different environmental strata and fieldwork capacities.
Monitoring programs	Coordinated program
Types of data access	Restricted access, under request
Data repositories	PECBMS site-level data (SLD), EBCC
Persistent identifier(s)	Not available
Metadata description	Best possible yearly estimations of site-level counts of breeding bird species, based on data from common bird monitoring projects.
Other provenance information	Regional monitoring data not included in PECBMS yet (Moldova, Western Balkans and other subnational monitoring projects; e.g., Balearic Islands)

(*) Monitoring projects including PECBMS plus the ones included in the last row of the table.

All the data provided contains the following information: survey id, 10-km square id, birdlife species id, country id, field method used, year of survey, and duration of survey (minutes). For the purpose of this study, we transformed the bird counts from PECBMS+ into presence/absence data (occurrence records). See section 1.2 for more information.

We used two different datasets to produce and validate the models of probability of occurrence for 2013–2017 and 2018–2022. Each dataset had particular characteristics and accomplished specific goals. The following is a description of each of these datasets:

- <u>2013–2017 Complete Dataset</u>: this dataset was used to generate maps for the EBBA2 period (2013–2017) using the EBBALF modelling approach (see section 4.3. for more details). It corresponds to EBBA2 timed visits, which consists of standardised data originating from any source that specifies the time used to compile a complete list of observed breeding bird

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species. Different types of standardised data compiled during the EBBA2 period were used, such as data from monitoring surveys, complete lists from online portals (e.g., Ornitho) and atlas specific censuses. The density of such timed visits greatly varied among countries and regions. EBBA2 uniformised this uneven coverage by selecting a maximum of ten randomized 10-km squares for each 50-km square within the EBBALF study area. In this project, the only difference between this dataset and that used in the EBBA2 modelling is the lack of data from Iceland, Russia, Ukraine, Belarus, Turkey, and the Caucasus, which were not included in the showcase (Fig. 5). We split this dataset between train (subset of 70% of data) and test (30%). The former was used to produce the weighted Ensemble Prediction (wEP) for each species and the second dataset to validate the wEPs.

- <u>2018–2022 Complete Dataset</u>: this dataset was used to generate maps for the period 2018–2022 using the EBBALF modelling approach (see section 4.3. for more details). These maps were produced using the PECBMS+ SLD (Table 1). As in EBBA2, we uniformised the uneven coverage of the PECBMS+ network of monitoring sites by selecting a maximum of ten randomized 10-km squares for each 50-km square within the EBBALF study area (Fig. 6). For each of these selected 10-km squares we selected a maximum of 5 bird surveys, prioritizing those of higher numbers of farmland bird species. We used this dataset to produce the wEP for each species and, using the same procedure as for the 2013–2017 complete dataset, to split the dataset between train and test to produce the spatial validation procedures.

As for the maps of probability of occurrence, change maps were produced after a specific data selection process. While the complete datasets mentioned above were generated to produce maps that would allow to produce the best modelled maps of species' distribution for each of the two specific time periods (2013–2017 and 2018–2022), the datasets used for the change maps (so-called comparable datasets) were not selected to maximise the best distribution per period but the most reliable change between the two periods. For this reason, EBBA2 timed visits (which derive from various field methodologies) were not used at all, and these analyses relied exclusively on data from the PECBMS network of monitoring sites, which is specifically designed to derive comparable information on change. However, not all PECBMS sites were selected because not all monitoring sites are carried out exactly under the same yearly frequency. Thus, the selection procedure of sites was as follows: (1) we selected 10-km squares with PECBMS data in the two periods; (2) from these squares, we selected only those whose monitoring sites were surveyed in the two periods; i.e., surveyed exactly on the same locations; (3) for these squares, we selected a single monitoring site at random to harmonise the amount of sites across 10-km squares; (4) since each period corresponds to 5 years and not all years were always surveyed, we selected the same number of surveyed years per site, so that some sites were visited 5, 4, 3, 2 or 1 year, depending on the availability of data per period and site; and finally (5) we randomly split the dataset between train (70%) to develop the SDMs and test (30%) to produce the change validation procedures. This process ended in two comparable datasets located in the same squares (Fig. 6), one for each period. A modelled map was produced for each period and the values of the change map were calculated as differences, square by square, between the values of these two maps.

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Figure 6. Location of PECBMS+ monitoring sites included in EBBALF for the update of the 10-km probability of occurrence maps (left) and location of PECBMS monitoring sites used to generate maps of change in the probability of occurrence between the periods 2013–2017 and 2018–2022 (right). Note: PECBMS refers to the set of monitoring schemes that participate in the PECBMS SLD, while PECBMS+ also includes other monitoring initiatives not integrated in PECBMS (Table 1).

Bird species included

In total, 596 species were recorded breeding in Europe in the 2010s, including 539 native species and 57 non-native species (Keller et al. 2020). In the EU27 the total number of breeding bird species is 472, including 55 non-native species (Keller et al. 2020). The Article 12 of the EU Birds Directive attempts to report on the population status of all wild bird species occurring within each country in a standardized manner.

The particular selection of farmland species was based on the information retrieved from the EBBA2 and includes a total of 50 species that breed in agricultural and grasslands in the EU (Table 2). The list of 50 farmland species was selected according to criteria including lessons learned during previous species modelling experiences for EBBA2. The 39 bird species included in the FBI (https://agridata.ec.europa.eu/extensions/IndicatorsEnvironmental/FarmlandBirdsIndex.html) have been included. Almost all European farmland bird species are included in the project and only five species with very restricted ranges across the EU were excluded (Table 2).

Table 2. Bird species selected for the EBBA Live Farmland project (EBBALF). Only 5 agricultural /grassland bird species were excluded because of their very restricted ranges across the study area, namely, Demoiselle Crane *Anthropoides virgo*, Great Bustard *Otis tarda*, Steppe Eagle *Aquila nipalensis,* Long-legged Buzzard *Buteo rufinus* and Red-footed Falcon *Falco vespertinus.* A total of 16 species (from the 50 selected farmland species) are currently included in the Annex I of the Birds Directive.

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Scientific name	English name	FBI	Annex I
Alauda arvensis	Eurasian Skylark	yes	no
Alectoris rufa	Red-legged Partridge	yes	no
Anthus campestris	Tawny Pipit	yes	yes
Anthus pratensis	Meadow Pipit	yes	no
Athene noctua	Little Owl	no	no
Bubulcus ibis	Cattle Egret	yes	no
Burhinus oedicnemus	Eurasian Thick-knee	yes	yes
Calandrella brachydactyla	Greater Short-toed Lark	yes	yes
Ciconia ciconia	White Stork	yes	yes
Circus pygargus	Montagu's Harrier	no	yes
Coracias garrulus	European Roller	no	yes
Corvus frugilegus	Rook	yes	no
Coturnix coturnix	Common Quail	no	no
Crex crex	Corncrake	no	yes
Emberiza calandra	Corn Bunting	yes	no
Emberiza cirlus	Cirl Bunting	yes	no
Emberiza citrinella	Yellowhammer	yes	no
Emberiza hortulana	Ortolan Bunting	yes	yes
Emberiza melanocephala	Black-headed Bunting	yes	no
Falco naumanni	Lesser Kestrel	no	yes
Falco tinnunculus	Common Kestrel	yes	no
Galerida cristata	Crested Lark	yes	no
Galerida theklae	Thekla's Lark	yes	yes
Hirundo rustica	Barn Swallow	yes	no
Lanius collurio	Red-backed Shrike	yes	yes
Lanius excubitor	Great Grey Shrike	no	no
Lanius meridionalis	Iberian Grey Shrike	no	no
Lanius minor	Lesser Grey Shrike	yes	yes

Lanius senator	Woodchat Shrike	yes	no
Limosa limosa	Black-tailed Godwit	yes	no
Linaria cannabina	Common Linnet	yes	no
Melanocorypha calandra	Calandra Lark	yes	yes
Motacilla flava	Western Yellow Wagtail	yes	no
Oenanthe hispanica	Black-eared Wheatear	yes	no
Passer hispaniolensis	Spanish Sparrow	no	no
Passer montanus	Eurasian Tree Sparrow	yes	no
Perdix perdix	Grey Partridge	yes	no
Petronia petronia	Rock Sparrow	yes	no
Pterocles alchata	Pin-tailed Sandgrouse	no	yes
Pterocles orientalis	Black-bellied Sandgrouse	no	yes
Saxicola rubetra	Whinchat	yes	no
Saxicola torquatus	Common Stonechat	yes	no
Serinus serinus	European Serin	yes	no
Streptopelia turtur	European Turtle-dove	yes	no
Sturnus unicolor	Spotless Starling	yes	no
Sturnus vulgaris	Common Starling	yes	no
Sylvia communis	Common Whitethroat	yes	no
Tetrax tetrax	Little Bustard	yes	yes
Upupa epops	Common Hoopoe	yes	no
Vanellus vanellus	Northern Lapwing	yes	no

Data validation

Managing large amounts of data coming from different sources required substantial efforts in data validation. Suspicious data were inspected at species level. An automatic filter detected suspicious species occurrences (defined by the geographic coordinates of the survey) outside the known breeding distribution at 50-km level in EBBA2 (period 2013–2017). Species occurrences flagged by the filter were not removed but checked individually for plausibility. Reports on suspicious data were discussed with national coordinators for a final approval or removal in the database (Fig. 7).

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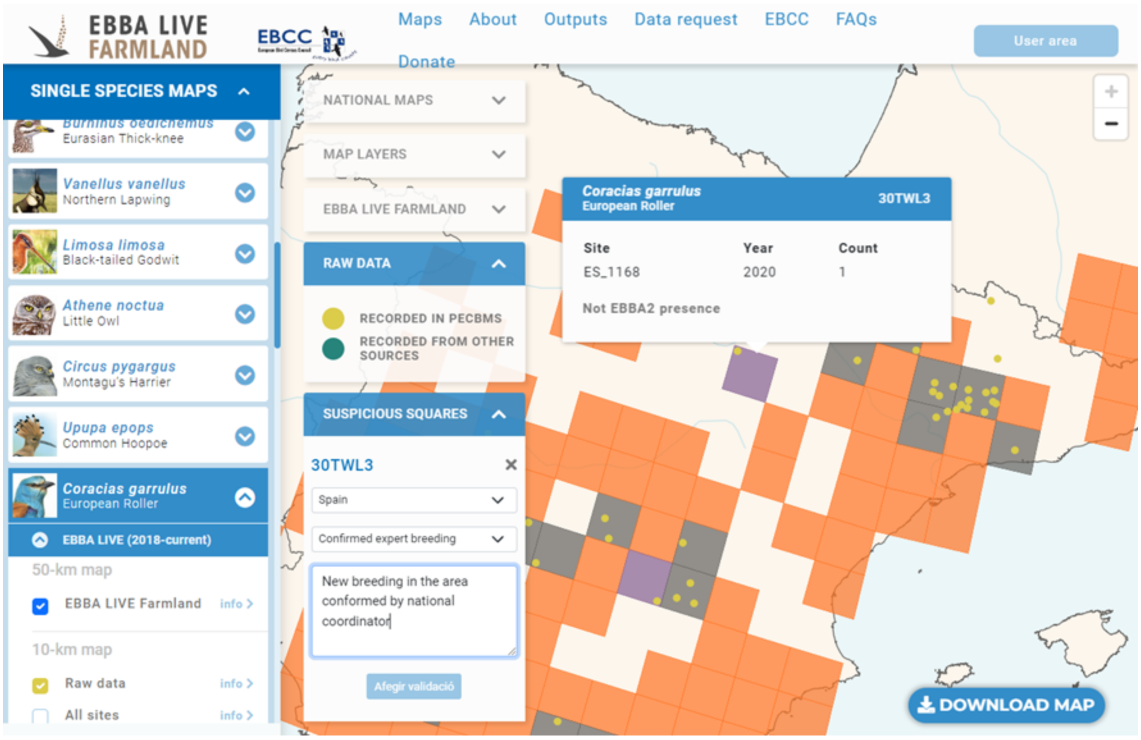

Figure 7. Data validation tool developed for the EBBA Live Farmland project (EBBALF). The location of a species is shown in a map. When the location was out of the EBBA2 distribution (period 2013–2017) it was flagged with a purple square and this was sent to national coordinators for confirmation or rejection (mainly data processing error, field misidentification or non-breeding bird).

Analysis at 50-km scale

A first analysis at 50-km scale was done with a double objective: (1) to map observed distributions of farmland species at 50-km scale based on monitoring data (PECBMS+) compiled by the European common bird monitoring network in the period 2018–2022; (2) to analyse gaps in data availability based on a comparison between the 50-km map of observations collected by the monitoring sites mentioned above and the intensive atlas work done in 2013–2017. This analysis was based on the assumption that the observed 50-km distribution of bird species in the period 2013–2017 (during a huge effort of coverage for the atlas) was the best proxy of that of the period 2018–2022; i.e., that variations in the number of occupied 50-km squares between the two periods were much more closely associated with differences in coverage than to real changes in distribution. This allowed to assess the quality of coverage of the network of PECBMS+ monitoring sites for the 50 farmland birds both for the whole of the study area and per country, expressed as the percentage of species for which the number of 50-km squares in which species occur in PECBMS+ data for the period 2018–2022 were lower than 50% in relation to the total number of 50-km squares reported in EBBA2 (period 2013–2017). In addition, it proved the capacity of bird monitoring data to properly update the observed species distributions. In other words, it showed the limitations in generating species' maps without modelling. Finally, this analysis also allowed us to determine the countries in which the monitoring coverage should be ideally reinforced, at least for farmland birds and in comparison, with other countries that have better coverage for this particular group of species (see output maps and ANNEX VI).

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Representativeness assessment

In both the EBBA2 Atlas and EBBALF, survey data were aggregated to the reference 10-km grid. This process might partially homogenize geographical data and alleviate geographical biases. However, despite this process, substantial differences persisted in both the number of sampled 10-km squares (sampling coverage) and the quantity of surveys conducted within each 10-km square (survey sampling size) between the two periods.

A first analysis of the 50-km squares sampled, which can be found in the main results, indicates a decrease in data coverage during the 2018–2022 period. Conversely, the implications arising from differences in survey sampling size were addressed and corrected through the process of modelling the detectability (refer to the *Detection Probability* section for more information).

To mitigate strong geographical biases, a filter was employed to reduce over-aggregated 10-km squares in highly sampled areas (e.g., Netherlands, Belgium, and the United Kingdom). This methodology was thoroughly described in the EBBA2 Atlas (Keller et al. 2020), and we systematically applied this process for the complete datasets. Conversely, the comparable datasets were utilized for predicting the distribution change, so we incorporated additional filters to avoid biases in modelling the change (see *Data* section for specific characteristics of both complete and comparable datasets). However, we deliberately did not reduce the over-aggregated 10-km squares (as it was done in the complete datasets) with the aim to: (1) analyse the impact of reducing over-aggregated 10-km squares on both the spatial and change performance of the SDMs, and (2) avoid the statistical consequences of reducing the sampling in over-aggregated areas (see ANNEX IV for more details on the methodology implemented to conduct this exercise).

4.3. The EBV model

The EBBALF modelling framework was designed to determine the 10-km distribution of farmland bird species in Europe, and to explore how it has changed in recent years. It relied on site-level bird monitoring data collected from PECBMS, spatially structured within 10-km grid squares and spanning the period 2018–2022. The EBBA2 modelling structure was used as the basis of the EBBALF modelling framework.

Species Distribution Models (SDMs) generated various predictive maps of the probability of occurrence, which served for the purposes of updating distributions and exploring how they have changed over time (see maps D to G in Fig. 8). The key outputs were updated maps for 2018–2022 (map G in Fig. 8) and change maps between 2013–2017 and 2018–2022 (map I in Fig. 8), while the others were used as part of the modelling framework. All modelled distributions were exclusively generated using the ensemble predictions of five independent modelling approaches (see next section entitled *Species Distribution Models* for more information). Predictions were produced within each European species' range, which derived from EBBA2 data, plus recent colonisations (no capacity to detect range contractions in the current phase of the project). Variations among maps lay from the use of either the complete input data (A and C, the best approach for generating modelled maps for a given period; Fig. 8) or only comparable PECBMS data from the same surveys on both periods (B, the best approach to model change between periods; Fig. 8), and also the use of environmental predictors specific for each period.

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Spatial validation was parameterized with the AUC statistic, comparing the predictive maps against independent observed data. The 2013–2017 predictive map (D; Fig. 8) was visually validated against the EBBA2 Atlas map (H; Fig. 8) because the modelling framework was slightly different and statistical validation was not possible. The 2018–2022 predictive map (G; Fig. 8) was spatially validated using AUC values (satisfactory performance at AUC > 0.7) for the entire species range and at PECBMS bioregion level (Fig. 9). The predicted change map was generated by subtracting the probability of occurrence of F to E. Negative values (in orange) represent places facing extinction processes, while positive values (in blue) represent colonisation ones. To validate the predicted change, we generated the accuracy and bias metrics through a comparison against observed change data from map B, following Rapacciuolo's et al. (2014) method also at the PECBMS bioregion level (Fig. 9). Confidence in the model to represent actual distribution change was established when accuracy was > 0.7, and confidence that the model did not overestimate colonisation or extinction was established within a bias range of –0.25 to 0.25. For change maps, if the E and F predictive maps had AUC > 0.7, and the change validation metrics for the change map laid inside the established intervals, it was assumed that it properly represented the species breeding distribution change, and therefore the I map was displayed. Additionally, the observed prevalence map (J; Fig. 8) was employed to visually validate the change within each PECBMS region, although it was not included in the main output.

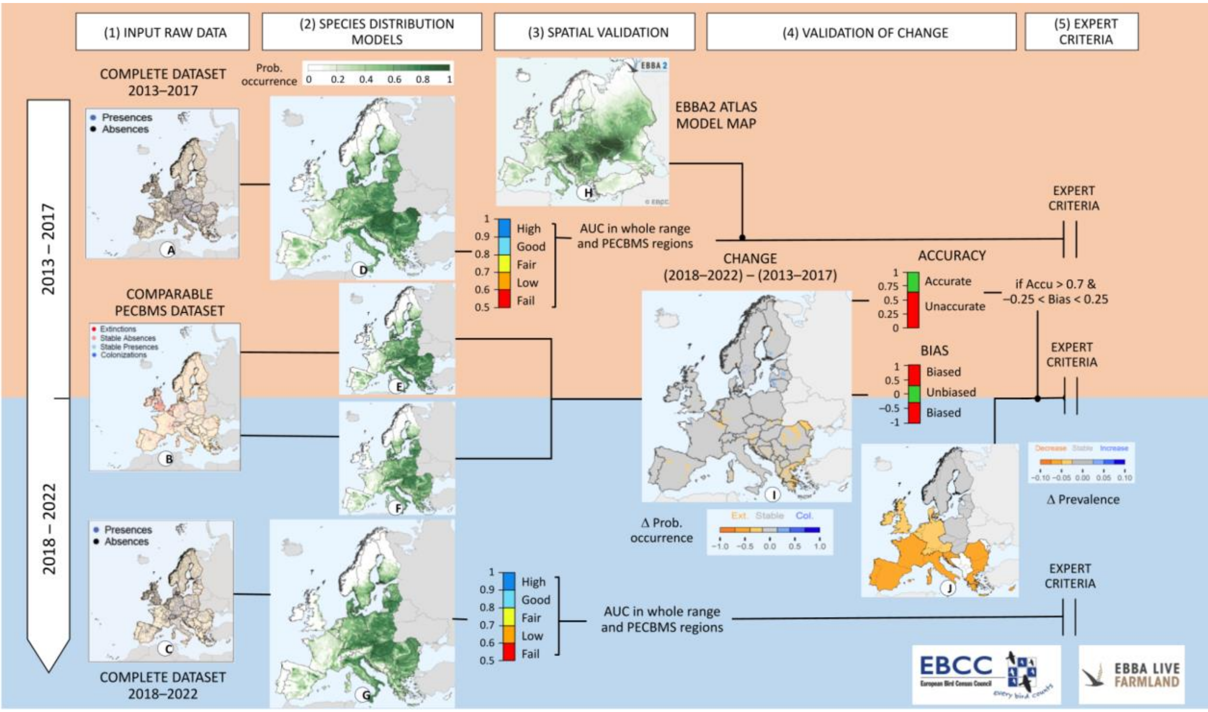

Figure 8. Modelling framework used in the first phase of the European Breeding Bird Atlas Live Farmland (EBBALF) and inspired by the EBBA2 modelling structure to determine the 10-km distribution of farmland bird species in Europe, and to explore how it has changed in recent years.

The final deliverable output comprises four case study examples of (1) the EBBA2 Atlas predictive map (H) and the 2013–2017 map from the EBBALF project (D), (2) the predictive map for 2018–2022 (G), along with spatial validation metrics for the entire species range and at PECBMS bioregion level, and (3) the predicted change map (I) accompanied by change metrics for the entire Europe and at PECBMS

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bioregion level. Only maps that have successfully gone through all validation processes (including approval by the EBCC Steering Committee and the EBCC Board) have finally been incorporated in the deliverable.

To develop the data analysis, SDM fitting, and to generate predictive maps of occurrence and change for the EBBALF project, the primary language and software environment utilized was R (version 4.1.2 in Linux operating system; R Core Team 2023).

Species Distribution Models

Species Distribution Models (SDMs) are statistical models that utilize observations of species along with environmental and landscape variables to predict the likelihood of species occurrence in space and time. The occurrence is typically represented as a probability function with values ranging from 0 to 1. This spatially explicit value is equivalent to the chance of encountering a species X within a specific square Y during the breeding season.

SDMs play a pivotal role in contemporary atlases, because they (1) can predict occurrence in non-surveyed areas, expanding our understanding of the species distribution, (2) offer methods to correct the spatial autocorrelation, (3) enable the production of maps that predict the temporal changes of the species, and (4) can be employed for making projections about future species distribution in response to changing environmental conditions.

The EBBA2 Atlas utilized a variety of SDMs because, as stated by Qiao et al. (2015), “no silver bullet exists in species distribution modelling”. The EBBALF project aims to maintain continuity by minimizing changes to reduce bias and variation from the EBBA2 models. Consequently, we employed the same correlative SDMs without altering their parameters as established in the EBBA2 Atlas script. The SDM models employed were the Artificial Neural Network (ANN, from the *nnet* package; Venables et al. 2002), Flexible Discriminant Analysis (FDA, from the *mda* package; Leisch et al. 2023), Generalised Additive Models (GAM; from the *gam* package; Hastie et al. 2023), Generalised Linear Models (GLM, from the part of R *stats* package; R Core Team 2023), and Multivariate Adaptive Regression Splines (MARS, from the *earth* package; Hastie and Tibshirani 2023). Importantly, Boosted Regression Trees (BRT) and Random Forest (RF) models were not used in this phase of the EBBALF project. This decision was driven by one of the main objectives of the EBBALF project, which is to prove our capacity in generating predictive models and testing their spatial and change performance. Given that BRT and RF models demand significantly higher computational resources and process time, we decided to disregard these SDMs in this first phase of the project. Furthermore, the site-occupancy model (OCC) was also excluded because we decided to further explore occupancy models independently from correlative ones in the future. It is important to emphasize that the SDMs were developed exclusively using observational data and predictor values within the geographical range of each species (more details in *Species’ geographical range* section).

Subsequently, we generated the weighted Ensemble Prediction (referred to as wEP), which represents the weighted average of the performance of the modelled maps. These weights are determined through testing the model performance based on True Skill Statistics (TSS) methodology with independent data. The TSS value is then multiplied by the predicted occurrence probability value for each pixel to generate the weighted average (Keller et al. 2020).

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Detection probability

As a broad definition, detection probability is the chance of successfully recording a species during a survey at a site where the species truly occurs (Kéry and Royle 2016). Detection probability is never perfect (always less than one). Low detection probability is associated with elusive species, low-experienced observers, or reduced sampling effort, while high detection probability is linked to visible and abundant species that are easily observable and, therefore, detectable (Chen et al. 2013). Consequently, detection probability serves to correct for the errors and biases introduced by the imperfect detectability of species.

Procedure to estimate the detection probability

The detection of a species is associated with its biology, but it is mainly translated on the occurrence of the species (due to true and false presences and absences) related with the field effort. Detection probability was modelled and estimated using a procedure extracted from site-occupancy models (MacKenzie et al. 2002, 2018; Kéry and Royle 2016).

In the EBBALF project, field effort was composed of two survey-related variables and one site-related variable.

On one hand, the survey-related variables were:

- *Method*: denotes the specific field method employed for field sampling. It can encompass a point count method, where an individual is observed at a specific location, a linear method, such as reporting a complete list on a transect, or territory mapping, where a small area is thoroughly sampled to identify territorial zones for individuals and pairs.
- *Time*: denotes the total time, measured in minutes, required to complete a specific field survey.

Both the *method* and *time* variables were modelled independently and as an interaction between them.

On the other hand, multiple surveys of the same site were needed to calculate the detection probability (Kéry and Royle 2016). Hence, a site-related variable that we called *years sampled* was introduced. This variable indicated the number of years with surveys conducted during each of the two periods, 2013–2017 and 2018–2022. The *years sampled* variable ranged from 1 to 5, and the yearly repeated surveys at each site were used in the EBBALF project to determine the probability of detection, following a similar procedure as in the EBBA2 Atlas (Williams et al. 2002).

In the EBBA2 Atlas, the variable *Julian day* was also employed as a survey variable to model the detection probability. However, in the EBBALF project, we opted to exclude the *Julian day* variable for both periods, due to the lack of *Julian day* data for the 2018–2022 period dataset.

The algebraic formula of the probability of detection (*Pdet*) is the following:

$$Logis(Pdet) = \alpha_0 + \alpha_1 time + \alpha_2 method_2 + \alpha_3 method_3 + \alpha_4 time * method_2 + \alpha_5 time * method_3$$

Where α are the parameters to be estimated in the logistic scale and $\alpha_0 = Intercept + \beta method_1$

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Procedure to incorporate the detection probability into the SDMs

The incorporation of detection probability into the correlative SDM models has been a subject of extensive discussion through the first phase of the EBBALF project. To address this, we finally decided on the following procedure:

1. Incorporation of detection probability: we integrated both the detection probability and the squared detection probability as explanatory variables within the SDMs.

2. Addition of surrogate detectability predictors: we appended the environmental predictors with two additional layers. Each of these layers was assigned a constant value of 1 across the entire study area. These added layers served as surrogates for the maximum detectability of both the detection probability and the squared detection probability variables.

3. Model predictions corrected for detection: we generated model predictions based on environmental variables, taking into account the corrections for detection probability.

Through this procedure, when the detection probability was imposed to a value of one (by incorporating the artificial predictor layers), the model predicted a proportionally higher probability of occurrence in locations where the detection probability was lower (always accounting for the influence of the environmental variables in generating the predictions).

While this approach serves as a valuable method to correct for imperfect detection within correlative models, we acknowledge that it may not be the optimal approach. A comprehensive correction for imperfect detection would ideally be achieved through the utilization of a formal site-occupancy model (MacKenzie et al. 2018).

Species' geographical range

Regarding the utilization of each species' geographical range, we implemented a distinct methodological approach compared to the EBBA2 Atlas. In the EBBA2 Atlas, a range layer was generated just for cropping the final modelled map. Instead, in our approach, prior to model development, we employed the range layer to eliminate observations located outside the range and to crop the predictor layers. The advantages of using this method are the following:

- The model functions are exclusively calibrated within the context of the species range, rather than being applied across the entire study area. This might enhance the significance of predictors that exhibit local variability, thereby influencing the model's capacity to accurately predict the occurrence of the species in their actual habitats.

- By restricting model predictions to the observed range, we mitigate the generation of artifacts often observed in the EBBA2 Atlas, particularly near the borders of species' ranges. In many cases, the probability of occurrence exhibited abrupt transitions that were biologically implausible. The approach employed in the EBBALF project serves to reduce this issue.

- In contrast to the EBBA2 Atlas, where we found that spatial model validation tended to be overly optimistic, especially for species with small ranges, our approach aims to provide a more accurate representation of the spatial performance.

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We employed the geographical ranges for each species developed in the EBBA2 Atlas. In summary, it consisted of using the 50-km squares that had any observational presence of the species and then including the adjacent 50-km squares. However, for both periods, we expanded the range of certain species using the following steps:

1. If observational presences from the 2018–2022 period extended outside the range defined in the EBBA2 Atlas, we included the 50-km squares where these observations were located.
2. We also included the 50-km contiguous queen-neighbouring squares (i.e., the squares sharing a common edge or a common vertex).
3. We then applied a smoothing process to the new range using the ksmooth method with a smoothing value of 6 (function 'smooth' in the *smoothr* package; Strimas-Mackey 2023).

Finally, we intersected the newly defined range with the 10-km grid system.

Generation of the predictor variables

The ANNEX II explains in detail how predictor variables were generated and what were their characteristics. As a summary, our primary approach involved utilizing the same EBBA2 Atlas predictors to develop the models for the EBBALF project. However, we made adjustments in both periods due to spatial data traceability issues, outdated sources, and project suitability. Therefore, we produced 34 environmental predictors, 30 of which were consistent with the EBBA2 Atlas. We categorized these predictors as static, or dynamic based on temporal variation or lack of it.

Spatial autocorrelation

Spatial autocorrelation refers to the similarity of values caused by their proximity in space (Legendre 1993; Dormann 2007; Dormann et al. 2007). As explained in the Keller et al. (2020), spatial autocorrelation typically occurs in SDMs because species' habitat preference tends to exhibit autocorrelation. This can be attributed to species behaviour such as competition, dispersion, attraction, etc., and it is highly influenced by nearby locations. Modelling spatial autocorrelation can thus enhance the quality of SDMs (Guélat and Kéry 2018).

To deal with spatial autocorrelation effectively, we followed the same procedure as in the EBBA2 Atlas. It was demonstrated that interpolating the residuals of the models using the thin-plate spline method (TPS) and subsequently adding the resulting map to the raw wEP proved to be the most effective approach for reducing spatial autocorrelation. Specifically, we employed the 'bam' function from the *mgcv* R package (Wood 2011). However, on some species with reduced geographical range, the k value was lowered to deal with issues related to the lack of degrees of freedom.

Change analysis

The distribution of species changes over time and it is usually driven by several factors. Understanding the changes in distribution is vital for conservation policies and identifying spatially explicit pressures and drivers influencing species occurrence (Keller et al. 2020). The creation of a standardized wEP that

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follows the same methodology for both 2013–2017 and 2018–2022 time periods facilitated the analysis of the change in species distribution over time.

The EBBALF project adopted a different methodological approach for analysing change than the one used in the EBBA2 Atlas. In the EBBA2 Atlas, change was measured using a metric called the *change index,* which quantified the occupancy of 50-km squares based on observations. Conversely, in the EBBALF project, we developed the *predicted change* that comes from the difference in the probability of occurrence between the wEPs generated from comparable datasets for the periods 2018–2022 and 2013–2017. We opted for this method due to the following benefits:

1. The production of a spatially detailed change map at 10-km resolution.
2. The predicted change provided a change value for all squares within the entire geographical range of each species.
3. Robust statistical methods were used to assess change performance at both European and at PECBMS regional level, as detailed in the *Uncertainty assessment of change* section.
4. We mitigated biases derived from variations in sampling locations and sample sizes, which were prominent issues in the EBBA2 Atlas. This was achieved by utilizing the same PECBMS surveys within the same 10-km squares for both time periods to construct the wEP models.

It is important to note that the change analyses conducted in the EBBALF project were limited to species occurrence data (during the breeding season). The project did not address changes in breeding evidence or abundance.

The distribution change map of a species might exhibit patterns not related with the species biological change, but to variations in sampling effort, or temporal variations on the data predictors. To address this, we produced several maps that alert us on the spatiotemporal performance and potential biases inherent in distribution change maps. See *Spatial performance of the models* and *Uncertainty assessment of change* sections for more details.

Concretely, the range of the predicted change values goes between –1 and 1. Areas with negative values represented a reduction of occurrence or in the worst-case-scenario, extinction processes. Positive values, on the other hand, represented an increase in occurrence and colonisation processes.

It is important to emphasize that the patterns observed in the change maps should be strictly analysed as change in the distribution of species, not as trends in the population dynamics (Koleček and Reif 2011). Additionally, colonisation processes tend to be more easily documented than extinction processes. As noted in the EBBA2 Atlas, a single breeding record per 10-km square is enough to designate a new square as an observational ‘presence’. True observed absences only become apparent when a species completely disappears from a square and is no longer recorded on any survey. However, both in the EBBA2 Atlas and the EBBALF project, we are confident that the predicted change of the distribution of the farmland species has been adequately modelled and represents genuine and low-biased results.

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Uncertainty assessment of updated distributions

Spatial performance of the models

As mentioned in Keller et al. (2020), assessing the performance of the models is crucial for evaluating the predictive accuracy of SDMs. We tested the performance of the wEP at the spatial dimension using two evaluation metrics: the Area Under the Curve of the receiver operating characteristics (AUC) and the True Skills Statistics (TSS). These validators were also employed in the EBBA2 Atlas. Given that AUC and TSS metrics are fairly proportional, we opted to only present the AUC metric in the deliverable outputs to prevent information overload.

We increased the spatial resolution of the AUC metric, by not only assessing the performance across the entire geographical range of each species, but also at the level of PECBMS geographical regions within the species range (Fig. 9).

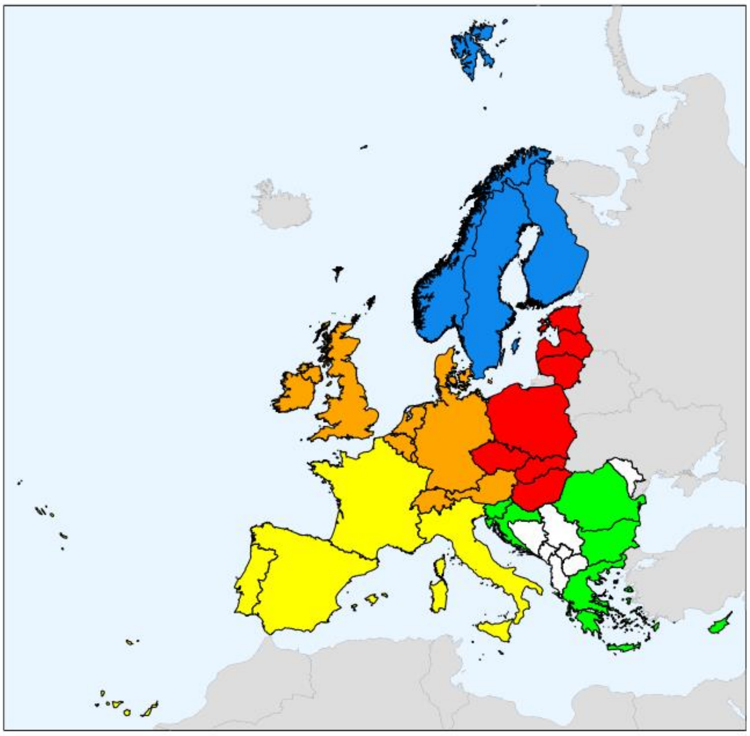

Figure 9. Categories of PECBMS geographical regions for the countries participating in the EBBA Live Farmland project. South-West Europe is indicated in yellow, South-East Europe in green, Central-East Europe in red, North Europe in blue, and West Europe in orange. As of 2023, non-PECBMS countries involved in the EBBA Life Farmland are represented in white.

To rigorously determine the statistical validators for each spatial level, we employed the statistical method called ‘K-fold cross-validation’, as in the EBBA2 project. This method involves randomly dividing the original dataset into two subdatasets, where 70% of the observations are used to train the model, while the remaining 30% were reserved to validate the model (aka testing the performance). While the EBBA2 project used a 90% training and 10% testing ratio, we increased the testing dataset to 30% to avoid low sample size problems in the validation procedure that came to light in small and poorly sampled regions. However, on some species, some PECBMS regions with recordings could not be validated due to the impossibility of obtaining validators when lacking both presences and

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absences. These regions were displayed as ‘validation unfeasible’. Three resampling iterations of the training and testing data were conducted to test the spatial performance.

Model quality thresholds

The AUC metric ranges between 0 and 1. We classified the AUC values based on Triviño et al. (2011), using the following scales: high performance models had an AUC > 0.9, good models 0.9 > AUC > 0.8, fair 0.8 > AUC > 0.7, poor 0.7 > AUC > 0.6 and finally models that fail had AUC values < 0.6.

TSS metric ranges between –1 and 1. We classified the TSS values based on Triviño et al. (2011), using the following scales: high performance models had an TSS > 0.8, good models 0.8 > TSS > 0.6, fair 0.6 > TSS > 0.4, poor 0.4 > TSS > 0.2 and finally models that fail had TSS values < 0.2.

After three resampling iterations, we obtained the AUC and TSS means and standard deviations (SDs).

Sample size and distribution

On the PECBMS regions model performance process, we also introduced another metric to help evaluate the SDM performance. Regions with adequate sampling are prone to have a more rigorous AUC metric due to its larger sampling size. On the other hand, in regions with poor sampling it is more suspicious that the AUC metric accurately represents the actual model performance. Therefore, we classified the regions according to a scale that measures if the region had adequate (>10% of the region squares sampled), poor (<10% squares sampled) or when validation was not possible (no sampling at all). We called this process *data collection quality* and was spatially represented along the AUC metric.

We define sampling distribution as the density of samplings across space and time. The issue of sampling distribution has been a subject of intense debate in the recent EBBA2 Atlas and within the EBBALF project. This is primarily because sampling distribution has spatiotemporal inhomogeneity, leading to significant gaps in data, which in turn, can introduce notable biases in the development of SDMs.

Consequently, we conducted an analysis to observe how the performance of SDMs was affected by uniformly reducing data density. These analyses are presented in the *Results* section and further developed in the *Discussion* section and ANNEX IV.

Uncertainty assessment of change

Validating how SDMs predict the distribution change of species over time is crucial to extract dynamic patterns of distribution with confidence (Rapacciuolo et al. 2014). The utility of change predictions clearly depends on how much they can be trusted (Piirainen et al. 2023). The validation of change performance represents a novel analysis, not conducted in the EBBA2 Atlas, but it is crucial to accomplish the EuropaBON main objectives of establishing a way to validate distribution change performance.

Static validation ignores change events (Piirainen et al. 2023) and usually (1) evaluates overoptimistically the predictive performance because it primarily focuses on the unchanged distribution (Rapacciuolo et al. 2012, 2014; Sofaer et al. 2018), (2) spurious species-environment correlations identified during model calibration may not be revealed by temporal validation across

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these unchanged areas; and (3) they lack fully independent model validation, as they rely on training data from the first period and testing with the second. Instead, change validation methods are well-suited for evaluating change performance (Rapacciuolo et al. 2014; Piirainen et al. 2023). In this project, we employed a change validation method developed by Rapacciuolo et al. (2014) to test the performance in predicting species' distribution changes over time.

The change validation method employed in EBBALF entails the use of observational data from the 2013–2017 and 2018–2022 time periods, which is then compared with the predicted change from models for both periods. This method overcomes the aforementioned issues by focusing on model performance only in squares where either observed data, model predictions, or both indicate range change over time and reflect species' observed colonisation and extinction processes separately (Rapacciuolo et al. 2014). The employed method has been extensively described in Rapacciuolo et al. (2014) and has served to quantify the calibration of SDMs in numerous papers (Pearce and Ferrier 2000; Boyce et al. 2002; Hirzel et al. 2006; Phillips and Elith 2010). It has also been a key reference for the design of novel validation methods (Piirainen et al. 2023).

Two metrics based on the Rapacciuolo et al. (2014) method were used to validate the change performance:

- Accuracy: this metric uses the difference in the probability of occurrence between the 2013–2017 and 2018–2022 periods, weighted by the probability of occurrence during the 2013–2017 period (Rapacciuolo et al. 2014). The resulting values are referred to as "difference on weighted predictions" (Δwp). The accuracy metric measures the difference between the ideal curve and the actual Δwp curve at each observation site (Fig. 9, left). The value of this metric ranges from a minimum of 0, indicating a model whose predictions are, on average, as distant as possible from the probabilities of observing change, to a maximum of 1, representing a perfectly predictive model (Rapacciuolo et al. 2014). We classified the accuracy values using the following scale: accuracy < 0.7 indicates an inaccurate model, while accuracy > 0.7 suggests an accurate model.

- Bias: this metric quantifies the asymmetric deviation between the ideal and model curves for colonisation and extinction. The bias metric measures the difference in the area below the ideal and the Δwp curve in the colonisation section, minus the area above in the extinction section. A predicted change map displays a bias of 0 if it perfectly predicts the overall change in the probability of observing a species across the Δwp. A negative bias indicates that the predicted change maps tend to underestimate observed colonisations and/or overestimate observed extinctions (Fig. 10, right). We considered predicted change maps with a bias < –0.25 to exhibit this pattern. Conversely, a positive bias indicates the opposite, suggesting that the predicted change map tends to overestimate observed colonisations and/or underestimate observed extinctions. We considered that predicted change maps with a bias > 0.25 manifest this pattern and classified the bias values between –0.25 and 0.25 as unbiased models. Bias can be affected by prevalence, with excessively positive bias values for low prevalences and excessively negative values for high prevalence values.

The following figure represents an example of how the accuracy and bias are extracted from modelling the relationship between observational and predicted change.

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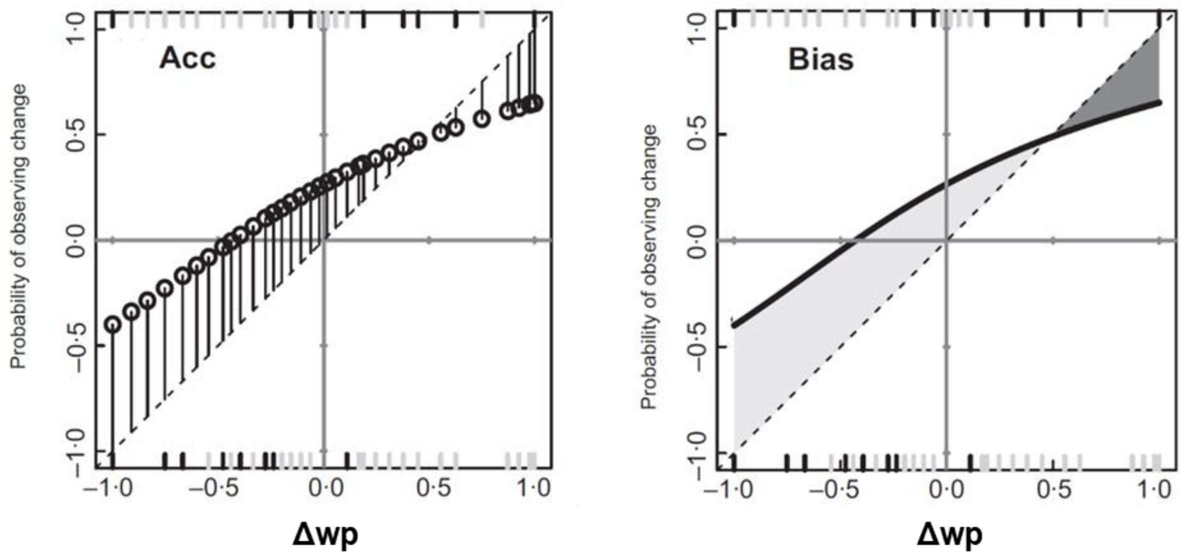

Figure 10. Visualization of the accuracy measure (left) and bias measure (right). The predicted change (Δwp) is shown on the x axis and the observed change is shown on the y axis. The accuracy is visualized as 1 minus the distance between the models' values (black lines of the left plot) and the ideal curve (dashed diagonal line). The bias is represented as the area under the ideal curve minus the area under the model curve (thick black). Extracted and modified from Rapacciuolo et al. (2014).

We evaluated the change performance across the entire geographical range of each species, as well as each PECBMS geographical region within the range (for more details, refer to the *Spatial performance of the models* section). Some regions with actual recordings could not be validated due to the impossibility of generating the metrics because of small dataset sizes. These regions were labelled as 'validation unfeasible'.

As detailed in Rapacciuolo et al. (2014), *achieving high predictive accuracy can only be accomplished by models that accurately capture the drivers of change in species distributions*. Therefore, we provided a table outlining the contribution of predictors for each period. This information accompanied the change performance metrics to gain understanding of the causes and drivers of the predicted changes (see ANNEX III for more details).

4.4. Performance of EBV-derived policy indicators

How to transition from the EBV product to indicators

The reference indicator for farmland bird species in Europe is the FBI (Gregory et al. 2005). The EU FBI is based on data from 26 EU MS on 39 species commonly breeding in Europe's fields and meadows (missing data from the only EU country, Malta, which hosts a tiny proportion of Europe's bird populations and systematic monitoring of breeding birds has not yet started). Between 1980 and 2022, farmland bird populations in the EU declined by 55% (PECBMS 2023). The FBI is also produced for the whole of Europe and at regional and national levels (PECBMS 2023), but few attempts have been made so far to map this indicator and how it varies across time. In this showcase we have included all the species that are needed to generate the FBI, plus some other farmland birds. We have modelled

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species distributions EBVs and eventually this can be integrated into species linked to farmland to derive a spatially explicit FBI that we interpret and value as a surrogate for farmland quality. The generation of this multi-species indicator, however, requires some analytical work and it is not a straightforward task. The main limitation is that this showcase has produced maps of probability of occurrence and maps of change in this value, while the FBI reports changes in the abundance of birds. Although preliminary analyses show that the spatial variation in the probability of occurrence at European level can be considered a surrogate of the spatial pattern of abundance for most species (ANNEX V), the particular manner in which variations of probability of occurrence along time matches that of abundance as reported by FBI requires further exploration.

Projection scenarios

Understanding how species will respond to climate change is currently one of the key challenges in ecology and nature conservation (Malhi et al. 2020; Sofaer et al. 2018). Correlative SDMs, such as those used in EBBALF, can be employed to project changes in species' distributions under ongoing global environmental change (Elith and Leathwick 2009). SDMs are a widely used tool for predicting the potential impacts of climate change on species' distributions (Pearson et al. 2003). However, they have limitations, often failing to account for other environmental constraints, biotic interactions, species' adaptive capacity or dispersive abilities (Beale et al. 2008). Recent research highlights the limitations of using only climate and land cover when projecting future changes in species' ranges at European scale (Howard et al. 2023). Given this complexity, we are not presenting maps or analyses involving future projection scenarios. However, this is a highly significant topic that some projects are currently addressing. In this context, the Biodiversa+ SPEAR project is attempting to identify areas important to future conservation within different scenarios of change (https://www.biodiversa.eu/2023/04/19/spear/).

5. Results

The following items are the products of this showcase:

1. Observed distributions of farmland species at 50-km scale based on the data compiled by the European common bird monitoring network (PECBMS+) in the period 2018–2022.

2. Analysis of gaps in data availability based on a comparison between the 50-km map of observations collected by the monitoring sites mentioned above and the intensive atlas work done in 2013–2017.

3. The SDM prediction map that depicts the occurrence probability displayed in the EBBA2 Atlas, alongside the resultant SDM prediction map for the period 2013–2017 developed within the EBBALF project accompanied by its spatial validation metric at the European level.

4. The resulting SDM prediction map of the occurrence probability for the period 2018–2022, accompanied by its spatial validation metric at the entire species range at the European level and at PECBMS regional level.

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5. The predicted change maps illustrate the differences in occurrence probability between the periods 2013–2017 and 2018–2022, accompanied by two temporal validation metrics at the European and PECBMS regional levels.

We show here the complete set of main outputs for four species (Common Hoopoe *Upupa epops*, Common Stonechat *Saxicola torquatus*, Eurasian Tree Sparrow *Passer montanus* and the Tawny Pipit *Anthus campestris*) as examples of the results obtained in this study.

These four cases nicely illustrate the difficulty to properly update the observed species' distributions using bird monitoring data; i.e., to generate species' maps without modelling (Fig. 11A1-A4). In all cases, the distribution observed at a coarse resolution of 50-km is more restricted than the one observed during the extensive fieldwork done for EBBA2 (Keller et al. 2020). In fact, 50-km distributions collected in the PECBMS+ network of monitoring data tend to detect the species' occurrence in areas where the species are relatively frequent (Fig. 11B1-B4), but this is only valid for areas in which the density of monitoring sites is relatively high (Fig. 6, left). This exercise allows to determine the main gaps of data species per species and in general for the set of 50 species analysed (Fig. 12). More specifically, differences between species with regard to the coverage by EBBA2 and EBBALF can often be explained fairly easily given: 1) gaps in coverage in common bird monitoring schemes, visible especially in Greece and the Balkans generally; 2) scarcity of certain species, which reduces the probability of coming across them in a monitoring survey (e.g., Meadow Pipit *Anthus pratensis,* European Roller *Coracias garrulus*); 3) colonial and localised species that were specifically searched for in EBBA2 but may be missed in standardised common bird monitoring surveys (e.g., Rook *Corvus frugilegus*); and 4) (partly) nocturnal species that are not often as well detected in common bird monitoring schemes as in atlas surveys (e.g., Eurasian Thick-knee *Burhinus oedicnemus,* Little Owl *Athene noctua,* Corncrake *Crex crex*). See also ANNEX VI for more detailed information on data gaps for each species within each country.

The modification of the EBBA2 modelling approach to the new modelling EBBALF framework provided very similar results to that produced in EBBA2 (Fig. 11B1-B4). In addition, we validated model predictions at the European levels. Therefore, using the EBBA2 data for the study area of this showcase (excluding Eastern Europe), with an ensemble prediction of five instead of eight models and adapting case by case the presence/absence data to the species' range (not the whole of Europe) provided modelled robust 10-km distributions for all species. Importantly, in the EBBALF project there were several modifications in relation to the environmental predictors used. While the EBBA2 Atlas used 40 environmental predictors, the EBBALF project used 34 due to spatial data traceability issues, outdated sources, and project suitability, sharing in total 30 environmental predictors.

Although we were not able to test the difference in the validation statistics (i.e., AUC) of the two approaches, the visual inspection by experts of the EBBA Live Farmland steering group provided very satisfactory results. Indeed, this new modelling approach resulted to come up with a few advantages with regards to the EBBA2 framework. The predictions of the new models did not stand out of the known species distributions and consequently in EBBALF there was no need to crop models outside known ranges as it happened in EBBA2 (e.g., compare EBBA2 and EBBALF 2013–2017 maps for the Tawny Pipit *Anthus campestris* in France, with blank areas in EBBA2 in France forced because the species did not breed there at all; Fig. 11B4). In addition, the EBBALF modelling approach produced maps for four out of the 50 farmland species for which EBBA2 was not capable of deriving a satisfactory

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model, such as for the Common Stonechat *Saxicola torquatus* (Keller et al. 2020; Fig. 11B2). In addition, the high predictive accuracy values achieved reflect models that accurately capture the drivers of change in species distributions.

The combination of the frequently updated site-level monitoring data from all Europe and the new EBBALF modelling framework was revealed to be a very useful analytical tool to update species distributions at 10-km resolution for the whole of the study area (Fig. 11C1-C4).

The seven most important predictors of the species distribution are climatic variables, which is expected taking into account the large scale at which this modelling exercise was carried out, while the herbaceous cover was ranked in 8th place, an essential variable for farmland species (ANNEX III). All the 50 farmland species for which we tried to generate a modelled map had AUC statistics higher than 0.7. In addition, validation statistics at the regional level were also higher than 0.7 almost in all regions in which the species occurs. Exceptions only occurred in regions where the species was very scarce, such as the Nordic countries for the Tawny Pipit, or in regions in which the coverage of monitoring sites was low, such as in south-eastern countries for the Eurasian Tree Sparrow and the Common Hoopoe (Fig. 10C1-C4). The impact of spatial reduction of data on model performance for 2018–2022 was also explored and we found that the model performance was robust when reducing up to 50% of over-aggregated sampled squares (ANNEX IV). This suggests that in some countries with good coverage of monitoring sites a subset of the data could be enough to produce robustly updated modelled maps at European scale.

Change maps were achieved for 42 species out of the total of 50 farmland species included in the showcase (Fig. 11D1-D4). For the remaining 8 species, validation statistics (bias and accuracy) did not reach satisfactory values for the whole of the study area. In addition, 20 out of the 42 species had validation statistics that failed in one or more of the studied regions (see example of Common Hoopoe in SE Europe, Fig. 11D1 and Tawny Pipit in W Europe, Fig. 11D4). In SE Europe, the proportion of species for which regional validations of change maps failed was 31%, whereas this percentage varied from 14% to 18% in the other four regions (Table 3A-B). The impact of spatial reduction of data on model performance for these change maps was also explored (ANNEX IV).

In general, the variation in the probability of occurrence between the period 2013–2017 and the period 2018–2022 was rather low and maps depict a prominent pattern of stability (Fig. 11D1-D4). This is completely normal taking into account that the probability of occurrence at 10-km resolution cannot easily change in the short time interval analysed here (two 5-year consecutive periods). However, decreases in the probability of occurrence are much more widespread than increases in this value, which is completely consistent with the known overall loss of abundance birds (Rigal et al. 2023). The detailed description of the eco-geographic patterns of change found in this showcase and the exploration of their potential causes falls beyond the aims of this exercise. However, it should be noted that substantial changes (difference between probability of occurrence > 0.2) were found in many species in parts of their distribution. In SW Europe, 92% of the species showed a general pattern of loss of probability of occurrence, while this value was 75% in the N and Central-E Europe, 67% in the W and 50% in SE (Table 3A-B).

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EBBA Live Farmland

Upupa epops

Common Hoopoe

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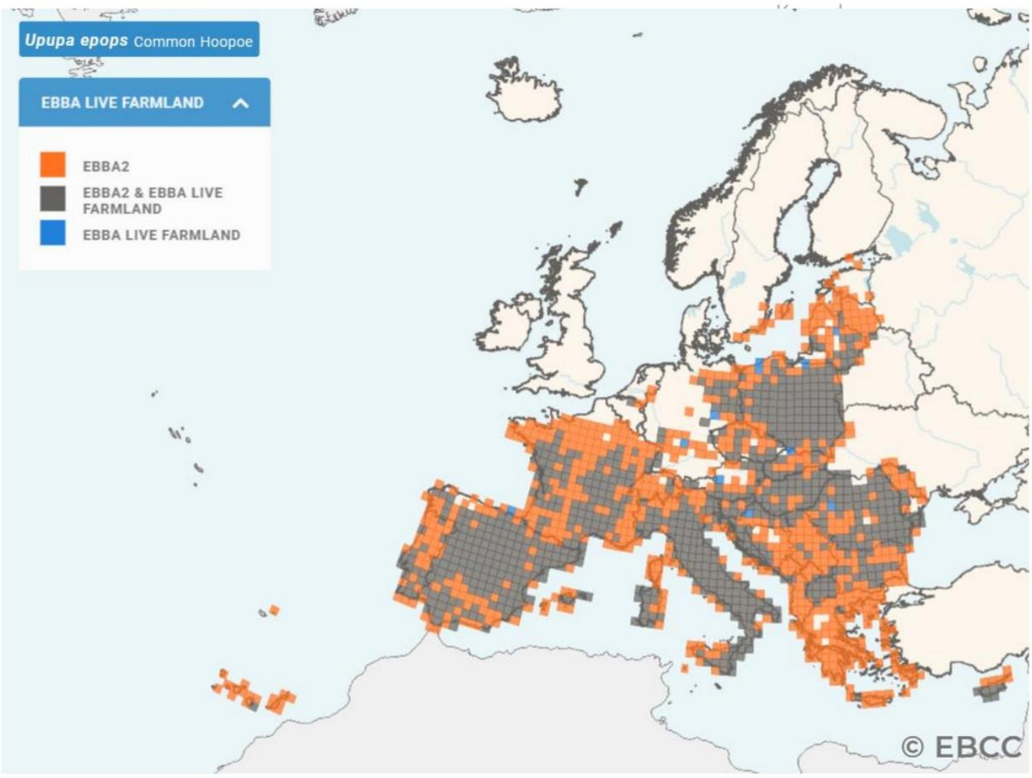

Figure 11A1. 50-km occurrence map showing the observed distribution in the period 2018–2022 for the Common Hoopoe *Upupa epops*. Data come from common bird monitoring projects. No modelling applied. In EBBALF, the species was found in 52% of the total number of 50-km squares where the species was found to breed in EBBA2 (percentage of coverage (x) = grey sq/orange sp+grey sq*100). Data gaps were relevant in AL (0%), EE (0%), FI (0%), LI (0%), NL (0%), SE (0%), XK (0%), EL (1%), LV (8%), CH (10%), MD (13%), RS (16%), BA (20%), ME (22%), BG (33%), PT (35%), DE (39%), FR (40%), SK (41%) and CZ (43%). As a whole, the EBBA Live Farmland 50-km occurrence map based on common bird monitoring data has medium quality (90%>x>50%). On the other hand, the percentage of new locations (blue sq/orange sp+grey sq*100) was 0.7%.

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EBBA Live Farmland
Saxicola torquatus
Common Stonechat

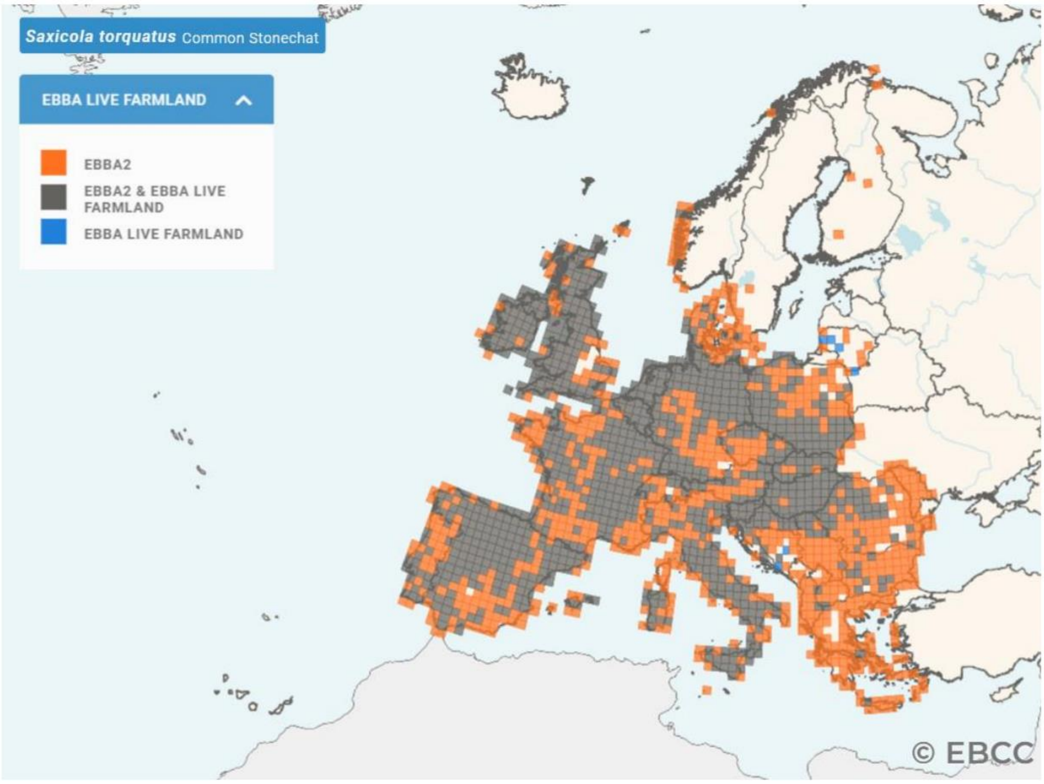

Figure 11A2. 50-km occurrence map showing the observed distribution in the period 2018–2022 for the Common stonechat *Saxicola torquatus*. Data come from common bird monitoring projects. No modelling applied. In EBBALF, the species was found in 56% of the total number of 50-km squares where the species was found to breed in EBBA2 (percentage of coverage (x) = grey sq/orange sp+grey sq*100). Data gaps were particularly relevant in AL (0%), FI (0%), LI (0%), LT (0%), LV (0%), MD (0%), ME (0%), SE (0%), XK (0%), EL (2%), BA (4%), NO (7%), BG (16%), RS (22%), DK (23%), MK (30%), CZ (36%), RO (37%), PT (37%), CH (39%) and AT (48%). As a whole, the EBBA Live Farmland 50-km occurrence map based on common bird monitoring data has medium quality (90%>x>50%). On the other hand, the percentage of new locations (blue sq/orange sp+grey sq*100) was 0.3%.

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EBBA Live Farmland

Passer montanus

Eurasian Tree Sparrow

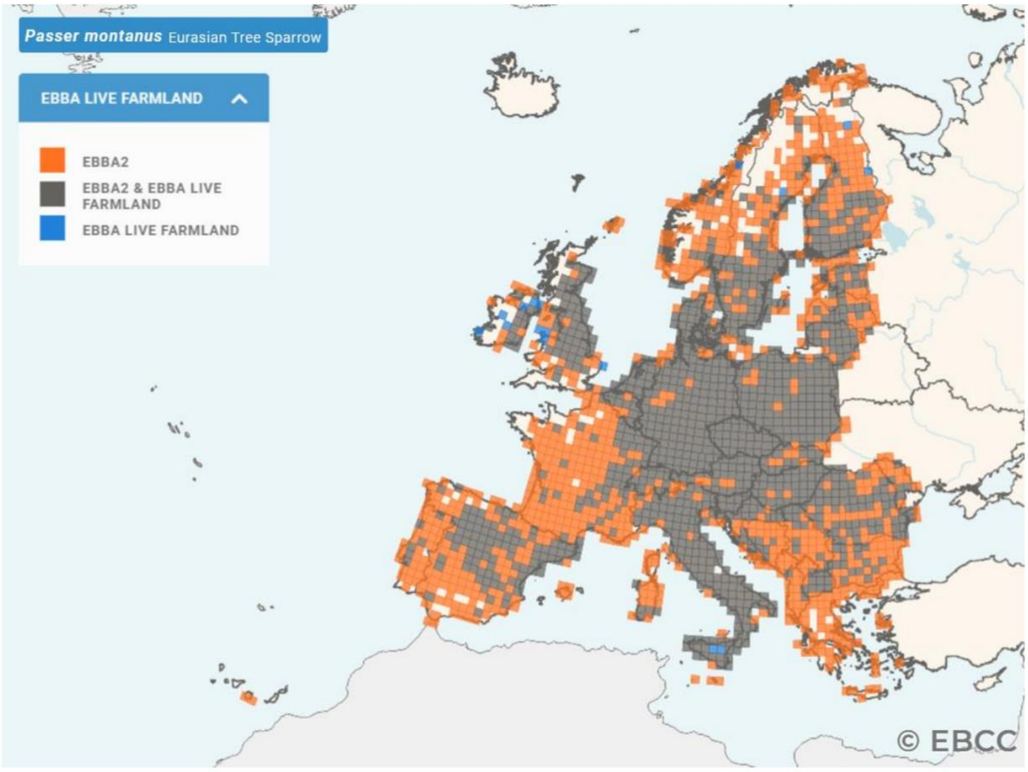

Figure 11A3. 50-km occurrence map showing the observed distribution in the period 2018–2022 for the Eurasian Tree sparrow *Passer montanus*. Data come from common bird monitoring projects. No modelling applied. In EBBALF, the species was found in 56% of the total number of 50-km squares where the species was found to breed in EBBA2 (percentage of coverage (x) = grey sq/orange sp+grey sq*100). Data gaps were particularly relevant in AL (0%), EL (0%), LI (0%), MT (0%), XK (0%), ME (12%), PT (15%), NO (17%), BA (18%), FR (22%), MD (23%), RS (24%), BG (25%), LV (36%), EE (42%), FI (42%), ES (44%), HR (48%) and SE (49%). As a whole, the EBBA Live Farmland 50-km occurrence map based on common bird monitoring data has medium quality (90%>x>50%). On the other hand, the percentage of new locations (blue sq/orange sp+grey sq*100) was 0.7%.

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EBBA Live Farmland

Anthus campestris

Tawny Pipit

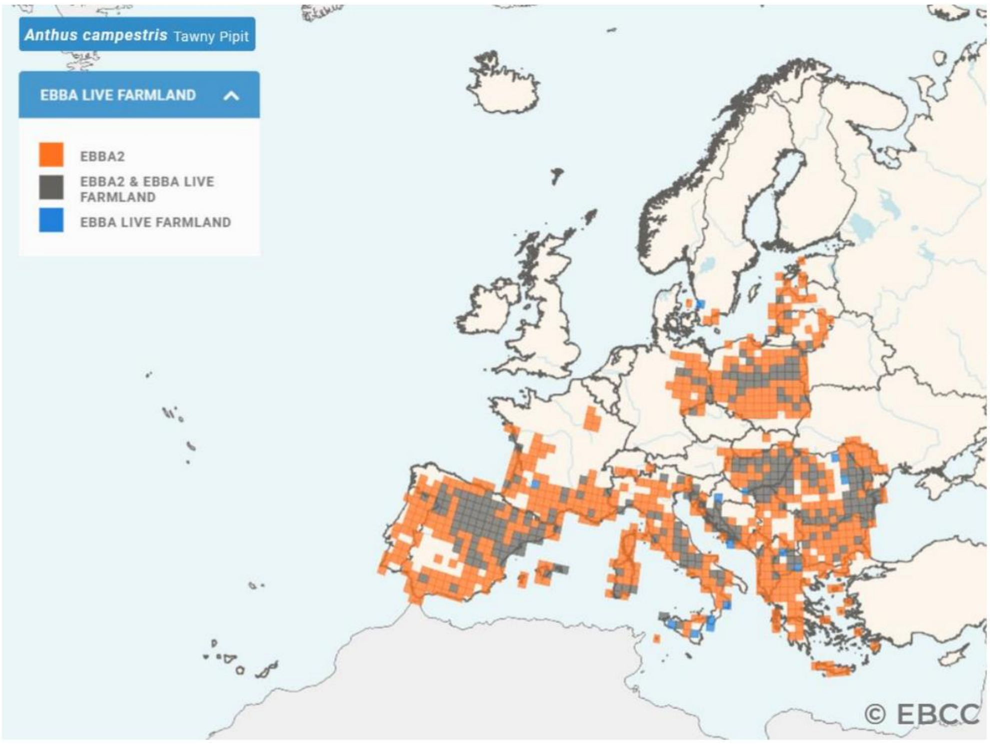

Figure 11A4. 50-km occurrence map showing the observed distribution in the period 2018–2022 for the Tawny Pipit *Anthus campestris*. Data come from common bird monitoring projects. No modelling applied. In EBBALF, the species was found in 30% of the total number of 50-km squares where the species was found to breed in EBBA2 (percentage of coverage (x) = grey sq/orange sp+grey sq*100). Data gaps were particularly relevant in AL (0%), AT (0%), CH (0%), DK (0%), EE (0%), EL (0%), SE (0%), SK (0%), XK (0%), PT (6%), LV (6%), MD (9%), FR (11%), LT (14%), BG (15%), CZ (20%), ME (20%), DE (21%), RS (22%), IT (28%), BA (30%), PL (31%) and ES (41%). As a whole, the EBBA Live Farmland 50-km occurrence map based on common bird monitoring data has low quality (x<50%). On the other hand, the percentage of new locations (blue sq/orange sp+grey sq*100) was 1.5%.

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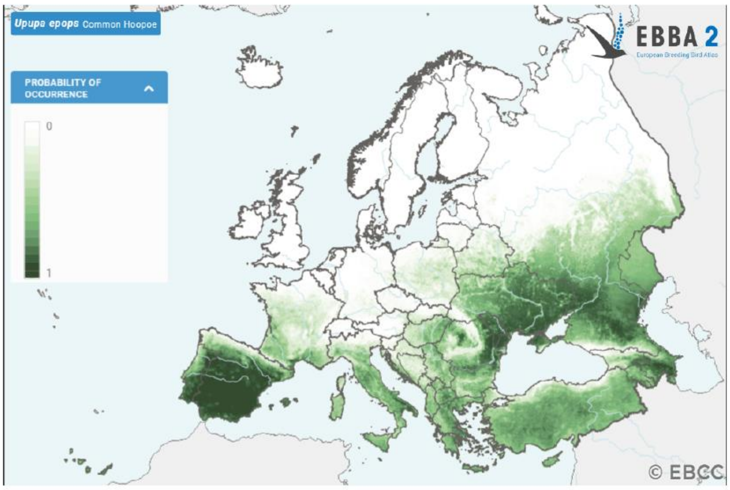
Upupa epops − Predictive model of the probability of occurrence

Predictive model of the EBBA2 Atlas



Predictive model for the 2013−2017 period of the EBBALF

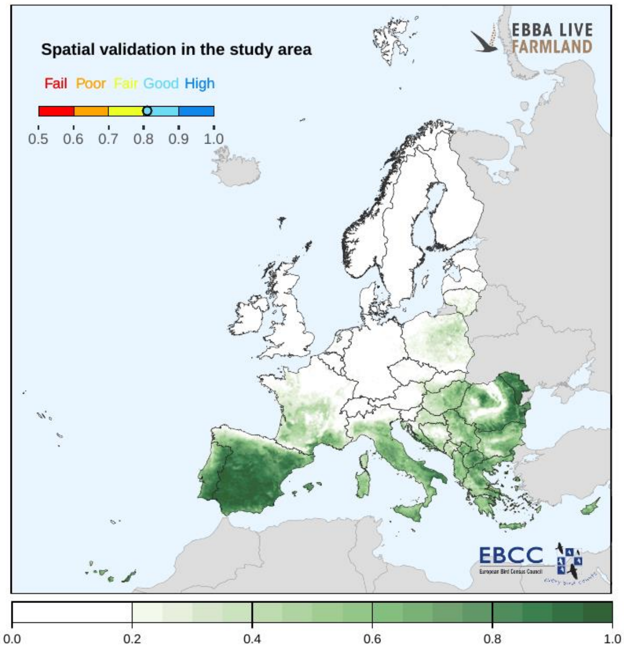


Figure 11B1. 10-km probability of occurrence map showing the modelled distribution in the period 2013–2017 for the Common Hoopoe *Upupa epops* in EBBA2 (up) and in the current modelling exercise in EBBALF (down). All come from EBBA2 data and spatial distribution modelling applied, but the study area and the modelling procedure is not exactly the same (see main text for further details on the procedure).

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Saxicola torquatus − Predictive model of the probability of occurrence

Predictive model of the EBBA2 Atlas

The EBBA2 atlas modelled map was not produced for this species

Predictive model for the 2013−2017 period of the EBBALF

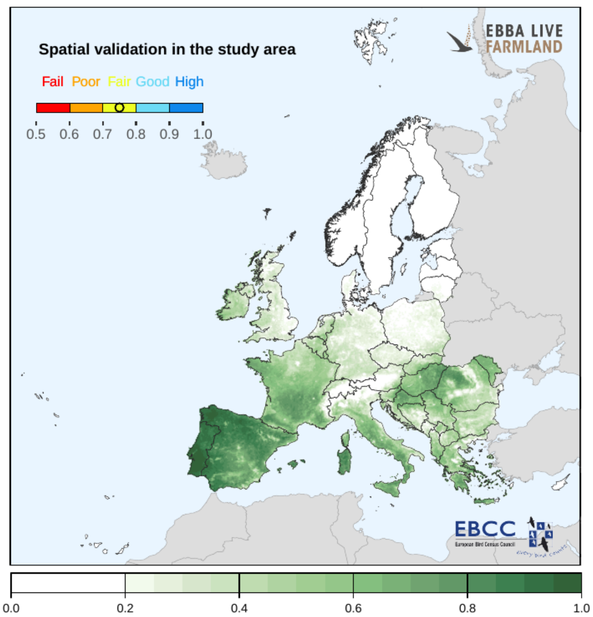

Figure 11B2. 10-km probability of occurrence map showing the modelled distribution in the period 2013–2017 for the Common Stonechat *Saxicola torquatus* in the current modelling exercise in EBBALF (down). Data come from EBBA2 and spatial distribution modelling applied (see main text for further details on the procedure). No modelled map was produced in EBBA2 (up).

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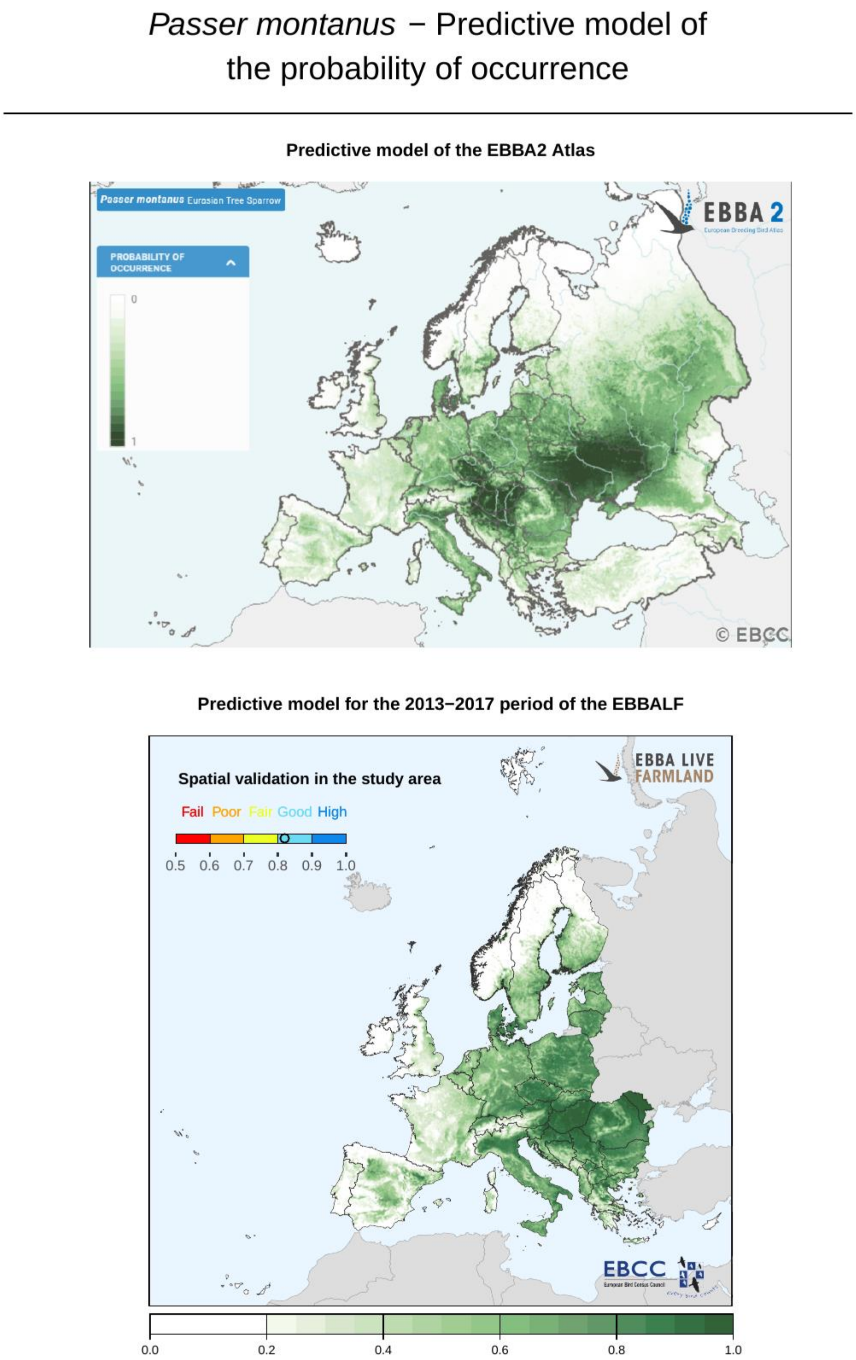

Figure 11B3. 10-km probability of occurrence map showing the modelled distribution in the period 2013–2017 for the Eurasian Tree Sparrow *Passer montanus* in EBBA2 (up) and in the current modelling exercise in EBBALF (down). All come from EBBA2 data and spatial distribution modelling applied, but the study area and the modelling procedure is not exactly the same (see main text for further details on the procedure).

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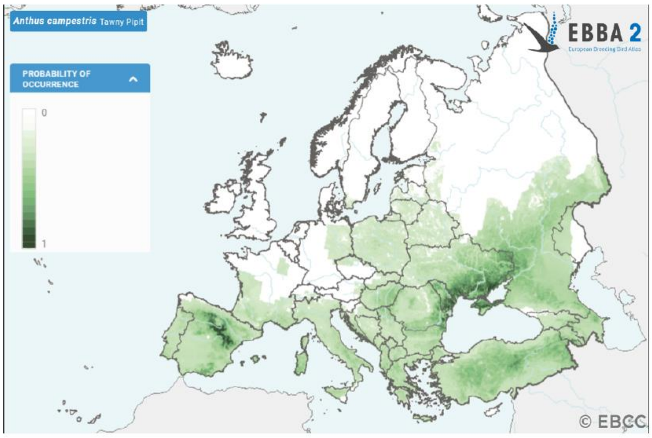
Anthus campestris − Predictive model of the probability of occurrence

Predictive model of the EBBA2 Atlas



Predictive model for the 2013−2017 period of the EBBALF

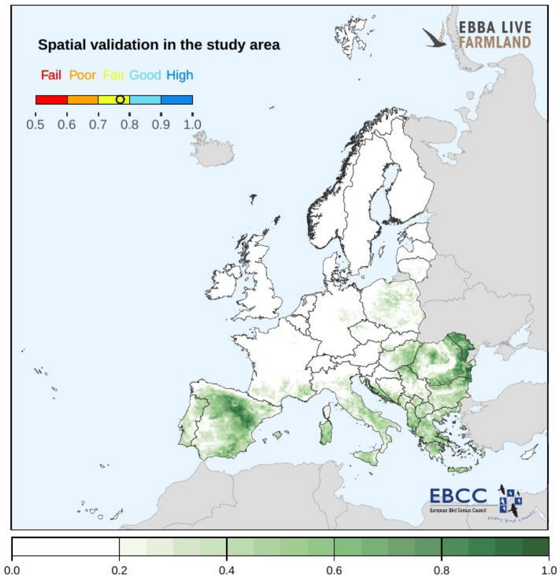


Figure 11B4. 10-km probability of occurrence map showing the modelled distribution in the period 2013–2017 for the Tawny Pipit *Anthus campestris* in EBBA2 (up) and in the current modelling exercise in EBBALF (down). All come from EBBA2 data and spatial distribution modelling applied, but the study area and the modelling procedure is not exactly the same (see main text for further details on the procedure).

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Upupa epops – Predictive model of
the probability of occurrence and performance

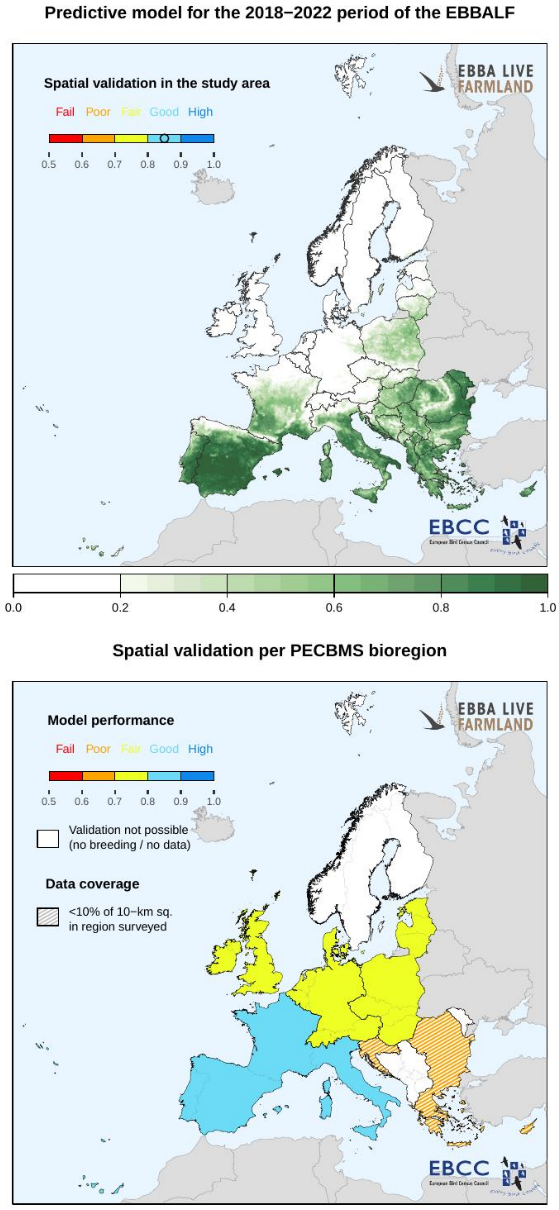

Figure 11C1. 10-km probability of occurrence map showing the modelled distribution in the period 2018–2022 for the Common Hoopoe *Upupa epops* in EBBALF (up) and validation at regional level (down). All data come from monitoring data (PECBMS+) and spatial distribution modelling applied (see main text for further details on the procedures).

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Saxicola torquatus − Predictive model of the probability of occurrence and performance

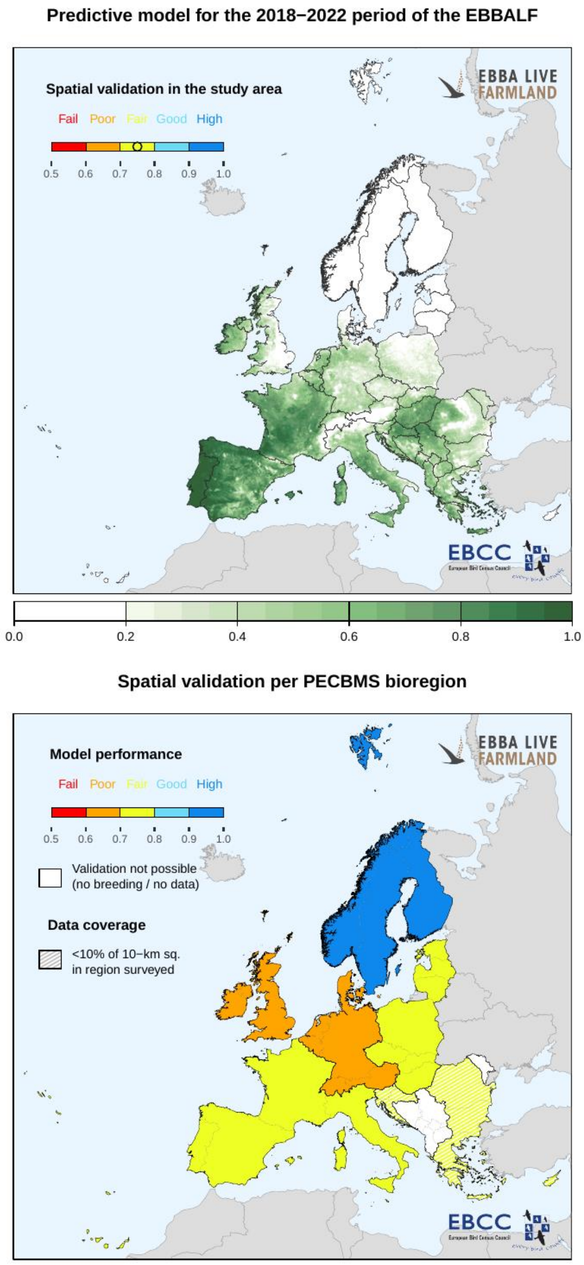

Figure 11C2. 10-km probability of occurrence map showing the modelled distribution in the period 2018–2022 for the Common Stonechat *Saxicola torquatus* in EBBALF (up) and validation at regional level (down). All data come from monitoring data (PECBMS+) and spatial distribution modelling applied (see main text for further details on the procedures).

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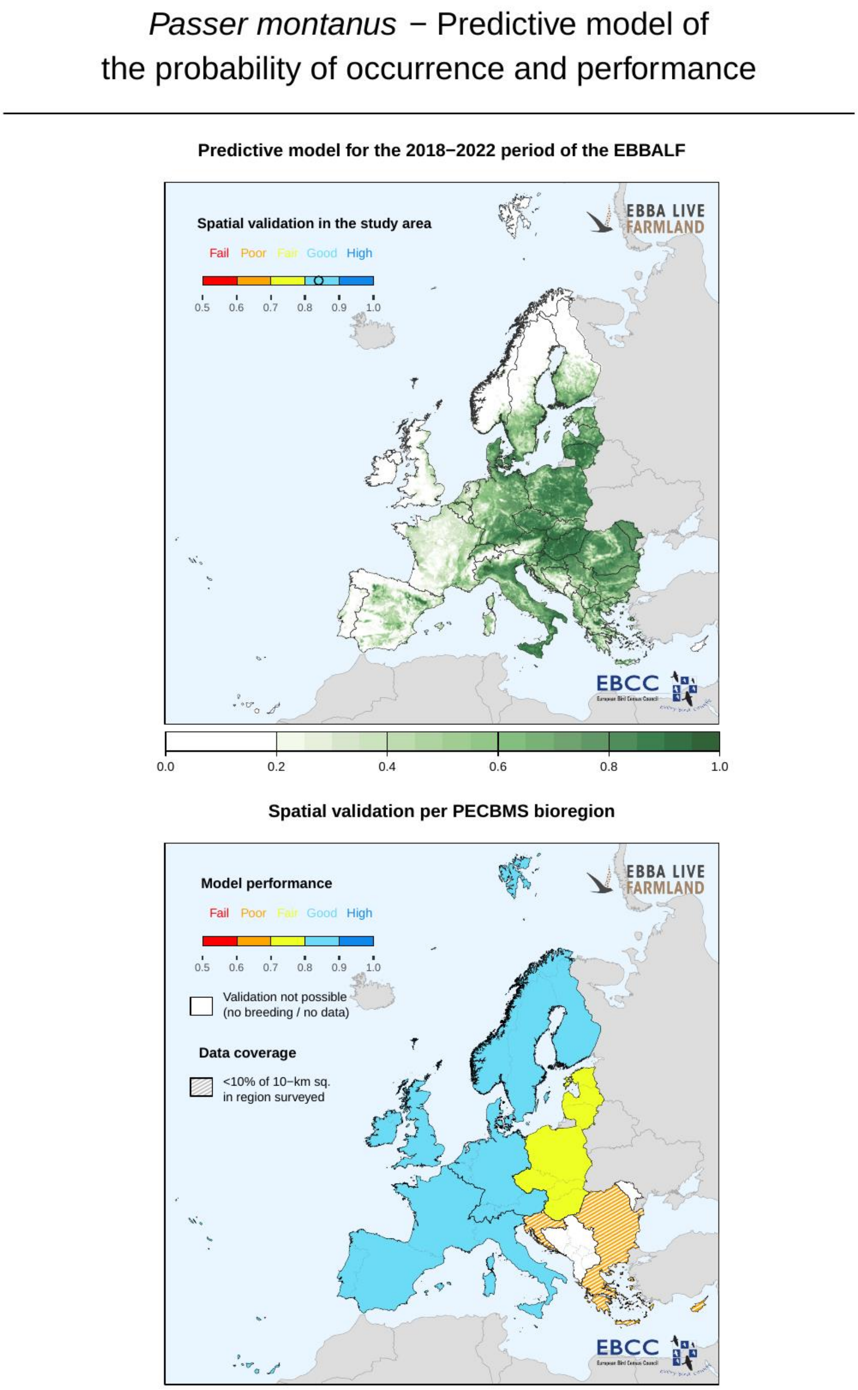

Figure 11C3. 10-km probability of occurrence map showing the modelled distribution in the period 2018–2022 for the Eurasian Tree Sparrow *Passer montanus* in EBBALF (up) and validation at regional level (down). All data come from monitoring data (PECBMS+) and spatial distribution modelling applied (see main text for further details on the procedures).

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Anthus campestris − Predictive model of the probability of occurrence and performance

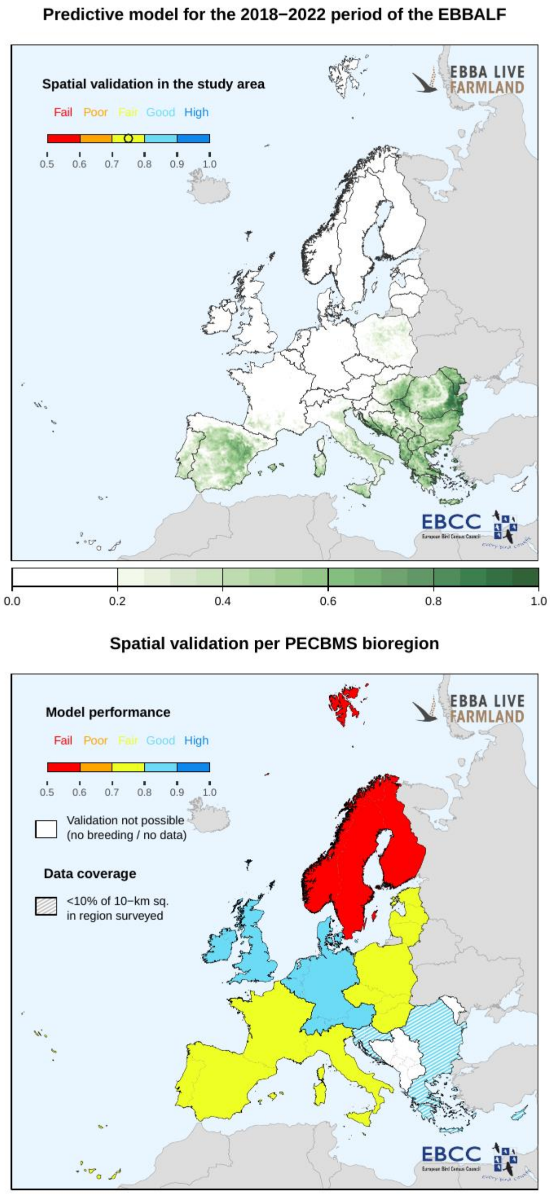

Figure 11C4. 10-km probability of occurrence map showing the modelled distribution in the period 2018–2022 for the Tawny Pipit *Anthus campestris* in EBBALF (up) and validation at regional level (down). All data come from monitoring data (PECBMS+) and spatial distribution modelling applied (see main text for further details on the procedures).

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EUROPABON

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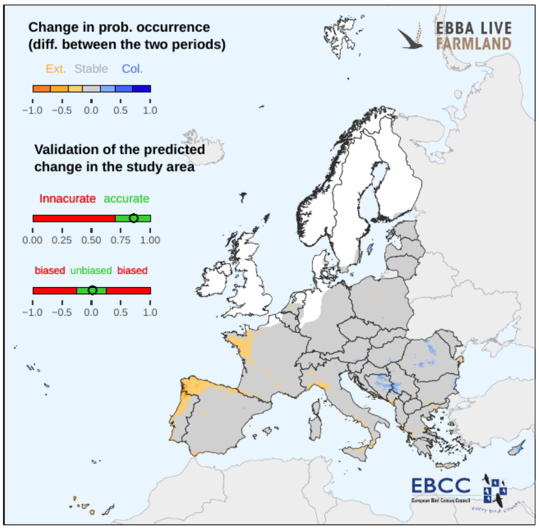
Upupa epops − Change distribution and performance

Predicted change in occurrence between 2013−17 and 2018−22 periods



Validation of the predicted change per PECBMS bioregion

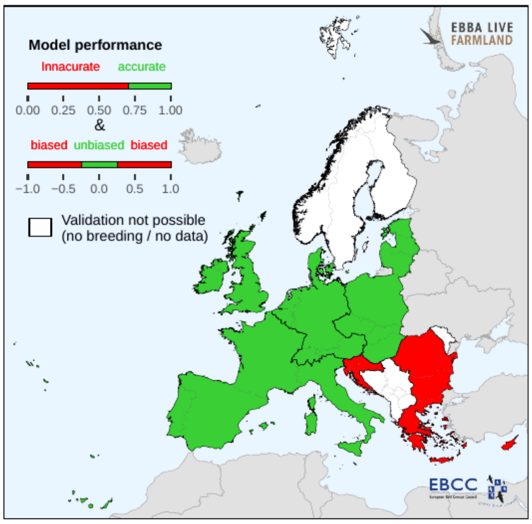


Figure 11D1. Change in the probability of occurrence at 10-km between the period 2013–2017 and the period 2018–2022 for the Common Hoopoe *Upupa epops* (up) and validation of change in the probability of occurrence at regional level (down). All data come from PECBMS monitoring sites repeated in the two periods (see main text for further details on the procedures).

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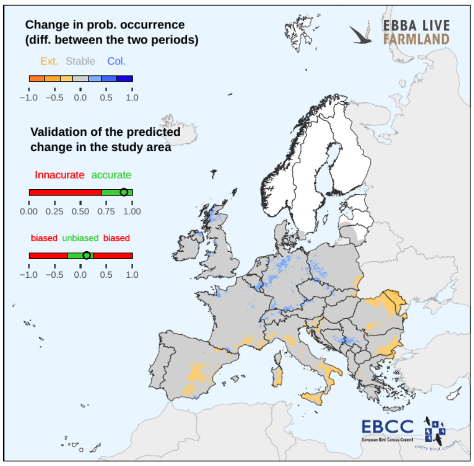
Saxicola torquatus – Change distribution and performance

Predicted change in occurrence between 2013–17 and 2018–22 periods



Validation of the predicted change per PECBMS bioregion

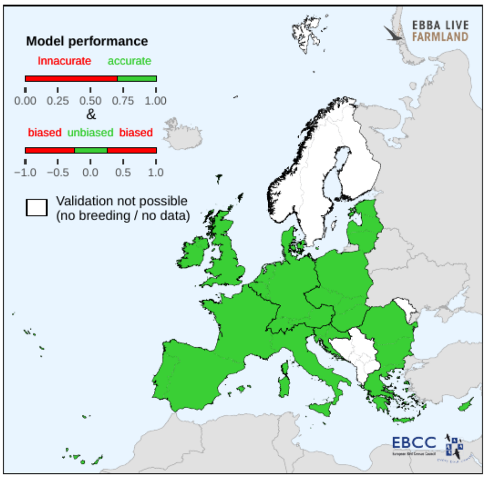


Figure 11D2. Change in the probability of occurrence at 10-km between the period 2013–2017 and the period 2018–2022 for the Common Stonechat *Saxicola torquatus* (up) and validation of change in the probability of occurrence at regional level (down). All data come from PECBMS monitoring sites repeated in the two periods (see main text for further details on the procedures).

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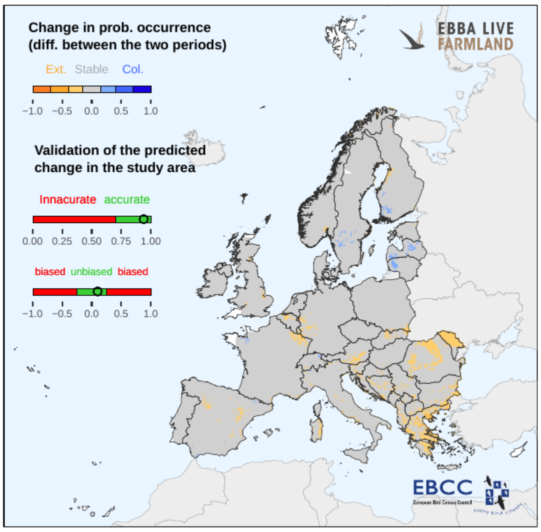
Passer montanus − Change distribution and performance

Predicted change in occurrence between 2013−17 and 2018−22 periods



Validation of the predicted change per PECBMS bioregion

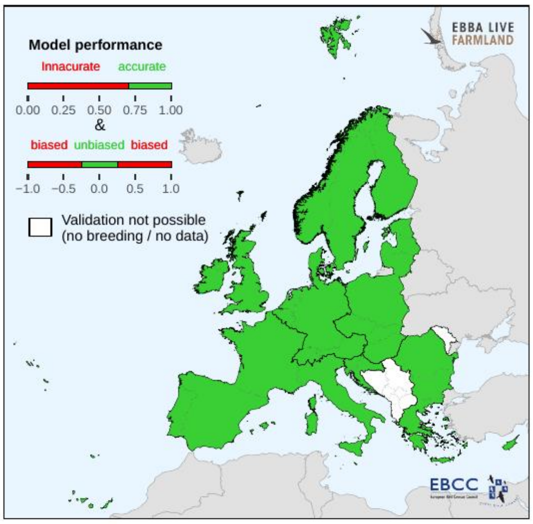


Figure 11D3. Change in the probability of occurrence at 10-km between the period 2013–2017 and the period 2018–2022 for the Eurasian Tree Sparrow *Passer montanus* (up) and validation of change in the probability of occurrence at regional level (down). All data come from PECBMS monitoring sites repeated in the two periods (see main text for further details on the procedures).

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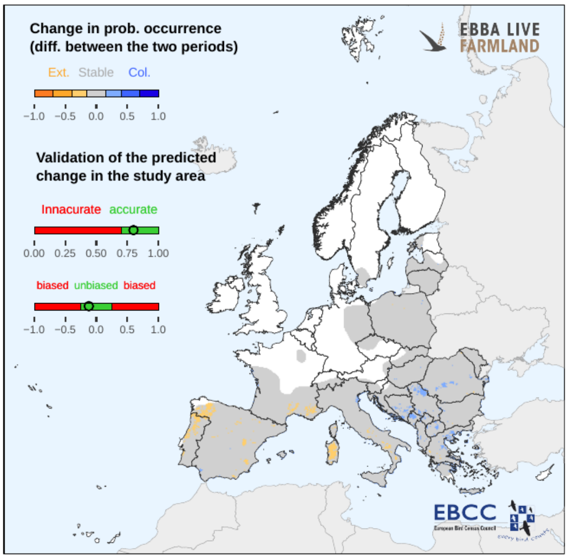
Anthus campestris − Change distribution and performance

Predicted change in occurrence between 2013−17 and 2018−22 periods



Validation of the predicted change per PECBMS bioregion

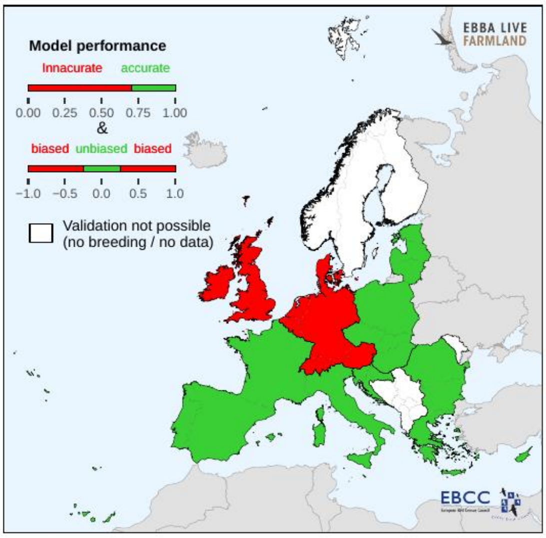


Figure 11D4. Change in the probability of occurrence at 10-km between the period 2013–2017 and the period 2018–2022 for the Tawny Pipit *Anthus campestris* (up) and validation of change in the probability of occurrence at regional level (down). All data come from PECBMS monitoring sites repeated in the two periods (see main text for further details on the procedures).

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Table 3A. Summary of change maps (first 25 species). Validation statistics at European and regional levels (SouthWest, West, SouthEast, Central-East, North, see Fig. 9). Trend for region, where *Gain* is defined as when the sum of areas of increase in probability of occurrence higher than 0.1 (blues) is greater than the sum of areas of decrease in probability of occurrence higher than 0.1 (oranges). Loss is the opposite of *Gain*, and *Stable* means equivalent areas for increases and decreases.

Scientific name	English name	Valid. (all)	Val. SW	Val. W	Val. SE	Val. C-E	Val. N	Trend SW	Trend W	Trend SE	Trend C-E	Trend N
Alauda arvensis	Eurasian Skylark	ok	ok	ok	ok	ok	ok	Stable	Stable	Loss	Stable	Stable
Alectoris rufa	Red-legged Partridge	ok	ok	ok				Loss	Stable	Stable		
Anthus campestris	Tawny Pipit	ok	ok	Failed	ok	ok		Loss		Gain	Stable	
Anthus pratensis	Meadow Pipit	ok	Failed	ok		ok	ok		Stable		Stable	Loss
Athene noctua	Little Owl	ok	ok	ok	Failed	Failed		Loss	Stable			
Bubulcus ibis	Cattle Egret	ok	ok					Gain				
Burhinus oedicnemus	Eurasian Thick-knee	ok	ok		Failed			Loss				
Calandrella brachydactyla	Greater Short-toed Lark	ok	ok		ok			Loss		Stable		
Ciconia ciconia	White Stork	ok	ok	ok	ok	ok		Gain	Gain	Gain	Gain	
Circus pygargus	Montagu's Harrier	ok	Failed	Failed	ok	ok				Stable	Loss	
Coracias garrulus	European Roller	ok	Failed		Failed	ok					Stable	
Corvus frugilegus	Rook	Failed										
Coturnix coturnix	Common Quail	ok	ok	ok	ok	ok	Failed	Loss	Stable	Loss	Stable	
Crex crex	Corncrake	ok		Failed	ok	ok	Failed			Loss	Loss	
Emberiza calandra	Corn Bunting	ok	ok	ok	ok	ok		Loss	Stable	Gain	Stable	
Emberiza cirlus	Cirl Bunting	ok	ok	Failed	Failed			Loss				
Emberiza citrinella	Yellowhammer	ok	ok	ok	ok	ok	ok	Loss	Loss	Stable	Stable	Stable
Emberiza hortulana	Ortolan Bunting	ok	ok	ok	ok	ok	Failed	Loss	Stable	Gain	Loss	
Emberiza melanocephala	Black-headed Bunting	ok			ok					Stable		
Falco naumanni	Lesser Kestrel	Failed										
Falco tinnunculus	Common Kestrel	ok	ok	ok	ok	ok	ok	Loss	Loss	Gain	Gain	Loss
Galerida cristata	Crested Lark	ok	ok	ok	ok	ok		Stable	Stable	Stable	Stable	
Galerida theklae	Thekla's Lark	ok	ok					Loss				
Hirundo rustica	Barn Swallow	ok	ok	ok	Failed	ok	ok	Stable	Stable		Stable	Stable
Lanius collurio	Red-backed Shrike	ok	ok	ok	ok	ok	ok	Loss	Stable	Stable	Stable	Loss

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Table 3B. Summary of change maps (next 25 species). Validation statistics at European and regional levels (SouthWest, West, SouthEast, Central-East, North, see Fig. 9). Trend for region, where *Gain* is defined as when the sum of areas of increase in probability of occurrence higher than 0.1 (blues) is greater than the sum of areas of decrease in probability of occurrence higher than 0.1 (oranges). Loss is the opposite of *Gain*, and *Stable* means equivalent areas for increases and decreases.

Scientific name	English name	Valid. (all)	Val. SW	Val. W	Val. SE	Val. C-E	Val. N	Trend SW	Trend W	Trend SE	Trend C-E	Trend N
Lanius excubitor	Great Grey Shrike	Failed										
Lanius meridionalis	Iberian Grey Shrike	ok	ok					Loss				
Lanius minor	Lesser Grey Shrike	ok	Failed		ok	Failed		Loss		Stable		
Lanius senator	Woodchat Shrike	ok	ok		Failed			Loss				
Limosa limosa	Black-tailed Godwit	Failed										
Linaria cannabina	Common Linnet	ok	ok	ok	ok	ok	ok	Stable	Stable	Stable	Stable	Stable
Melanocorypha calandra	Calandra Lark	ok	ok		ok			Loss		Loss		
Motacilla flava	Western Yellow Wagtail	ok	ok	ok	ok	ok	ok	Stable	Stable	Gain	Stable	Loss
Oenanthe hispanica	Black-eared Wheatear	ok	ok		Failed			Stable				
Passer hispaniolensis	Spanish Sparrow	Failed										
Passer montanus	Eurasian Tree Sparrow	ok	ok	ok	ok	ok	ok	Loss	Loss	Loss	Stable	Gain
Perdix perdix	Grey Partridge	ok	Failed	ok	ok	Failed	ok		Gain	Gain		Gain
Petronia petronia	Rock Sparrow	ok	ok					Loss				
Pterocles alchata	Pin-tailed Sandgrouse	Failed										
Pterocles orientalis	Black-bellied Sandgrouse	Failed										
Saxicola rubetra	Whinchat	ok	ok	ok	ok	ok	ok	Stable	Stable	Stable	Loss	Stable
Saxicola torquatus	Common Stonechat	ok	ok	ok	ok	ok		Loss	Gain	Loss	Stable	
Serinus serinus	European Serin	ok	ok	ok	Failed	ok		Stable	Stable		Stable	
Streptopelia turtur	European Turtle-dove	ok	Failed	ok	Failed	ok			Stable		Stable	
Sturnus unicolor	Spotless Starling	ok	ok					Loss				
Sturnus vulgaris	Common Starling	ok	ok	ok	ok	Failed	ok	Stable	Loss	Stable		Stable
Sylvia communis	Common Whitethroat	ok	ok	ok	ok	ok	ok	Loss	Loss	Loss	Loss	Loss
Tetrax tetrax	Little Bustard	Failed										
Upupa epops	Common Hoopoe	ok	ok	ok	Failed	ok		Loss	Stable		Stable	
Vanellus vanellus	Northern Lapwing	ok	ok	ok	Failed	ok	ok	Stable	Loss		Loss	Loss

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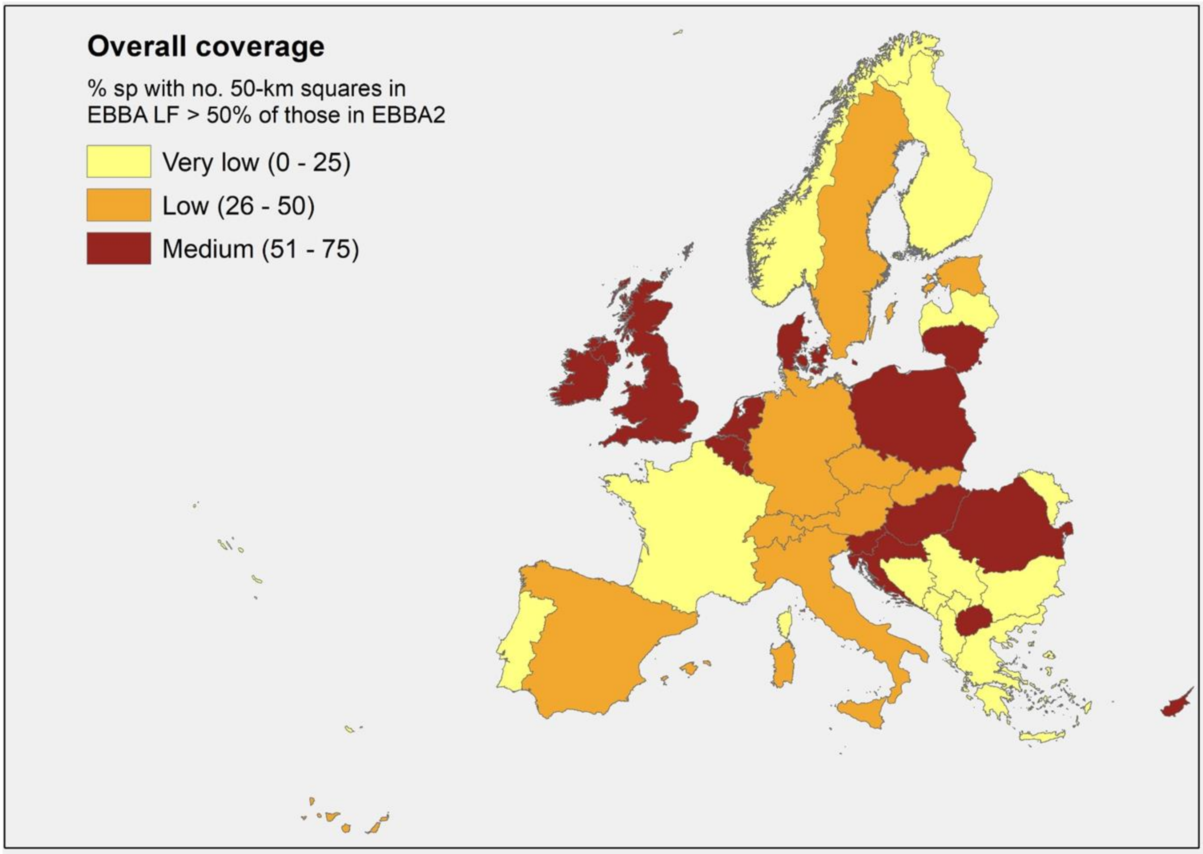

Figure 12. Quality of coverage of the network of PECBMS+ monitoring sites for farmland birds per country, expressed as the percentage of species for which the number of 50-km squares in which the species occurred in PECBMS data for the period 2018–2022 were lower than 50% of the total number of 50-km squares reported in EBBA2 (period 2013–2017). See particular examples in Figures 11A1-A4.

6. Discussion

6.1. Advantages and caveats of the EBV result

In this deliverable, we have proved the capacity of the European bird monitoring network, represented by the EBCC, to update breeding bird distributions on a regular basis, matching the temporal and spatial resolutions of the required EBV characteristics (see section 4.1. for more details). Therefore, this exercise shows the ability and limitations to map species' distributions without launching an atlas but using all the atlas infrastructure produced previously. In some particular cases, the new approach could even be as effective (or even more) as an atlas. While EBBA2 products have divergences in taxonomic completeness, with only 222 species modelled at 10-km resolution, the new implemented models seem to have the capacity to be replicated to the same or even a higher number of species, at least if restricted to the geographic area covered in the EBBALF project (e.g., the modelled map for the Little Owl *Athene noctua* was not produced in EBBA2). The technical advances (programming skills and model knowledge gained to model species distributions) made because of the present deliverable may allow relatively easy implementation of models across a large set of species. This of course includes

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the capacity to generate distribution maps at least for some of the species included in the Annex I of the Birds Directive, which approaches the goals of the EBV "Species abundances of terrestrial birds: priority and rare birds" (see Morán-Ordónez et al. 2023). In this sense, EBBALF is a first step to contribute to the reporting of the Birds Directive with standardized data and methods across the whole of Europe. As stated before, the current EBV generated in this showcase could eventually be compiled at different scales, such as a product of the national data aggregation in the Birds Directive reporting process or as an EBV produced at EU level for the EEA. This could ultimately translate into an improvement on the information tools used to evaluate the conservation policy. Given that this showcase represents a demonstrative case study on how biodiversity monitoring data could be used to derive harmonised information on distribution across European MS, the procedures implemented here could be useful to build similar EBVs for other well monitored species included in the reporting of the Article 17 of the Habitats Directive, such as the case of butterflies (see section 3). Similarly, another key potential application for the EBVs flows described in this deliverable is the Nature Restoration Law to identify priority areas for restoration as areas that have experienced either more losses in species occurrence or, from a different ecological perspective, areas that have already shown signals for population recovery (where gains have already started). Another important contribution resulting from modelled species distribution EBVs could be the eventual integration into species linked to farmland to derive a spatially explicit Farmland Bird Indicator (FBI) that we interpret and value as a surrogate for farmland quality (see section 4.4.).

We have already mentioned that the EBBALF models of probability of occurrence have been improved with respect to EBBA2. Some of these improvements are related to the inclusion of the species range for predicting species distributions, a variable that was not fully available when the EBBA2 models were run, because the modelling was run in parallel to the production of the 50-km maps. Therefore, the EBBALF SDMs were developed exclusively using observational data and predictor values within the geographical range of each species. The advantages of using this approach include the fact that model functions are exclusively calibrated within the context of the species range, which may enhance the significance of predictors that exhibit local variability and consequently influence the model's capacity to accurately predict the occurrence of the species in their actual habitats. This approach also served to reduce abrupt transitions in the probability of occurrence, especially near the borders of species' ranges, and consequently cropping of predicted probabilities of occurrence values outside the range was not required anymore. Overall, we aimed to provide a more accurate representation of the spatial model performance (see more details in the *Species' geographical range* section). In addition, EBBALF adopted a different methodological approach for analysing change based on the *predicted change*, which corresponds to the difference in the probability of occurrence between the wEPs generated from comparable datasets for two periods, whose basis has already been implemented at the national level, for example in the latest Swiss Breeding Bird Atlas (Knaus et al. 2018). Some of the benefits of the method used to evaluate change include the production of a spatially detailed change map at 10-km resolution for all squares within the entire geographical range of each species, and mitigated biases derived from variations in sampling locations and sample sizes when using the same surveys within the same 10-km squares for both time periods to construct the wEP models (see *Change analysis* section). Equally important were the uncertainty assessments made for both updated distribution maps and change maps. On one hand, the analysis of the spatial performance of updated distributions allowed to increase the spatial resolution of the AUC metric by not only assessing the performance across the entire geographical range of each species, but also at the level of PECBMS geographical

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regions. On the other hand, the validation of change performance also represents a novel analysis, which is crucial to accomplish the EuropaBON main objectives of establishing a way to validate distribution change performance. The employed method has been extensively described in Rapacciuolo et al. (2014) and has served to quantify the calibration of SDMs in numerous papers (Pearce and Ferrier 2000; Boyce et al. 2002; Hirzel et al. 2006; Phillips and Elith 2010). It has also been a key reference for the design of novel validation methods (Piirainen et al. 2023). Lastly, another important outcome resulting from the modelling framework developed here, complemented with the analysis performed at 50-km, is the identification of regions showing low validation statistics as a result of important spatial gaps in the amount and distribution of monitoring sites. This is particularly evident in south-east Europe and represents an opportunity to quantify the impact of the low coverage of monitoring sites in that region.

Although the results shown in this showcase represent a significant step towards the target of updating species distribution in a regular and frequent manner, there are, however, some relevant aspects that could be considered as caveats of this product as such or in their future development.

From our perspective, the most important caution that should be considered in this showcase is that the network of bird monitoring schemes currently running across Europe cannot be taken for granted without the proper recognition and funding at national and European scales. The amount and quality of the data used to develop the maps of this showcase is collected by tens of thousands of skilled volunteers and coordinated by ornithological organisations under the umbrella of the EBCC. Thus, a major part of the fieldwork is carried out on a voluntary basis but this does not mean it is collected with no cost. Coordinators recruit, train, and support volunteers; provide them with feedback; validate records; ensure timely reporting to the central database and provide reports of results to governments and academic institutions. In many countries, this work relies on volunteers or is partially contracted, and they are consequently especially vulnerable to collapse. PECBMS is actually the European project that coordinates the flow of site-level monitoring data and maintains the communication within the partnership of national coordinators. The future development of EU initiatives on monitoring, such as the Biodiversity Monitoring Coordination Centre (BMCC), should be able to understand the fundamentals of this collaborative network to strengthen the overall monitoring infrastructure to develop a robust EBV workflow.

In this showcase we have developed the EBV “Species distributions terrestrial birds”. Modelled maps of probability of occurrence show in general good validation statistics but the rarer the species the lower the confidence we may have in these maps. This means that common bird monitoring data could be, at least in some cases, insufficient to generate reliable outcomes for the EBV “Species abundances of terrestrial birds: priority and rare birds”. For widespread and common species, the PECBMS network may not be able to capture information at the edges of the species distributions or in areas where the coverage is low (Fig. 11A1-4), and regional validations are not always completely satisfactory (Fig. 11C1-4). Given these limitations of the monitoring schemes it would be very important to evaluate the complementary role that casual or semi-structured observations may have to produce these modelled maps. These data may be relevant not only as input data for models but also as relevant information to define species ranges, which cannot be assumed to be constant over time. In this context data from the EuroBirdPortal (EBP; https://eurobirdportal.org) project seems of particular relevance. EBP

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includes data from all online portals in Europe and consists not only of a common repository updated every day but is also validated by national ornithological organisations (see also section 6.3).

Other potential limitations of this showcase are the taxonomic completeness. The total number of terrestrial birds goes beyond the list of farmland birds included in this study. We can expect that the coverage of monitoring data could be also useful to develop maps for forest or urban birds, but it is less clear that this is possible for other relevant groups such as waterbirds, waders or seabirds. For the latter, a specific EBV ("Species distributions of marine birds") has been considered of particular importance in EuropaBON. Finally, suitable data to inform on distributions outside the breeding season or for some colonial species is much more challenging. Definitely, common bird monitoring does not properly cover all types of birds all year around and the potentialities of EBP data could be especially important to be unfolded.

It is particularly important to note that the maps conducted in the EBBALF project were based on species occurrence data. The project did not explicitly address spatial patterns of abundance, neither in each time period nor for the change between two time periods. Therefore, the current approach did not build spatially explicit models of species abundance and its change over time, although some preliminary analyses show that the probability of occurrence could be considered as a surrogate of abundance at European level for most farmland species (ANNEX V). Future development of change maps based on trends in abundance should be ideally developed.

6.2. Breakthroughs and lessons learned

The most important advancement of this showcase is the demonstration of the capacity of the European network of bird monitoring schemes to update robust distribution maps. This could be achieved thanks to the comparison with the recently made European Atlas, which involved an amount of effort much more important than that of the common bird monitoring. Therefore, the EBV "Species Distributions of Terrestrial Birds", where maps are expected to be produced every few years at a minimum resolution of 10-km seems to be a feasible and cost-effective objective.

The main lesson learned in this showcase is that these updated distributions can only be achieved by means of spatial modelling techniques and that the simple compilation of observations from monitoring projects do not allow to produce robust information on distribution, particularly for uncommon species. Nevertheless, information on the species ranges is critically important to produce robust predictions, and this requires more information than that provided by monitoring schemes, which suggest that there is a key role for including casual observations in the future.

6.3. Challenges and proposed solutions

So far, the data flowing to the reporting of the Habitats (92/43/EEC) and Birds (2009/147/EC) Directives does not originate from standardized data (e.g., expert opinion is frequently used to assess the conservation status of specific species/habitats) and it integrates a wide variety of monitoring programs and species data that do not follow the same standard harmonization procedures in most cases. In these cases, it can be difficult to understand the flows of data and the criteria and methods used for data collection and integration at local and subnational levels. Additionally, it is uncertain if these methods will be compatible for generating the desired terrestrial EBV at the required spatial and

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temporal resolution and with the appropriate taxonomic focus. However, as stated before, the role of BMCC will be crucial to develop robust EBV workflows and strengthen the data integration processes between the different initiatives using common standards at the European level.

It is important to note that there will be another phase of implementation of the EBBALF project. In this first phase, the time span covered by the updated maps is the 5-year period following the end of EBBA2 fieldwork (which was mostly 2013–2017), that is, 2018–2022, i.e., the main outcomes of this deliverable. In the second phase, we expect to incorporate EuroBirdPortal (EBP) data. EBP (https://www.eurobirdportal.org/) aims to create a common data repository that will hold data from each of the existing portal systems. This will contain the minimum aggregated information required to realise the full potential for large scale spatiotemporal analyses of such data and for other research and applied uses that are appropriately undertaken at a European scale. This initiative has the potential to collect data on all bird species occurring in Europe, also covering less represented habitats (e.g., wetlands) and other seasons of the year (wintering season), which remains a challenge for common bird monitoring schemes such as PECBMS. Currently, however, only the data for 137 species are stored in the EBP central data repository. Despite the present limitation of EBP, the vast amount of data contained in these portals and the sheer amplitude of their combined geographical and taxonomic coverage offer great potential for research on the temporal and spatial distribution of birds across large geographical areas. Such knowledge is urgently needed in order to increase understanding of bird distributions and movements and to address issues concerned with conservation and management (e.g., wind farms). Nonetheless, we should acknowledge the challenge associated with the integration of different data sources and massive amounts of data. Unlike traditional monitoring projects, which focus on structured data collection, bird online portals aim mainly to obtain year-round data from the relatively unstructured but intensive and widespread activities of birdwatchers. The integration of structured data coming from monitoring initiatives (i.e., PECBMS) with data gathered following simple standardised protocols (e.g., complete lists), or in some cases even no protocol (casual observations), will obviously require big computational efforts, also in terms of technical programming skills and model knowledge. However, current methods exist to model such data. For instance, AdaSTEM (Adaptive Spatio-Temporal Exploratory Model) is a framework for analysing large-scale patterns with an ensemble of local regression models (Fink et al. 2020).

We have developed maps that show the change in the probability of occurrence but not an explicit change in abundance. With this in mind, one could check if the results of change in the probability of occurrence between the two studied periods (2013–2017 and 2018–2022) are consistent or not with the results of population changes (in abundance) of PECBMS for the species and regions for which the two types of data (change map values and PECBMS trends) are available. This could be conceived as an analysis conceptually equivalent to the one done on the relationship of probability of occurrence, but this time for the probability of occurrence change and abundance change.

Regarding specific methodological challenges, there is a need to further explore and revise the method used for generating change maps. For instance, it would be important to assess to what extent the fact of reducing the datasets in the two periods (to obtain the exact same change data) and then subtracting both models alters the final result (i.e., change map). The simple fact of data selection, which implies some loss of information, could certainly influence the species relationships with their habitats. In this sense, a similar approach to the one taken in the latest Swiss Breeding Bird Atlas, where no data reduction is applied (Knaus et al. 2018), could be used to generate new change maps and see whether potential distortions could emerge as a result of data selection.

Another methodological challenge is to properly estimate the detection probability of each species and squares sampled. As explained in this deliverable, we have used a new method for introducing the detection probability in correlative SDMs. While this approach serves as a valuable method to correct for imperfect detection, we acknowledge that it may not be the optimal approach. In this sense, a comprehensive correction for imperfect detection would ideally be achieved through the utilization of a formal site-occupancy model (MacKenzie et al. 2018).

We should mention that all the work done in this showcase ends at the level of EBVs, and we do not address indicators. We think that there is a need to spatialise multi-species indicators such as the FBI because this type of summary metrics can be more useful as tools for evaluation of conservation policies than species-specific EBVs.

Finally, it is important to say a few words on the multi-scalarity of the governance of the production of this EBV. For informed decision-making purposes and to fulfil reporting obligations, information is required on different spatial scales: local, subnational, national, regional and EU (e.g., Birds Directives) and global (e.g., CBD) (Silva del Pozo et al. 2023). Several options to aggregate the information and deliver EBVs are possible, from one common strict protocol and a joint analysis of raw data to flexible protocols and an analysis of locally produced EBVs. The latter has been recently recommended when there are already existing monitoring protocols in use (Silva del Pozo et al. 2023), as in the case of PECBMS and EBP. In this context, the role of EBCC national partners participating in EBBALF is not that of data providers but they are responsible to produce EBVs locally and work together in the context of the EBCC to produce the European EBVs. The combination of national and European information processes should be aligned with overarching strategies implemented in the BMCC.

7. Conclusion

The results of this showcase suggest that the robust monitoring network well distributed across Europe is a very useful basis for the regular production of updated distribution maps for 5-year periods and maps showing change between these time frames. Importantly, these results can be well aligned with the requirements of the EBV “Species distribution of terrestrial birds”, in particular, the spatial resolution of 10-km, the contiguous information across the EU, the temporal interval of 3-6 years (5 in our showcase) and the probability of occurrence as a suitable metric. Although further progress should be done to unfold the possibilities of more unstructured non-monitoring observations in this and other bird-related EBVs, the results of this showcase demonstrate that the development of this approach for birds is not a technical problem and only depends on finding the most appropriate governance system to be fully implemented and maintained. Finally, the modelling approach used here could be a robust basis to explore the production of other EBVs on distribution in other biological groups for which monitoring networks exist.

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10. Supplementary material

- List of participating countries and ornithological organisations (ANNEX I)
- List of environmental predictors and explanation of predictor characteristics (ANNEX II)
- Importance of predictors for updated models for 2018–2022 (ANNEX III)
- Impact of spatial reduction of data on model performance for 2018–2022 (ANNEX IV)
- Surrogacy analysis between probability of occurrence and abundance (ANNEX V)
- Gaps in coverage for each study species and country resulting from the quality assessment of the 50-km occurrence maps (ANNEX VI)

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ANNEX I. List of participating countries and ornithological organisations

Country	Organisation Name
Andorra	Andorra Research + innovation
Austria	BirdLife Austria
Belgium	AVES/Natagora
	Research Institute Nature and Forest
Bosnia and Herzegovina	Naše Ptice and Society for Research and Protection of Biodiversity
Bulgaria	Bulgarian Society for the Protection of Birds
Croatia	Ministry of Energy and Sustainable Development, Institute for Environmental and Nature Protection
	Croatian Society for Protection of Birds and Nature
Cyprus	BirdLife Cyprus
Czechia	Institute of Environmental Studies, Faculty of Science, Charles University
	Czech University of Life Sciences, Faculty of Environmental Sciences, Prague
	Czech Society for Ornithology
Denmark	Danish Ornithological Association (BirdLife Denmark)
Estonia	Estonian Ornithological Society / BirdLife Estonia
Finland	Zoological Museum, Finnish Museum of Natural History
France	National Natural History Museum
	Ligue pour la protection des oiseaux
Germany	Federation of German Avifaunists
Greece	Hellenic Ornithological Society
Hungary	University of Nyiregyhaza
	Hungarian Ornithological and Nature Conservation Society (BirdLife Hungary)
Ireland	BirdWatch Ireland
Italy	Italian League for Bird Protection
Latvia	Latvian Ornithological Society

Latvia	Department of Zoology and Animal Ecology, Faculty of Biology, University of Latvia
Liechtenstein	Liechtenstein Botanical-Zoological Society
Lithuania	Lithuanian Ornithological Society
Luxembourg	Centre Ornithological of Luxembourg
Moldova	Society for Birds and Nature Protection
Montenegro	Centre for Protection and Research of Birds
Netherlands	Sovon, Dutch Center for Field Ornithology
North Macedonia	Macedonian Ecological Society
Norway	Norwegian Institute for Nature Research
	Norwegian Ornithological Society / BirdLife Norway
Poland	Museum and Institute of Zoology, Polish Academy of Sciences
	Polish Society for the Protection of Birds
Portugal	University of Évora
	Portuguese Society for the Study of Birds
Romania	Romanian Ornithological Society
Serbia	University of Novi Sad, Faculty of Sciences, Department of Biology and Ecology
	Bird Protection and Study Society of Serbia / BirdLife Serbia
Slovakia	Slovak Ornithological Society / BirdLife Slovakia
Spain	Spanish Society of Ornithology / SEO BirdLife
	Catalan Ornithological Institute, GOB Mallorca, SOM Menorca
Sweden	Lund University, Department of Biology
	Swedish University of Agricultural Sciences, The Swedish Species Information Centre
Switzerland	Swiss Ornithological Institute
United Kingdom	British Trust for Ornithology

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ANNEX II. List of environmental predictors and explanation of predictor characteristics

Table A2.1. Predictors used to develop the EBBALF models.

Category	Name predictor	Units	Type	Source
Anthropogenic	Human population density	person/km2	dynamic	Gridded Pop. of the World
Climate	Annual evapotranspiration	ET/PET	dynamic	MODIS NASA EARTHDATA
Climate	Mean temperature of the warmest month	K	dynamic	ERA5-Copernicus
Climate	Mean annual temperature	K	dynamic	ERA5-Copernicus
Climate	Mean temperature in the breeding period *	K	dynamic	ERA5-Copernicus
Climate	Mean temperature of the coldest month	K	dynamic	ERA5-Copernicus
Climate	Total annual precipitation	mm	dynamic	ERA5-Copernicus
Climate	Total precipitation in the breeding period *	mm	dynamic	ERA5-Copernicus
Climate	Surface net solar radiation	J m-2	dynamic	ERA5-Copernicus
Geography	Distance to the coastline	m	static	EBBA Live Farmland
Geography	Longitude (centre of 10-km square)	m	static	EBBA2
Habitat struct.	Accumulated NDVI in the breeding period *	DHI cum	dynamic	MODIS13 Vegetation Index
Habitat struct.	Minimum NDVI in the breeding period *	DHI min	dynamic	MODIS13 Vegetation Index
Habitat struct.	Seasonality NDVI in the breeding period *	DHI var	dynamic	MODIS13 Vegetation Index
Habitat struct.	Shannon Habitat Diversity Index	-	dynamic	EBBA2 and EBBALF
Land cover	Bare areas	%	dynamic	ESA CCI Land Cover
Land cover	Broadleaved forests	%	dynamic	ESA CCI Land Cover
Land cover	Coniferous forests	%	dynamic	ESA CCI Land Cover
Land cover	Continental water bodies	%	dynamic	ESA CCI Land Cover
Land cover	Grassland	%	dynamic	ESA CCI Land Cover
Land cover	Herbaceous cover	%	dynamic	ESA CCI Land Cover
Land cover	Irrigated crops	%	dynamic	ESA CCI Land Cover
Land cover	Mixed broadleaved and coniferous forests	%	dynamic	ESA CCI Land Cover
Land cover	Mosaic cropland-natural vegetation	%	dynamic	ESA CCI Land Cover
Land cover	Mosaic natural vegetation	%	dynamic	ESA CCI Land Cover
Land cover	Permanent ice	%	dynamic	ESA CCI Land Cover
Land cover	Rainfed cropland	%	dynamic	ESA CCI Land Cover
Land cover	Rainfed tree crop	%	dynamic	ESA CCI Land Cover
Land cover	Shrublands	%	dynamic	ESA CCI Land Cover
Land cover	Sparse vegetation	%	dynamic	ESA CCI Land Cover
Land cover	Urban areas	%	dynamic	ESA CCI Land Cover
Land cover	Wetlands	%	dynamic	ESA CCI Land Cover
Topography	Mean elevation	m	static	FAO; Fischer et al. 2008
Topography	Mean slope	%	static	FAO; Fischer et al. 2008

* Breeding period is from April to July

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Methodology to generate the predictor variables

We utilized 34 environmental predictors in the development of the SDMs, 30 of which are shared with the EBBA2 Atlas (which employed 40 environmental predictors). In our approach, we reconstructed all the predictors, even if they had been previously utilized in the EBBA2 Atlas. We divided these predictors into two categories: static predictors, which exhibit minimal variation over short time intervals, and dynamic predictors, which may change over the years. Consequently, we generated unique static predictors, but several dynamic predictors for each distinct period.

Our primary approach involved utilizing the same EBBA2 Atlas predictors to develop the models for the EBBALF project. However, certain modifications were applied on both 2013–2017 and 2018–2022 periods due to (1) the lack of traceability of the original spatial layers, (2) the finding of outdated sources for the 2018–2022 period and (3) the appropriateness of the predictor layers to the characteristics of the EBBALF project.

An R script is available online where functions from the packages *terra* (Hijmans 2023) and *sf* (Pebesma and Bivand 2023) were used to develop the spatial analyses. The script generally follows these steps to build all the raster map predictors:

- Instructions for manually or automatically downloading data from global open-access databases.
- Cropping layers to match the EBBA2 Atlas European borders extent.
- Transforming the projection to ETRS89-LAEA Europe, also known as EPSG:3035.
- Calculating the mean of all the raster values that lay inside the 10-km squares reference grid system.
- Filling the gaps (NAs) in coastal squares using a highly local BAM model, i.e., a GAM with an enhanced function for large datasets (‘bam’ function in the mgcv R package; Wood 2011), which prevents nearby mountainous areas from significantly influencing the coastal pixels. BAM models predict values based on gaussian smoothing the neighbouring values.

Table A2.1. lists the predictors along with various characteristics such as units, source, resolution, etc. Notably, we avoided using soil type predictors, because we could not replicate their calculation methodology. Consequently, the Shannon Soil Diversity Index was not generated either.

For specific procedures on specific predictors, please refer to the following sections.

<u>Static</u>

We built the following static predictors: distance to the coastline, longitude centre of the 10-km square, mean elevation, and mean slope. All four layers were generated following the steps explained in the preceding section.

<u>Dynamic</u>

We built 30 dynamic predictors for each period. Whenever possible, we utilized data from all the years within each respective period. However, for certain layers not all the years were available in the databases. Despite this limitation, we consistently generated all the dynamic predictors for each period, computing the mean value for each available year independently within each period.

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Land cover

We first split the various Land Cover (LC) categories and reclassified them according to the same categories employed in the EBBA2 Atlas. The following table illustrates this process.

Table A2.2. Recategorization of Land Cover by the European Space Agency's Climate Change Initiative (ESA CCI) from the EBBA2 Atlas reference.

Project categories names	ESA CCI Land Cover categories
Bare areas	200, 201, 202
Broadleaved forests	50, 60, 61, 62
Coniferous forests	70, 71, 72, 80, 81, 82
Continental water bodies	210
Grassland	130
Herbaceous cover	11
Irrigated crops	20
Mixed broadleaved and coniferous forests	90
Mosaic cropland-natural vegetation	30, 40
Mosaic natural vegetation	100, 110
Permanent ice	220
Rainfed cropland	10
Rainfed tree crop	12
Shrublands	120, 121, 122
Sparse vegetation	140, 150, 151, 152, 153
Urban areas	190
Wetlands	160, 170, 180

Given that the Land Cover layers had a 300-m resolution, we proceeded to calculate the percentage of coverage for each category within each 10-km square, following the same procedure as in the EBBA2 Atlas.

Climate

Temperature and precipitation predictors were environmental layers produced by a reanalysis of forecasts and meteorological observations averaged for each month. These layers initially had a resolution of 11 km (0.1º), so we performed a disaggregation process to achieve a resolution of 5.5 km, ensuring the removal of the remaining empty pixels. The following modifications were then applied to calculate climatic variables for each period:

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- Annual temperature: average of the monthly mean temperature.
- Temperature in the breeding period: average of the monthly mean temperature from April to July.
- Average temperature of the warmest month: we identified that the warmest month was July for both periods, so we calculated the average temperature of July.
- Average temperature of the coldest month: we identified that the coldest month was January for both periods, so we calculated the average temperature of January.
- Annual precipitation: the raw data consisted of the average daily precipitation in meters. This required several steps: (1) determination of the number of days in each month for each year, considering the leap years and months of varying lengths, (2) summation of daily precipitation to obtain the annual precipitation, (3) calculation of the mean value for all the years for each period and (4) converting the units from meters to millimetres of water.
- Precipitation in the breeding period: following the same procedure as for Annual precipitation but just summing daily precipitation for the months of April, May, June, and July.
- Solar radiation: calculated average solar radiation across all months.

In addition to these climatic predictors, we developed the evapotranspiration predictor, but based on a different methodology. This involved calculating the ratio of real evapotranspiration (RET) and potential evapotranspiration (PET). The average RET and PET values were calculated over each period yearly, and six categories were reclassified as Not Available (NA), representing background values for marine areas, flooded areas, urban areas, ice, etc. The RET/PET ratio was computed to obtain the evapotranspiration predictor layer, following the same procedure as in the EBBA2 Atlas.

Given the presence of numerous NA values on the evapotranspiration layer (on urbanized areas, ice, water, etc.), we employed a two-step process. Firstly, if one or more 500-m pixels fell inside a 10-km square, their values were averagely incorporated. Secondly, any remaining gaps were filled using the BAM model procedure, as previously described for coastal pixels, but applied to the entire remaining gaps.

Habitat structure

The Dynamic Habitat Indices (DHI) comprise a collection of metrics related to vegetation productivity, specifically designed for biodiversity assessments and the characterization of species habitats (Radeloff et al. 2019). In our analysis, we proceeded to utilize the Normalized Difference Vegetation Index (NDVI) type of DHI, that is the same type of DHI employed in the EBBA2 Atlas. We also adhered to the same breeding period between April and July (from Julian day 90 to 215) as in the EBBA2 Atlas. However, we increased the number of NDVI subindices. While the EBBA2 Atlas solely generated the cumulative NDVI predictor, we introduced two additional predictors derived from the following subindices: the minimum NDVI and variation NDVI. These subindices, originally developed by the SilvisLab team (https://silvis.forest.wisc.edu/data/dhis/), were incorporated into the EBBALF project. We calculated them yearly for each period and subsequently determined the mean values for each period. The methodology used to derive each NDVI subindices is described below:

- Cumulative NDVI: the area under the phenological curve during the breeding period.
- Minimum NDVI: the minimum value of the phenological curve within the breeding period.

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- Variation NDVI: the coefficient of variation, represented by the standard deviation by the mean, of the phenological curve during the breeding period.

In addition to the NDVI-related predictors, we also developed another predictor pertaining to habitat structure. Following the EBBA2 Atlas approach, we considered adding the Shannon Habitat Diversity Index (SHDI). The SHDI was estimated using the Shannon diversity formula: *H’ = – sum(pi x ln(pi))*, where *pi* represents the proportion of each of the seventeen LC layers (as detailed in the *Land Cover* section).

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ANNEX III. Importance of predictors for updated models for 2018–2022

Importance of each predictor on the SDMs is extracted from the *biomod2* package (Thuiller et al. 2021). The available SDMs in *biomod2* were Artificial Neural Network (ANN), Boosted Regression Trees (BRT), Flexible Discriminant Analysis (FDA), Generalized Linear Models (GLM) and Multivariate Adaptive Regression Splines (MARS) (see *Species Distribution Models* section for more information). Therefore, the importance of predictors as shown in Fig. A3 is extracted from a subset of the complete set of models used in EBBALF. This figure shows that the variables that mainly predict the farmland species distribution in the 2018–2022 period are related to climate, especially temperature, evapotranspiration, and surface solar radiation. It also highlights the 'longitude' variable, a geographical measure, and herbaceous cover, a direct measure of farmland coverage.

On the other hand, neither irrigated crops, mosaic cropland-natural vegetation, nor rainfed tree crops have significant importance for the prediction of the farmland bird species distribution.

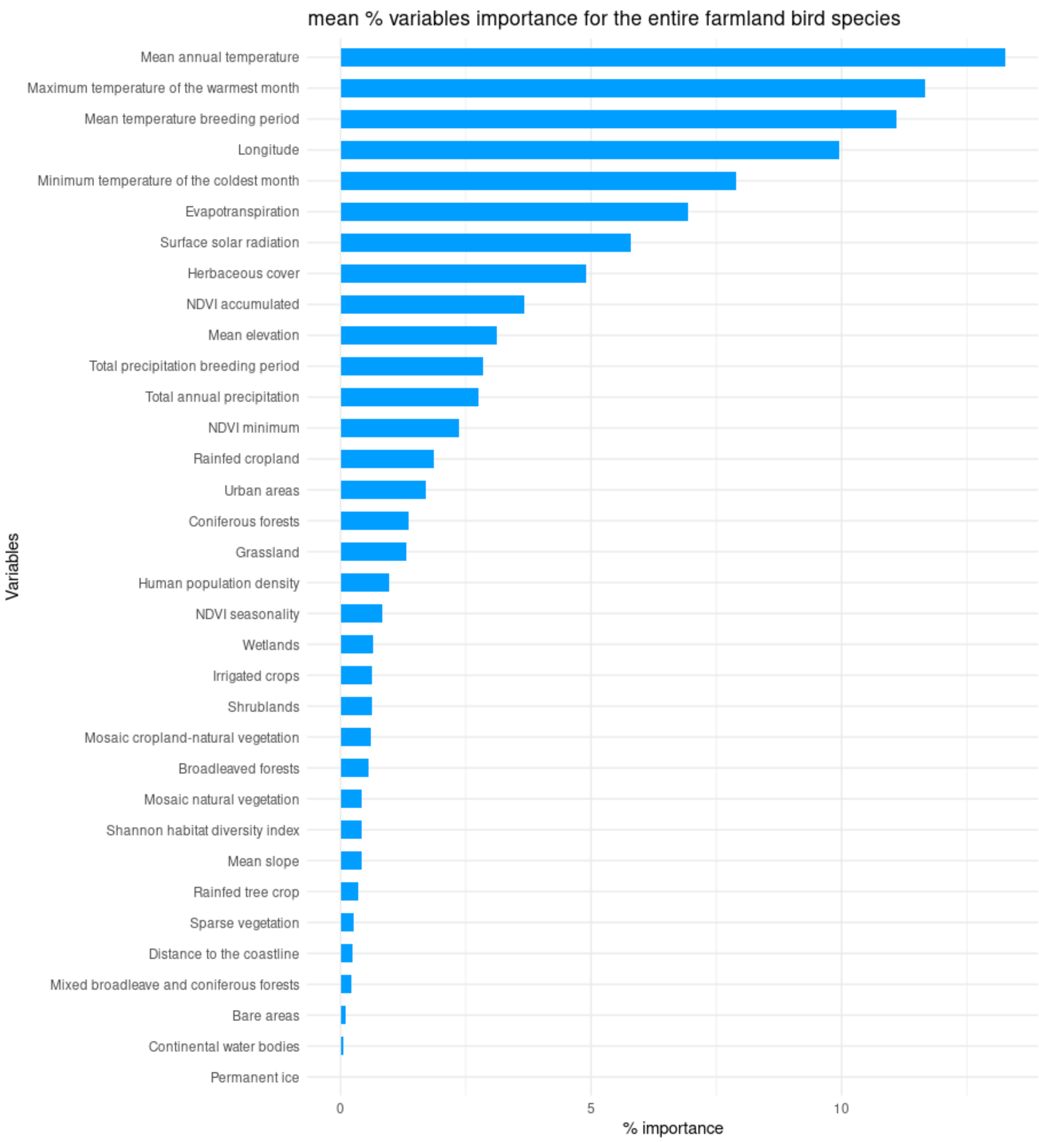

Fig. A3. Barplot of the mean importance of predictor variables for the 50 farmland bird species in the 2018–2022 period in percentage.

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ANNEX IV. Impact of spatial reduction of data on model performance for 2018–2022

The impact of spatial reduction of data on model performance for change maps was explored. We used the comparable datasets as a showcase to test the performance when reducing spatial data. This decision was motivated because (1) both spatial and change performances could be assessed with comparable datasets, and (2) the reduction of over-aggregated 10-km squares was not applied to comparable datasets, so the performance consequences on data thinning would hypothetically be clearer.

Our methodology involved identifying the centroids of 10-km squares in both comparable datasets and gradually removing observations from squares with centroids closer than 15, 20, 25, 30, 50, 70, 90, 200, 400, 600, 800, and 1000 km. This process was repeated three times using a cross-validation procedure using a 70-30 ratio of training-testing data. Subsequently, we evaluated the performance at both spatial (using the AUC metric) and change level (utilizing accuracy and bias metrics).

Spatial performance

To better visualize the trend for all species, we standardized the AUC metrics values resulting from testing the performance of the data thinning process. We set the AUC metric of each SDM of each species to a value of 1 as the optimal standard value, and subsequently, the remaining values were standardized in relation to this optimal value using the formula: *standardized thinned AUC = thinned AUC – optimal AUC + 1.*

The following figure shows the spatial performance trend when gradually reducing aggregation. We observe that the SDMs performance is robust when reducing the initial 50% over-aggregated sampled squares. Then, a more pronounced reduction in spatial performance becomes evident when reducing beyond 50% of the over-aggregated squares.

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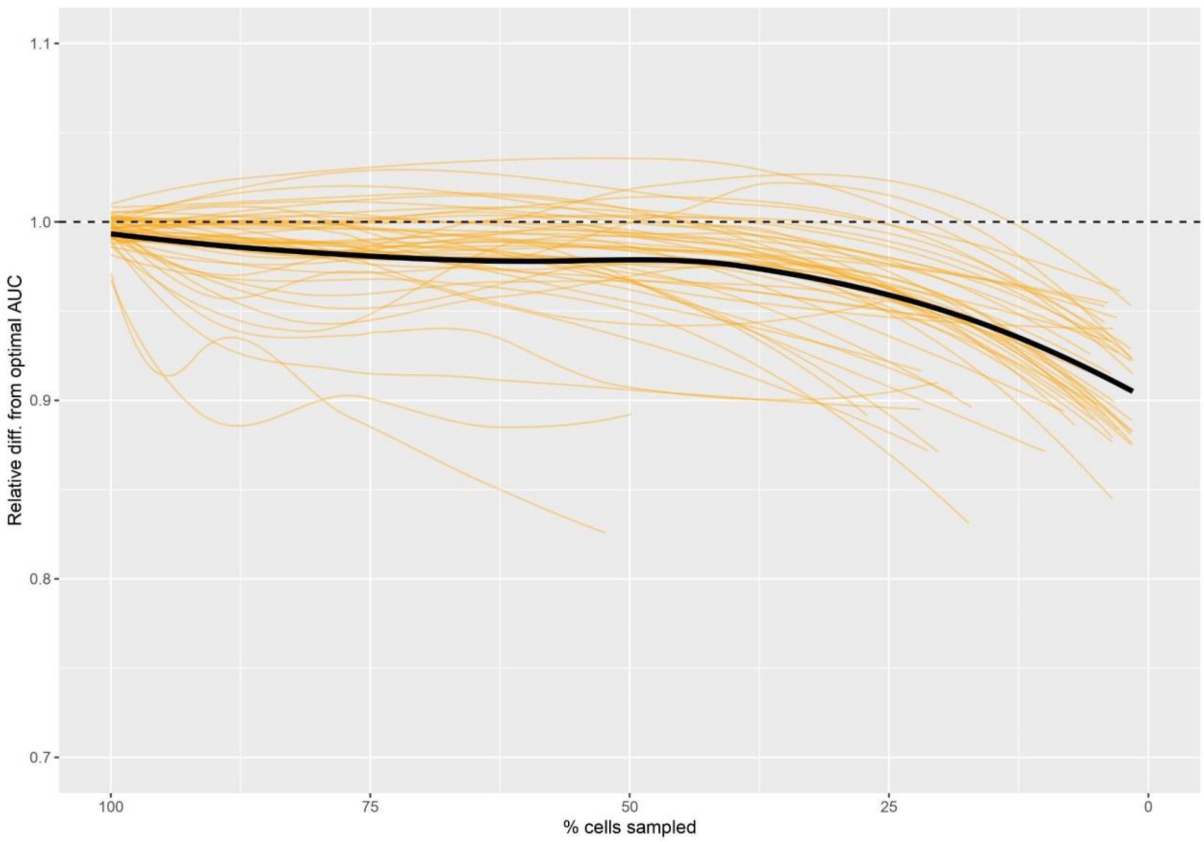

Fig. A4.1. Spatial performance (AUC metric) trend on over-aggregated squares (cells) sampled reduction. Mean AUC trend for all species (thick black line), mean trend for each fifty species (orange lines), optimal trend (horizontal dashed black line). The Y-axis represents the standardized AUC metric, while the X-axis indicates the percentage of the number of 10-km squares utilized in each data thinning process relative to all the training 10-km squares used.

Change performance

Change performance when reducing over-aggregated 10-km squares was tested through accuracy and bias metrics.

<u>Accuracy</u>

To better visualize the trend for all species, we standardized the accuracy metrics values resulting from testing the performance of the data thinning process. We set the accuracy metric of each SDM of each species to a value of 1 as the optimal standard value, and subsequently, the remaining values were standardized in relation to this optimal value using the formula: *standardized thinned accuracy = thinned accuracy – optimal accuracy + 1.*

The following figure shows the change performance trend by the accuracy proxy, when gradually reducing aggregation. We observe that the change prediction remains quite robust during the initial reduction of 50% of over-aggregated sampled squares. Beyond this threshold, a rapid decline in accuracy performance is observed when more than 50% of over-aggregated squares are reduced.

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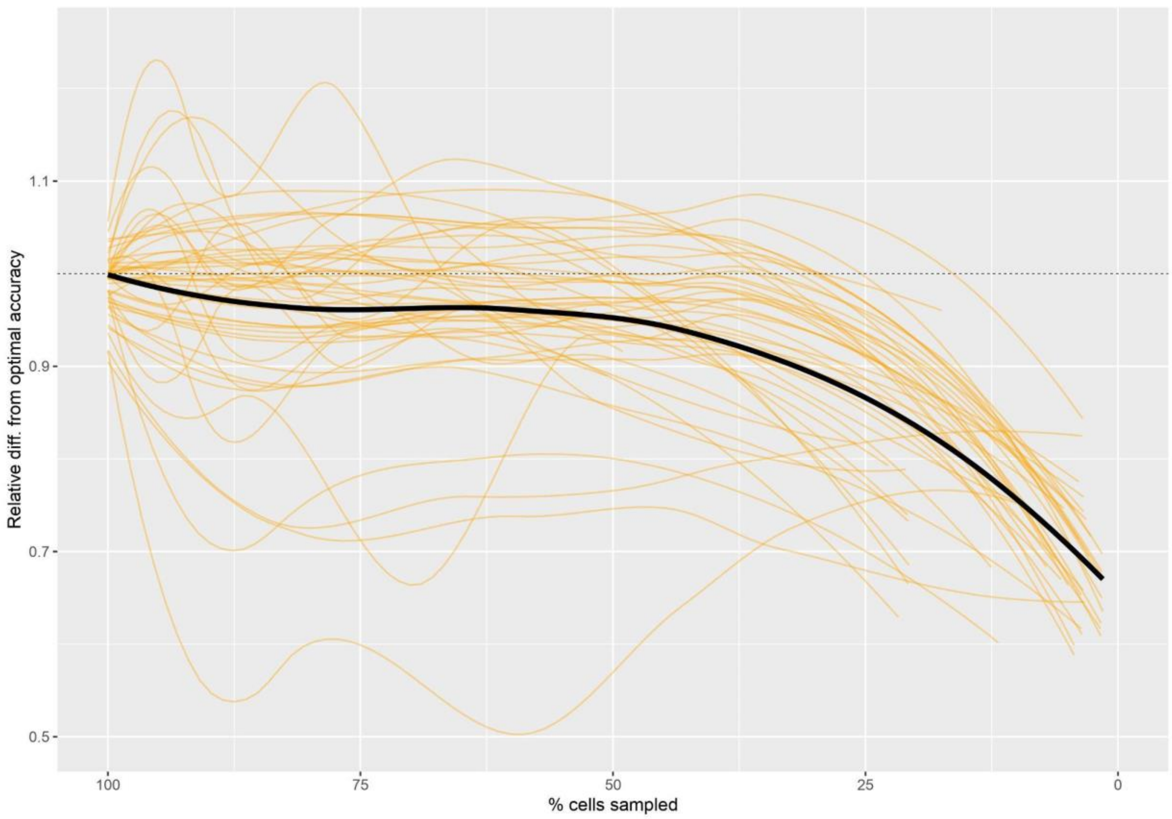

Fig. A4.2. Accuracy trend on over-aggregated squares (cells) sampled reduction. Mean accuracy trend for all species (thick black line), mean trend for each fifty species (orange lines), optimal trend (horizontal dashed black line). The Y-axis represents the standardized bias metric, while the X-axis indicates the percentage of the number of 10-km squares utilized in each data thinning process relative to all the training 10-km squares used.

<u>Bias</u>

To better visualize the trend for all species, we standardized the bias metrics values resulting from testing the performance of the data thinning process. We set the bias metric of each SDM of each species to a value of 0 as the optimal standard value, and subsequently, the remaining values were standardized in relation to this optimal value using the formula: *standardized thinned bias = thinned bias – optimal bias.*

The following figure shows the change performance trend by the bias proxy, when gradually reducing aggregation. We observe that the bias consistently increases as the over-aggregated sampled squares are reduced. It implies that change models tend to overestimate colonisation or underestimate extinction processes when reducing square samples.

We considered that the model properly predicts change when the bias falls within the range of –0.25 and 0.25 (refer to the *Uncertainty assessment of change* section in the main document). Consequently, for most species, their bias does not deviate by more than a value of 0.25 when reducing the initial 50% of over-aggregated sampled squares. However, further research needs to be done on this matter.

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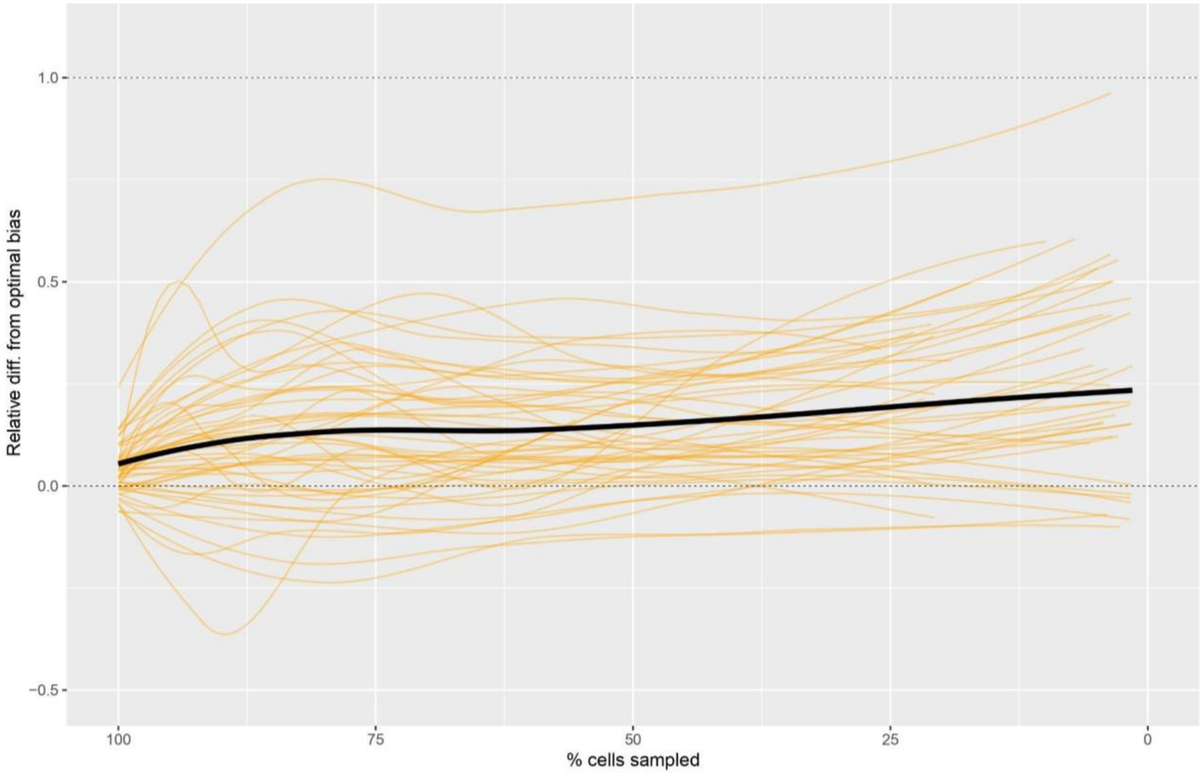

Fig. A4.3. Bias trend on over-aggregated squares (cells) sampled reduction. Mean bias trend for all species (thick black line), mean trend for each fifty species (orange lines), optimal trend (horizontal dashed black line). The Y-axis represents the standardized bias metric, while the X-axis indicates the percentage of the number of 10-km squares utilized in each data thinning process relative to all the training 10-km squares used.

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ANNEX V. Surrogacy analysis between probability of occurrence and abundance

This study has developed 10-km modelled maps of probability of occurrence. Although no spatially explicit abundance (no. of individuals/area) models are generated within the framework of this showcase, we explored the relationship between the probabilities of occurrence (PO) generated from the EBBALF models (period 2013–2017) and abundance (Ab) using information on the number of breeding pairs from EBBA2 for the same period (Keller et al. 2020).

For this analysis, each 10-km square was allocated to a 50-km square by means of the geographic location of its centroid and the sum of PO values. PO values (ranging from 0 to 1) were summed up for all the 10-km squares included in each 50-km square to obtain a value to compare the overall modelled suitability of these squares with the absolute abundance of the species (EBBA2 population estimates).

More precisely, to evaluate the usability of EBBALF 10-km modelled maps of probability of occurrence (PO) as surrogates of absolute abundance (Ab), we studied the type of relationship (linear, quadratic and exponential) between abundance and PO values for each of the study species using a generalised linear mixed model (GLMM) were Ab was included as the response variable and the sum of PO values was defined as the predictor. An observation level random effect (OLRE) was defined as a random effect with a different level for each observation which, combined with a Poisson distribution, can capture moderate overdispersion. For each species, we run a Poisson log-normal mixture via the OLRE technique using three model combinations: one including the linear sum of the probability of occurrence of all 10-km squares within each 50-km square, the second defined as the quadratic sum of PO, and the third defined as the exponential sum of PO. In all cases, the sum of PO values was first log-transformed and then standardised to really get the zero mean and the unit variance and to make the variables comparable and thus their estimated effects. Scaling also helped at the computational level, since models reached convergence more easily. While selecting the best model we look for maximum marginal R2 value (R2m), which estimates the fraction of the variance explained by the fixed effects in the model, and minimum AIC value. This analysis was carried out using R software version 4.3.0 (R Core Team 2023) in R package *lme4* (Bates et al. 2015).

Importantly, we removed cases where abundance was “NA” (cases corresponding to species where the abundance EBBA2 estimate for that particular 50-km square could be calculated with a minimum of reliability or because there was no probability of occurrence in that square). Second, we removed cases where the sum of PO values was “0”. This was done because estimating occurrence considering only sites that are possible for the species to colonise consequently leads to a more robust assessment of abundance-occupancy relationships (Ten Caten et al. 2022).

There were certain cases of species for which the EBBA2 estimate for a particular 50-km square could not be calculated with a minimum of reliability; therefore, a total of four species were excluded from the analysis (i.e., Little Owl, Lesser Kestrel *Falco naumanni*, Black-tailed Godwit *Limosa limosa* and Common Stonechat), resulting in 46 species for which the significance of different relationships between Ab and PO was tested.

We found that almost all species (N = 41) had significant relationships between Ab and PO (either linear, quadratic and/or exponential). The only exceptions were Corncrake, Lesser Grey Shrike *Lanius minor*, Grey Partridge *Perdix perdix*, Pin-tailed Sandgrouse *Pterocles alchata* and Northern Lapwing

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Vanellus vanellus. Only 33% of the species showed a clear preference for the quadratic relationship with Ab. Among these, the strongest relationship was found for Meadow Pipit (R2m = 0.953), followed by Common Starling *Sturnus vulgaris* (R2m = 0.918) and Rook (R2m = 0.855), whereas the lowest correlations were found for Common Whitethroat *Sylvia communis* (R2m = 0.272), Little Bustard *Tetrax tetrax* (R2m = 0.347) and European Serin *Serinus serinus* (R2m = 0.349). Importantly, very few species whose quadratic relationship was selected included a significant term for first and second order PO terms (only Meadow Pipit, Greater Short-toed Lark *Calandrella brachydactyla* and Rock Sparrow *Petronia petronia*). In most cases only the first order of the quadratic relationship (i.e., linear term) was significant (11/15), whereas in one case none of the quadratic terms were found to be significant (Little Bustard).

Although the rest of the study species (N = 31) did not show a significant preference for any of the three relationships with Ab, all R2m values were in almost 70% of cases higher for the polynomic relationship as compared to the linear or the exponential one. Nonetheless, correlation values varied substantially from very high correlations (max. 0.759 for Corn Bunting *Emberiza calandra*) to almost no correlation (min. 0.019 for Grey Partridge).

In conclusion, the results of this surrogacy analysis reveal that in general the patterns shown by the models showing the probability of occurrence can be considered as a surrogate of an abundance pattern. The farmland bird species for which this relationship failed to be valid are scarce species. We should highlight that these results cannot directly be extrapolated to other species and to other geographical scales and resolutions. However, the third Catalan Breeding Bird Atlas (CBBA) proved that abundance and probabilities of occurrence at 1-km^2 resolution were also well correlated for most species and can even be used to calculate population sizes (Herrando et al. 2021).

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ANNEX VI. Tables showing the gaps in coverage for each study species (N = 50) and country (N = 40) resulting from the quality assessment of the 50-km occurrence maps (see main outputs). Percentages refer to the total number of 50-km squares where the species was found to breed in EBBA Live Farmland as compared to EBBA2. Countries are assigned a two-letter code following the ISO Alpha-2 code. Mean coverage per country is shown at the end of the last table.

Country	*Alauda arvensis*	*Alectoris rufa*	*Anthus campestris*	*Anthus pratensis*	*Athene noctua*	*Bubulcus ibis*	*Burhinus oedicnemus*	*Calandrella brachydactyla*	*Ciconia ciconia*	*Circus pygargus*
AD										
AL	0%		0%		0%		0%	0%	0%	
AT	61%		0%	13%	7%		0%		38%	50%
BA	19%		30%		0%			0%	7%	55%
BE	85%	0%		85%	31%	0%			25%	0%
BG	36%		15%		4%	0%	0%	7%	24%	16%
CH	64%		0%	41%	0%				10%	
CY					54%		45%			
CZ	71%		20%	40%	0%	0%	0%		42%	29%
DE	86%		21%	38%	18%				27%	9%
DK	84%		0%	65%	0%				33%	0%
EE	82%		0%	75%					37%	34%
EL	3%		0%		1%	0%	0%	0%	0%	0%
ES	70%	66%	41%		49%	49%	40%	50%	57%	45%
FI	44%			50%					0%	0%
FO	0%			0%						
FR	53%	24%	11%	8%	9%	16%	21%	4%	17%	5%
HR	71%		54%		10%	0%	0%	25%	33%	81%
HU	80%		51%		23%	0%	0%	0%	49%	26%
IE	94%	0%		94%						
IT	52%	26%	28%	0%	47%	77%	42%	27%	22%	39%
LI	0%								0%	
LT	70%		14%	72%	0%				73%	44%
LU				60%	50%				0%	
LV	45%		6%	39%					36%	5%
MD	25%		9%		13%			16%	17%	
ME	0%		20%		20%	0%	0%	0%	0%	0%
MK	58%		66%		30%		0%	25%	57%	54%
MT								0%		
NL	93%			93%	48%	0%			66%	0%
NO	17%			67%						
PL	88%		31%	66%	3%				74%	44%
PT	8%	29%	6%		17%	25%	13%	15%	30%	10%
RO	82%		52%	0%	18%	0%	17%	70%	45%	26%
RS	24%		22%		12%	0%	0%	0%	9%	0%
SE	44%		0%	55%					20%	13%
SI	72%	0%	75%		8%			0%	64%	
SK	64%		0%	23%	0%				43%	0%
UK	92%	79%		92%	65%	20%	38%			12%
XK	0%		0%		0%				0%	0%

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Country	*Coracias garrulus*	*Corvus frugilegus*	*Coturnix coturnix*	*Crex crex*	*Emberiza calandra*	*Emberiza cirlus*	*Emberiza citrinella*	*Emberiza hortulana*	*Emberiza melanocephala*	*Falco naumanni*
AD			0%		0%			0%		
AL	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
AT		50%	36%	11%	42%	66%	74%	0%		
BA		0%	26%	33%	20%	16%	15%	33%	25%	0%
BE		73%	57%	0%	36%		85%			
BG	14%	24%	27%	6%	39%	9%	16%	24%	25%	0%
CH		0%	35%	0%	11%	34%	75%	0%		
CY	60%		66%		50%				45%	
CZ		32%	59%	23%	46%		75%	11%		
DE		21%	57%	9%	55%	36%	86%	56%	0%	
DK		87%	38%	0%	71%		86%			
EE		40%	12%	57%	0%		74%	14%		
EL	0%	0%	0%	0%	2%	1%	0%	0%	4%	1%
ES	18%	40%	61%		65%	49%	51%	39%		44%
FI		4%	2%	28%			68%	5%		
FO										
FR	8%	43%	25%	2%	40%	51%	53%	7%	0%	0%
HR	66%	66%	59%	36%	64%	33%	51%	30%	64%	0%
HU	58%	47%	70%	9%	74%		70%		0%	
IE			0%	0%			77%			
IT	39%		61%	4%	71%	74%	42%	24%	16%	40%
LI			0%	0%	0%	0%	0%			
LT	20%	46%	69%	66%	35%		63%	25%		
LU		60%	50%							
LV	0%	10%	13%	31%	0%		47%	4%		
MD	0%	8%	16%	4%	25%		18%	13%	0%	
ME	33%		14%	0%	11%	0%	0%	0%	40%	0%
MK	42%	20%	46%	0%	82%	76%	53%	57%	0%	20%
MT			0%		0%					
NL		86%	82%	38%	0%		80%	0%		
NO		0%	1%	2%			35%	0%		
PL	0%	59%	78%	47%	85%		89%	60%		
PT	0%		25%		36%	27%	0%	0%		9%
RO	44%	69%	72%	23%	73%	11%	53%	56%	48%	
RS	12%	21%	19%	0%	27%	11%	16%	18%	0%	0%
SE		41%	5%	5%	0%		61%	20%		
SI	0%	80%	62%	18%	50%	40%	65%	66%	33%	
SK	0%	9%	45%	36%	23%		72%			
UK		86%	19%	7%	67%	22%	82%			
XK		0%	0%	0%	0%	0%	0%	0%	0%	

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Country	*Falco tinnunculus*	*Galerida cristata*	*Galerida theklae*	*Hirundo rustica*	*Lanius collurio*	*Lanius excubitor*	*Lanius meridionalis*	*Lanius minor*	*Lanius senator*	*Limosa limosa*
AD									0%	
AL	0%	0%		0%	0%			0%	0%	
AT	78%	28%		77%	67%	0%		0%		33%
BA	17%	0%		25%	26%			20%	12%	
BE	86%			90%	42%	60%				50%
BG	31%	24%		39%	39%			15%	8%	
CH	84%			82%	77%					
CY	50%	46%		46%					40%	
CZ	77%	8%		77%	73%	37%				20%
DE	79%	21%		83%	77%	27%				8%
DK	79%	0%		82%	51%	0%				12%
EE	18%			75%	72%	45%				58%
EL	2%	3%		2%	2%			0%	1%	
ES	63%	67%	53%	75%	57%	7%	50%	0%	59%	0%
FI	23%			53%	29%	8%				0%
FO				0%						0%
FR	49%	12%	0%	56%	39%	6%	7%	0%	7%	12%
HR	58%	51%		57%	63%			61%	47%	
HU	59%	64%		64%	77%	16%		50%		52%
IE	72%			90%						
IT	81%	71%		81%	64%			20%	50%	0%
LI	0%			0%	0%					
LT	14%			75%	71%	18%				18%
LU	83%			83%	50%	0%				
LV	2%	0%		34%	34%	14%				0%
MD	8%	22%		26%	24%	0%		0%		
ME	0%	25%		18%	20%			25%	14%	
MK	68%	66%		70%	76%			57%	73%	
MT	0%			0%						
NL	89%	0%		89%	56%					77%
NO	31%			38%	20%	3%				0%
PL	63%	25%		88%	84%	62%		0%		11%
PT	21%	33%	17%	38%	0%		30%		27%	
RO	67%	44%		78%	71%	36%		32%	25%	50%
RS	26%	8%		22%	35%			8%	7%	0%
SE	51%			69%	53%	16%				0%
SI	68%	64%		73%	73%			33%	60%	
SK	57%	34%		71%	67%	29%		7%		0%
UK	79%			88%	0%					20%
XK	0%	0%		0%	0%			0%	0%	

Country	*Linaria cannabina*	*Melanocorypha calandra*	*Motacilla flava*	*Oenanthe hispanica*	*Passer hispaniolensis*	*Passer montanus*	*Perdix perdix*	*Petronia petronia*	*Pterocles alchata*	*Pterocles orientalis*
AD						0%		0%		
AL	0%	0%	0%	0%	0%	0%	0%	0%		
AT	45%		41%			75%	42%			
BA	28%		27%	28%	50%	18%	37%			
BE	86%		88%			52%	66%			
BG	8%	19%	30%	0%	13%	25%	22%	0%		
CH	71%		15%			57%	0%			
CY	50%	0%	66%		50%					
CZ	73%		46%			75%	40%			
DE	81%		71%			83%	34%			
DK	84%		58%			80%	57%			
EE	57%		53%			42%	7%			
EL	0%	0%	4%	0%	0%	0%	6%	0%		
ES	66%	55%	34%	43%	31%	44%	20%	55%	42%	31%
FI	31%		44%			42%	1%			
FO										
FR	49%	0%	27%	8%	0%	22%	18%	12%	0%	
HR	58%	25%	56%	31%	55%	48%	42%			
HU	57%		64%		0%	79%	13%			
IE	91%					50%	0%			
IT	66%	38%	68%	23%	52%	78%	10%	44%		
LI	0%					0%				
LT	72%		65%			71%	58%			
LU			83%			83%	0%			
LV	20%		21%			36%	17%			
MD	18%		21%		0%	23%	0%			
ME	11%	0%	40%	16%	14%	12%				
MK	68%	66%	57%	16%	66%	64%	44%	0%		
MT					0%	0%				
NL	93%		89%			79%	65%			
NO	17%		32%			17%	0%			
PL	85%		85%			83%	57%			
PT	34%	33%	11%	7%	19%	15%		21%	0%	0%
RO	35%	60%	79%		35%	59%	22%			
RS	3%	0%	28%	0%	5%	24%	10%			
SE	52%		67%			49%	17%			
SI	62%	0%	53%		0%	73%	20%			
SK	57%		42%			52%	0%			
UK	85%		71%			65%	76%			
XK	0%	0%	0%		0%	0%	0%			

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Country	*Saxicola rubetra*	*Saxicola torquatus*	*Serinus serinus*	*Streptopelia turtur*	*Sturnus unicolor*	*Sturnus vulgaris*	*Sylvia communis*	*Tetrax tetrax*	*Upupa epops*	*Vanellus vanellus*	Mean
AD						0%			0%		0%
AL	0%	0%	0%	0%		0%	0%		0%		0%
AT	34%	48%	58%	50%		77%	39%		50%	59%	45%
BA	31%	4%	27%	13%		30%	16%		20%	33%	22%
BE	50%	86%	14%	52%		90%	95%			80%	63%
BG	23%	16%	3%	30%		40%	40%		33%	19%	21%
CH	62%	39%	77%	25%		63%	29%		10%	9%	39%
CY			50%	54%					54%		48%
CZ	61%	36%	79%	73%		77%	73%		43%	56%	53%
DE	43%	63%	70%	48%		86%	82%		39%	46%	52%
DK	48%	23%	0%	0%		84%	84%			83%	50%
EE	80%		14%	26%		63%	80%		0%	77%	44%
EL	0%	2%	1%	3%		2%	1%		1%	0%	1%
ES	21%	65%	72%	59%	74%	50%	45%	32%	64%	28%	46%
FI	62%	0%	0%	0%		28%	53%		0%	53%	24%
FO						0%				0%	0%
FR	9%	52%	43%	51%	0%	63%	56%	3%	40%	24%	23%
HR	63%	63%	45%	58%		61%	68%		59%	69%	52%
HU	64%	80%	47%	80%		79%	73%		60%	58%	54%
IE	14%	83%				94%	88%			43%	54%
IT	43%	54%	82%	79%	80%	74%	60%	16%	70%	68%	51%
LI	0%	0%	0%	0%		0%	0%		0%	0%	0%
LT	73%	0%	22%	57%		63%	75%		51%	75%	50%
LU		80%	33%	50%		83%				20%	54%
LV	43%	0%	9%	15%		44%	46%		8%	47%	20%
MD	20%	0%	0%	26%		24%	23%		13%	8%	13%
ME	0%	0%	0%	25%		11%	14%		22%	0%	13%
MK	66%	30%	33%	68%		70%	76%		75%	28%	51%
MT			0%			0%					0%
NL	45%	93%	0%	51%		93%	96%		0%	93%	61%
NO	31%	7%	0%			23%	30%			7%	15%
PL	87%	56%	72%	37%		90%	88%		75%	79%	63%
PT	0%	37%	37%	26%	38%	0%	4%	12%	35%	0%	18%
RO	58%	37%	26%	64%		79%	72%		71%	58%	52%
RS	12%	22%	4%	27%		34%	30%		16%	28%	15%
SE	79%	0%	0%			50%	57%		0%	46%	33%
SI	44%	73%	77%	61%		73%	63%		58%	58%	52%
SK	58%	58%	63%	60%		64%	69%		41%	25%	41%
UK	57%	80%	0%	42%		86%	82%			76%	57%
XK	0%	0%	0%	0%		0%	0%		0%	0%	0%

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