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# Surprisingly good fit of pressure-based cropland condition map and bird census data at the national scale

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A R T I C L E  I N F O

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A B S T R A C T

As the world is struggling to halt the rapid decline of biodiversity, the assessment and mapping of ecosystem condition is getting ever increasing attention. Croplands are artificial ecosystems, but as they occupy a large portion of land, they significantly influence biodiversity. Yet, there is a knowledge gap about their suitability to support and maintain wildlife on a national scale. Large-scale condition mapping is meant to address this gap; the good condition of croplands includes their ability to support biodiversity. However, the lack of suitable databases is often a challenge when creating such maps. As there is a strong causal relation between pressures on the ecosystem and its condition, pressure indicators can be used as proxies to approximate condition when more direct indicators are lacking. The validation of condition maps based on pressure proxies is a key but challenging step. In this study, we tested a previously designed pressure-based cropland condition map for Hungary using bird census data. Besides validating the composite condition indicator, we also tested some key elements of the mapping process, such as the choice of variables and thresholds.

Using multiple comparisons of means by Tukey's contrast and Random Forest modelling, we examined the relationship of (1) the continuous pressure-based cropland condition variables, (2) their rescaled, ordinal version (called sub-indicators), and (3) the composite cropland condition indicator (sum of the sub-indicators) with a biodiversity measure, the standardised relative richness of characteristic farmland bird species (rRRCS). To get a picture of the spatial patterns of the examined relationships across Hungary, individual Random Forest models were constructed for all the spatial units of the bird census database, using focal analysis with a 30 km radius moving window.

We found significant differences in the mean rRRCS for nearly all sub-indicator categories, signifying that the literature-derived thresholds were mostly sound. Categories with higher (better) condition scores had higher mean rRRCS; the differences are significant in the mid-range but not in the extreme categories, indicating a need for a meaningful simplification of the categories. The goodness-of-fit ($R^2$) of the Random Forest models was found to be high, but it is spatially heterogeneous (ranged from 0.69 to 0.89, with a median value of 0.81), similarly to the variable importance. The proportion of semi-natural areas proved to be the most important condition variable. The proportion of maize and alfalfa were more important than parcel size. Our results show that condition maps based on pressure proxies can reflect patterns of biodiversity surprisingly well. They also highlight the spatial context dependence of the uncertainty of condition maps.

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## 1. Introduction

Evidence shows that biodiversity is rapidly declining worldwide, suggesting previous policies were inefficient in tackling the process (Tryjanowski et al., 2011, Díaz et al., 2019, Rounsevell et al., 2020, Báldi et al., 2023). However, new policies, like the EU's Green Deal and Biodiversity Strategy or the Kunming-Montreal Global Biodiversity Framework of the Convention on Biological Diversity, set ambitious new targets (Báldi et al., 2023). All these policies highlight the need for robust monitoring and assessment programs to provide reliable and meaningful data for planning and evaluation. Only such data can provide the knowledge needed for successful progress in halting the decline of biodiversity.

The EU's conservation strategies for 2020 and 2030 have introduced the mapping and assessment of ecosystems and their services, in order to prevent their further deterioration. The requirements to produce national ecosystem services and condition assessments significantly increased national-scale mapping efforts in the Member States (Vári et al., 2024). In order to ensure the consistency of the mapping and assessments across the Member States, a European Commission Working Group on Mapping and Assessment of Ecosystems and their Services (MAES) was formed (Maes et al., 2013). Throughout the process ecosystem condition gained an ever increasing emphasis (EC, 2020). Besides the inherent value represented by biodiversity, ecosystem condition also underpins the ability of ecosystems to provide the services indispensable to the survival of humanity (Díaz et al., 2019). The need to produce consistent assessments across countries with very different environments and data led to reignited discussion about both the definition of ecosystem condition and its relation to earlier, similar terms (like naturalness or ecosystem health) (Rendon et al., 2019, Roche and Campagne, 2017). Further methodological challenges include (i) the selection of the condition variables to use (Maes et al., 2018, Keith et al., 2020, Czúcz et al., 2021) (ii) the selection of reference values for the variables, which is necessary for them to be used in condition mapping (Keith et al., 2020, Jakobsson et al., 2020, Maes et al., 2020) and (iii) quantifying the uncertainty of the result maps (Agudelo et al., 2020). These steps and the related decisions are fundamental parts of the condition mapping process even if other types of models are used (see e.g. the IBECA method of Jakobsson et al., 2021). Reference levels and condition are especially in the focus. Keith et al. (2020) define reference level as 'the value of a variable at the reference condition, against which it is meaningful to compare past, present or future measured values of the variable'. The aim of the discussions is to enable a well-standardised description of ecosystem condition, to support – among others – the proper integration of condition in ecosystem accounting and ultimately to help promote the conservation of biological diversity (Hein et al., 2015).

The lack of good-quality primary data is a common hindering issue in large-scale mapping, both for ecosystem services (Eigenbrod et al., 2010) and ecosystem condition (Maes et al., 2020). At smaller spatial scales, measuring biodiversity is one of the most common ways to describe ecosystem condition (Maes et al., 2012, Maes et al., 2018; Tryjanowski and Morelli, 2017); however, the necessary large, national- or continental-scale data are often lacking. In addition, to get a comprehensive picture, several taxa with different ecological requirements should be included (Carignan and Villard, 2002, Maes and van Dyck, 2005). Thus, it is extremely resource-intensive and nearly impossible to accomplish a thorough biodiversity-based condition mapping at the national scale. Furthermore, such mapping ideally requires wall-to-wall data of uniform quality. A common solution is the use of proxies – usually, some estimate based on known relationships with data from existing large-scale datasets such as land use maps (e.g. Rendon et al., 2020, Maes et al., 2023) or forest inventories (Zoltán et al., 2023). Sometimes, even a proxy chain is applied, e.g. using data on vegetation types to estimate flower abundance, which in turn is supposed to reflect pollinator richness (Zulian et al., 2013). However, the use of proxy variables increases uncertainty, which can affect the reliability of the final maps (Eigenbrod et al., 2010). Thus, the validation of proxy-based maps (both ES and condition) is a crucial step (Vallecillo et al., 2022), but it is still rarely done (Agudelo et al., 2020, Boerema et al., 2017). It is not even obvious what data to use for validation in order to reflect the goodness of the proxy-based map rather than methodological differences between the two (proxy-based and validation) maps (Schulp et al., 2014). In condition mapping, available large-scale variables often describe pressure rather than state. As there is a strong causal relation between pressures on the ecosystem and its condition, pressure indicators can be used as proxies to approximate condition when more direct indicators are lacking (Maes et al., 2018, Rendon et al., 2019, Smit et al., 2021). Yet, due to a temporal mismatch between pressure and its effect on biodiversity (Figueiredo et al., 2019, Rédei et al., 2020) and the nonlinearity of pressure-response relationships (Burkett et al., 2005, Large et al., 2015), condition maps using pressure-based proxies have an added element of uncertainty. One possible way to validate such condition maps and get a measure of their uncertainties is to compare them to primary biodiversity data (Ritterbusch et al., 2022). Birds often provide the only primary biodiversity data of large-scale, systematic sampling (Gregory et al., 2003, Fraixedas et al., 2020) for terrestrial ecosystems. Given the avifauna's popularity with both researchers and enthusiasts, bird census data are relatively common, even for larger areas. Birds are relatively easy and efficient to monitor, appear in all types of habitats and are sensitive to environmental change (Carignan and Villard, 2002, Chin et al., 2015, Nagy et al., 2017, Roilo et al., 2023).

In this study, we used bird census data to test how primary biodiversity data fit our proxy-based cropland condition map. Croplands are *"land area under temporary and permanent cultivation, land temporarily fallow, horticultural and domestic habitats"* (Vallecillo et al., 2022). It is an important land cover type; in 2020, EU farms used 157 million hectares of land for agricultural production (38 % of the EU's total land area (EUROSTAT, 2022). Even though they are highly artificial ecosystems, they can contribute to maintaining biological diversity. Open-space bird species, like the yellow wagtail (*Motacilla flava*) or the skylark (*Alauda arvensis*) even breed in crop fields, and management intensity influences their abundance (Kovács-Hostyánszki et al., 2011). Many other bird species use croplands temporarily, e.g. as feeding areas (Bruun and Smith, 2003) or wintering ground (Siriwardena et al., 2006). However, defining the condition of croplands (in terms of their capacity to retain and support biological diversity) represents a unique challenge, as there is no natural reference. According to Maes et al., 2018 *Agroecosystems are modified ecosystems, they are in good condition when they support biodiversity, abiotic resources are not depleted, and they provide a balanced supply of ecosystem services (provisioning, regulating, cultural).*" Certain farmland bird species have been shown to indicate High Nature Value farmlands (Morelli et al., 2014). Still, most existing large-scale cropland condition maps use proxies or modelled data complemented with other, often partial or coarse-scale datasets (Vallecillo et al., 2022, Rendon et al., 2022).

Locally, landscape characteristics define biodiversity, ecosystem functions and services (Olimpi et al., 2022). However, their importance is not uniform over the landscape (Batáry et al., 2010, Tscharntke et al., 2012, Stjernman et al., 2019). As we are using precisely these characteristics as proxies to describe cropland condition, and usually the applied models (including variable weights) are uniform within a country, this raises the question of how the uncertainty of the condition maps changes spatially. Spatial context has been shown to influence ecosystem services (Andersson et al., 2015), but its implications for terrestrial ecosystem condition mapping have, so far, not received much attention.

Following the requirements of the EU Biodiversity Strategy to 2020, various ecosystem services and ecosystem condition maps were created for Hungary within the frameworks of a national project (MAES-HU – Vári et al., 2022). Action 5 of the Strategy required member states to map and assess their ecosystems and their services. In the frames of this project, Tanács et al. (2022) developed condition maps for all major ecosystem types, among them croplands, focusing on their ability to support and maintain biodiversity. They chose the indicators as well as the thresholds (corresponding to the already mentioned reference values) for mapping cropland condition on the basis of the relevant scientific literature (see Table 1), which is one possible way of defining these (Keith et al., 2020).

Many European countries have completed some form of condition assessment for their ecosystems (Vári et al., 2024) but work explicitly related to cropland (Rendon et al., 2020, Grondard et al., 2021) is not common in the literature. The uncertainty of these maps and their spatial context dependence are even more poorly studied. Furthermore, there is a general lack of consensus on reference values and definitions of reference conditions for terrestrial ecosystems (Maes et al., 2020), including croplands. With this paper, we would like to address some of the above-mentioned challenges related to the mapping of cropland ecosystem condition, using the cropland condition map developed in MAES-HU (Tanács et al., 2022). Our questions are as follows:

**Table 1**
The variables, spatial units and rules applied in the condition mapping and the assigned scores (Tanács et al. 2022). The 'Stands for' column signifies what aspect the variable was chosen to describe, including literature that supports its use. For more details, see the Discussion.

| Variable | Unit | Stands for | Rule → Score |
|---|---|---|---|
| Number of cultivated crops (no or no/ha) | LPIS block* | Landscape diversity Fahrig et al. 2011, Sirami et al. 2019 | Block size below 1 ha: IF no >=2 → +1 point<br>In all other cases: 0 point<br>Block size above 1 ha: IF no/ha > 0.2 → +1 point<br>In all other cases: 0 point |
| Proportion of fallow land | LPIS block | The amount of available hiding and feeding places (Busch et al. 2020) | IF proportion >=20 % → +1 point<br>In all other cases: 0 point |
| Proportion of alfalfa or green fallow** | LPIS block | The amount of available hiding and feeding places (González del Portillo et al., 2022, Kovács, 2005) | IF value >= 20 % → +2 point<br>IF value 2–19 % → +1 point<br>IF value < 2 % → 0 point |
| Proportion of maize | LPIS block | Landscape homogeneity, management intensity Sauerbrei et al., 2014, Jerrentrup et al. 2017, Hass et al. 2019, Busch et al. 2020 | IF proportion > 50 % → −1 point<br>In all other cases: 0 point |
| Average parcel size | LPIS block | Edge density (indirectly available hiding places); Fahrig et al. 2015, Batáry et al. 2017, Marcacci et al. 2020 | IF value < 5 ha → +2 point<br>IF value >= 5 AND < 10 ha → +1 point<br>IF value > 10 ha → 0 point |
| Proportion of protected areas (AES*** or HVNA****) | LPIS block | Management intensity (incl. the reduced use of fertilizers and pesticides) (Maes et al. 2018) | IF AES and HVNA proportion together > 20 % → +1<br>In all other cases: 0 point |
| Proportion of semi-natural areas | 300 m radius circle around each 20-m unit of the Ecosystem Map of Hungary; averaged for each LPIS block | The amount of available hiding and feeding places Zingg et al. 2018, Marcacci et al. 2020, Klein et al. 2023 | IF proportion >= 20 % → +2 point<br>IF proportion 2–19 % → +1 point<br>IF proportion < 2 % → 0 point |

*See Appendix A.
**Green fallow is permanent or periodic green cover (lasting for at least three years), consisting of at least three native species, including at least one of the Fabaceae family.
***Proportion of land included in an agri-environmental scheme (AES).
****Proportion of land subsidised under 'High Nature Value Areas' (HNVA).

(1) How well does a pressure-based cropland condition map fit the patterns of the relative richness of characteristic farmland bird species?
(2) Are the thresholds applied to the condition variables meaningful?
(3) Which were the most important proxy variables included in the cropland condition map?
(4) What are the spatial patterns of the relations examined in questions 1 and 3? Are the results consistent over larger areas?

## 2. Materials and methods

### 2.1. Data

#### 2.1.1. Cropland condition map

The MAES-HU cropland condition map we used for this analysis as a proxy-based condition map was specifically created for the area of Hungary for the base year 2015 (Tanács et al., 2022, Fig. 1A, Fig. 2). The map aimed to reflect the state of these artificial ecosystems from the point of view of their ability to sustain biodiversity. It was based on a set of proxy variables, chosen according to relevance based on the related scientific literature. Certain other requirements were also observed for the chosen variables: (1) being spatially explicit, (2) being available as well as consistent over the entire country, (3) being based on already existing and regularly updated databases, and (4) conforming to the suggestions of the MAES group (Maes et al., 2018). The data source was the Farmer's Subsidy Claims database of the Hungarian State Treasury, containing information related to the Single Area Payment Scheme (Henits et al., 2022). The spatial units were derived from those of the Hungarian Land Parcel Identification System (LPIS – Csonka et al., 2011; Appendix A). Tanács et al. (2022) defined specific rules and thresholds for all variables based on relevant literature (e.g. Fahrig et al., 2015, Martin et al., 2019). Following these rules, the continuous variables were rescaled to ordinal sub-indicator categories and scores were assigned to each category. Table 1. summarises the sub-indicators, the spatial units, the applied rules and the assigned scores. Then, the sub-indicator scores were summed to form the final ordinal indicator to measure the overall ecosystem condition. The final indicator was simplified into five categories (please refer to Fig. 7A). Vineyards and orchards were not included for reasons of information scarcity, only croplands.

#### 2.1.2. Relative richness of characteristic bird species

For the validation of the cropland condition map, we used another, biodiversity-based condition map for agricultural land (incl. grassland), created within the frames of MAES-HU (Tanács et al., 2022, Fig. 1B). This map was created using an entirely different approach, based on the Hungarian MAP database of bird observations, which contains data in a 2.5 × 2.5 km grid collected by volunteers according to a predefined method (Szép et al., 2021). The units of the map are referred to as UTM squares. The map shows the ratio of the number of characteristic farmland bird species actually present to the number of those species expected in favourable agricultural areas (from now on called "relative richness of characteristic bird species", RRCS). The values range from 0 to 1, 0 meaning none of the characteristic species are present in the area while 1 means all of them were observed. As only those UTM squares were considered relevant where the duration of observation was

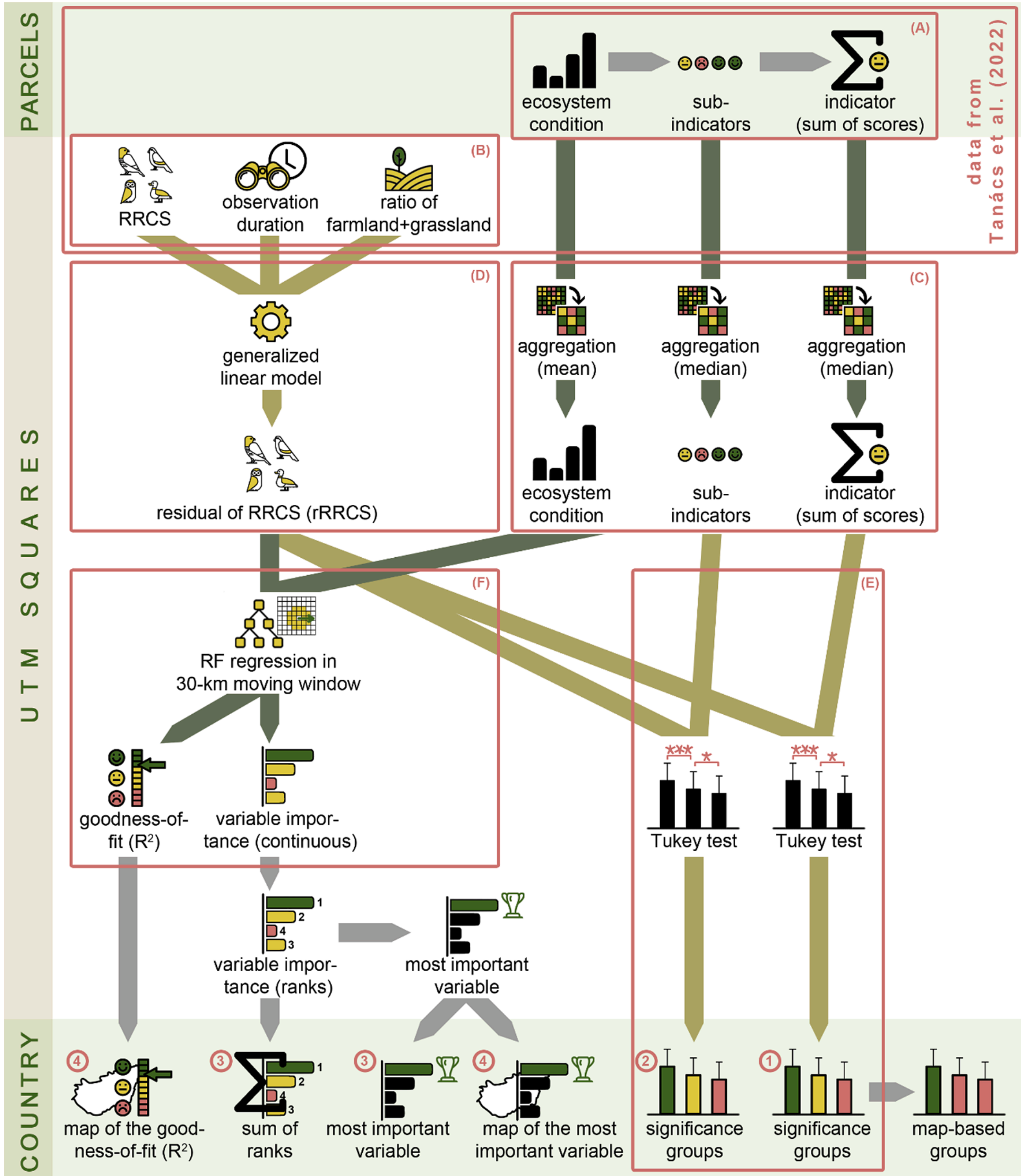


**Fig. 1.** The graphic summary of the work process. The main input datasets and analysis steps are highlighted with red blocks and indicated with letters (referenced in the text). The red numbers signify the research questions to which the results contribute. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

regarded as sufficient (at least 60 min in the period between 2014 and 2018), the RRCS map only has values in 6335 UTM squares (out of the 15,444 that cover the entire area of Hungary). For a more detailed description, refer to Appendix B.

## 3. Methods

All the analyses were conducted in ESRI ArcGIS 10.8 geoinformation software and R statistical software (R Core Team, 2023), and the packages of the latter called "emmeans" (Lenth, 2024), "multcomp" (Hothorn et al., 2008), "randomForest" (Liaw and Wiener, 2002), and "sf" (Pebesma, 2018, Pebesma and Bivand 2023).

### *3.1. Aggregation of the condition variables to the spatial units of the bird observation database*

As the proxy-based condition indicators were calculated for a different, finer scale, the variables and indicators needed to be aggregated to the scale of the bird database to enable comparison (Fig. 1C, Fig. 3). The aggregation was carried out using the Zonal tool of ArcGIS 10.8 Spatial Analyst. For each 2.5 km UTM square, we calculated the mean of the continuous variables and the median of the ordinal variables (i.e. the values of the summed and final condition indicators and the scores of the sub-indicator categories).

### *3.2. Removing the effect of ecosystem extent and duration of observation on RRCS*

In earlier work, we found that the RRCS correlated significantly with the duration of observation and also with the ratio of farmland within the UTM squares (Tanács et al., 2022). For further analysis, we considered it necessary to remove the influence of these factors and the possible bias they may cause. Ecosystem extent and condition are interrelated; disentangling their effect was considered important

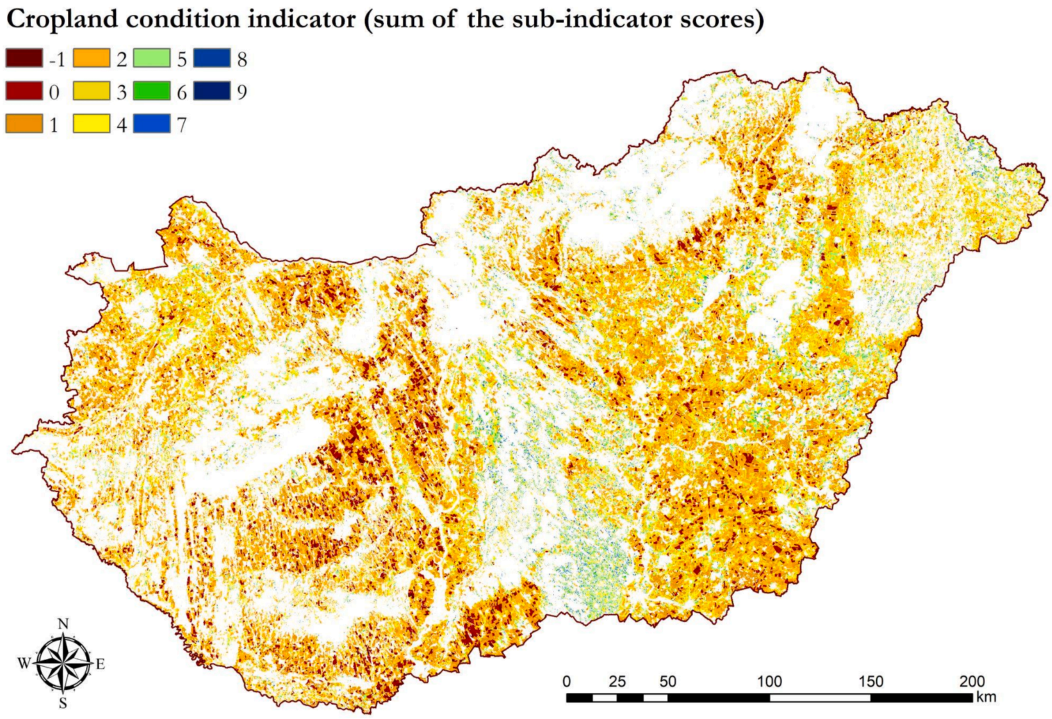


**Fig. 2.** The map of the MAES-HU pressure-based cropland condition indicator for Hungary (the sum of scores – Tanács et al. 2022). Higher values mean a favourable state for maintaining and supporting biodiversity. The white colour indicates non-cropland areas.

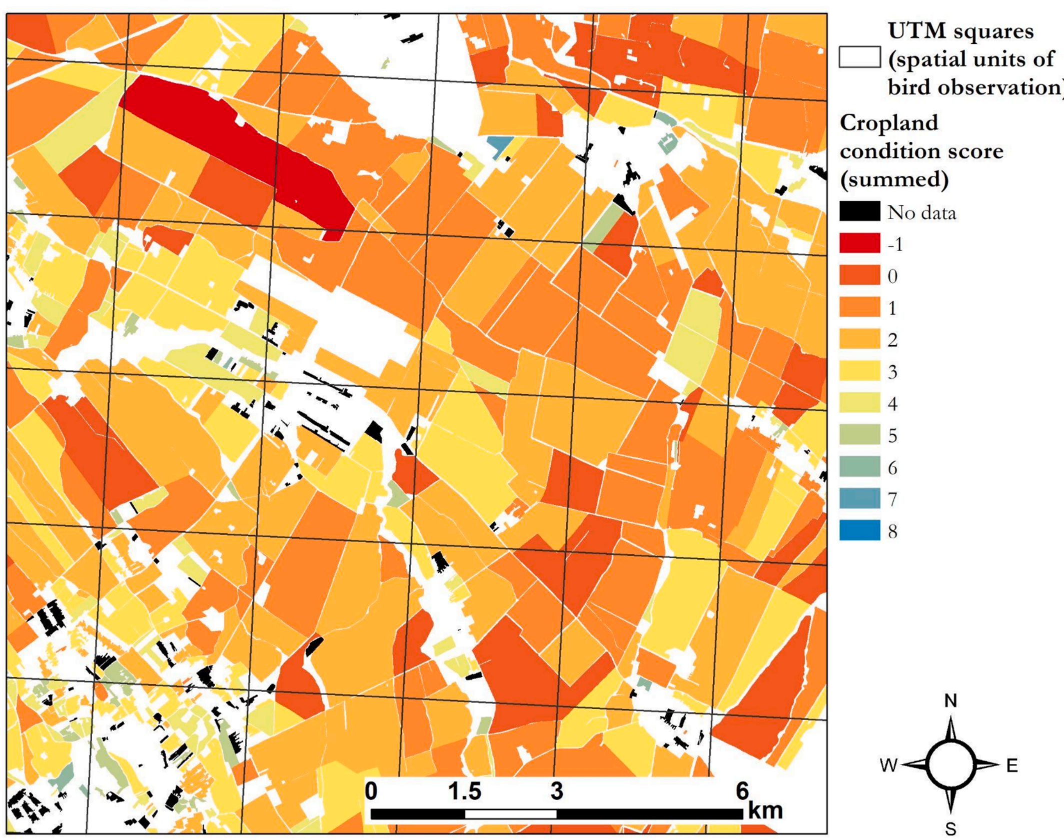


**Fig. 3.** The original spatial units of the two maps compared in the analysis – the UTM squares are units of the bird census data, while the blocks represent the units of the cropland condition map.

because eventually the results of these maps and assessments would contribute to ecosystem accounting in the EU) where the two are required to be separated (Keith et al., 2020). To achieve this, we fitted a generalised linear model (GLM) using the RRCS for farmland birds as a response variable and assuming a binomial distribution with logit link due to the range of the RRCS values (Dobson and Barnett, 2008; Fig. 1D). The background variables were (1) the duration of observation and the ratio of (2) agricultural, (3) urban and (4) forested land within the UTM square. The ratio of wetlands was omitted as it could be generated as a linear combination of the others, thus making the background variables fully multicollinear. The part of the response variable unaffected by the background variables (the residual of RRCS, hereinafter rRRCS) was used for further analysis (Fig. 4). We consider the rRRCS an indicator of the 'goodness' of agricultural areas in terms of supporting a diverse bird population and, thus, indirectly, an indicator of their general ecological condition.

### 3.3. Validation of the cropland condition indicator and the thresholds applied to the variables

To validate our proxy-based cropland condition indicator, we compared the differences in the mean rRRCS between the categories represented by the sub-indicator and indicator scores. In each case, we performed multiple comparisons of means by Tukey's contrast (hereinafter "Tukey test") and classified the indicator and sub-indicator scores into significance groups at $\alpha = 0.05$ level (Fig. 1E).

As a further test of our choice of indicators, we ran a series of Random Forest regressions (with parameters detailed below) in a 30-km-radius moving window (focal analysis; Hagen-Zanker, 2016, Davis, 2024, Jing et al., 2020) around each UTM square (Fig. 1F). Thus a total of 15,444 Random Forest models were created. The 30 km radius was defined as an optimum distance to have sufficient data for modelling while still keeping to a local scale. rRRCS was selected as the response variable for the Random Forest regression models. The explanatory variables were the same as those listed in Table 1, but those variable pairs that form combined indicators (alfalfa and green fallow; areas subsidised under HNVA or AES) were included individually to allow a more nuanced analysis. Thus, we included nine separate variables in these models. The models built 500 trees of (potentially) unlimited depth. The number of variables to possibly split at each node was set to three (i.e., the default value for nine background variables). Unweighted sampling of cases was done with replacement. Due to the above-mentioned trade-off between the sample size and the local scale of the analysis, instead of splitting the squares situated within the moving window to independent training and test subsets, all the squares of the window were used for training the model. Consequently, as the measurement of the models' goodness-of-fit, $R^2$ values were calculated for each model using all predicted and observed values of the rRRCS within the window instead of calculating the out-of-bag $R^2$. Please note that in this attempt to optimize the sample size, the model goodness-of-fit values may become too optimistic. Finally, the $R^2$ values were mapped by allocating each goodness-of-fit value to the focal UTM square.

Only those UTM squares were included in any of the analyses that had a valid rRRCS value and where the ratio of arable land was at least 10 % within the UTM square. That means 4957 squares. A map showing the number of suitable squares (i.e. the number of inputs) for each Random Forest model is shown in Appendix C.

### 3.4. The importance of the applied condition variables in predicting the rRRCS

Besides measuring the combined explanatory power of the chosen condition variables in the different regions of Hungary, the Random Forest regression also allowed the mapping of their individual local importance. To define variable importance, we used the "increase of the mean squared error" (IncMSE) measure. IncMSE measures the effect on

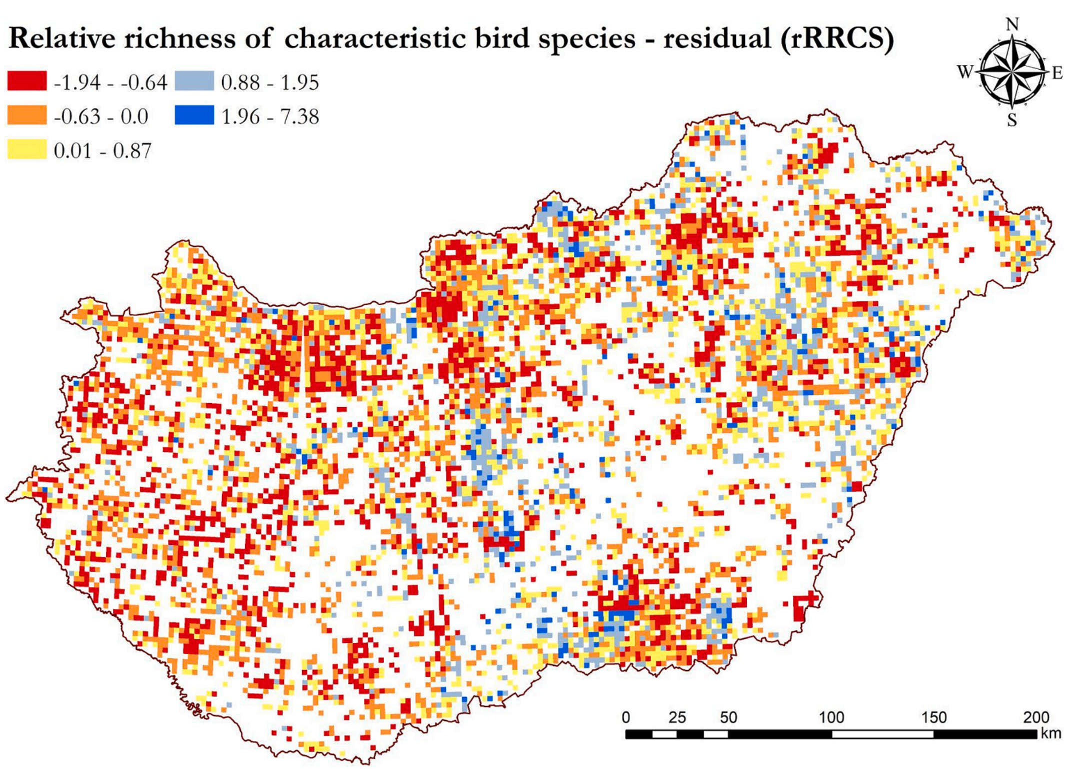


**Fig. 4.** Map of the relative richness of characteristic bird species residual (rRRCS). RRCS is the ratio of the number of characteristic farmland bird species actually present to the number of these species expected in favourable agricultural areas. rRRCS is a modelled value where the extent of agricultural areas and the duration of observation within the examined spatial units are accounted for. White areas signify missing data, where the duration of observation was not sufficiently long to provide meaningful data.

the predictive power of the model (i.e., the mean decrease in accuracy) when the value of a certain variable is randomly permuted (Breiman, 2001). Based on the IncMSE, we defined a rank for each variable for each model, and thus, we had 9 × 15,444 rankings. In order to define overall variable importance, we looked at the number of times each variable was the most important (i.e., rank is #1). We then created a map to see the spatial patterns of the most important variables. We also looked at the sum of ranks, which provides a more nuanced picture (the lower the sum, the more important the variable).

## 4. Results

### 4.1. Validation of the condition indicators and the applied thresholds

We have found significant differences in the mean rRRCS for nearly all sub-indicators and categories (Fig. 5; for specific mean values, see Appendix D Table 1). Categories with higher condition scores (signifying better condition) had significantly higher rRRCS values. The only exception is parcel size, where we found no significant difference between UTM squares with a median score of 0 (dominated by large blocks, with > 10 ha average parcel size) and UTM squares with a median score of 1.

When comparing the means of the rRRCS between the categories of the summed condition indicator, we found that they generally increased with the values of the condition indicator (Fig. 6; for mean values, see Appendix D Table 2). The categories in the middle show significant differences, whereas the differentiation works less well in the case of low and high values (categories with a score of 0 vs 1 as well as 5 vs 6, and 4 vs 6 do not differ significantly in terms of the rRRCS). There are no UTM squares with a median score of 8 or 9, while only a few squares have 'extreme' scores of −1 and 7 (2 and 9 UTM squares, respectively). This may explain the lack of consistency of these categories with the otherwise clear trend. According to these results, the map can be meaningfully simplified. While the significantly different categories (with scores 1 to 5) should be separated, the extreme categories, where the element number is smaller than 100, can be merged with their neighbours. Thus, the first three (−1 to 1) and the last five (5 to 9) categories would be aggregated. Categories 8 and 9 are present in only small areas and are included in the highest category. Fig. 7A shows the result of the original simplification used in MAES-HU, and Fig. 7B shows the modification suggested on the basis of our present results. The updated map has increased contrast, which helps to highlight the differences more effectively.

### 4.2. Variable importance

Measures describing variable importance based on the ranks calculated from the IncMSE measures of all the RF models are shown in Table 2. Based on the number of UTM squares (and the corresponding models) where a specific variable was found to be the most important (rank #1), the variables are listed in order of variable importance, starting with the most important. The proportion of semi-natural areas stands out, as well as the proportion of land subsidised under High Nature Value Areas. In contrast, there are much smaller differences between the next three variables.

Considering the sum of ranks, the order is approximately the same, but only the proportion of semi-natural areas stands out, whereas there is little difference between the next four variables. The number of cultivated plants replaces the proportion of fallow land as the 5th most important variable.

### 4.3. Spatial patterns of Random Forest model's goodness-of-fit and variable importance

$R^2$ values range from 0.69 to 0.89 (with a median value of 0.81), meaning that the models built on our chosen set of variables describe the

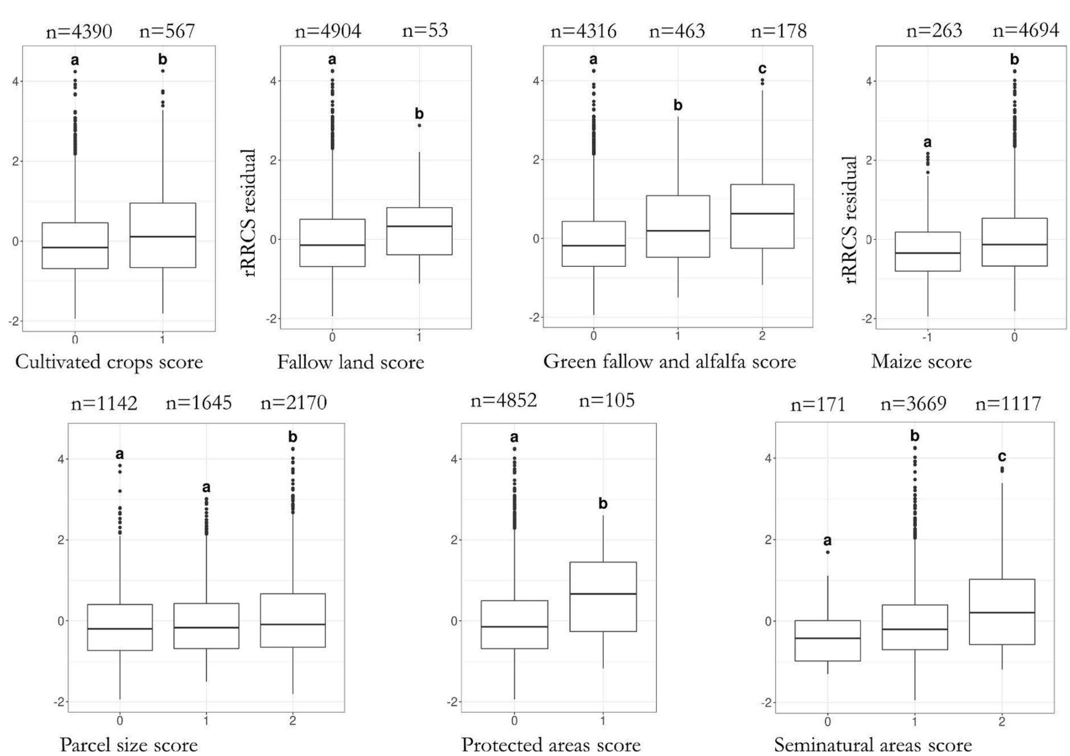


**Fig. 5.** Differences in the residual of the relative richness of characteristic bird species (rRRCS) according to the cropland condition sub-indicator categories used in the Hungarian pressure-based cropland condition mapping. RRCS is the ratio of the number of characteristic farmland bird species actually present to the number of these species expected in favourable agricultural areas. rRRCS is a modelled value where the extent of agricultural areas and the duration of observation within the examined spatial units are accounted for.

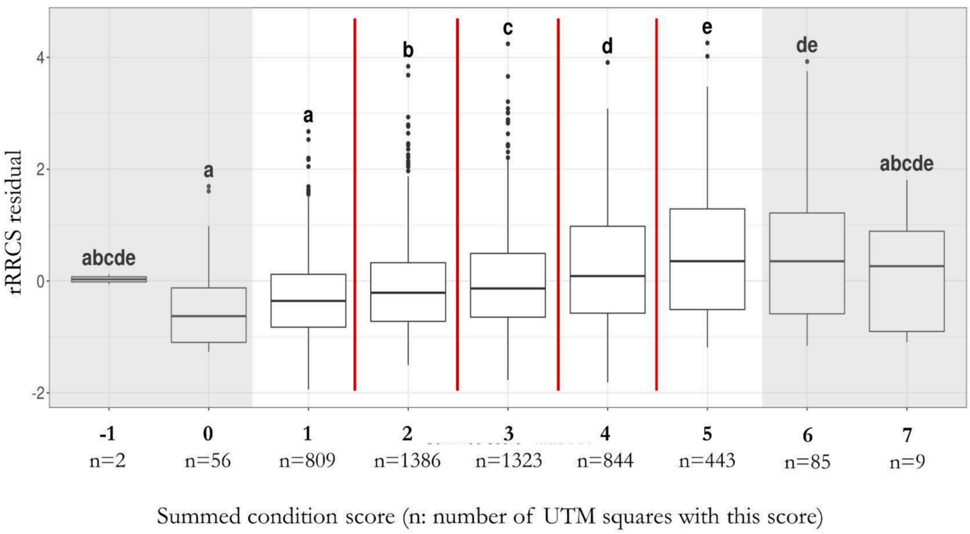


**Fig. 6.** Differences in the residual of the relative richness of characteristic bird species (rRRCS) according to the pressure-based cropland condition indicator categories. RRCS is the ratio of the number of characteristic farmland bird species actually present to the number of these species expected in favourable agricultural areas. rRRCS is a modelled value where the extent of agricultural areas and the duration of observation within the examined spatial units are accounted for. Red lines show the possible aggregation of categories for a simplified map, suggested on the basis of the results, whereas the grey background signifies rare categories (n < 100). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 2**
Variable importance according to the results of the Random Forest models for all (15,444) UTM squares.

| Condition variable | Rank #1 (% of all squares) | Sum of ranks |
|---|---|---|
| Proportion of semi-natural areas | 37.2 | 44,805 |
| Proportion of land subsidised under 'High Nature Value Areas' (HNVA) | 16.1 | 72,153 |
| Proportion of maize | 9.2 | 72,261 |
| Proportion of alfalfa | 8.8 | 76,588 |
| Proportion of fallow land | 8.2 | 83,613 |
| Number of cultivated plants (no or no/ha) | 6.6 | 79,323 |
| Average parcel size | 5.9 | 83,816 |
| Proportion of land included in an agri-environmental scheme (AES) | 4.7 | 85,776 |
| Proportion of green fallow | 3.3 | 96,555 |

variance in the rRRCS fairly well. The spatial distribution of the $R^2$ values (Fig. 8) shows that the best results are achieved in the central and eastern parts of the country, while the models work less well in the west.

The map of the most important variable (Fig. 9) also shows higher variability in the western, mostly hilly and forested regions of Hungary. Nearly all of the chosen variables were shown to have high importance in at least certain areas.

## 5. Discussion

The national-scale cropland condition indicator developed in MAES-HU was found to reflect differences in the presence of characteristic farmland birds – higher condition scores in an area generally mean more of the expected bird species to be present. The thresholds applied to the individual variables constituting the condition indicator were also found to be meaningful, with only a single exception. The results show

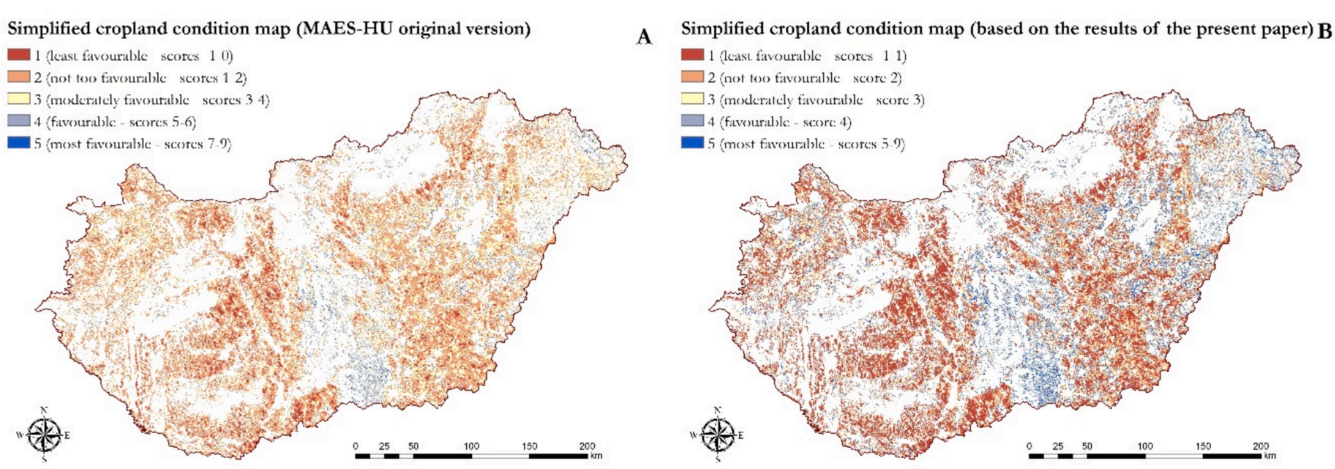


**Fig. 7.** A: the spatial distribution of the original five simplified categories of the cropland condition map applied in the Hungarian MAES (Tanács et al. 2022). B: the same cropland condition map, simplified with different thresholds based on the results of the current study (the differences of the mean rRRCS between areas with different condition scores). RRCS is the ratio of the number of characteristic farmland bird species actually present to the number of these species expected in favourable agricultural areas. rRRCS is a modelled value where the extent of agricultural areas and the duration of observation within the examined spatial units are accounted for. On both maps, higher values mean a favourable state for maintaining and supporting biodiversity. The white colour indicates non-cropland areas.

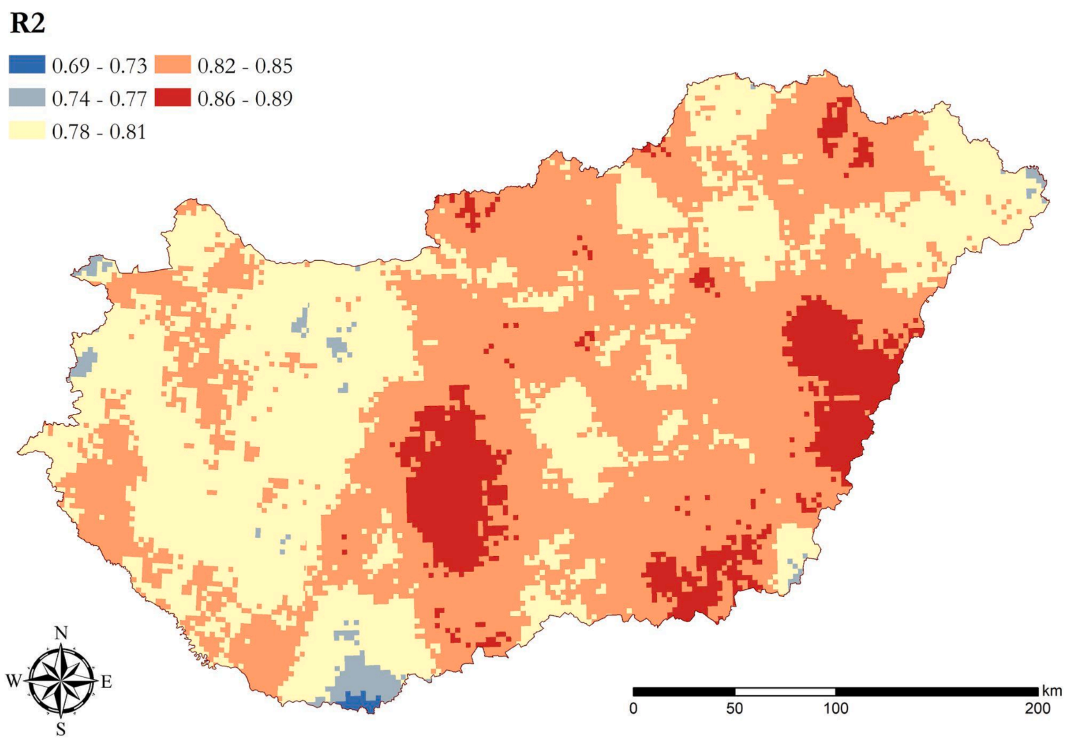


**Fig. 8.** The spatial distribution of the model's goodness-of-fit. To each UTM square we assigned the $R^2$ value of the Random Forest regression calculated for its 30 km-radius window.

that pressure and management-related proxies can serve as useful substitutes in large-scale condition mapping when biodiversity data are scarce or nonexistent. They also suggest that the uncertainty of these condition maps varies in space, which should be taken into consideration when designing the models.

### *5.1. Is the MAES-HU pressure-based cropland condition indicator sound?*

#### *5.1.1. Differences in characteristic bird species presence according to the condition classes*

When comparing the mean rRRCS between the categories formed by the summed condition scores, we found that the higher condition scores generally meant higher rRRCS values, especially in the middle of the condition range.

Large-scale condition maps based on pressure proxies could not and should not replace biodiversity monitoring. However, if their uncertainty is known and taken into account, they can be useful tools for national-level conservation planning, especially in data-scarce areas (Maes et al., 2018). The MAES-HU pressure-based cropland condition map was designed as a general indicator of the ability of agricultural land to support wildlife. We used bird census data for validation as farmland birds can be useful surrogates for trends in other elements of biodiversity in this habitat (Gregory et al., 2005), and that was also the most comprehensive available database. Croplands are artificial ecosystems covering a large part of Europe. Their suitability for birds varies according to their management, as it may limit food and nesting sites (Wilson et al., 1999, Blösch et al., 2023). Thus, agricultural intensification is widely accepted as the main pressure for farmland bird decline (Rigal et al., 2023). Our results suggest that the MAES-HU cropland condition map, based on pressure-response evidence from the literature, is indeed indicative of the suitability of croplands to support farmland bird species in the landscape. The lack of significant differences between the more extreme condition categories is probably caused by the interactions between the different types of pressure (Chiron et al., 2014). The 'saturation effect' at the higher scores is in line with research showing that enhancing artificial habitats may have significant positive effects on biodiversity, but such measures cannot entirely replace the restoration of (semi)-natural habitats in a landscape (Lengyel et al., 2023).

#### *5.1.2. The spatial context-dependence of ecosystem condition mapping*

When examining the goodness-of-fit of our RF models across space, we found that the chosen variables together can explain a high percentage of the variance in the rRRCS. There was some definite spatial variation; the best results were achieved in the central and eastern parts of Hungary, while goodness-of-fit was generally weaker in the west. There is also a much higher spatial variability of the most important variable in the west. This phenomenon is consistent with findings related to the context-dependence of the importance of landscape features in the success of conservation measures aiming to increase biodiversity in farmlands. The success of such measures was found to be the function of several factors, e.g. landscape context and agricultural land-use intensity (Batáry et al., 2010, Heath and Long, 2019, Kleijn et al., 2011). The western hilly regions of Hungary have a more humid climate. They are also different from the eastern plains both in terms of ecosystem extent (more forests, less cropland) and elevation (Kocsis, 2018). As a consequence, they also differ in the character and configuration of the semi-natural landscape elements (Csorba et al., 2018). The rRRCS map itself can be considered a biodiversity-based condition map; the choice of characteristic species may affect the spatial patterns. Hungary is a small country and thus we used a single list for the whole area. However, it could be argued that even the list of birds chosen to calculate the RRCS could be adjusted to major regions for more precise results.

Our results suggest a spatial context-dependence of the goodness-of-fit of the modelled cropland condition. This shows that the uncertainty of condition maps may be locally higher and if one model is used across a larger region, their usefulness (e.g. in planning) may vary according to regions.

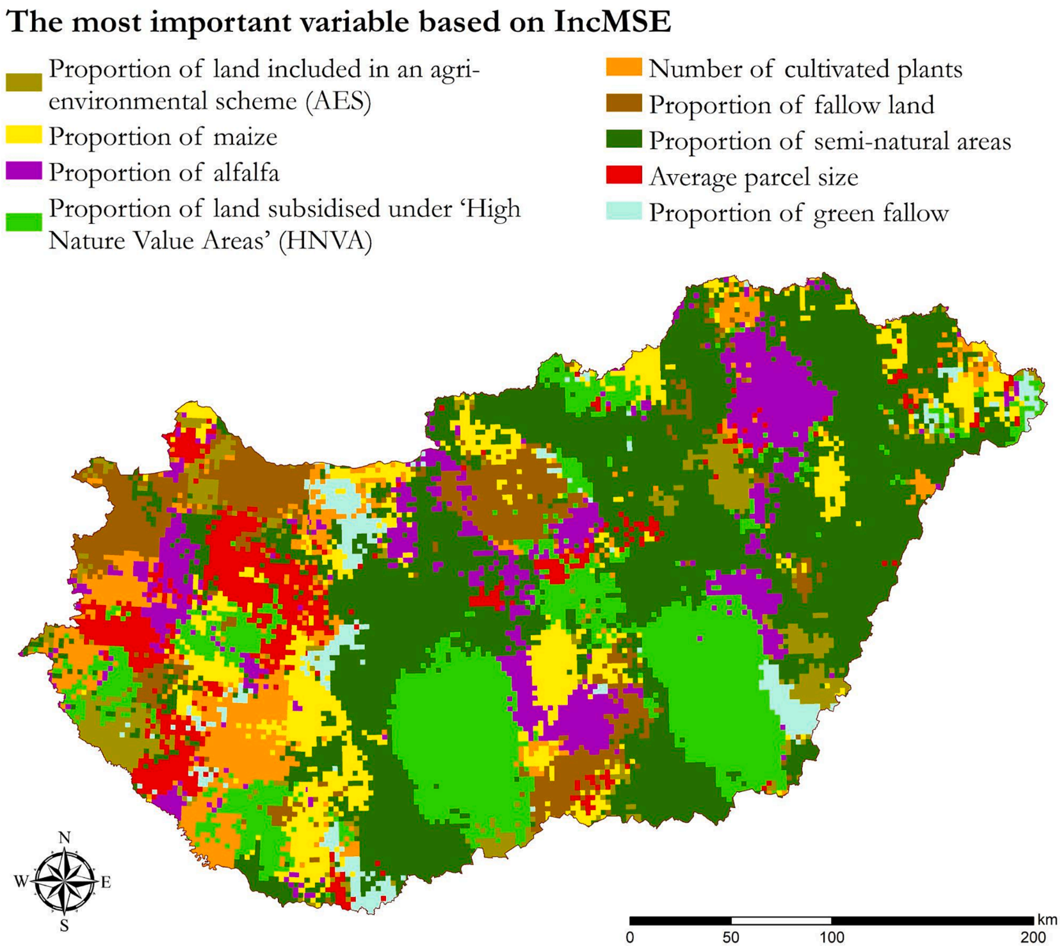


**Fig. 9.** The spatial distribution of the most important variable of the Random Forest regression calculated for a 30 km-radius window around each UTM square. Variable importance was defined using the "increase of the mean squared error" (IncMSE) measure. To each UTM square we assigned the most important variable (the one with the highest IncMSE) of the Random Forest regression calculated for a 30 km-radius window around it.

### 5.2. The importance of the individual condition variables

We examined the importance of the individual variables that serve as the basis for the cropland condition indicator. While there is a clear order of importance, with the proportion of semi-natural areas outstanding, we also found that any of the included variables can become the most important in certain areas.

The proportion of semi-natural areas was the most significant factor in predicting rRRCS, aligning with previous studies that highlight the critical role of these areas in supporting biodiversity (Zingg et al., 2018, Marcacci et al., 2020, Klein et al., 2023). While this variable may not directly reflect the condition of cropland, recent research shows that the success of nature-friendly farming practices, such as adding hedges, is heavily influenced by the amount of surrounding semi-natural areas (Batáry et al., 2010, Katayama et al., 2023).

Intensification leads to species loss (Wilson et al., 1999, Pal et al., 2013, Rigal et al., 2023). We included the proportion of area subsidised under some form of agri-environmental scheme (AES and High Nature Value Areas – HNVA) as proxies for management intensity, since farmers in these programs must implement measures to enhance biodiversity. Although AES and HNVA form a combined sub-indicator in the model, we analysed them separately to gain a nuanced understanding. The results showed that the HNVA proportion was one of the most important variables, while the AES was among the least. Despite similar regulations, HNVA subsidies are limited to areas with existing high biodiversity, implying lower management intensity and diverse land cover (Beaufoy and Cooper, 2009, Andersen et al., 2004). The HNVA concept aligns closely with our condition mapping approach (Matin et al., 2020, Andersen et al., 2004). The measures specified as requirements for the subsidies in these schemes often include elements already featured in our model (e.g. planting alfalfa, setting aside fallow land, smaller field size, etc.). However, while there is potential overlap in input information, HNVA remains a useful indicator according to our results. It comprises some information (related to the limited use of pesticides and fertilisers in the subsidised areas), for which currently no other national-scale spatial data of the appropriate quality are available. The low importance of the AES-related variable can probably be attributed to the correlation of the two. However, there is also evidence of contrasting responses of different bird guilds to AES measures (Gamero et al., 2017) (Appendix E Table 1).

The proportion of maize was found to be the third most important variable but the reason for its prominent role is unclear. It was included based on scientific evidence concerning its adverse effects on biodiversity (Busch et al., 2020, Hass et al., 2019, Jerrentrup et al., 2017, Sauerbrei et al., 2014). This was the only variable where we applied a negative score and the most controversial. Interestingly, most authors don't explain why the increasing proportion of maize in the landscape may have such an effect. Possible explanations include the large-scale homogenization and simplification of land use at the landscape level (Jerrentrup et al., 2017). The results of our present analysis certainly justify its inclusion as part of a cropland condition indicator.

Alfalfa was included in the model as most agree on its positive effects on biodiversity and importance in nature-friendly farming. Alfalfa fields, as perennial crops, tend to maintain a stable arthropod community, which in turn attracts vertebrates, especially birds. However, these advantages also depend on the management method (González del Portillo et al., 2022). Our results support its significance.

The proportion of fallow land had also been found to influence bird populations (Busch et al., 2020). We found it to be moderately important in our models, possibly due to its correlation with both the proportion of maize and semi-natural areas (Appendix E Table 1).

Average parcel size was the only variable where an applied threshold wasn't meaningful (Fig. 5). It's often used as a proxy for management intensity (e.g., Batáry et al., 2017, Marcacci et al., 2020), so we expected it to be highly significant—but it wasn't. This may be because increasing mean field size causes species richness to decline more sharply in the lower field size range (<6 ha, Clough et al., 2020), making this variable less effective in areas with larger parcels. Potential collinearity with other variables may have further reduced its importance (Appendix E Table 1, Fahrig et al., 2015). While average parcel size was included to account for field margin density, which benefits wildlife (Marshall and Moonen, 2002; Martin et al., 2019), it doesn't capture differences in margin quality, whereas field margins can vary greatly in habitat suitability (Jobin et al., 2001, Heath et al., 2017).

The number of cultivated crops was included to refer to the variety of crops, also generally considered an important factor in maintaining biodiversity in farmlands (Sirami et al., 2019). In our models, its overall importance was moderate. This is in line with the findings of Jerrentrup et al. (2017).

The low importance of the proportion of green fallow in itself is probably due to the fact that it can only be found in a few areas and mostly in those subsidised under agri-environmental schemes.

### 5.3. Implications for the further development of cropland condition maps

The key steps of condition mapping with the additive method used in MAES-HU are (i) selecting the variables, (ii) defining the thresholds and (iii) defining the scores (in fact weighting the variables). A possible fourth step (iv) is simplifying the result to make it better interpretable, comparable to other condition maps, and easier to communicate to stakeholders. These steps or the related decisions usually form part of condition mapping, even if a different modelling method is applied. In the following, we discuss the implications of our findings to these steps.

#### 5.3.1. Variable selection

There are now general guidelines to support the process of variable selection and suggested lists of variables are available for each major ecosystem type (Maes et al., 2018, Keith et al., 2020, Czúcz et al., 2021). These need to be adjusted to the specific area to be mapped and assessed, with data availability being an important limitation (Maes et al., 2020). While the set of proxy variables applied in MAES-HU was found to reflect the rRRCS well, the overall analysis of importance shows that some of the variables may be redundant. However, the spatial analysis showed that according to different geographical settings, practically any of the examined variables can become the most important.

Certain variables, considered key in the evaluation of cropland condition (Maes et al., 2018), were omitted from the mapping due to a lack of consistent, good-quality countrywide datasets. Spatially explicit data on (actual and not estimated) pesticide and fertiliser use should eventually be included as they are major drivers of biodiversity loss (Chiron et al., 2014, Rigal et al., 2023). Another useful addition could be the proximity or amount of wooded field margins. With easier access to remote sensing data, accurate large-scale maps of such green linear elements can be expected to become increasingly available.

#### 5.3.2. Thresholds and scoring

Reference-based approaches have high policy and management relevance as they are suitable for following the progress (or identifying degradation) (Jakobsson et al., 2020, Keith et al., 2020). The thresholds we applied to the pressure proxy variables can also be considered reference levels; they are meant to mark a level of pressure beyond which there is a noticeable decline in biodiversity. There is a considerable knowledge gap concerning ecologically meaningful reference levels in terrestrial ecosystems (Jakobsson et al., 2020). The thresholds examined here were based on scientific evidence collected from the literature (see Table 1) and experience from conservation projects (e.g. Kovács et al., 2005); our results mostly support their relevance.

It would be possible to further optimise the thresholds for each variable using the biodiversity data as the study of pressure-response relationships can provide information to set individual evidence-based thresholds (Ritterbusch et al., 2022). However, as different taxa tend to respond differently to pressure (Chiron et al., 2014, Martin et al., 2019, Mallet et al., 2023), the optimisation should ideally be carried out using the data of several species groups. Furthermore, the optimal weighting of the condition sub-indicators would still be a challenge to address (Herzog et al., 2006). Sensitivity analysis is a possible option to test the relevance of the chosen variables and thresholds (Borgonovo and Plischke, 2016).

If suitable reference data are available, there are further options to carry out condition mapping besides the additive model used in MAES-HU (Keith et al., 2020). Random Forest, which we used here to define variable importance, can be a viable option, but there are several different analytical approaches worth considering before making a choice (Kosicki, 2020).

#### 5.3.3. Simplifying the map

Based on our results, we suggest simplifying the condition map into five classes, which all significantly differ according to characteristic bird species presence. This simplification into a manageable number of categories can be useful beyond offering the possibility to create more distinct final categories. Effective communication towards potential users (both stakeholders and decision-makers) is necessary to improve the uptake potential of the condition maps (Mea et al., 2016). The visual representation of information on a map affects understanding and decision-making (Lecours, 2017, Thompson et al., 2018). Both decision-makers and the wider public seem to prefer a simple communication of scientific results (Borja et al., 2014, Tulloch et al., 2016). However, the more detailed results (in our case the individual sub-indicators and summed scores behind the simplified map) should also be made available to keep the complexity underpinning the results (Thompson et al., 2015) and provide a deeper insight for more effective decision-making.

## 6. Conclusions

The large-scale condition mapping of ecosystems is a useful tool in conservation and restoration planning, and such maps are increasingly in demand. However, the scarcity of suitable primary datasets means that the maps need to be based on proxy variables, designed on the basis of scientific evidence concerning pressure-response relationships. Our results show that for croplands, pressure-based proxies can reflect patterns of biodiversity reasonably well. The pressure variables we used are quite common in describing cropland management intensity and condition, and are usually easily accessible in most countries. Therefore, both our mapping method and the related findings on variable importance can be considered widely applicable. However, the results also draw attention to the fact that when mapping ecosystem condition in larger, geographically heterogeneous areas, a 'one size fits all' approach may increase the uncertainty of the condition maps. Thus, there is a tradeoff to be considered between the level of uncertainty and the complexity of the mapping process.

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### Declaration of competing interest

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

### Data availability

The data are available from the data owner (Ministry of Agriculture) on request. Please contact corresponding author

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.112665.

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