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Short Note

Expert-based model of the potential for natural pest control with landscape and field scale drivers in intensively managed cereal-dominated agricultural landscapes

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ABSTRACT

Agricultural intensification has contributed to the loss of biodiversity and of the ecosystem services that it supports, such as natural pest control. Decision support tools are needed to understand and predict where natural pest control can be enhanced and pesticide applications decreased. While many studies have assessed the impact of field and landscape-scale management in a range of crops, few attempts have been made to synthesize this knowledge in a single model. In this study, we developed an expert-based moving window model of natural pest control potential. This model builds on the knowledge of 52 experts across Europe regarding the importance of herbaceous areas, forest interiors, and edges, and field scale agricultural management practices (i.e. farming system, field size and crop diversity) for the abundance of generalist predators (e.g. carabids, spiders), specialist predators (e.g. coccinelids) and parasitoid natural enemies. We assessed the model's performance by comparing its predictions to field data on natural enemy abundance from 117 sites in Sweden. The natural pest control potential scores predicted by the model explained 11% of the variation in carabid field abundances. However, the model's performance was less satisfactory for spiders and parasitoids. We provide guidance for improving this indicator, particularly by incorporating more ecological processes, such as accounting for the functional diversity of spiders and the density-dependent effects of parasitoid-host interactions. In addition, the model could be further refined by accounting for non-linear relations and potential threshold effects and interactions among field and landscape-scale management practices. In its current state, the developed indicator can be used to identify areas where further ecological intensification practices can be promoted to enhance natural pest control potential, especially for carabids.

1. Introduction

To increase crop production, natural habitats have been transformed into large agricultural monocrop fields, and farms have intensified and specialized on few cash crops, reducing crop diversity in space and time, and increasing cropping system reliance on pesticide for pest control (Robinson and Sutherland, 2002). This intensification has led to declines in biodiversity as well as the many ecosystem services it supports, including soil health, pollination and natural pest control (Hallmann et al., 2017; Landis, 2017; Rusch et al., 2016). Natural pest control is here defined as the service delivered by natural enemies to suppress pests in managed ecosystems (Bianchi et al., 2006). Declines in natural enemy abundances and the pest control services they support increase cropping systems' vulnerability to pest outbreaks, insecticide dependence and resistance, and crop yield losses due to pests (Deutsch et al., 2018; IPCC, 2021). Managing agricultural landscapes by, for example, increasing non-crop habitats, reducing pesticide applications, reducing large-scale mono-cropping systems and increasing crop diversity to support populations of natural enemies, is key to the supply of natural pest control services and agroecosystem sustainability (Bonato et al., 2023; Bommarco et al., 2013). These management practices allows for ecological intensification of agrosystems in which natural processes

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replace human inputs, such as pesticides and fertilizers, while maintaining or increasing food production per unit area (Bommarco et al., 2013). The influence of these practices on natural pest control services depends on the spatial organization of agricultural landscapes (Bianchi et al., 2006; Chopin et al., 2019) such as the proximity between non-crop and crop habitats. Therefore, replacing insecticide use with natural pest control services requires spatially-explicit tools to, for example, identify areas with low natural pest control potential and target implementation of ecological intensification practices (Alexandridis et al., 2021; Bommarco et al., 2013; Perennes et al., 2023). Despite this need, natural pest control is one of the least spatially mapped ecosystem services (1 % of studies, among 17 major ecosystem services, Englund et al., 2017). Existing models primarily focus on landscape-scale land-use composition (Rega et al., 2018), seldom accounting for field-scale management practices, potentially misestimating natural pest control potential in agroecosystems.

Up-scaling the findings on natural enemy abundance and pest control from field surveys and experiments to larger spatial scales is difficult as pest control potential depends on the complex interactions between local field management practices, landscape composition and natural enemy traits (Petit et al., 2020). At the field scale, organic farming and temporal crop diversity (e.g. diversity in crop rotation) can promote natural pest control potential by providing natural enemies with complementary food and shelter resources (Muneret et al., 2018; Redlich et al., 2018; Scheiner and Martin, 2020). Additionally, small field size can enhance natural pest control potential, by facilitating natural enemies' movement from field margins or nearby semi-natural habitats (SNH) to field interiors and by increasing spatial crop diversity within the foraging range of many natural enemies (Haan et al., 2020; Redlich et al., 2021). At the landscape scale, increasing SNH cover generally supports source populations of natural enemies and favours their movement into crops (Chaplin-Kramer et al., 2011). However, these local and landscape scale effects on natural pest control services can be highly variable as they interact with each other (Bianchi et al., 2006; Petit et al., 2020). In addition, generalist and specialist natural enemies display different preferences for different types of SNH with, for instance, a general avoidance of forest interiors by generalist natural enemies (Moonen et al., 2016). To improve natural pest control services prediction and target the implementation of ecological intensification management practices, the complex interactions between local and landscape scale practices on different natural enemy functional groups (e.g. generalists and specialists) need to be included in spatially-explicit models of natural pest control services.

Mapping pest control potential using, for instance, participatory approaches (Raymond et al., 2009), field experiments (Petz and van Oudenhoven, 2012), and mechanistic approaches based on natural enemies (Jonsson et al., 2014) have allowed for scale-up of natural pest control potential from field to landscape scales. However, these models remain limited in their scope, focusing on one system or not accounting for a diversity of land uses (e.g., field management practices, forest and herbaceous areas) and natural enemies. More complex models of natural enemy abundance at the European scale have accounted for the influence of different types of SNH on flying natural enemies (Rega et al., 2018). However, there was little correlation between field observations and the level of natural pest control potential predicted by these models (Bonato et al., 2023). This is likely because they do not account for diversity in field-scale management practices in the landscape, such as the diversity of crops, the proportion and spatial organization of organic fields and field borders. Assessing the effect of several field-scale management practices and other land uses (i.e., forest and herbaceous areas) at multiple spatial scales is very difficult in the field. Currently, there are no *meta*-analyses estimating the relative effects of these practices on natural pest control services. To overcome this, estimates based on experts' knowledge can allow the assessment of the relative effect of several land-use practices at multiple spatial scales (Burkhard et al., 2012).

In this paper, we aimed to develop a spatially-explicit, fine-resolution model to quantify and map the potential of intensively managed landscapes to support generalist and specialist predators and parasitoid natural enemy abundances. Including experts' knowledge of natural enemy abundances and building on the model by Rega et al (2018), our model accounts for both field and landscape scale management practices influencing natural enemy abundance. Model performance was assessed using field data on natural enemies' abundance from southern Sweden. Variation in model performance between natural enemy groups is further discussed as well as model potential application and further improvements.

2. Materials and methods

2.1. Model building and rationale

We combined data from expert-based surveys on the capacity of various land uses including field management practices, herbaceous and forest areas (edge and interior) to support various natural enemy groups with a spatial model to estimate a score of natural pest control potential (Fig. 1). Predicted model scores were compared to field data on natural enemy abundances in Sweden to assess the model's performance (Fig. 1). This pest control model is adapted for pest-predator systems in intensively managed temperate landscapes, which encompass oilseed rape and cereal systems. In these crops, pests such as aphids (Hemiptera: Aphididae), weevils (Coleoptera: *Ceutorhynchus obstrictus, C. Assimilis*), or pollen and flea beetles (Coleoptera: *Brassicogethes aeneus*, *Psylliodes chrysocephala*) are controlled by generalist and specialist predators as well as parasitoids. These pest-predator systems have specific resource and habitat requirements (Kröber and Carl, 1991; Williams, 2010) which may differ from other pest-predator systems.

2.2. Experts survey on land-use and agricultural management practices

We aimed to quantify the potential of an intensively managed cereal-based agricultural landscape to support natural enemy (generalist and specialist predators and parasitoid) abundance and thereby its natural pest control service potential in a spatially-explicit way. Pest control services are the result of complex natural enemy-prey-environment dynamics that determine natural enemy species composition and abundance (Mei et al., 2023; Snyder, 2019). Nevertheless, the abundance of natural enemies is a good proxy to assess the natural pest control potential across crop systems as a positive correlation between the two variables has been reported extensively in the literature (Bianchi et al., 2006; Tschumi et al., 2016). Therefore, we assumed that natural enemy abundance enhances pest suppression in agroecosystems (Chaplin-Kramer et al., 2011). Natural enemies can be broadly divided into three groups: 'Generalist predators' (i.e. includes ground and rovebeetles (Coleoptera: Carabidae, Staphylinidae), spiders (Arachnida: Araneae)…), 'Specialist predators' (includes aphidophagous predators such as coccinellids (Coleoptera: Coccinellidae), lacewing (Neuroptera: Chrysopidae), hoverfly larvae (Diptera: Syrphidae)…) and 'Parasitoids' (includes: parasitic wasps (Hymenoptera)…). For each natural enemy functional group, experts from around Europe were asked to rate the influence of forest and herbaceous areas and field management practices on their abundance and indicate their level of confidence as 1 ('not confident'), 2 ('fairly confident') and 3 ('confident') (Campagne et al., 2017) (Fig. 1). The survey used the example of an average intensive cereal-based agricultural region, i.e. producing at least 60 % cereals, commonly found in many productive regions in Europe (Figure S1).

Experts were asked to rate the capacity of various land uses, including forest edge, forest interior, herbaceous and agricultural habitats for supporting generalist and specialist predators and parasitoid natural enemy abundances. A Likert-scale from 0 – 10, ranging from '*no relevant capacity*' to '*very high relevant capacity*', was used to assess the capacity of one specific land-use type to support each natural enemy

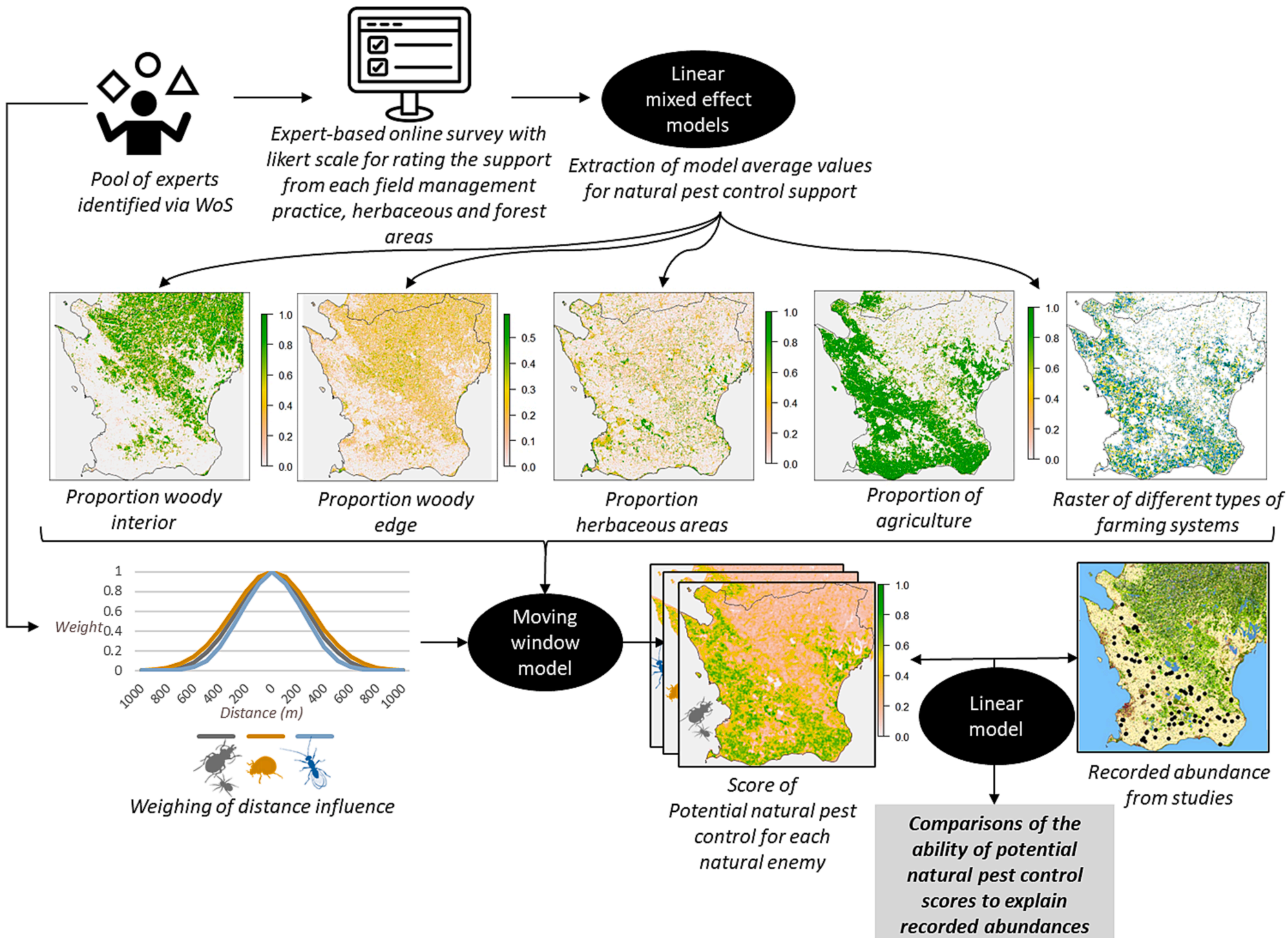

Fig. 1. Methodological framework adopted in the paper that combines expert surveys and a spatial model to determine the potential level of natural pest control for generalist and specialist predators and parasitoid natural enemies.

group (Burkhard and Maes, 2017). The option '*I don't know*' was included to avoid 'pseudo opinions' (Rowley, 2014). Forest habitat was categorized as an area with more than 30 % of forest canopy cover (i.e. perennial plants such as trees or shrubs at a height > 1 m). Forest interior (large forest cores) were separated from forest edges and tree lines of up to 10 m width, as natural enemy abundances are differently affected by these features (Haan et al., 2020; Moonen et al., 2016). Herbaceous habitats (i.e. permanent and semi-natural pastures and permanent ley fields) were defined as habitats containing less than 30 % of forest canopy cover that were not ploughed for at least 5 years but could be mowed or grazed. The agricultural land use baseline was defined as a conventionally managed average field (with an average field size of 3–7 ha, fertilization and pesticide application compared to the region of interest) of medium crop diversity with three functional groups over 4 years (e.g., cereal, oilseed crop, root crop).

Field-scale management changes in crop rotation diversity, production system (from conventional to organic) and field size from the baseline agricultural system were rated for each natural enemy functional group. Here, experts were asked to give a percentage indicating how much better or worse this changed scenario could support each natural enemy group compared to the score they provided for the agricultural land-use baseline. Experts could choose between 8 levels of change, ranging from −100 % ('*considerably worse*') to + 200 % ('*extremely better*'). For field size, experts were asked to compare the baseline (3–7 ha) to small (<3 ha) and larger (>7 ha) field sizes. These sizes correspond to the average size, first quartile and third quartile of the distribution of field size in southern Sweden (Jordbruksverket, 2020). The average size of cereal fields declared by farmers in Scania is 6.7 ha on average (median of 4.3 ha). In other cereal-producing regions in Europe, studies have reported similar order of magnitudes, with average field sizes around 4–5 ha in the Niort Plain in France (Barbottin et al., 2018) and in Saxony-Anhalt, Brandenburg, Lower Saxony, and Bavaria in Germany (Jänicke et al., 2022). For crop diversity in the rotation, experts were asked to compare the baseline crop diversity (3 functional crop groups) with a lower level of diversity (max. 2 functional crop groups) and a higher level of diversity (min. 4 functional crop groups and/or containing ley). These levels of functional crop diversity are representative of the dominant types of crop rotations in European cereal landscapes, namely: i) a largely cereal-dominated crop sequence with two functional crops (e.g., oilseed rape-winter wheat-spring barley), ii) a crop sequences with several break crops (e.g., potatoes-spring barley-winter oilseed rape-winter wheat) and iii) a more diversified sequence with three functional crops or with leys (e.g., potatoes-spring barley-winter oilseed rape-peas or potatoes with two year of leys followed by one year of wheat). These rotation types covered the functional crop diversity found in Skåne as we found a crop diversity of 2.6 ± 0.7 crops per field from 2014 to 2017 (see details for calculation in the Supplementary material). Finally, experts were asked to grade the effect that a conversion from conventional to organic agriculture would have on each natural enemy group. Each factor was assessed separately and compared to the baseline. Finally, experts were asked to provide an estimate of the landscape radius (between 0–2000 m) affecting each natural enemy group.

2.3. Expert selection and implementation of the survey

To identify experts in the natural pest control field, we selected authors who had published papers in the past 5 years on the topic in Web of Science (on January 30, 2021) and had affiliations with academia, government or relevant NGOs. We filtered out authors without publications in the European Union or the UK and without expertise in cereal-based cropping systems. We identified 124 experts that we contacted individually. The survey was conducted online through a questionnaire implemented with Alchemer for 3 weeks, from the 20th of April 2021 until the 7th of May 2021. In total, 52 experts replied to the survey (response rate of 42 %). On average the survey lasted 27 min (±SD 12 min). Those experts worked in Sweden (n = 11), France (n = 14), Germany (n = 7), Switzerland (n = 5), Finland (n = 4), UK (n = 4), Italy (n = 2), Austria (n = 1), Denmark (n = 1), Hungary (n = 1), Portugal (n = 1) and the Netherlands (n = 1). The surveyed experts had on average 13.6 years (+/- 8.5) of experience in the field of natural pest control. Most of them were from academia (n = 45) and the rest were working in governmental organisations (n = 5), NGOs (n = 1) or environmental consultancies (n = 1).

2.4. Analyses of survey responses

To assess differences in experts' scoring of natural enemies' group land-use preference, survey responses scored with high and medium confidence (i.e. confidence level > 1) were analysed using cumulative link mixed effect models (*clmm* function), appropriate for ordered categorical data such as Likert-scores, with land use type as the main factor and respondent identity as a random effect. Including low-confidence responses did not qualitatively change the results (Table S1b, S2b). Scores of individual alternative management practices were calculated for each respondent by adding or subtracting the percentage change from the baseline scenario. To compare scores of field-scale agricultural management practice changes for each natural enemy group, high confidence survey scores (i.e. confidence level > 1) were analysed using linear mixed models (*glmmTMB*), with agricultural practice as a fixed factor and respondent as a random factor. Post-hoc tests were performed using *emmeans* package (Lenth, 2021). All analyses were performed in R (version 4.1.3) (R Core Team, 2020).

2.5. Model building for Sweden

2.5.1. Input data used for crop and non-crop habitats

Forest interiors and edge and herbaceous areas were identified using Sweden's land cover dataset ("Nationella Marktackedata") distributed by the Swedish Environmental Protection Agency (https://www.naturvardsverket.se, accessed on 9th June 2023). Pine, spruce, coniferous, deciduous, and hardwood were all considered forest habitats. Open land with vegetation and temporary non-forest were considered as herbaceous areas. In addition, leys and grassland under production which are part of the arable land were added to the map of herbaceous areas using the Land Parcel Identification System (LPIS) data from 2017 which represent farmers' declaration (Trubins, 2013). The differentiation between forest interior and forest edge was done using morphological spatial pattern analysis of all forest patches and forest lines across the landscape using the Morphological indices from Vogt et al. (2007) to delimitate a 10 m forest edge around all forest patches. Field size and crop diversity were obtained from the Land Parcel Identification System (LPIS). More details on the production of data are provided in the Supplementary material.

2.5.2. Calculation of the natural pest control potential

Each land use type was assigned a value of natural pest control potential using the predicted value from the experts' survey mixed effect models for forest edge, forest interior, herbaceous area, and agriculture baseline. This analysis excluded low confidence responses. The agriculture baseline was defined as an agricultural area which comprises a cropping system of average diversity in an average field size with conventional management - for each natural enemy group. The average score of individual alternative management practices was extracted from the models' predictions. For land uses that combined several practices, we summed the differences of all individual alternative management practices effects. This encompasses differences between cropping systems with either lower or higher crop diversity, smaller or larger field size, and those managed conventionally or organically. While assuming additive effects between land-use practices does not account for interactive effects, this is likely a more conservative and realistic approach than other available aggregation methods. The natural pest control potential was calculated by a weighted sum of the contributions from all surrounding source cells whose centre is at a given distance as done in Rega et al. (2018). The distances considered were the average buffer area provided by experts in the survey for each natural enemy group (mean ± se for generalist predators: 775 ± 57 m, specialist predators: 831 ± 63 m, and parasitoids: 765 ± 81 m). In the same way as Rega et al. (2018), we used a rotationally symmetrical 2Dt-distribution as a distance-weighted function, shaped like a normal distribution and rescaled so as to assign a value of 1 at distance = 0 and a value of 0 beyond the average buffer area. The outcome is a value of natural pest control potential produced on a 100 m resolution basis. Mathematically, this index is calculated based on the equation below (adapted from Rega et al. (2018)):

$$NPC_x = \sum_{i=1}^{n} f(r_i)^* p_k^* LU_k$$

Where NPC_x is the natural pest control potential indicator in target cell x, r_i is the Euclidian distance between cell i (source) and cell x (target), f (r_i) is the weight extracted from the distance function, n is the number of cells surrounding x for which $f(r_i) > 0$ and LU_k is the score of natural pest control support from land use k in cell i and p_k is the proportion of land use k.

2.6. Model validation

We retrieved 234 field-measured values for natural enemy abundances across 117 Swedish landscapes from several published datasets (Table 1). This included 116 measurements for carabids across 6 studies), 93 for spiders in 5 studies and 25 for parasitoids in 2 studies). We used a linear models approach to assess the relationship between in-field measurements of natural enemies' abundance (the sum of all collections per field) and the calculated indicator of natural pest control potential. The value of natural pest control used for this comparison was the average value over all pixels included within the field boundaries. Prior to analyses, natural enemy field abundances were log-transformed to improve normality. Natural enemy abundance and the value of natural pest control potential were scaled and centred within studies for each natural enemy functional group to account for in-between studies variations in sampling methods and years. Linear models (*lme4* package) for each natural enemy group were built with the observed field abundances (scaled and centred) as the response variable and the modelled values of natural pest control potential (scaled and centred) in interaction with study identity as explanatory variables. For all models, assumptions were visually checked.

3. Results

3.1. Analyses of survey responses

Survey scores for all three natural enemy groups' land-use preference were higher for herbaceous and forest edge habitats compared to the agricultural land baseline and the forest interior habitats (Fig. 2a, Table S1). In addition, for parasitoids, the agriculture habitat had higher

Table 1
Characteristics of the studies from which data were extracted for this study. Values shown are the mean; min–max SNH (%) cover in 1-km landscapes.

Original study/project	N° of landscapes	Crop	System	SNH cover (%)	Organisms studied	Year
Rus: Rusch et al., 2014	42	barley	Conventional	30; 2–67	carabids; spiders	2011
Lib: Gagic et al., 2017 (Swedish data)	16	wheat	Conventional	17; 4–36	carabids; spiders	2014
Cab: Caballero-López et al., 2012	24	barley/wheat	Organic	25; 1–89	carabids	2007
Tam: Aguilera et al., 2020 (Tamburini, G. 2017. raw data.)	10	oilseed rape	Conventional	19; 8–34	carabids; spiders	2017
Rig: Riggi et al., 2017	14	oilseed rape	Conventional	43; 14–87	carabids; spiders; parasitoids	2013
Agu: Aguilera et al., 2020 (Aguilera, G. 2017. raw data.)	11	oilseed rape	Conventional	12; 0.4–33	carabids; spiders; parasitoids	2017

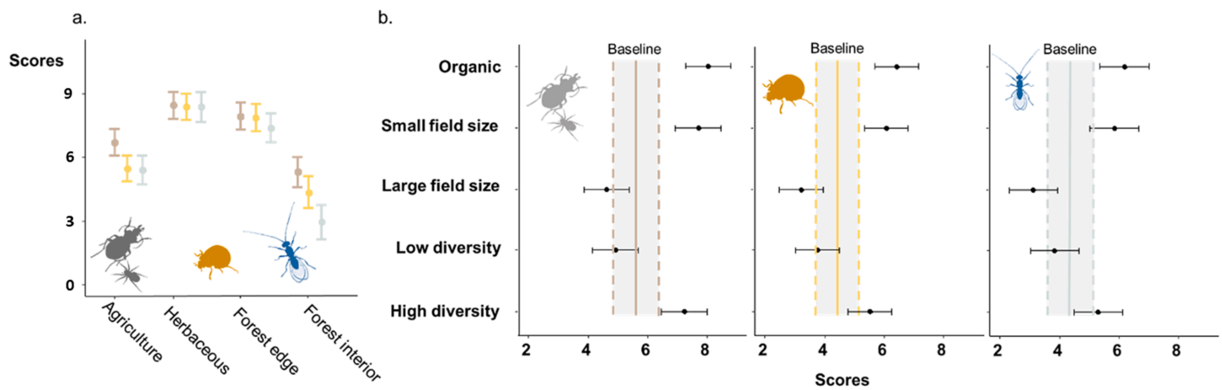

Fig. 2. Model predictions of the expert scores (Likert-scale from 0 to 10) showing the influence of **(a)** land-use on each natural enemy group and **(b)** field scale agricultural practices relative to the baseline system (conventional, average field size and average crop diversity) on each natural enemy group (Table S1 and S2). Error bars indicate 95 % CI (confidence intervals). Colours represent the different functional groups of natural enemies with generalist predators in grey, specialist predators in yellow and parasitoids in blue. Shaded areas and vertical lines in panel (b) indicate CI and the mean of the baseline system. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

scores than forest interior habitats (Fig. 2a, Table S1). When comparing experts' scores for local scale agricultural practices, organic management, small field size and high diversity in the crop rotation all had higher scores, while large field size had lower scores compared to the baseline for all natural enemies (Fig. 2b, Table S2). The positive effect of transition from conventional to organic, of decreasing field size and increasing crop diversity were greater for generalist predators (Table S2).

3.2. Model simulation

The value for natural pest control potential in the Skåne region showed similar patterns for the different natural enemy groups, with high values in cereal and oilseed production areas and much lower values in the north of the region where the proportion of forest cover increases from 5 % to 60 % (Fig. 3). Scores closer to 100 % were more frequently found for generalist predators (Fig. 3B) than for specialist predators and parasitoids natural enemies (Fig. 3C and D). Those were driven by higher scores for conventionally managed agricultural habitats for generalist natural enemies.

3.3. Model validation

Natural pest control potential scores were associated with in-field abundances for carabids ($p = 0.001$, Fig. 4a, Table S4) and explained 11.3 % of the variation measured. Individual studies did not interact, indicating that in-field abundances of carabids for each study positively related to model predictions (Table S4). However, the model differed in how well it fitted each individual study, explaining 42 % in one case study (Fig. 4b "Cab") and between 0 and 21 % for the other studies (Fig. 4b). The model predictions did not relate to field abundances of spiders and parasitoids and explained low percentages of the variation in each model (Figure S3). For spiders, the relation between the natural pest control potential indicator and field measurements varied from positive to negative amongst case studies (Figure S3). To note, spider and carabid species richness did not relate to the natural pest control index (Table S4).

4. Discussion

4.1. Current model limitations and potential developments

The predictive power of the model varied greatly between natural enemies' functional groups. Despite variation between datasets, carabid abundances in the field positively related to the model's predictions for natural pest control potential. However, the model performed worse for parasitoids and spiders. Previous work assessing the model by Rega et al. (2018) on flying predators pest control potential, indicated little or no evidence of correlations between modelled and field-measured values of natural pest control (Bonato et al., 2023). Our indicator, which included local field agricultural practices and expert knowledge on generalist predator abundance, explained 11 % of the variation in carabids abundance in the field. Many carabid species found in crop habitats are agrobionts, crop field specialists which rely on crop resources throughout their life cycle, and cropping practices greatly impact their abundances and distribution in agroecosystems (Labruyere et al., 2016; Muneret et al., 2023). Variation in model performance for the different carabid datasets might be related to crop types and farming system with greater predictability in organically managed cereal systems ('Cab', R^2: 42 %, Caballero-López et al., 2012) compared to conventionally managed oilseed rape and cereal systems. This difference in predictability might be due to interactive effects between local farming system practices and landscape scale land use on carabid abundances. Local-scale field habitat quality for natural enemies mediates the effects of landscape on field communities and abundances, i.e. *the intermediate landscape-complexity hypothesis* (Jonsson et al., 2015; Tscharntke et al., 2012). We could therefore expect greater benefits of increasing SNH cover on carabid communities in generally more intensive conventional

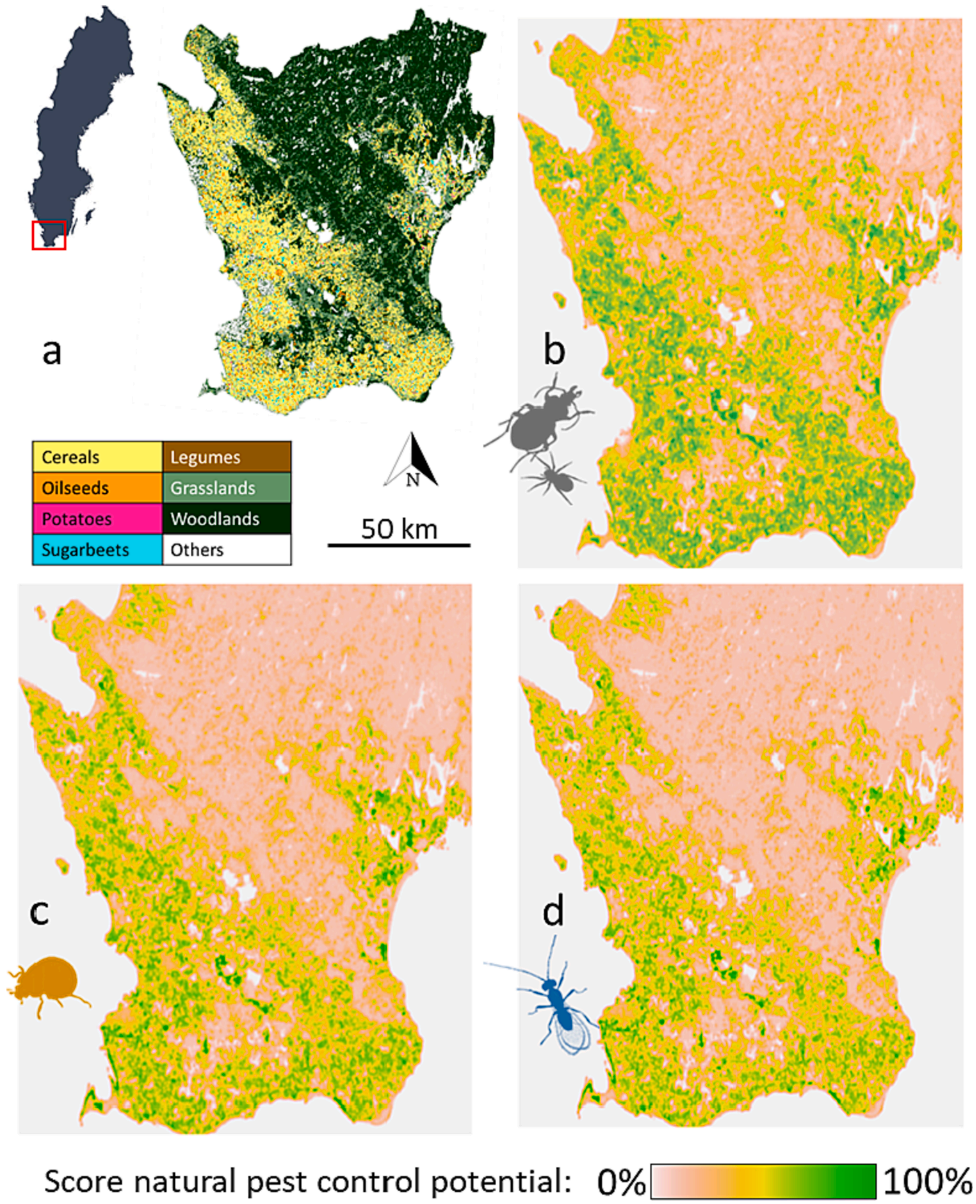

Fig. 3. Map of Sweden and the area of interest (Skåne) with its agricultural land **(A)** (provided in larger format with site locations in the Supplementary Material Figure S5), Score of natural pest control for generalist predators **(B)**, specialist predators natural enemies **(C)** and parasitoids **(D)**. The score is normalized from 0 to 1 for each natural enemy group separately.

systems compared to organic systems. Our current model does not account for interactive effects between land use and farming practices and could therefore underestimate their combined effects. In addition, our model does not allow for non-linear relationships between natural enemy abundances and practices. However, carabid responses to many farming practices, including pesticide applications, were found to be hump-shaped (Muneret et al., 2023). Therefore, to improve model performance, the model should account for non-linear relations and interactions between local and landscape scales habitat quality for natural enemies. In addition, current landscape elements included in the model, such as herbaceous land uses and crop diversity, could be further refined. This could be done by distinguishing low and high-intensity herbaceous systems (e.g. meadows versus pastures), and by weighting crops' pest control potential so that perennial crops (such as leys) that generally benefit natural enemies get a higher score.

The model did not predict spider or parasitoid abundance in the field. For spiders, field data represented only a subset of the overall spider community as spiders were sampled using pit-fall traps placed in the ground. Therefore, spiders inhabiting the vegetation, which can represent a high portion of the spider community (Spafford and Lortie, 2013), are not accounted for. Testing our model's predictions with data including both ground and vegetation dwelling spiders might improve model fit. Similarly, we are lacking data on parasitoid and specialist predator natural enemy field abundances. Only two field datasets were available for parasitoids. However, an important factor that the model did not account for is pest abundance. Parasitoids, as well as specialist predator natural enemies, show density-dependent reproductive and/or aggregative numerical responses to pest densities (Onstad and Flexner, 2023). Pest densities generally increase with host crop cover (i.e. *resource concentration hypothesis*) and are expected to concentrate in landscapes with interannual host crop reduction and dilute in landscapes with interannual host crop expansion. These dynamics might result in lower pest control potential with interannual host crop expansions (Thies et al., 2008). Future spatially-explicit models for parasitoid and specialist predator natural pest control potential should account for interannual changes in host crop cover. Ultimately,

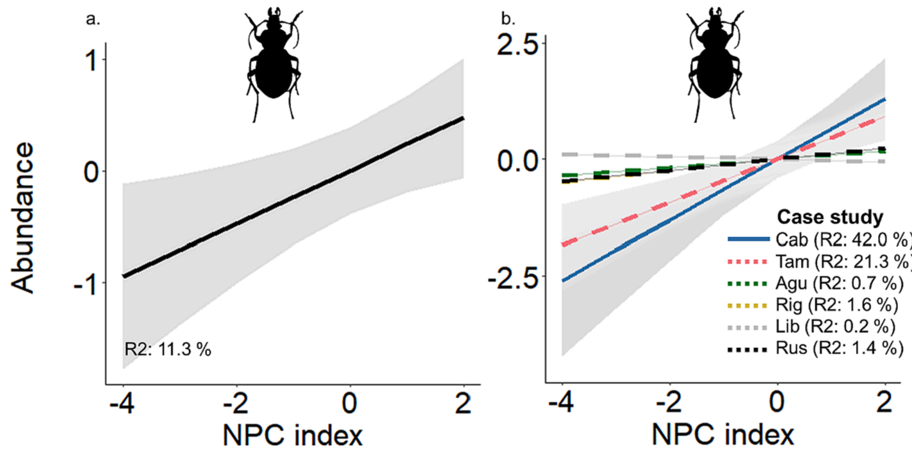

Fig. 4. Model prediction of in-field carabids abundance (scaled and centred) and potential for natural pest control indicator (scaled and centred) (a) across all case studies (est ± se = 0.64 ± 0.20, p = 0.001) and (b) for each case study, for "Cab" case study there was a positive and significant relation (est ± se = 0.66 ± 0.20, p < 0.001). Solid lines indicate significant and dashed lines non-significant relationships. Band indicates 95 % confidence intervals for significant relationships. For studies' abbreviations, see Table 1 and for regressions with data points per study see Figure S4.

combining indicators for natural enemy distribution with information on pest traits (e.g. transient or resident pests) would allow for identification of vulnerable areas and targeting of pest management interventions (Alexandridis et al., 2022; Rouabah et al., 2022). Models simulating both the demand and provision of natural pest control potential (based on natural enemy species richness), using bioclimatic variables and land-use cover have shown some success in predicting pest control mismatches in crop fields (Perennes et al., 2023). Eventually, we need to assess our model predictions using field data on biological control rather than natural enemy abundances to avoid bias due to sampling artefacts or species interactions (Redlich et al., 2018).

When assessing experts survey results, high variability in scoring was found for 'forest interior', especially for generalist predators, indicating that there is disagreement and generally low confidence in the value of this habitat type across natural enemy groups (Table S3, Figure S2). For generalist predators, combining carabid beetles and spiders might explain the variation in respondents' results, as spiders rely more on forest habitats for overwintering than carabids (Mestre et al., 2018). Therefore, weighing of forest interior might be improved by accounting for different habitat requirements between carabid and spider groups.

4.2. Model applications and improvements compared to previous ecosystem assessment models

Although our regression analysis explains a small proportion of variability, our indicator shows a positive correlation with the abundance of carabids in the field. This is a significant contribution to the development of an indicator for natural pest control services. However, we acknowledge that the predictive power of our indicator is low. In its current state the indicator can nevertheless serve as a proxy for natural pest control services as it is able to capture the level of adoption of ecological intensification practices known to sustain natural enemies' populations (e.g. crop diversity, organic practices, SNHs, Kremen, 2020). Our indicator allows for scenario analysis of management changes at various spatial scales, from field to regional, as to pinpoint potential pathways of desired changes in terms of practices (Verburg et al., 2016). In landscapes with high potential natural pest control services, pesticides could be reduced or used carefully to avoid negatively impacting local natural enemy populations. On the other hand, landscapes with low natural pest control potential might benefit from targeted integrated pest management approaches or ecological intensification practices such as integration of field margins/buffer strips which have been shown to be accepted practices among farmers (Jowett et al., 2022). Increasing crop diversity in crop rotations can promote natural enemy communities by increasing crop and resource diversity for natural enemies at the landscape scale (Thenail et al. 2009).

Accounting for landscape-scale influence on natural pest control potential is relevant as it is the scale at which the processes underlying ecosystem services take place (Dale et al., 2013). Moreover, our indicator contributes to more spatially-explicit assessment of natural pest control services as it goes beyond landscape composition by also accounting for landscape configuration, via including a measure of distance between the different types of land uses in the landscape, which is still very much lacking in ecosystem services assessments (Metzger et al., 2021). This is important as landscape configuration impacts arthropod distribution (González-Chaves et al., 2020). As current research on ecosystem services in agrosystems predominantly considers only a limited number of ecosystem services (Agudelo et al., 2020; Tancoigne et al., 2014), adding our indicator for assessing the magnitude of adoption of ecological intensification practices supporting natural enemy abundances is of value. With further development, this indicator could be added to existing tools and models allowing the assessment of ecosystem services. As an example, the InVEST model (Sharp et al., 2018), a widely used GIS-tool collection developed under the Natural Capital Project, can assess food supply, soil conservation, water conservation, and habitat quality for biodiversity or pollination but currently does not integrate natural pest control. Our indicator could allow for assessment of the trade-offs between magnitude of adoption of ecological intensification practices supporting natural enemy abundance and other ecosystem services.

Our approach to evaluate natural pest control potential is relatively simple and can be easily integrated to assess other ecosystem services in agroecosystems, such as pollination. The model can be applied on local to large scales by taking advantage of the wealth of high-resolution spatial and temporal data. Crop and semi-natural habitat maps are becoming widely available using Land Parcel Identification Systems or outputs from large-scale remote sensing studies like the crop map produced by d'Andrimont et al. (2021) at European level or semi-natural habitats maps from land cover information such as Corine land cover (Büttner et al., 2021). For crop diversity, extra processing is required to derive crop rotation diversity but methods are available with for instance combining land parcel identification system data (Levavasseur et al., 2016), statistical model of crop rotation (Castellazzi et al., 2008) or expert-based assessment of typical crop rotations in landscapes (Dury et al., 2012). Characterizing cropping systems requires collection of farm-level information regarding certificate of organic farming and link it to field information at global scale (Malek et al., 2019). In the same way, field size can be obtained from existing maps (Lesiv et al., 2019) or can eventually be manually drawn from satellite images. The integration of data from various sources and locations would yield spatially-explicit synthesized information to guide targeted policy interventions at different scales.

5. Conclusion

Our results show that a simple indicator integrating the magnitude of adoption of different ecological intensification practices that support natural enemy abundances positively correlated with the abundance of carabids, despite a very large variation in predictions and a low explanatory power. In its current state, this indicator can be used to identify areas with low levels of adoption of ecological intensification practices (e.g. crop diversity, SNHs, organic practices) where we expect low natural pest control services. These areas should be targeted to foster and support the adoption of ecological intensification practices. Predictions can ultimately be improved by developing models which include more specific associations between local and landscape-scale habitat interactions. Experimental research and *meta*-analyses investigating multiple ecological intensification practices along land-use gradients are necessary to quantify such interactive effects between scales. We also stress that to ultimately support farmers' decisions and support a shift toward low-pesticide agriculture, models need to be trained and tested using field data. Given the huge amount of field research on natural pest control, we urgently need field data to be readily accessible and spatially explicit in online databases.

6. Data statement

The code for the model is provided with the manuscript, along with a training dataset. The experts' survey data used to parameterize the model are provided with the manuscript and will be made available in the data repository Zenodo. Field collected data can be either found in the respective published papers or by directly contacting the authors of the papers.

CRediT authorship contribution statement

Laura G.A Riggi: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Guillermo Aguilera:** Writing – review & editing, Data curation. **Pierre Chopin:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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. The expert data and model can be found on DataverseNL: doi:10.34894/QJDFDY.

Data availability

We are sharing the code to calculate the indicators and some training datasets. The data used for agricultural fields is confidential. The datasets with natural enemies abundance are published online.

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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.2024.111684.

References

Agudelo, C.A.R., Bustos, S.L.H., Moreno, C.A.P., 2020. Modeling interactions among multiple ecosystem services. A Critical Review. Ecol. Model. 429, 109103 https://doi.org/10.1016/j.ecolmodel.2020.109103.
Aguilera, G., Roslin, T., Miller, K., Tamburini, G., Birkhofer, K., Caballero-Lopez, B., Lindström, S.-A.-M., Öckinger, E., Rundlöf, M., Rusch, A., Smith, H.G., Bommarco, R., 2020. Crop diversity benefits carabid and pollinator communities in landscapes with semi-natural habitats. J. Appl. Ecol. 57, 2170–2179. https://doi.org/10.1111/1365-2664.13712.
Alexandridis, N., Marion, G., Chaplin-Kramer, R., Dainese, M., Ekroos, J., Grab, H., Jonsson, M., Karp, D.S., Meyer, C., O'Rourke, M.E., Pontarp, M., Poveda, K., Seppelt, R., Smith, H.G., Martin, E.A., Clough, Y., 2021. Models of natural pest control: Towards predictions across agricultural landscapes. Biol. Control 163, 104761. https://doi.org/10.1016/j.biocontrol.2021.104761.
Alexandridis, N., Marion, G., Chaplin-Kramer, R., Dainese, M., Ekroos, J., Grab, H., Jonsson, M., Karp, D.S., Meyer, C., O'Rourke, M.E., Pontarp, M., Poveda, K., Seppelt, R., Smith, H.G., Walters, R.J., Clough, Y., Martin, E.A., 2022. Archetype models upscale understanding of natural pest control response to land-use change. Ecol. Appl. 32, e2696.
Barbottin, A., Bouty, C., Martin, P., 2018. Using the French LPIS database to highlight farm area dynamics: The case study of the Niort Plain. Land Use Policy 73, 281–289. https://doi.org/10.1016/j.landusepol.2018.02.012.
Bianchi, F.J.J.A., Booij, C.J.H., Tscharntke, T., 2006. Sustainable pest regulation in agricultural landscapes: a review on landscape composition, biodiversity and natural pest control. Proc. Biol. Sci. 273, 1715–1727. https://doi.org/10.1098/rspb.2006.3530.
Bommarco, R., Kleijn, D., Potts, S.G., 2013. Ecological intensification: harnessing ecosystem services for food security. Trends Ecol. Evol. 28, 230–238. https://doi.org/10.1016/j.tree.2012.10.012.
Bonato, M., Martin, E.A., Cord, A.F., Seppelt, R., Beckmann, M., Strauch, M., 2023. Applying generic landscape-scale models of natural pest control to real data: Associations between crops, pests and biocontrol agents make the difference. Agric. Ecosyst. Environ. 342, 108215 https://doi.org/10.1016/j.agee.2022.108215.
Burkhard, B., Kroll, F., Nedkov, S., Müller, F., 2012. Mapping ecosystem service supply, demand and budgets. Ecol. Indic. Challenges Sustaining Natural Capital Ecosystem Services 21, 17–29. https://doi.org/10.1016/j.ecolind.2011.06.019.
Burkhard, B., Maes, J., 2017. Mapping Ecosystem Services. Adv. Books 1, Advanced Books. https://doi.org/10.3897/ab.e12837.
Büttner, G., Kosztra, B., Maucha, G., Pataki, R., Kleeschulte, S., Hazeu, G.W., Vittek, M., Schroder, C., Littkopf, A., 2021. Copernicus Land Monitoring Service-CORINE Land Cover. User Manual. Copernicus Publications.
Caballero-López, B., Bommarco, R., Blanco-Moreno, J.M., Sans, F.X., Pujade-Villar, J., Rundlöf, M., Smith, H.G., 2012. Aphids and their natural enemies are differently affected by habitat features at local and landscape scales. Biol. Control 63, 222–229. https://doi.org/10.1016/j.biocontrol.2012.03.012.
Campagne, C.S., Roche, P., Gosselin, F., Tschanz, L., Tatoni, T., 2017. Expert-based ecosystem services capacity matrices: Dealing with scoring variability. Ecol. Indic. 79, 63–72. https://doi.org/10.1016/j.ecolind.2017.03.043.
Castellazzi, M.S., Wood, G.A., Burgess, P.J., Morris, J., Conrad, K.F., Perry, J.N., 2008. A systematic representation of crop rotations. Agric. Syst. 97, 26–33. https://doi.org/10.1016/j.agsy.2007.10.006.
Chaplin-Kramer, R., O'Rourke, M.E., Blitzer, E.J., Kremen, C., 2011. A meta-analysis of crop pest and natural enemy response to landscape complexity. Ecol. Lett. 14, 922–932. https://doi.org/10.1111/j.1461-0248.2011.01642.x.
Chopin, P., Bergkvist, G., Hossard, L., 2019. Modelling biodiversity change in agricultural landscape scenarios - A review and prospects for future research. Biol. Conserv. 235, 1–17. https://doi.org/10.1016/j.biocon.2019.03.046.
d'Andrimont, R., Verhegghen, A., Lemoine, G., Kempeneers, P., Meroni, M., van der Velde, M., 2021. From parcel to continental scale – A first European crop type map based on Sentinel-1 and LUCAS Copernicus in-situ observations. Remote Sens. Environ. 266, 112708 https://doi.org/10.1016/j.rse.2021.112708.
Dale, V.H., Kline, K.L., Kaffka, S.R., Langeveld, J.W.A. (Hans), 2013. A landscape perspective on sustainability of agricultural systems. Landsc. Ecol. 28, 1111–1123. https://doi.org/10.1007/s10980-012-9814-4.
Deutsch, C.A., Tewksbury, J.J., Tigchelaar, M., Battisti, D.S., Merrill, S.C., Huey, R.B., Naylor, R.L., 2018. Increase in crop losses to insect pests in a warming climate. Science 361, 916–919. https://doi.org/10.1126/science.aat3466.
Dury, J., Schaller, N., Garcia, F., Reynaud, A., Bergez, J.E., 2012. Models to support cropping plan and crop rotation decisions. A Review. Agron. Sustain. Dev. 32, 567–580. https://doi.org/10.1007/s13593-011-0037-x.
Englund, O., Berndes, G., Cederberg, C., 2017. How to analyse ecosystem services in landscapes—A systematic review. Ecol. Indic. 73, 492–504. https://doi.org/10.1016/j.ecolind.2016.10.009.

Gagic, V., Kleijn, D., Báldi, A., Boros, G., Jørgensen, H.B., Elek, Z., Garratt, M.P.D., de Groot, G.A., Hedlund, K., Kovács-Hostyánszki, A., Marini, L., Martin, E., Pevere, I., Potts, S.G., Redlich, S., Senapathi, D., Steffan-Dewenter, I., Świtek, S., Smith, H.G., Takács, V., Tryjanowski, P., van der Putten, W.H., van Gils, S., Bommarco, R., 2017. Combined effects of agrochemicals and ecosystem services on crop yield across Europe. Ecol. Lett. 20, 1427–1436. https://doi.org/10.1111/ele.12850.

González-Chaves, A., Jaffé, R., Metzger, J.P., Kleinert, de M.P., 2020. Forest proximity rather than local forest cover affects bee diversity and coffee pollination services. Landsc. Ecol. 35, 1841–1855. https://doi.org/10.1007/s10980-020-01061-1.

Haan, N.L., Zhang, Y., Landis, D.A., 2020. Predicting Landscape Configuration Effects on Agricultural Pest Suppression. Trends Ecol. Evol. 35, 175–186. https://doi.org/10.1016/j.tree.2019.10.003.

Hallmann, C.A., Sorg, M., Jongejans, E., Siepel, H., Hofland, N., Schwan, H., Stenmans, W., Müller, A., Sumser, H., Hörren, T., Goulson, D., de Kroon, H., 2017. More than 75 percent decline over 27 years in total flying insect biomass in protected areas. PLOS ONE 12, e0185809.

IPCC, 2021. Intergovernmental pannel on Climate Change.

Jänicke, C., Goddard, A., Stein, S., Steinmann, H.-H., Lakes, T., Nendel, C., Müller, D., 2022. Field-level land-use data reveal heterogeneous crop sequences with distinct regional differences in Germany. Eur. J. Agron. 141, 126632 https://doi.org/10.1016/j.eja.2022.126632.

Jonsson, M., Bommarco, R., Ekbom, B., Smith, H.G., Bengtsson, J., Caballero-Lopez, B., Winqvist, C., Olsson, O., 2014. Ecological production functions for biological control services in agricultural landscapes. Methods Ecol. Evol. 5, 243–252. https://doi.org/10.1111/2041-210X.12149.

Jonsson, M., Straub, C.S., Didham, R.K., Buckley, H.L., Case, B.S., Hale, R.J., Gratton, C., Wratten, S.D., 2015. Experimental evidence that the effectiveness of conservation biological control depends on landscape complexity. J. Appl. Ecol. 52, 1274–1282. https://doi.org/10.1111/1365-2664.12489.

Jordbruksverket, 2020. Kartor och Geografiska informationssystem [WWW Document]. URL https://jordbruksverket.se/e-tjanster-databaser-och-appar/e-tjanster-och-databaser-stod/kartor-och-gis (accessed 2.1.21).

Jowett, K., Milne, A.E., Potts, S.G., Senapathi, D., Storkey, J., 2022. Communicating carabids: Engaging farmers to encourage uptake of integrated pest management. Pest Manag. Sci. 78, 2477–2491. https://doi.org/10.1002/ps.6878.

Kremen, C., 2020. Ecological intensification and diversification approaches to maintain biodiversity, ecosystem services and food production in a changing world. Emerg. Top. Life Sci. 4, 229–240. https://doi.org/10.1042/ETLS20190205.

Kröber, T., Carl, K., 1991. Cereal aphids and their natural enemies in Europe - a literature review. Biocontrol News Inf. 12, 357–371.

Labruyere, S., Ricci, B., Lubac, A., Petit, S., 2016. Crop type, crop management and grass margins affect the abundance and the nutritional state of seed-eating carabid species in arable landscapes. Agric. Ecosyst. Environ. 231, 183–192. https://doi.org/10.1016/j.agee.2016.06.037.

Landis, D.A., 2017. Designing agricultural landscapes for biodiversity-based ecosystem services. Basic Appl. Ecol. 18, 1–12. https://doi.org/10.1016/j.baae.2016.07.005.

Lenth, R., 2021. Emmeans: Estimated marginal means, aka least-squares means. 2018; R package version 1.3. 1. View Article.

Lesiv, M., Bayas, J.C.L., See, L., Duerauer, M., Dahlia, D., Durando, N., Hazarika, R., Sahariah, P.K., Vakolyuk, M., Blyshchyk, V., Bilous, A., Perez-Hoyos, A., Gengler, S., Prestele, R., Bilous, S., Akhtar, I.U.H., Singha, K., Choudhury, S.B., Chetri, T., Malek, Z., Bungnamei, K., Saikia, A., Sahariah, D., Narzary, W., Danylo, O., Sturn, T., Karner, M., McCallum, I., Schepaschenko, D., Moltchanova, E., Fraisl, D., Moorthy, I., Fritz, S., 2019. Estimating the global distribution of field size using crowdsourcing. Glob. Change Biol. 25, 174–186. https://doi.org/10.1111/gcb.14492.

Levavasseur, F., Martin, P., Bouty, C., Barbottin, A., Bretagnolle, V., Thérond, O., Scheurer, O., Piskiewicz, N., 2016. RPG Explorer: A new tool to ease the analysis of agricultural landscape dynamics with the Land Parcel Identification System. Comput. Electron. Agric. 127, 541–552. https://doi.org/10.1016/j.compag.2016.07.015.

Malek, Ž., Tieskens, K.F., Verburg, P.H., 2019. Explaining the global spatial distribution of organic crop producers. Agric. Syst. 176, 102680 https://doi.org/10.1016/j.agsy.2019.102680. ISSN 0308-521X.

Mei, Z., Scheper, J., Kleijn, D., 2023. Arthropod predator identity and evenness jointly shape the delivery of pest control services. Pest Manag. Sci. https://doi.org/10.1002/ps.7779.

Mestre, L., Schirmel, J., Hetz, J., Kolb, S., Pfister, S.C., Amato, M., Sutter, L., Jeanneret, P., Albrecht, M., Entling, M.H., 2018. Both woody and herbaceous semi-natural habitats are essential for spider overwintering in European farmland. Agric. Ecosyst. Environ. 267, 141–146. https://doi.org/10.1016/j.agee.2018.08.018.

Metzger, J.P., Villarreal-Rosas, J., Suárez-Castro, A.F., López-Cubillos, S., González-Chaves, A., Runting, R.K., Hohlenwerger, C., Rhodes, J.R., 2021. Considering landscape-level processes in ecosystem service assessments. Sci. Total Environ. 796 https://doi.org/10.1016/j.scitotenv.2021.149028.

Moonen, A.C., Bocci, G., Bartual, A.M., Albrecht, M., Sutter, L., 2016. Beneficials database management and scoring system development. EU FP7 QUESSA project Deliverable 2.4. available online at: http://docs.wixstatic.com/ugd/3ccd83_67154bd3e2314acf9c8a080e8d4b7925.pdf?index=true.

Muneret, L., Mitchell, M., Seufert, V., Aviron, S., Djoudi, E.A., Petillon, J., Plantegenest, M., Thiery, D., Rusch, A., 2018. Evidence that organic farming promotes pest control. Nat. Sustain. 1, 361–368. https://doi.org/10.1038/s41893-018-0102-4.

Muneret, L., Ricci, B., Vialatte, A., Aviron, S., Ducourtieux, C., Biju-Duval, L., Petit, S., 2023. Carabid beetles have hump-shaped responses to disturbance and resource gradients within agricultural landscapes. J. Appl. Ecol. 60, 581–591. https://doi.org/10.1111/1365-2664.14357.

Onstad, D.W., Flexner, J.L., 2023. Chapter eleven - Insect resistance, natural enemies, and density-dependent processes. In: Onstad, D.W., Knolhoff, L.M. (Eds.), Insect Resistance Management, (Third Edition). Academic Press, pp. 381–399. https://doi.org/10.1016/B978-0-12-823787-8.00012-X.

Perennes, M., Diekötter, T., Hoffmann, H., Martin, E.A., Schröder, B., Burkhard, B., 2023. Modelling potential natural pest control ecosystem services provided by arthropods in agricultural landscapes. Agric. Ecosyst. Environ. 342, 108250 https://doi.org/10.1016/j.agee.2022.108250.

Petit, S., Muneret, L., Carbonne, B., Hannachi, M., Ricci, B., Rusch, A., Lavigne, C., 2020. Chapter One - Landscape-scale expansion of agroecology to enhance natural pest control: A systematic review. In: Bohan, D.A., Vanbergen, A.J. (Eds.), Advances in Ecological Research, the Future of Agricultural Landscapes, Part I. Academic Press, pp. 1–48. https://doi.org/10.1016/bs.aecr.2020.09.001.

Petz, K., van Oudenhoven, A.P.E., 2012. Modelling land management effect on ecosystem functions and services: a study in the Netherlands. Int. J. Biodivers. Sci. Ecosyst. Serv. Manag. 8, 135–155. https://doi.org/10.1080/21513732.2011.642409.

R Core Team, 2020. R: A Language and Environment for Statistical Computing R Foundation for Statistical Computing. Austria -, Vienna https://www.R-project.org/.

Raymond, C.M., Bryan, B.A., MacDonald, D.H., Cast, A., Strathearn, S., Grandgirard, A., Kalivas, T., 2009. Mapping community values for natural capital and ecosystem services. Ecol. Econ. 68, 1301–1315. https://doi.org/10.1016/j.ecolecon.2008.12.006.

Redlich, S., Martin, E.A., Steffan-Dewenter, I., 2018. Landscape-level crop diversity benefits biological pest control. J. Appl. Ecol. 55, 2419–2428. https://doi.org/10.1111/1365-2664.13126.

Redlich, S., Martin, E.A., Steffan-Dewenter, I., 2021. Sustainable landscape, soil and crop management practices enhance biodiversity and yield in conventional cereal systems. J. Appl. Ecol. 58, 507–517. https://doi.org/10.1111/1365-2664.13821.

Rega, C., Bartual, A.M., Bocci, G., Sutter, L., Albrecht, M., Moonen, A.-C., Jeanneret, P., van der Werf, W., Pfister, S.C., Holland, J.M., Paracchini, M.L., 2018. A pan-European model of landscape potential to support natural pest control services. Ecol. Indic. 90, 653–664. https://doi.org/10.1016/j.ecolind.2018.03.075.

Riggi, L.G., Gagic, V., Rusch, A., Malsher, G., Ekbom, B., Bommarco, R., 2017. Pollen beetle mortality is increased by ground-dwelling generalist predators but not landscape complexity. Agric. Ecosyst. Environ. 250, 133–142. https://doi.org/10.1016/j.agee.2017.06.039.

Robinson, R.A., Sutherland, W.J., 2002. Post-war changes in arable farming and biodiversity in Great Britain. J. Appl. Ecol. 39, 157–176. https://doi.org/10.1046/j.1365-2664.2002.00695.x.

Rouabah, A., Meiss, H., Villerd, J., Lasserre-Joulin, F., Tosser, V., Chabert, A., Therond, O., 2022. Predicting the abundances of aphids and their natural enemies in cereal crops: Machine-learning versus linear models. Biol. Control 169, 104866. https://doi.org/10.1016/j.biocontrol.2022.104866.

Rowley, J., 2014. Designing and using research questionnaires. Manag. Res. Rev. 37 https://doi.org/10.1108/MRR-02-2013-0027.

Rusch, A., Birkhofer, K., Bommarco, R., Smith, H.G., Ekbom, B., 2014. Management intensity at field and landscape levels affects the structure of generalist predator communities. Oecologia 175, 971–983. https://doi.org/10.1007/s00442-014-2949-z.

Rusch, A., Chaplin-Kramer, R., Gardiner, M.M., Hawro, V., Holland, J., Landis, D., Thies, C., Tscharntke, T., Weisser, W.W., Winqvist, C., Woltz, M., Bommarco, R., 2016. Agricultural landscape simplification reduces natural pest control: A quantitative synthesis. Agric. Ecosyst. Environ. 221, 198–204. https://doi.org/10.1016/j.agee.2016.01.039.

Scheiner, C., Martin, E.A., 2020. Spatiotemporal changes in landscape crop composition differently affect density and seasonal variability of pests, parasitoids and biological pest control in cabbage. Agric. Ecosyst. Environ. 301, 107051 https://doi.org/10.1016/j.agee.2020.107051.

Sharp, R., Chaplin-Kramer, R., Wood, S., Guerry, A., Tallis, H., Ricketts, T., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J., Cameron, D.R., Arkema, K., Lonsdorf, E., Douglass, J., 2018. InVEST User's Guide. https://doi.org/10.13140/RG.2.2.32693.78567.

Snyder, W.E., 2019. Give predators a complement: Conserving natural enemy biodiversity to improve biocontrol. Biol. Control 135, 73–82. https://doi.org/10.1016/j.biocontrol.2019.04.017.

Spafford, R.D., Lortie, C.J., 2013. Sweeping beauty: is grassland arthropod community composition effectively estimated by sweep netting? Ecol. Evol. 3, 3347–3358. https://doi.org/10.1002/ece3.688.

Tancoigne, E., Barbier, M., Cointet, J.-P., Richard, G., 2014. The place of agricultural sciences in the literature on ecosystem services. Ecosyst. Serv. 10, 35–48. https://doi.org/10.1016/j.ecoser.2014.07.004.

Thies, C., Steffan-Dewenter, I., Tscharntke, T., 2008. Interannual landscape changes influence plant–herbivore–parasitoid interactions. Agric. Ecosyst. Environ. 125, 266–268. https://doi.org/10.1016/j.agee.2007.12.011.

Trubins, R., 2013. Land-use change in southern Sweden: Before and after decoupling. Land Use Policy 33, 161–169. https://doi.org/10.1016/j.landusepol.2012.12.018.

Tscharntke, T., Tylianakis, J.M., Rand, T.A., Didham, R.K., Fahrig, L., Batáry, P., Bengtsson, J., Clough, Y., Crist, T.O., Dormann, C.F., Ewers, R.M., Fründ, J., Holt, R. D., Holzschuh, A., Klein, A.M., Kleijn, D., Kremen, C., Landis, D.A., Laurance, W., Lindenmayer, D., Scherber, C., Sodhi, N., Steffan-Dewenter, I., Thies, C., van der Putten, W.H., Westphal, C., 2012. Landscape moderation of biodiversity patterns and processes - eight hypotheses. Biol. Rev. 87, 661–685. https://doi.org/10.1111/j.1469-185X.2011.00216.x.

Tschumi, M., Albrecht, M., Collatz, J., Dubsky, V., Entling, M.H., Najar-Rodriguez, A.J., Jacot, K., 2016. Tailored flower strips promote natural enemy biodiversity and pest control in potato crops. J. Appl. Ecol. 53, 1169–1176. https://doi.org/10.1111/1365-2664.12653.

Verburg, P.H., Dearing, J.A., Dyke, J.G., van der Leeuw, S., Seitzinger, S., Steffen, W., Syvitski, J., 2016. Methods and approaches to modelling the Anthropocene. Glob. Environ. Change 39, 328–340. https://doi.org/10.1016/j.gloenvcha.2015.08.007.

Vogt, P., Riitters, K.H., Estreguil, C., Kozak, J., Wade, T.G., Wickham, J.D., 2007. Mapping spatial patterns with morphological image processing. Landsc. Ecol. 22, 171–177.

Williams, I.H. (Ed.), 2010. Biocontrol-Based Integrated Management of Oilseed Rape Pests. Springer, Netherlands. https://doi.org/10.1007/978-90-481-3983-5.