TEXTE
58/2024

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German Environment Agency

TEXTE 58/2024

Ressortforschungsplan of the Federal Ministry for the Environment, Nature Conservation, Nuclear Safety and Consumer Protection

Project No. (FKZ) 3719 65 412 1

FB001322/ENG

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On behalf of the German Environment Agency

Imprint

Publisher
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Report completed in:
August 2023

Edited by:
Section IV 1.3-1 Plant Protection Products
Urwa Alalouni (Fachbegleitung)

Publication as pdf:
http://www.umweltbundesamt.de/publikationen

ISSN 1862-4804

Dessau-Roßlau, April 2024

Abstract: Evaluating the impact of landscape structure and source-sink dynamics on non-target arthropod pesticide risk assessments in Germany

The ELONTA project reported here aimed at understanding the relationships between landscape structure, source-sink dynamics and the risk of pesticide use for Non-Target Arthropods (NTAs). It also investigated the effectiveness of introducing two landscape-based mitigation measures: grassy field boundaries and unsprayed field margins. The project used a model NTA species, *Bembidion lampros*, a small, univoltine, spring-breeding carabid beetle that is common in temperate European agricultural landscapes. The project combined high-resolution dynamic landscape models with advanced spatially-explicit population models to simulate changes in *B. lampros* population dynamics in agroecosystems. The impact of pesticide use on *B. lampros* populations and the effectiveness of mitigation measures were assessed in a set of 611 study plots of 10x10 km^2 in Brandenburg and Lower Saxony regions, varying in landscape and farmland heterogeneity. Our analysis showed that beetle populations were better supported in more diverse and heterogeneous landscapes with a high proportion of herbaceous semi-natural habitats and permanent pastures. The negative impact of pesticide use was greater in more homogeneous landscapes with low initial beetle populations, high arable land coverage and low beetle source habitat coverage. The study showed that grassy field boundaries were a more effective mitigation measure than unsprayed field margins. It also revealed the influence of source-sink dynamics on the effect of pesticide application on *B. lampros* populations, with significant exclusive off-field effects that persisted despite mitigation measures. Landscape management in agroecosystems should focus on maintaining and protecting these habitats, especially in highly homogeneous landscapes.

Kurzbeschreibung: Bewertung der Auswirkungen der Landschaftsstruktur und der Source-Sink-Dynamik auf die Pflanzenschutzmittel-Risikobewertung von Nicht-Ziel-Arthropoden in Deutschland

Das ELONTA-Projekt hatte zum Ziel, die Beziehungen zwischen Landschaftsstruktur, der Source-Sink -Dynamik und dem Risiko des Einsatzes von Pflanzenschutzmitteln für Nicht-Ziel-Arthropoden (NTAs) zu verstehen. Außerdem wurde die Effektivität von zwei landschaftsbezogenen Risikominderungsmaßnahmen: von grasbewachsenen Feldgrenzen und ungespritzten Feldrändern untersucht. Im Rahmen des Projekts wurde als NTA-Modellart *Bembidion lampros* (Herbst, 1784) genutzt. Bei diesem handelt es sich um einen kleinen, univoltinen, frühlingsbrütender Laufkäfer (Carabidae), der im klimatisch gemäßigten Europa in Agrarlandschaften weit verbreitet vorkommt. Das Projekt kombinierte hochauflösende dynamische Landschaftsmodelle mit fortschrittlichen räumlich expliziten Populationsmodellen, um Veränderungen der Populationsdynamik von *B. lampros* in Agrarökosystemen zu simulieren. Die Auswirkungen des Einsatzes von Pflanzenschutzmitteln auf die Populationen von *B. lampros* und die Wirksamkeit von Risikominderungsmaßnahmen wurden auf 611 10x10 km^2 großen Untersuchungsflächen in Brandenburg und Niedersachsen in Regionen mit unterschiedlicher Heterogenität der Landschaft und der landwirtschaftlichen Nutzung bewertet. Unsere Analyse zeigte, dass die Käferpopulationen in vielfältigeren und heterogeneren Landschaften mit einem hohen Anteil an natürlichen Grünlandlebensräumen und Dauergrünland besser gedeihen. Die negativen Auswirkungen des Pflanzenschutzmitteleinsatzes waren in homogeneren Landschaften mit wenigen initialen Käferpopulationen, einem hohen Anteil an Ackerland und einem geringen Anteil an Lebensräumen für Käfer größer. Die Studie zeigte außerdem, dass grasbewachsene Feldränder eine wirksamere Maßnahme zur Risikominderung darstellen als ungespritzte Feldränder. Sie zeigte auch den Einfluss der Source-Sink -Dynamik auf die Auswirkungen des Einsatzes von Pflanzenschutzmitteln auf die Populationen von *B. lampros*. Hier blieben die signifikanten off-field Effekte, trotz der Risikominderungsmaßnahmen bestehen. Die Landschaftspflege in Agrarökosystemen sollte sich auf die Erhaltung und den Schutz dieser Lebensräume konzentrieren, insbesondere in sehr homogenen Landschaften.

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ALMaSS	Animal, Landscape and Man Simulation System
AOR	Abundance to Occupancy Relationship
ATKIS	Authorative Topographic-Cartographic Information System (Amtliches Topographisch-Kartographisches Informationssystem) in Germany
DT_{50}	Environmental decay value
EFSA	European Food Security Authority
ERA	Environmental Risk Assessment
IACS	Integrated Administration and Control System
LC_{50}	Median Lethal Concentration
LD_{50}	Median Lethal Dose
LPIS	Land parcel Identification System
LSU	LifeStock Unit
NTA	Non-Target Arthropod
PCA	Principal Component Analysis
PPP	Plant Protection Product
TOLE	Type of Landscape Element

Summary

Project overview

The richness and population size of many species, including non-target arthropods (NTAs), have declined significantly in recent decades in agroecosystems (e.g., Potts et al., 2010). The loss of biodiversity is mainly related to the widespread use of pesticides and the impoverishment of the structural and functional heterogeneity of the landscape, including the loss of semi-natural habitats (e.g., Carvalheiro et al., 2011). Pesticides can significantly impact NTA populations, both within fields and in uncultivated areas, and their effects may be strongly dependent on landscape structure (Topping et al., 2015).

The ELONTA project, reported here, aimed to elucidate the relationships between landscape structure, source-sink dynamics and the risk of pesticide use for NTAs, exemplified by carabid beetle *Bembion lampros*. It also investigated the effectiveness of introducing two landscape-based mitigation measures: grassy field boundaries and unsprayed field margins. The former are strips created within fields and managed as permanent grass strips. They are not subject to the same agricultural practices as the crop itself, such as tillage, harvesting or pesticide application. They can therefore act as additional source and overwintering habitats for NTAs. The second are within-field unsprayed margins. They are managed the same way as the crop but not exposed to pesticides. As such, they reduce the area exposed to pesticides and act as a 'buffer zone' to limit exposure in adjacent off-field habitats.

The impact of pesticides and the effectiveness of mitigation measures were investigated using a model NTA species, *B. lampros*. This small, univoltine, spring-breeding carabid beetle is common in temperate European agricultural landscapes. It is a useful natural enemy of pests and is relevant for pesticide risk assessment (EFSA 2015). The project applied a modelling approach using the Animal, Landscape and Man Simulation System (ALMaSS) (Topping et al., 2003). ALMaSS integrates high-resolution dynamic landscape models with advanced spatially-explicit population models to simulate changes in species population dynamics in agroecosystems. Although an ALMaSS agent-based model for the carabid beetle *B. lampros* is well established (Bilde and Topping, 2004), it had to be adapted to German climatic conditions. A high-resolution dynamic ALMaSS landscape model for Germany had to be generated from scratch, following the methodology described in Topping et al. (2016).

Due to data limitations, we focused our analyses on two federal states, Brandenburg and Lower Saxony, which exhibit significant landscape and farmland heterogeneity. The Brandenburg region represents large-scale agriculture with a predominance of large fields and a low proportion of semi-natural areas and permanent pastures. The region of Lower Saxony, on the other hand, is dominated by medium and small fields and a higher proportion of semi-natural herbaceous habitats. Some parts of the region are dominated by permanent pasture. For modelling purposes, the Lower Saxony and Brandenburg regions were divided into a regular grid of 611 non-overlapping study areas of 10x10 km each. Each study area was characterised by a set of landscape metrics describing the diversity, area, and spatial arrangement of landscape elements as well as the intensity of farming. The impact of pesticides and the effectiveness of mitigation measures were analysed separately in each study area and related to the landscape metrics.

The ELONTA project was carried out by a consortium of three institutes from Denmark (Aarhus University), PL (Jagiellonian University) and DE (Julius Kühn Institute) with specific expertise in the development of landscape-scale approaches to NTA ecology and toxicology.

Methods

The simulation system used, ALMaSS, is an open source project available on GitLab (https://gitlab.com/ALMaSS/) with online documentation (https://projects.au.dk/almass/documentation/) based on the ODdox (Overview Design doxygen) protocol (Topping et al., 2010). ALMaSS has been designed as a highly flexible modelling system for predicting the impacts of human landscape management on a range of important animal species. It is an agent-based modelling system in which animals are modelled as individuals (agents) that move, reproduce, and die within an environment (landscape), just as real animals do in their natural environment.

ALMaSS models landscapes using a detailed spatio-temporal representation. This representation consists of two components: spatial and temporal. The spatial component is a raster land cover/land use map with a resolution of 1 m^2, including fine-scale landscape elements for focal species. Agricultural land is modelled with particular care, with individual fields (agricultural parcels) spatially delineated and assigned to farm units of different types. Temporal landscape modelling allows for changes in cropping patterns and farming practices over time, including crop management plans and multi-year crop rotations. Changes in vegetation growth are tracked daily and respond to weather conditions. Such an approach provides a highly realistic, daily updated, and dynamic modelling environment where vegetation grows in response to weather and patterns of farming activity associated with each crop, farm, and field (Topping et al., 2016).

The generation of the ALMaSS landscape model for Germany largely followed the methodology described in Topping et al. (2016) and was based on previous experience with landscape model generation for Denmark (Topping et al., 2016), Poland (Ziółkowska et al., 2021) and the Netherlands (Ziółkowska et al., 2022). The whole process included (i) collection and quality control of spatial and non-spatial data, (ii) generation of ALMaSS land use/land cover maps (spatial component) by stepwise linking of individual thematic data, and (iii) incorporation of crop management and vegetation growth (dynamic component). For the generation of the ALMaSS landscape model the following data were included:

a) *Land cover / land use information* derived from the Digital Basic-Landscape model (Basis-DLM) for the year 2019, which is part of the Authorative Topographic-Cartographic Information System (ATKIS) of the Federal Republic of Germany (https://www.adv-online.de/Products/Geotopography/Digital-Landscape-Models/Basis-DLM/). Individual layers of land use/land cover information, together with information on agricultural field boundaries (see below), were then combined in a stepwise process into a single raster landscape map.

b) *Agricultural and animal data* from the Integrated Administration and Control System (IACS). These data were collected for the year 2019 for two federal states: Lower Saxony and Brandenburg. We used spatial data on the boundaries of agricultural fields (parcels), as well as information on the type of crops grown on agricultural fields, identification numbers of agricultural holdings (which allowed individual fields to be grouped into agricultural units - farms), and information on livestock and organic production. Combining crop and livestock information made it possible to classify farms into nine main types, such as pig, arable or cattle farms, which were further classified as either conventional or organic (18 farm types in total).

c) *Soil data* obtained from the national soil map BUEK200 of the German Federal Institute for Geosciences and Natural Resources (BGR). This information was used to adapt farming practices to the soil type.

d) *Up-to-date crop management plans*. These plans for the most important German field crops including time windows and probabilities of occurrence of the main soil management practices, as well as of the use of fertilisers and pesticides (together with information on the product used and its dosage), were provided by the Julius Kühn Institute (JKI) and derived from interviews with farmer advisors. Where necessary, additional information from the reports on integrated crop production methods was included.

All spatial data handling and analysis was done in Python 2.7 and the Python library arcpy for calling ArcGIS functions (ESRI, 2010) or directly in ArcGIS 10.4. Python scripts using the pandas tools (McKinney et al., 2010) were used to program the entire process of generating a German landscape model for ALMaSS. The scripts were applied to each of the 611 delineated 10x10 km^2 study areas in the regions of Brandenburg and Lower Saxony to generate landscape inputs for ALMaSS (landscape-related scenario 'Regular'). Based on the generated ALMaSS landscape models for each of the study areas, various landscape metrics (characterising diversity, area, spatial arrangement of landscape elements and agricultural intensity) were calculated at 1 m resolution using the GIS and the FRAGSTATS v4 software package (McGarigal et al. 2012).

We also generated two artificially manipulated forms of the 'Regular' ALMaSS landscape models by adding (1) grassy field boundaries (landscape-related scenario 'FB') and (2) unsprayed field margins (landscape-related scenario 'UM') of 10 m width to all fields larger than 1 ha and wider than 40 m. Grassy field boundaries were not added if the field already bordered a grassy field boundary or another herbaceous habitat, such as managed or unmanaged grassland. Both grassy field boundaries and unsprayed field margins were separated from existing fields (i.e., as part of them but under different management).

In addition to landscape-related scenarios (i.e., 'Regular', 'FB' and 'UM'), we also simulated pesticide application and its effects on our model species, *B. lampros*. Exposure to a pesticide in the ALMaSS *B. lampros* model is determined based on the predicted environmental concentration at the location of an individual beetle over time. The concentration is based on the implementation of a detailed pesticide application model as described in the EFSA NTA SO recommendations. This approach divides the applied pesticide into soil and vegetation compartments and models the degradation of the pesticide in these compartments over time. The exposure pattern therefore integrates the application schedule in space and time with the location and life stage of the beetle and environmental degradation as determined by weather conditions. The exposure model runs at a very fine resolution (1 m) and can therefore represent fine-scale distributions of the pesticide that may be relevant to field boundary conditions.

We chose the pesticide properties in such a way as to highlight the issues to be addressed in the project and to be realistic. We assumed that normal fungicide and herbicide applications would have no effect on carabid beetles. Insecticides were applied to all crops according to normal practice in the regions of Brandenburg and Lower Saxony (according to crop management plans). For the insecticides, we chose a single toxicity level defined as an insecticide-driven beetle field lethality rate (LR) of 80%, measured for a foliar insecticide spray application over 10 days. This gives a daily beetle mortality probability p of 0.1489. The environmental decay value (DT_{50}) at 20°C was set at 10 days. The temperature dependence of the DT_{50} value in ALMaSS was defined according to equations provided by EFSA (2007). An application rate of twice the trigger concentration was used for all crops to ensure that beetles could be exposed above the trigger threshold for at least the period defined by DT_{50}=10 days, with an LR of 80%. A spray drift was applied up to 12 m from the edge of each sprayed field, following the equation of Rautmann et al. (2001) with a reduction of 90% (a reduction of 50% is considered to be the minimum requirement for sprayers in field crops using modern sprayers) (JKI, 2020).

We run a fully factorial experiment combining all study areas and scenarios, i.e., three landscape-related scenarios (‘Reg(ular)’, ‘FB’ and ‘UM’) and two pesticide-related scenarios (without and with pesticide effects; ‘NoPest’ and ‘Pest’ respectively). However, it should be noted that for the species analysed, the ‘UM_NoPest‘ scenario gives the same results as the ‘Reg_NoPest‘ scenario (because unsprayed field margins are still subject to normal agricultural practices, including soil cultivation, which affects beetle mortality). Therefore, the ‘UM_NoPest‘ and ‘Reg_NoPest‘ scenarios were not compared.

In addition, for two exemplary landscapes (one from the region of Brandenburg and the other from the region of Lower Saxony) with an arable land coverage of 84-85%, the same factorial experiment was carried out, but with the assumption of a winter wheat monoculture and a modified pesticide scenario. Both normal pesticide application (5% of farmers applying insecticide after sowing, 50% of farmers applying insecticide in May and 25% of farmers applying insecticide in June) and forcing 100% probability of all three applications were tested. The results allowed us to investigate the impact of pesticides and the effectiveness of mitigation measures in an extreme scenario (where arable land covers most of the study area and all fields are treated with pesticides) and compare it with the realistic scenario of pesticide use presented above.

All simulation runs were performed over 30 simulation years with no burn-in period. Due to the large number of study areas processed (611), the number of replicates for each scenario combination was limited to two replicates. Each simulation started with the same number of super-individuals (200 000 per 100 km^2), with beetles randomly distributed over suitable habitats within the study area. Although the initial number of super-individuals was always the same, beetle populations approached densities that were independent of the initial population size after a few years of simulation runs. Weather conditions were chosen to represent the period 2009-2019 and were defined individually for each of the 10x10 km2 study areas using the ERA5-Land dataset (Muñoz Sabater 2021).

From each simulation, three endpoints (SE) were analysed: (SE1) overall beetle population density (i.e., total number of adult female beetles divided by the landscape area, i.e. 100 km^2), (SE2) occupancy (i.e., beetle distribution defined as the proportion of grid cells in the landscape with at least 100 adult female beetles), and (SE3) abundance (mean density of adult females in the occupied areas). The latter two endpoints were presented as Abundance-Occupancy Relationship (AOR) plots (Høye et al., 2012). Although the spatial resolution of the landscape model in ALMaSS is 1 m^2, grid cells of 50 m^2 were used for the calculation of occupancy and abundance. The endpoints were measured on day 185 of each year (4th July) and averaged over the last 10 years and across replicate runs for each scenario. They were measured for the whole study area and within the in-field and off-field areas. In-field and off-field areas were delineated in two ways: (1) inclusive, i.e. all grid cells within fields or crossing the field boundary (inclusive in-field) or within non-arable land or crossing the boundary or non-arable land (inclusive off-field); or (2) exclusive, i.e. all grid cells completely within fields (exclusive in-field) or completely within non-arable land (exclusive off-field).

The impact of each scenario *S* relative to the baseline was used and compared over time, separately for each of the study areas ($SA_{i=1...611}$), i.e., a relative change in each of the simulation endpoints ($SE_{j=1,2,3}$) to the baseline was calculated as:

relative change of $SE_{j=1,2,3}$ *in* $SA_{i=1...611}$ *= (endpoint* $SE_{j=1,2,3}$ *value in scenario S – endpoint* $SE_{j=1,2,3}$ *value in baseline)/ endpoint* $SE_{j=1,2,3}$ *value in baseline * 100 [%]*

The 'baseline' conditions were set to the scenario with no pesticide application and no changes in landscape structure (scenario 'Reg_NoPest').

In addition, the effectiveness of the tested mitigation measures (grassy field boundaries and unsprayed field margins) was calculated as the reduction in the negative impact of pesticide use after application of the measure, i.e., the difference in the relative change in the simulation endpoints between 'Reg_Pest' and 'FB_Pest'/'UM_Pest'.

The influence of landscape metrics on (1) simulation endpoints in the baseline scenario (‘Reg_NoPest’ scenario), and (2) changes in simulation endpoints in response to applied pesticides (scenario ‘Reg_Pest’ relative to ‘Reg_NoPest’), and (3) changes in simulation endpoints in response to applied landscape-related mitigation measures (scenarios ‘FB_Pest’ and ‘UM_Pest’ relative to ‘Reg_NoPest’) was tested with multiple regression models. Highly correlated landscape metrics (i.e., with a Pearson correlation coefficient ≥ |0.7|) were excluded from the analysis. After running the initial models, a backward stepwise selection procedure was used to remove non-significant variables, starting with those with the highest *p*-values, until only variables with $p \leq 0.05$ remained in the model, and the normal distribution of the residuals was formally tested using the Kolmogorov-Smirnov test. All statistical analyses were performed with Statgraphics 19.

Results and discussion

The study found significant differences in *B. lampros* populations in the baseline scenario (‘Reg_NoPest’) between landscapes and farming systems, and this variability was explained very well by the regression models. *B. lampros* populations were larger and distributed over larger areas in landscapes with a significant proportion of arable land and a high proportion of herbaceous semi-natural habitats and permanent pastures. This fits well with the ecology and biology of the beetles, as they require arable land for foraging and reproduction, while grassland habitats are essential for overwintering and recolonisation. High numbers and densities of beetles were found in more diverse and heterogeneous landscapes, with highly diverse landscapes better supporting effective colonisation of arable fields by beetles.

The addition of grassy field boundaries led to an average increase in beetle populations of 9.8% across all landscapes studied, mainly due to increased local beetle abundance. However, changes in occupancy were small, with only four landscapes showing an increase of more than 5%. But the original beetle populations in these four landscapes were very low because of the low proportion of cropland, permanent grassland and herbaceous semi-natural habitat. The change in mean overall beetle density due to grassy field boundaries varied significantly between the landscapes studied, depending on the initial beetle numbers and the composition of other landscape elements. This change was related to the relative change in grassy habitat cover.

Under the pesticide scenario ('Reg_Pest'), beetle populations decreased significantly in all study areas analysed (the average decrease was around 14.0%, slightly higher in Brandenburg than in Lower Saxony: 15.7% and 13.4% respectively), but the effects varied between study areas (from 2.5 to 27.2%). These negative impacts were higher in homogeneous landscapes with low initial beetle populations, high arable land coverage and low beetle source habitat coverage. These results are consistent with previous studies on *B. lampros* populations in agricultural landscapes in Poland (Ziółkowska et al. 2021) and the Netherlands (Ziółkowska et al. 2022).

Importantly, beetles were also affected in exclusive off-field areas where the pesticide was not applied or drifted (action at a distance). The effect of pesticide use on beetles in off-field areas decreased with decreasing density of field boundaries and increasing area of suitable overwintering and breeding habitat nearby (in this case permanent pasture). This is because beetles are exposed to pesticides over time where field boundaries are present, whereas pasture populations are physically distant from pesticide application areas.

The study showed that grassy field boundaries were a more effective mitigation measure than unsprayed field margins, as they reduced the negative impact of pesticide use on mean overall beetle density by an average of 13.4% (maximum 27.2%), whereas unsprayed field margins only reduced it by an average of 2.7% (maximum 10.1%). In both cases, the positive effect was mainly on mean beetle abundance, not occupancy, and varied between study areas. In heterogeneous landscapes, grassy field boundaries were less effective due to better initial conditions for beetles supporting the population in the surrounding landscape. Consequently, in arable-dominated, more homogeneous landscapes, the effect of grassy field boundaries was proportionally greater than that of unsprayed field margins due to the lack of buffering effect of other non-crop habitats.

The study found that under worst-case assumptions of monoculture, the beetle population in the study area could be almost eradicated, in contrast to a more realistic scenario of pesticide use. Under the assumption of normal pesticide use in wheat monoculture, the observed effects on beetle populations were comparable to those obtained with crop rotation, due to the relatively low level of pesticide application. However, increasing the application probability to the point where all farmers applied pesticides resulted in pronounced effects. The more extreme scenario showed that the observed effects in the more homogeneous landscape with intensive agriculture were much higher than in the more heterogeneous landscape dominated by small fields and included large effects on beetle occupancy. Mitigation positively affected beetles in the more homogeneous landscape, but there were still large reductions in beetle occupancy. In the more heterogeneous landscape, impacts on beetle occupancy were only observed when all farmers applied pesticides in the wheat monoculture, and these impacts could only be reduced by providing more source habitats (i.e., grassy field boundaries). This suggests that there may be population tipping points at certain levels of stressor impact.

B. lampros, a focal species for Coleoptera in environmental risk assessment, is an important natural pest control species in agricultural landscapes in central and northern Europe, including Germany. It is sensitive to disturbance due to its low dispersal rates. This is because larger movement ranges increase the probability of reaching the favourable habitat and thus have a positive effect on population growth. This means that *B. lampros* is more exposed to pesticides in homogeneous landscapes with high-intensity agriculture, where source habitats are difficult to reach, and fields are barriers to gene flow.

The migration and aggregation behaviour of *B. lampros* is not typical of all carabid beetles in agricultural landscapes. The spatial distribution of carabid beetles within agricultural landscapes varies due to their preferences for overwintering sites and ability to invade field areas. The effects of pesticide use may vary for beetles with different ecologies, including spring and autumn breeders, by altering exposure over time. Investigation of a wider range of carabids with different habitat preferences and functional traits would allow a more detailed assessment of the potential negative effects of pesticides and their dependence on landscape structure.

Conclusions and recommendations

This study highlighted the complexity of population responses to mitigation measures and the need for decision-making in relation to farming systems, policy objectives and landscape structure. The magnitude of pesticide effects could be highly variable and modified by spatially dynamic factors such as the distribution of source and sink habitats or underlying habitat suitability. It is important to clearly specify the target of the intervention in any future modelling study. This study focused on the effect of mitigation measures on pesticide impacts on beetles, and thus focused on relative changes in beetle numbers and occupancy. An alternative view could be to consider changes in beetle populations in absolute terms, which may have a greater impact in heterogeneous landscapes.

Our analysis has revealed that pesticide use affects *B. lampros* populations through source-sink dynamics, resulting in significant off-field effects that persist even with mitigation measures in place. We recommend that agroecosystem landscape management prioritises the conservation and protection of these habitats, especially in highly homogeneous landscapes. For future modelling studies, developing a standard set of scenarios from more realistic to more extreme in terms of pesticide use and landscape structure, with a range of pesticide toxicity levels and application probabilities, is recommended. This can provide a full range of resulting effects and estimate how close a realistic scenario is to a tipping point. A wider range of focal carabid beetles should also be considered, allowing an environmental risk assessment to cover different habitat preferences and functional traits. This combination of scenarios and species will provide a richer picture for understanding the effects of pesticides on carabid populations.

Zusammenfassung

Überblick über das Projekt

Der Artenreichtum und die Populationsgrößen vieler Arten in Agrarökosystemen, einschließlich der Nicht-Ziel-Arthropoden (NTA), sind in den letzten Jahrzehnten erheblich zurückgegangen (z. B. Potts et al., 2010). Der Verlust an biologischer Vielfalt steht hauptsächlich im Zusammenhang mit dem weit verbreiteten Einsatz von Pflanzenschutzmitteln und der Verarmung der strukturellen und funktionalen Heterogenität der Landschaft, einschließlich des Verlusts naturnaher Lebensräume (z. B. Carvalheiro et al., 2011). Pflanzenschutzmittel können erhebliche Auswirkungen auf NTA-Populationen haben, sowohl innerhalb von Agrarflächen als auch in nicht bewirtschafteten Gebieten. Ihre Auswirkungen können stark von der Landschaftsstruktur abhängen (Topping et al., 2015).

Das hier vorgestellte ELONTA-Projekt, hatte zum Ziel, die Beziehungen zwischen der Landschaftsstruktur, der Sink-Source-Dynamik und dem Risiko des Einsatzes von Pflanzenschutzmitteln für Nicht-Ziel-Arthropoden (NTAs) am Beispiel der Laufkäferart *Bembion lampros* zu klären. Darüber hinaus wurde die Effektivität von zwei landschaftsbezogenen Risikominderungsmaßnahmen untersucht: grasbewachsene Feldgrenzen und ungespritzte Feldränder. Bei ersteren handelt es sich um Streifen, die innerhalb von Feldern angelegt und als dauerhafte Grasstreifen bewirtschaftet werden. Sie unterliegen nicht denselben landwirtschaftlichen Praktiken wie der Anbau selbst, z. B. Bodenbearbeitung, Ernte oder dem Einsatz von Pflanzenschutzmitteln. Sie können daher als zusätzliche Herkunfts- und Überwinterungshabitate für NTAs dienen. Das Zweite sind ungespritzte Randstreifen innerhalb eines Feldes. Sie werden auf die gleiche Weise bewirtschaftet wie die Kulturpflanzen auf dem Feld, sind aber keinen Pflanzenschutzmitteln ausgesetzt. Dadurch verringern sie die Fläche, die Pflanzenschutzmitteln ausgesetzt ist, und wirken als "Pufferzone", um die Exposition in angrenzenden Lebensräumen außerhalb des Feldes zu begrenzen.

Die Auswirkungen von Pflanzenschutzmitteln und die Effektivität der Ausgleichsmaßnahmen wurden anhand einer NTA-Modellart, *B. lampros*, untersucht. Bei diesem handelt es sich um einen ein kleinen, univoltinen, frühlingsbrütenden Laufkäfer (*Carabidae*), der im klimatisch gemäßigten Europa in Agrarlandschaften weit verbreitet ist. Er stellt einen nützlichen natürlichen Feind von Schädlingen dar und ist für die Risikobewertung von Pestiziden relevant (EFSA 2015). Im Rahmen des Projekts wurde ein Modellierungsansatz unter Verwendung des „Animal, Landscape and Man Simulation System“ (ALMaSS) (Topping et al., 2003) angewendet. ALMaSS integriert hochauflösende dynamische Landschaftsmodelle mit fortschrittlichen räumlich expliziten Populationsmodellen, um Veränderungen der Populationsdynamik von Arten in Agrarökosystemen zu simulieren. Obwohl ein agentenbasiertes ALMaSS-Modell für den Laufkäfer *B. lampros* bereits gut etabliert ist (Bilde und Topping, 2004), musste es an die deutschen Klimabedingungen angepasst werden. Ein hochauflösendes dynamisches ALMaSS-Landschaftsmodell für Deutschland musste von Grund auf neu erstellt werden, wobei die in Topping et al. (2016) beschriebene Methodik angewendet wurde.

Aufgrund von Datenbeschränkungen haben wir uns bei unseren Analysen auf die beiden Bundesländer Brandenburg und Niedersachsen konzentriert, die eine große Heterogenität der Landschaft und der landwirtschaftlichen Nutzflächen aufweisen. Die Region Brandenburg steht für eine großflächige Landwirtschaft in der große Feldflächen überwiegen und die nur einen geringen Anteil an Dauergrünland aufweist. In Niedersachsen hingegen dominieren mittlere und kleine Ackerschläge und ein höherer Anteil an natürlichen Grünlandlebensräumen. Einige Teile des Gebietes werden von Dauergrünland dominiert. Für die Modellierung wurden die Regionen Niedersachsen und Brandenburg in ein regelmäßiges Raster von 611 sich nicht überschneidenden Untersuchungsgebieten von jeweils 10x10 km unterteilt. Jedes Untersuchungsgebiet wurde durch eine Reihe von „Landscape Metrics" charakterisiert, die Vielfalt, Fläche und räumliche Anordnung von Landschaftselementen sowie die Intensität der landwirtschaftlichen Bewirtschaftung beschreiben. Die Auswirkungen von Pflanzenschutzmitteln und die Wirksamkeit von Minderungsmaßnahmen wurden in jedem Untersuchungsgebiet separat analysiert und mit den „Landscape Metrics" in Beziehung gesetzt.

Das ELONTA-Projekt wurde von einem Konsortium aus drei Instituten aus Dänemark (Universität Aarhus), Polen (Jagiellonen-Universität) und Deutschland (Julius-Kühn-Institut) durchgeführt, die über besondere Fachkenntnisse bei der Entwicklung von landschaftsbezogenen Ansätzen für die Ökologie und die Toxikologie von NTA verfügen.

Methoden

Das verwendete Simulationssystem ALMaSS ist ein Open-Source-Projekt, das auf GitLab (https://gitlab.com/ALMaSS/) mit einer Online-Dokumentation (https://projects.au.dk/almass/documentation/) fußt, welches auf der Grundlage des ODdox-Protokolls (Overview Design doxygen) basiert (Topping et al., 2010). ALMaSS wurde als hochflexibles Modellierungssystem für die Vorhersage der Auswirkungen der menschlichen Landschaftspflege auf eine Reihe wichtiger Tierarten entwickelt. Es handelt sich um ein agentenbasiertes Modellierungssystem, in dem Tiere als Individuen (Agenten) modelliert werden, die sich in einer Umgebung (Landschaft) bewegen, fortpflanzen und sterben, so wie es auch echte Tiere in ihrer natürlichen Umgebung tun.

ALMaSS modelliert Landschaften anhand einer detaillierten räumlich-zeitlichen Darstellung. Diese Darstellung besteht aus zwei Komponenten: einer räumlichen und einer zeitlichen. Die räumliche Komponente ist eine Raster-Landbedeckungs-/Bodennutzungskarte mit einer Auflösung von 1 m^2, die feinskalierte Landschaftselemente für Schwerpunktarten enthält. Die landwirtschaftlichen Flächen werden besonders sorgfältig modelliert, wobei einzelne Felder (landwirtschaftliche Parzellen) räumlich abgegrenzt und Betriebseinheiten unterschiedlicher Art zugeordnet werden. Die zeitliche Modellierung der Landschaft ermöglicht es, Änderungen der Anbaumuster und landwirtschaftlichen Praktiken im Laufe der Zeit, einschließlich der Anbaupläne und mehrjährigen Fruchtfolgen vorzunehmen. Veränderungen im Vegetationswachstum werden täglich verfolgt und reagieren auf die hinterlegten Wetterbedingungen. Ein solcher Ansatz bietet eine äußerst realistische, täglich aktualisierte und dynamische Modellierungsumgebung, in der die Vegetation als Reaktion auf das Wetter und die mit den einzelnen Kulturen, Betrieben und Feldern verbundenen landwirtschaftlichen Tätigkeiten wächst (Topping et al., 2016).

Die Erstellung des ALMaSS-Landschaftsmodells für Deutschland folgte weitgehend der in Topping et al. (2016) beschriebenen Methodik und basierte auf früheren Erfahrungen mit der Erstellung von Landschaftsmodellen für Dänemark (Topping et al., 2016), Polen (Ziółkowska et al., 2021) und die Niederlande (Ziółkowska et al., 2022). Der gesamte Prozess umfasste (i) die Sammlung und Qualitätskontrolle räumlicher und nicht-räumlicher Daten, (ii) die Erstellung von ALMaSS-Landnutzungs-/Bodenbedeckungskarten (räumliche Komponente) durch schrittweise Verknüpfung einzelner thematischer Daten und (iii) die Einbeziehung von Anbaumaßnahmen und Vegetationswachstum (dynamische Komponente). Für die Erstellung des ALMaSS-Landschaftsmodells wurden die folgenden Daten herangezogen:

a) *Landbedeckungs-/Landnutzungsinformationen* aus dem Digitalen Basis-Landschaftsmodell (Basis-DLM) für das Jahr 2019, das Teil des Amtlichen Topographisch-Kartographischen Informationssystems (ATKIS) der Bundesrepublik Deutschland ist (https://www.adv-online.de/Products/Geotopography/Digital-Landscape-Models/Basis-DLM/). Die einzelnen

Layer der Landnutzungs-/Bodenbedeckungsinformationen wurden dann zusammen mit den Informationen über die landwirtschaftlichen Feldgrenzen (siehe unten) verschnitten und in einem schrittweisen Prozess zu einer einzigen Raster-Landschaftskarte zusammengeführt.

b) *Landwirtschaftliche Daten und Nutztierhaltungsdaten* aus dem Integrierten Verwaltungs- und Kontrollsystem (IVKS). Diese Daten wurden für das Jahr 2019 für zwei Bundesländer erhoben: Niedersachsen und Brandenburg. Wir verwendeten räumliche Daten über die Grenzen landwirtschaftlicher Felder (Parzellen) sowie Informationen über die Art der auf den landwirtschaftlichen Feldern angebauten Kulturen, Identifikationsnummern landwirtschaftlicher Betriebe (die es ermöglichten, einzelne Felder zu landwirtschaftlichen Betriebseinheiten zusammenzufassen) und Informationen über Viehbestand und ökologische Erzeugung. Durch die Kombination von Informationen über Anbau und Viehbestand konnten die Betriebe in neun Haupttypen eingeteilt werden, z. B. Schweine-, Ackerbau- oder Rinderbetriebe, die wiederum entweder konventionell oder ökologisch geführt wurden (insgesamt 18 Betriebstypen).

c) *Bodendaten*. Diese stammen aus der nationalen Bodenübersichtskarte 1:200.000 (BUEK200) der Bundesanstalt für Geowissenschaften und Rohstoffe (BGR). Diese Informationen wurden verwendet, um die landwirtschaftlichen Anbaumethoden an den Bodentyp anzupassen.

d) *Aktuelle Anbaupläne*. Diese Pläne für die wichtigsten deutschen Ackerkulturen mit Zeitfenstern und Eintrittswahrscheinlichkeiten der wichtigsten Bodenbearbeitungsverfahren sowie des Dünge- und Pflanzenschutzmitteleinsatzes (mit Angaben zu den verwendeten Produkten und deren Dosierung) wurden vom Julius-Kühn Institut (JKI) zur Verfügung gestellt und aus Interviews mit Landwirtschaftsberatern abgeleitet. Soweit erforderlich, wurden zusätzliche Informationen aus den Berichten über integrierte Anbaumethoden in die Analyse einbezogen.

Die gesamte Verarbeitung und Analyse der Geodaten erfolgte in Python 2.7 und der Python-Bibliothek arcpy zum Aufruf von ArcGIS-Funktionen (ESRI, 2010) oder direkt in ArcGIS 10.4. Python-Skripte mit den Pandas-Tools (McKinney et al., 2010) wurden verwendet, um den gesamten Prozess der Erstellung eines deutschen Landschaftsmodells für ALMaSS zu programmieren. Die Skripte wurden auf jedes der 611 abgegrenzten 10x10 km^2 großen Untersuchungsgebiete in den Regionen Brandenburg und Niedersachsen angewendet, um den Landschaftseinfluss für ALMaSS zu generieren (landschaftsbezogenes Szenario 'Regular'). Basierend auf den generierten ALMaSS-Landschaftsmodellen für jedes der Untersuchungsgebiete wurden verschiedene „Landscape Metrics“ (zur Charakterisierung von Diversität, Fläche, räumlicher Anordnung von Landschaftselementen und landwirtschaftlicher Intensität) mit einer Auflösung von 1 m unter Verwendung des GIS und des FRAGSTATS v4 Softwarepakets (McGarigal et al. 2012) berechnet.

Wir erzeugten auch zwei künstlich manipulierte Formen der "regulären" ALMaSS-Landschaftsmodelle, indem wir (1) grasbewachsene Feldränder (landschaftsbezogenes Szenario ‘FB’) und (2) ungespritzte Feldränder (landschaftsbezogenes Szenario ‘UM’) von 10 m Breite zu allen Feldern hinzufügten, die größer als 1 ha und breiter als 40 m waren. Grasbewachsene Feldränder wurden nicht hinzugefügt, wenn das Feld bereits an einen grasbewachsenen Feldrand oder einen anderen Grünlandlebensraum grenzte, wie z. B. bewirtschaftetes oder nicht bewirtschaftetes Grünland. Sowohl grasbewachsene Feldränder als auch ungespritzte Feldränder wurden von bestehenden Feldern getrennt (d. h. als Teil von ihnen, aber unter anderer Bewirtschaftung).

Zusätzlich zu den landschaftsbezogenen Szenarien (d. h. 'Regular', 'FB' und 'UM') simulierten wir auch die Anwendung von Pflanzenschutzmitteln und deren Auswirkungen auf unsere Modellart *B. lampros*. Die Exposition von *B. lampros* gegenüber einem Pflanzenschutzmittel im ALMaSS-Modell wird auf der Grundlage der vorhergesagten Umweltkonzentration am Standort eines einzelnen Käfers über die Zeit bestimmt. Die Konzentration basiert auf der Anwendung eins detaillierten Pflanzenschutzmittelausbringungsmodells, wie es in den NTA-Sci-Op der EFSA beschrieben ist. Bei diesem Ansatz wird das ausgebrachte Pflanzenschutzmittel in Boden- und Vegetationskompartimente aufgeteilt und der Abbau des Pflanzenschutzmittels in diesen Kompartimenten über die Zeit modelliert. Das Expositionsmuster integriert daher den Ausbringungsplan in Raum und Zeit mit dem Standort und dem Lebensstadium des Käfers und dem durch die Witterungsbedingungen bedingten Abbau in der Umwelt. Das Expositionsmodell läuft mit einer sehr hohen Auflösung (1 m) und kann daher kleinräumige Verteilungen des Pflanzenschutzmittels darstellen, die für die Bedingungen am Rand des Feldes relevant sein können.

Wir haben die Eigenschaften der Pflanzenschutzmittel so gewählt, dass sie die im Projekt zu behandelnden Problemen hervorheben und realistisch darstellen. Wir gingen davon aus, dass normale Fungizid- und Herbizidanwendungen keine Auswirkungen auf Laufkäfer haben würden. Die Insektizide wurden in allen Kulturen gemäß der in Brandenburg und Niedersachsen üblichen Praxis (entsprechend der Bewirtschaftungspläne) eingesetzt. Für die modellierten Insektizide wurde ein einziges Toxizitätsniveau gewählt, das als eine insektizid bedingte Käfer-Feldsterblichkeitsrate (LR) von 80% definiert ist, gemessen an einer Insektizid-Blattspritzung über 10 Tage. Dies ergibt eine tägliche Käfersterblichkeitswahrscheinlichkeit p von 0.1489. Der Halbwertszeit (DT_{50}) bei 20°C wurde auf 10 Tage festgelegt. Die Temperaturabhängigkeit des DT_{50}-Wertes in ALMaSS wurde gemäß den von der EFSA (2007) aufgestellten Gleichungen definiert. Für alle Kulturen wurde eine Ausbringungsmenge verwendet, die doppelt so hoch war wie die Auslösekonzentration, um sicherzustellen, dass die Käfer mindestens für den durch DT_{50}=10 Tage definierten Zeitraum oberhalb der Auslöseschwelle exponiert werden konnten, wobei eine LR von 80% galt. Die Abdrift wurde in einem Abstand von bis zu 12 m vom Rand jedes besprühten Feldes nach der Gleichung von Rautmann et al. (2001) mit einer Reduktion von 90% berücksichtigt (eine Reduktion von 50% gilt als Mindestanforderung für Sprühgeräte in Feldkulturen mit modernen Sprühgeräten, JKI, 2020).

Wir führten ein vollständiges Experiment, unter Berücksichtigung aller Faktoren durch, in dem alle Untersuchungsgebiete und Szenarien kombiniert wurden, d. h. drei landschaftsbezogene Szenarien ('Reg(ular)', 'FB' and 'UM') und zwei pflanzenschutzmittelbezogene Szenarien (ohne und mit Pflanzenschutzmittelwirkung; 'NoPest' bzw. 'Pest'). Es ist jedoch anzumerken, dass für die untersuchten Arten das Szenario 'UM_NoPest' zu denselben Ergebnissen führt, wie das Szenario 'Reg_NoPest' (weil ungespritzte Feldränder noch immer den normalen landwirtschaftlichen Praktiken unterliegen, einschließlich der Bodenbearbeitung, die sich auf die Käfersterblichkeit auswirkt). Daher wurden die Szenarien 'UM_NoPest' und 'Reg_NoPest' nicht miteinander verglichen.

Außerdem wurde für zwei exemplarische Landschaften (eine aus der Region Brandenburg und die andere aus der Region Niedersachsen) mit einem Ackerflächenanteil von 84-85% das gleiche Experiment durchgeführt, allerdings unter der Annahme einer Winterweizen-Monokultur und eines modifizierten Pflanzenschutzmittelapplikationsszenarios. Es wurde sowohl die normale Anwendung von Pflanzenschutzmitteln (5 % der Landwirte wenden Insektizide nach der Aussaat an, 50 % der Landwirte wenden Insektizide im Mai an und 25 % der Landwirte wenden Insektizide im Juni an) als auch die Umsetzung einer 100-prozentigen Applikations-Wahrscheinlichkeit für alle drei Anwendungen getestet. Anhand der Ergebnisse konnten wir die

Auswirkungen von Pflanzenschutzmitteln und die Effektivität der Maßnahmen in einem Extremszenario (bei dem der größte Teil des Untersuchungsgebiets von Ackerland bedeckt ist und alle Felder mit Pflanzenschutzmitteln behandelt werden) untersuchen und mit dem oben dargestellten realistischen Szenario des Pflanzenschutzmitteleinsatzes vergleichen.

Alle Simulationsläufe wurden über 30 Simulationsjahre ohne Einlaufphase durchgeführt. Aufgrund der großen Anzahl der bearbeiteten Untersuchungsgebiete (611) war die Anzahl der Wiederholungen für jede Szenario-Kombination auf zwei Wiederholungen beschränkt. Jede Simulation begann mit der gleichen Anzahl von „Superindividuen" (200 000 pro 100 km^2), wobei die Käfer nach dem Zufallsprinzip über geeignete Lebensräume innerhalb des Untersuchungsgebiets verteilt wurden. Obwohl die anfängliche Zahl der „Superindividuen" immer gleich war, näherten sich die Käferpopulationen nach einigen Jahren der Simulationsläufe Populationsdichten an, die von der anfänglichen Populationsgröße unabhängig waren. Die Wetterbedingungen wurden so gewählt, dass sie den Zeitraum 2009-2019 repräsentieren, und wurden für jedes der 10x10 km^2 großen Untersuchungsgebiete einzeln mit Hilfe des ERA5-Land-Datensatzes definiert (Muñoz Sabater 2021).

Aus jeder Simulation wurden drei Endpunkte (SE) analysiert: (SE1) die Gesamtpopulationsdichte der Käfer (d. h. die Gesamtzahl der adulten weiblichen Käfer geteilt durch die Landschaftsfläche, d. h. 100 km^2), (SE2) der Besetz (d. h. die Käferverteilung, definiert als der Anteil der Gitterzellen in der Landschaft mit mindestens 100 adulten weiblichen Käfern) und (SE3) die Abundanz (mittlere Dichte der adulten Weibchen in den besetzten Gebieten). Die beiden letztgenannten Endpunkte wurden als Abundance-Occupancy Relationship (AOR) Plots dargestellt (Høye et al., 2012). Obwohl die räumliche Auflösung des Landschaftsmodells in ALMaSS 1 m^2 beträgt, wurden für die Berechnung von Besatz und Abundanz Gitterzellen von 50 m^2 verwendet. Die Endpunkte wurden am Tag 185 eines jeden Jahres (4. Juli) gemessen und über die letzten 10 Jahre und über Wiederholungsläufe für jedes Szenario gemittelt. Sie wurden für das gesamte Untersuchungsgebiet sowie für die Bereiche In-Field and Off-Field gemessen. Für die Abgrenzung von In-Field- und Off-Field-Gebieten gab es zwei Möglichkeiten: (1) inklusiv, d.h. alle Gitterzellen innerhalb von Feldern oder über die Feldgrenze hinweg (inklusiv In-Field) oder innerhalb von nicht bebaubarem Land oder über die Grenze oder nicht bebaubares Land hinweg (inklusiv Off-Field); oder (2) exklusiv, d.h. alle Gitterzellen vollständig innerhalb von Feldern (exklusiv In-Field) oder vollständig innerhalb von nicht bebaubarem Land (exklusiv Off-Field).

Die Auswirkung jedes Szenarios *S* im Vergleich zur Basislinie wurde analysiert und im Laufe der Zeit verglichen, und zwar getrennt für jedes der Untersuchungsgebiete ($SA_{i=1...611}$), d. h. eine relative Änderung jedes der Simulationsendpunkte ($SE_{j=1,2,3}$) zur Basislinie wurde wie folgt berechnet:

relative Änderung von $SE_{j=1,2,3}$ *in* $SA_{i=1...611}$ *= (Endpunkt* $SE_{j=1,2,3}$ *Wert in Szenario S - Endpunkt* $SE_{j=1,2,3}$ *Wert in der Basislinie) / Endpunkt* $SE_{j=1,2,}$*3 Wert in der Basislinie * 100 [%]*

Als "Ausgangsbedingung" wurde das Szenario ohne Pflanzenschutzmitteleinsatz und ohne Veränderungen der Landschaftsstruktur (Szenario 'Reg_NoPest') festgelegt.

Darüber hinaus wurde die Wirksamkeit der getesteten Minderungsmaßnahmen (grasbewachsene Feldränder und ungespritzte Feldränder) als Maß der Verringerung der negativen Auswirkungen des Pflanzenschutzmitteleinsatzes nach Anwendung der Minderungsmaßnahme berechnet, d. h. als die Differenz der relativen Veränderung der Simulationsendpunkte zwischen 'Reg_Pest' und 'FB_Pest'/'UM_Pest'.

Der Einfluss von „Landscape Metrics“ auf (1) die Simulationsendpunkte im Basisszenario ('Reg_NoPest'-Szenario) und (2) die Veränderungen der Simulationsendpunkte als Reaktion auf eingesetzte Pflanzenschutzmittel (Szenario 'Reg_Pest' im Vergleich zu 'Reg_NoPest') und (3) die Veränderungen der Simulationsendpunkte als Reaktion auf eingesetzte landschaftsbezogene Minderungsmaßnahmen (Szenarien 'FB_Pest' und 'UM_Pest' im Vergleich zu 'Reg_NoPest') wurde mit multiplen Regressionsmodellen getestet. Hoch korrelierte „Landscape Metrics“ (d. h. mit einem Pearson-Korrelationskoeffizienten ≥ |0,7|) wurden von der Analyse ausgeschlossen. Nach der Durchführung der ersten Modelle wurde ein schrittweises Rückwärtsauswahlverfahren angewandt, um nicht signifikante Variablen zu entfernen, beginnend mit den Variablen mit den höchsten p-Werten, bis nur noch Variablen mit $p \leq 0{,}05$ im Modell verblieben. Die Normalverteilung der Residuen wurde formal mit dem Kolmogorov-Smirnov-Test geprüft. Alle statistischen Analysen wurden mit Statgraphics 19 durchgeführt.

Ergebnisse und Diskussion

Die Studie erbrachte signifikante Unterschiede in den *B. lampros*-Populationen im Basisszenario (‘Reg_NoPest') zwischen den verschiedenen Landschaften und Bewirtschaftungssystemen. Diese Variabilität wurde durch die Regressionsmodelle sehr gut erklärt. Die *B. lampros*-Populationen waren größer und verteilten sich über größere Gebiete in Landschaften mit einem hohen Anteil an Ackerland und einem hohen Anteil an natürlichen Lebensräumen und Dauerweiden. Dies stimmt gut mit der Ökologie und Biologie der Käfer überein, die Ackerland zur Nahrungssuche und Fortpflanzung benötigen, während Grünlandhabitate für die Überwinterung der Käfer und für Wiederbesiedlung von Flächen von entscheidender Bedeutung sind. Hohe Anzahlen und Dichten von Käfern wurden in vielfältigeren und heterogeneren Landschaften gefunden, wobei sehr vielfältige Landschaften die effektive Besiedlung von Ackerflächen durch Käfer besonders unterstützen.

Das Hinzufügen von grasbewachsenen Feldrändern führte zu einem durchschnittlichen Anstieg der Käferpopulationen in allen untersuchten Landschaften von 9.8%, was hauptsächlich auf eine erhöhte lokale Käferhäufigkeit zurückzuführen ist. Die Veränderungen bei der Besiedlung waren jedoch gering. Nur vier Landschaften wiesen eine Zunahme von mehr als 5% auf. Die ursprünglichen Käferpopulationen in diesen vier Landschaften waren jedoch aufgrund des geringen Anteils an Ackerland, Dauergrünland und naturnahen Lebensräumen sehr gering. Die Veränderung der mittleren Gesamtkäferdichte durch grasbewachsene Feldränder variierte erheblich zwischen den untersuchten Landschaften, in Abhängigkeit von den ursprünglichen Käferzahlen und der Zusammensetzung anderer Landschaftselemente. Diese Veränderung hing mit der relativen Veränderung der Habitatbedeckung mit Gras zusammen.

Unter dem Pflanzenschutzmittel-Szenario ('Reg_Pest') gingen die Käferpopulationen in allen untersuchten Gebieten deutlich zurück (der durchschnittliche Rückgang lag bei 14.0%, in Brandenburg etwas höher als in Niedersachsen: 15.7% bzw. 13.4%), doch die Auswirkungen variierten stark zwischen den Untersuchungsgebieten (von 2.5 bis 27.2%). Diese negativen Auswirkungen waren in homogenen Landschaften mit geringen initialen Käferpopulationen, einem hohen Anteil an Ackerland und einem geringen Anteil an Käfer-Herkunftshabitaten stärker ausgeprägt. Diese Ergebnisse stimmen mit früheren Studien über *B. lampros*-Populationen in Agrarlandschaften in Polen (Ziółkowska et al. 2021) und den Niederlanden (Ziółkowska et al. 2022) überein.

Auffällig ist, dass auch Käfer in „Off-Field“-Bereichen, also außerhalb des Feldes betroffen waren, in denen das Pflanzenschutzmittel nicht ausgebracht wurde oder es dorthin verdriftete (Einwirkung aus der Ferne). Die Auswirkung des Einsatzes des Pflanzenschutzmittels auf die Käfer in den „Off-Field“-Bereichen nahm mit abnehmender Anzahl an Feldgrenzen und zunehmender Fläche an geeignetem Überwinterungs- und Bruthabitat in der Nähe (in diesem Fall Dauergrünland) ab. Dies ist darauf zurückzuführen, dass die Käfer dort, wo Feldränder vorhanden sind, im Laufe der Zeit den Pflanzenschutzmitteln ausgesetzt sind, während die Populationen von Wiesen und Weiden räumlich weit von den Gebieten mit Pflanzenschutzmittelanwendungen entfernt sind.

Die Studie zeigte, dass grasbewachsene Feldränder eine wirksamere Risikominderungsmaßnahme waren als ungespritzte Feldränder, da sie die negativen Auswirkungen des Einsatzes von Pflanzenschutzmitteln auf die durchschnittliche Gesamtkäferdichte um durchschnittlich 13.4% (maximal 27.2%) verringerten, während ungespritzte Feldränder diese nur um durchschnittlich 2.7% (maximal 10.1%) reduzierten. In beiden Fällen wirkte sich die positive Wirkung hauptsächlich auf die durchschnittliche Käferhäufigkeit und nicht auf die Besatzdichte aus und variierte zwischen den Untersuchungsgebieten. In heterogenen Landschaften waren grasbewachsene Feldränder hingegen weniger wirksam, da sie bereits bessere initiale Ausgangsbedingungen für Käfer boten, die die Population in der umgebenden Landschaft unterstützten. In ackerbaulich geprägten, homogeneren Landschaften war die Wirkung von grasbewachsenen Feldrändern proportional größer als die Auswirkung von ungespritzten Feldrändern, da hier die Pufferwirkung anderer, nicht landwirtschaftlich genutzter Habitate fehlte.

Die Studie ergab, dass die Käferpopulation im Untersuchungsgebiet unter der worst-case-Annahme einer Monokultur im Extremfall im Untersuchungsgebiet fast ausgerottet werden könnten, im Gegensatz zu einem realistischeren Szenario des Einsatzes von Pflanzenschutzmitteln.

Unter der Annahme eines normalen Pflanzenschutzmitteleinsatzes in der Weizenmonokultur waren die beobachteten Auswirkungen auf die Käferpopulationen aufgrund des relativ geringen Pflanzenschutzmitteleinsatzes mit denen vergleichbar, die bei Anwendung einer Fruchtfolge erzielt werden. Eine Erhöhung der Anwendungswahrscheinlichkeit von Pflanzenschutzmitteln bis zu dem Punkt, an dem alle Landwirte Pflanzenschutzmittel einsetzten, führte jedoch zu starken Auswirkungen auf die Käferpopulationen. Das extremere Szenario zeigte, dass die beobachteten Auswirkungen in der homogeneren Landschaft mit intensiver Landwirtschaft viel höher waren als in der heterogeneren, von kleinen Feldgrößen dominierten Agrarlandschaft und große Auswirkungen auf die Käferbesiedlung beinhalteten. Risikominderungsmaßnahmen wirkten sich positiv auf die Käferpopulationen in der homogeneren Landschaft aus, aber es gab immer noch große Rückgänge bei der Besiedlung durch die Käfer. In der heterogeneren Landschaft wurden Auswirkungen auf die Besiedlung mit Käfern nur dann beobachtet, wenn alle Landwirte in der Weizenmonokultur Pflanzenschutzmittel einsetzten. Diese Auswirkungen konnten nur durch die Bereitstellung von mehr Käferherkunftshabitaten (d. h. „Source“-Habitaten, wie grasbewachsene Feldränder) verringert werden. Dies deutet darauf hin, dass die Käferpopulationen bei bestimmten Stressfaktoren Kipppunkte erreichen können.

B. lampros, eine Schwerpunktart für Käfer (*Coleoptera*) in der Umweltrisikobewertung, ist eine wichtige in Agrarlandschaften in Mittel- und Nordeuropa (einschließlich Deutschland) natürlich vorkommende Art, die hier Schädlinge bekämpfen kann. Aufgrund ihrer geringen Ausbreitungsrate ist sie empfindlich gegenüber Störungen. Größere Aktionsradien (Ausbreitungsraten) erhöhen die Wahrscheinlichkeit, Lebensraum mit günstigeren Habitat Bedingungen zu erreichen, und wirken sich somit positiv auf das Populationswachstum aus. Das bedeutet, dass *B. lampros* in homogenen Landschaften mit intensiver Landwirtschaft, in denen Source-Habitate schwer zu erreichen sind und Felder Barrieren für den Genfluss darstellen, stärker von den Auswirkungen von Pflanzenschutzmitteln betroffen ist.

Das Wanderungs- und Aggregationsverhalten von *B. lampros* ist nicht typisch für alle Laufkäferarten in Agrarlandschaften. Die räumliche Verteilung von Laufkäferarten in Agrarlandschaften variiert aufgrund ihrer Vorlieben für Überwinterungsplätze und ihrer Fähigkeit, in Feldgebiete zu besiedeln. Die Auswirkungen von Pflanzenschutzmitteln können für Käferarten mit unterschiedlichen ökologischen Ansprüchen, einschließlich Frühjahrs- und Herbstbrütern, unterschiedlich sein, da sich die Exposition gegenüber Pflanzenschutzmitteln im Laufe der Zeit verändert. Die Untersuchung eines breiteren Spektrums von Laufkäferarten mit unterschiedlichen Habitat Präferenzen und funktionalen Merkmalen, wie Ausbreitungsvermögen, würde eine detailliertere Bewertung der potenziellen negativen Auswirkungen der Ausbringung von Pflanzenschutzmitteln in Agrarlandschaften und ihrer Abhängigkeit von der umgebenden Landschaftsstruktur ermöglichen.

Schlussfolgerungen und Empfehlungen

Diese Studie zeigte die Komplexität der Auswirkungen von Risikominderungsmaßnahmen auf die Populationen von Käfern und die Notwendigkeit, Entscheidungenprozesse im Zusammenhang mit landwirtschaftlichen Systemen, politischen Zielen und der Landschaftsstruktur zu treffen. Das Ausmaß der Auswirkungen von Pflanzenschutzmitteln kann sehr variabel sein und wird durch räumlich dynamische Faktoren wie die Verteilung von Quell- und Senken Habitaten (Source- Sink-Habitate) oder der zugrunde liegenden Lebensraumeignung der Habitate beeinflusst werden. Es ist wichtig, das Ziel der Beeinflussung im Modell in jeder zukünftigen Modellierungsstudie klar zu spezifizieren. Die Studie konzentrierte sich darauf, die Effektivität der Risikominderungsmaßnahmen bei der Ausbringung von Pflanzenschutzmitteln zu analysieren. Eine alternative Sichtweise könnte darin bestehen, den Erhaltungszustand der Käferpopulationen zu betrachten, was in heterogenen Landschaften größere Auswirkungen haben kann.

Unsere Analyse hat gezeigt, dass der Einsatz von Pestiziden die Populationen von *B. lampros* durch eine Quelle-Senke-Dynamik beeinflusst, die erhebliche Auswirkungen außerhalb des Feldes hat und auch nach der Umsetzung von Gegenmaßnahmen anhält. Wir empfehlen, bei der Bewirtschaftung von Agrarökosystemen der Erhaltung und dem Schutz dieser Lebensräume Priorität einzuräumen, insbesondere in sehr homogenen Landschaften. Für zukünftige Modellierungsstudien wird empfohlen, eine Reihe von Standardszenarien zu entwickeln, die von realistischeren bis zu extremeren Szenarien für den Pestizideinsatz und die Landschaftsstruktur reichen und eine Reihe von Pestizidtoxizitätswerten und Anwendungswahrscheinlichkeiten enthalten. Auf diese Weise kann die gesamte Bandbreite der resultierenden Auswirkungen erfasst und abgeschätzt werden, wie nahe einem realistischen Szenario an einem Kipp-Punkt liegt. Es sollte auch ein breiteres Spektrum von Laufkäferarten berücksichtigt werden, so dass eine Umweltrisikobewertung verschiedene Habitat Präferenzen und funktionelle Merkmale abdecken kann. Diese Kombination von Szenarien und Arten wird ein umfassenderes Bild für das Verständnis der Auswirkungen von Pestiziden auf Laufkäferpopulationen liefern.

1 Introduction

The richness and population sizes of many species in agroecosystems, including non-target arthropods (NTAs), have declined dramatically in recent decades (e.g., Potts et al., 2010). Along with the widespread use of pesticides, the current pattern of agricultural intensification leading to the simplification of the landscape is seen as one of the main causes of this loss of biodiversity (e.g., Carvalheiro et al., 2011). To date, mitigation strategies have mainly focused on landscape elements considered as refuges from agricultural activities, thereby subsuming the internal heterogeneity and potential of farmland as a habitat of varying suitability. In reality, what controls species population dynamics in agro-ecosystems is the structural and functional heterogeneity of the landscape as a whole, with its mosaic of semi-natural habitats and cultivated fields (Vasseur et al., 2012). In particular, pesticides can strongly affect NTA populations both within fields and in uncultivated areas (through 'action at a distance'), and their effects seem to strongly depend on landscape structure (Topping et al., 2015). Therefore, this project was designed to elucidate the links between landscape structure, source-sink dynamics and the risk of pesticide use for NTAs.

The ELONTA project consisted of three research work packages and was carried out by a consortium of three institutes from Denmark (Aarhus University), PL (Jagiellonian University) and DE (Julius Kühn Institute) with specific expertise in the development of landscape scale approaches to NTA ecology and toxicology. The methods used are updated protocols of those previously used by the European Food Safety Authority (EFSA) to produce its scientific opinion on the risk assessment of NTA pesticides (EFSA Panel on Plant Protection Products and their Residues (PPR) 2015). These methods are also used to develop other risk assessments for EFSA and widely in European research projects. The basis of the methods is the generation of dynamic and realistic landscape representations in which NTA agent-based models are placed. In these models, the populations of NTAs are represented as individuals that reproduce, move, and die according to very realistic patterns. Modelled NTAs respond to local contexts and can be affected by environmental or management changes. This is used to create scenarios to assess the impact of changes, such as those caused by pesticides or mitigating measures. These scenarios take into account the spatio-temporal patterns of pesticide use, including detailed modelling of the fate and exposure of pesticides.

The project was originally planned to run scenarios on only three landscapes. However, it became clear that this would not achieve the project's objectives of looking for links between landscape composition and configuration and the results of the environmental risk assessment (ERA). Therefore, it was agreed that the consortium would extend the analysis to the entire area of two available federal states, Brandenburg and Lower Saxony, from three to 611 landscapes. Due to the increase in scale, the initial focus of the scenarios to be run was changed to compare baseline scenarios with a pesticide application scenario and two forms of landscape-related mitigation measures (unsprayed field margins and grassy field boundaries).

We acknowledge the support of a DeiC National HPC grant for the use of the LUMI supercomputer (grant agreement DeiC-AU-L5-0011), which made it possible to run these scenarios.

1.1 Objective of the report

The report details the results and analysis of the ELONTA project presenting the impact of pesticide and mitigation scenarios in the German states of Lower Saxony and Brandenburg. It first introduces the issues related to the spatial dynamics of non-target arthropods and their interactions with pesticide impacts and risk assessment. It then describes the methods used to characterize the study areas and to generate the landscape simulations as input to the Animal, Landscape and Man Simulation System (ALMaSS) from data from the two states are described. Finally, we present the simulated scenarios, the results obtained and the analysis relating the results obtained to landscape characteristics.

2 Short review of spatial dynamics issues related to environmental risk assessment

Agricultural intensification has led to profound structural changes in farmlands, resulting in the loss of semi-natural habitats and an increase in landscape homogeneity.

These changes are particularly evident in intensive agriculture, where the farmland has changed from small fields separated by hedges and meadows to large fields surrounded by small strips of grass vegetation (Bianchi et al., 2006; Djoudi et al., 2018; Galle et al., 2019; Iles et al., 2018). This may have a significant negative impact on NTAs, as it has been shown, in both field studies and empirical models, that landscape heterogeneity (or, conversely, homogenisation) has a profound effect on the composition of arthropod communities (Raven and Wagner, 2021), and many NTA species depend on both in-field and off-field areas during their life cycle (Djoudi et al., 2019), implying an automatic dependence on local spatial dynamics.

Non-target arthropods include a large number of different taxa (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015), which often provide many ecosystem services (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015). These services include natural pest control, e.g., by ladybirds, ground beetles and spiders (Roubos et al., 2014), pollination by bees, hoverflies, butterflies, etc., which is crucial for maintaining the diversity of flowering plants and an important part of human food production (Uhl and Brühl, 2019). More generally, NTAs are central to ecosystem functioning as part of food webs (Muller, 2018; Seibold et al., 2019), and biodiversity itself is thought to be important for ecosystem stability. Since the Second World War, NTA species have been disappearing from landscapes and there is a strong assumption that this is due to changes in agriculture, namely the homogenisation of landscapes and the increased use of pesticides (Bianchi et al., 2006; Galle et al., 2019; Habel, Ulrich, et al., 2019; Seibold et al., 2019).

As an important part of agro-ecosystems, NTAs are protected by the Pesticides Regulation 1107/2009, which aims to ensure that there are no unacceptable effects on non-target species. Currently, the impact of pesticides is determined by their effects on individuals in the field, or separately in in-crop or off-crop assessments. However, most NTA populations do not remain within field boundaries and fall into both in-field and off-field groups. For many species, their home ranges include several different landscape elements, both in-field and off-field (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015). Therefore, assuming that NTAs are confined to an in-field or off-field area in risk assessment will undoubtedly lead to incorrect conclusions (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015). At the landscape scale, NTA populations typically function as networks of subpopulations that influence each other, including source-sink dynamics (Pulliam, 1988). In addition, because pesticide applications in one area can have effects in another area by acting at a distance (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015), this effect will change in space and time as the landscape is dynamic rather than static.

Here, we assess the evidence on the effects of landscape structure and population spatial dynamics on how pesticides affect NTA populations. Our review uses two EFSA outputs as a starting point (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015; EFSA Scientific Committee, 2016), as these were based on the majority of literature available on the topic at the time. However, to include new literature on the topic, an extensive search was conducted using Web of Science, Google Scholar and Mendeley, focusing on papers published since 2016. However, some pre-2016 papers of particular relevance were also included. The keywords used included the following terms and their combinations: "non-target arthropods", "arthropods", "agriculture", "pesticide", "source-sink dynamics", "action at a distance", "farming", "landscape", "spatial dynamics", "in- and off-field", "insect", "mitigation", "landscape structure", "spatial structure", "risk assessment", "plant protection products" and "recovery". Other studies were obtained from relevant papers referenced literature.

The search identified 166 papers with titles or abstracts that suggested they might be relevant to the topic. All abstracts of the 166 papers were read, after which 67 papers were excluded as it was clear that they would not be suitable for this review. The remaining 99 papers were then read in full, and 52 papers were excluded as they did not address the topic in a way that was relevant to this review.

The following sections first consider some aspects of exposure and effects, before moving on to population-level effects and the importance of interactions with source-sink dynamics for recovery and risk assessment.

2.1 Exposure routes

NTAs can be exposed to pesticides by several routes. In general, the exposure routes considered for NTAs are overspray, direct contact with contaminated surfaces and oral exposure. Species living in crops and field margins are more likely to be exposed by overspray, either directly in the field or by drift. The uptake rate for direct overspray is much higher than when an NTA is exposed by contact with dried PPP substances (EFSA Panel on Plant Protection Products and their Residues (PPR) 2015), as in the case of herbivores walking on sprayed leaves. In risk assessment, exposure through overspray and surface contact is the most recognised, but it is important not to overlook the impact that oral exposure can have on herbivores and pollinators (EFSA Panel on Plant Protection Products and their Residues (PPR) 2015). During the life cycle of NTA, these pathways may change; for example, butterflies are herbivores in the larval stage (overspray, surface contact and oral exposure), then many pupate in the soil (medium exposure) and as adults they are pollinators (oral exposure and overspray) (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015). Different life stages of NTA may also prefer different habitats: for example, butterfly caterpillars feed on wild plants in hedgerows or meadows, while adults are attracted to flowering crops. Similarly, many carabid beetles overwinter mainly in field margins and hedgerows but disperse into arable land for breeding and feeding. As a result, individuals are likely to be affected by multiple exposures and different exposure pathways during their lifetime, and different parts of the population may be exposed by different pathways in space and time. None of these phenomena are considered in a standard risk assessment under current legislation. However, because population effects result from the sum of individual effects on different life stages and their movement across the landscape, the inclusion of source-sink population dynamics is crucial for a reliable risk assessment.

As a result, movement may be an important factor to consider, as pesticide concentrations vary in space and time, and exposure by different routes may be a function of small-scale movement. This is very important at field margins, but even within a sprayed field, pesticide concentrations are highest in the upper parts of plants, so species that move primarily in these regions, for example for thermoregulation, mating or orientation, are likely to be exposed to higher doses of a pesticide than species living further down the stem (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015). However, for the purposes of this review, we will only consider movement between habitat patches and not fine-scale movement within a patch. Movement, time of exposure and duration of exposure are all expected to influence the effects of the pesticide by altering exposure.

2.2 Impact of PPP

The actual effects of pesticides are highly dependent on the ecology and behaviour of the arthropod at the time of exposure and shortly afterwards (EFSA Scientific Committee, 2016). There are many life history factors that can influence how pesticides affect NTAs at both population and individual levels. These include voltinism (number of generations per year), overwintering site, time of reproduction and dispersal ability (EFSA Scientific Committee, 2016). Exposure to insecticides is generally thought to affect traits such as number of offspring, survival and intrinsic reproductive rate (Almasi et al., 2018; Amarasekare et al., 2016; Bayram et al., 2010).

2.2.1 Impact of PPP on individual-level

Population effects result from effects on the individual, so it is important to understand PPP effects at the individual level before considering population and spatial dynamics.

The effect of a pesticide on an individual is determined by a combination of exposure and the individual's physiological state. For example, sensitivity to pesticides can vary depending on life stage - a species may be less sensitive if it is in a sessile or hibernating stage when pesticides are applied (EFSA Scientific Committee, 2016). These effects may be direct or indirect. A direct effect is an interaction between the NTA and a pesticide that results in a measurable response, a typical example being death, paralysis, etc. as a result of overspray exposure (EFSA Scientific Committee, 2016). For indirect effects, there is no direct interaction with the pesticide, but the transmission or effect occurs through another medium, such as a reduction in food supply (EFSA Scientific Committee, 2016). Individuals in a population will vary in their exposure due to spatial location and co-occurrence with the pesticide. This has the potential to drive significant spatial dynamics. Differential exposure of individuals can lead to low population densities, which in turn are indirect drivers of spatial dynamics and can potentially lead to source-sink effects (see below).

Although NTAs are often exposed to herbicides at the edge of the field through spray drift or run-off, herbicides are not usually directly toxic to them (although there are examples where this can happen, even by affecting the next generation (Stark et al., 2012)). However, they can have indirect effects by killing the NTAs' food source or destroying their habitat (Sharma et al., 2018). For example, in web-spinning spiders, a decline in abundance after plants disappeared was due to the lack of structures to build their webs (Gibson et al., 1992).

For insecticides, effects are generally determined by acute mortality, measured as either the median lethal dose (LD_{50}) or the median lethal concentration (LC_{50}), and in most cases insecticides will kill NTAs, but the degree of lethality varies considerably even between similar compounds. However, mortality alone does not provide an accurate assessment of the potential effects of pesticides, as sub-lethal effects can also occur, resulting in reduced fecundity, longevity, and developmental rates, as well as changes in sex ratio, morbidity and altered behaviour (e.g., Roubos et al., 2014). Behavioural changes due to insecticides may include impaired locomotion (knockdown effect, trembling, incoordination, excessive grooming), problems with navigation and orientation to prey. There may also be changes in social behaviour, which can have important implications for disease susceptibility; in termites (*Reticulitermes flavipes*), the neonicotinoid imidacloprid disrupted grooming behaviour and prevented them from removing fungal spores from their conspecifics (Boucias et al., 1996). Insecticides can also affect pheromone production and perception, altering intraspecific communication. For example, in parasitoids this led to changes in the ability to find a mate, and neonicotinoids have also been shown to alter the calling behaviour of tortricid moths (Navarro-Roldan and Gemeno, 2017), and in the parasitoid wasp *Nasonia vitripennis*, courtship behaviour was hindered (Tappert et al., 2017). Pesticides can also affect foraging behaviour and may reduce foraging efficiency. For example, bees had longer or less successful foraging trips (Gill and Raine, 2014), and the predatory beetle *Platynus assimilis* (Carabidae) exposed to pyrethroids became hyperactive immediately after exposure and hypoactive later (Tooming et al., 2014).

The effects of neonicotinoids on aquatic species can be nearly irreversible, with the effects of exposure increasing as more exposure events occur (Morrissey et al., 2015; Tennekes, 2010). This can result in species showing delayed effects of exposure (Beketov and Liess, 2008) as individual-toxicity level thresholds are reached over time. Exposure can also cause sub-lethal effects similar to those observed in terrestrial arthropods, altering growth, reproduction, mobility, feeding, swimming behaviour and emergence success (Morrissey et al., 2015). Examples of these effects have been seen in mayflies (Ephemerotera) exposed to neonicotinoids, which showed feeding inhibition (Alexander et al., 2007) and reduced adult size (Alexander et al., 2008).

Exposure to pesticides depends on their environmental chemistry. In aquatic systems, environmental conditions such as high turbidity, acidity, depth and shading by algae/macrophytes can alter the fate of neonicotinoids in the environment and increase the duration of exposure of aquatic arthropods. This type of interaction may in turn affect the ecology of non-target organisms. For example, those aquatic invertebrates with a long larval stage are likely to be exposed to neonicotinoids for a prolonged period, either due to repeated pulse events or low chronic exposure. This means that bioassays based on short pulse exposures may not provide meaningful information on the ultimate effects that may occur after such prolonged exposure, including possible slowing or halting of recovery (Morrissey et al., 2015). As shown in many field studies, all of these effects eventually lead to a reduction in the abundance and diversity of aquatic macroinvertebrates and ultimately to a reduction in ecosystem functioning (Schafer et al., 2012).

In conclusion, the effects of specific toxicology, multiple exposure, long-term exposure, sub-lethal effects, environmental fate, and ecology/phenology of non-target organisms can and will influence the response of individuals to pesticide exposure. This will further interact with population level effects.

2.2.2 Impact of PPP on population-level

Population effects result from the combination of individual-level effects over the space and time in which population effects are measured. This is not simply the average of individual effects, but also a function of the interactions between affected individuals and the population response. In general, the population response should be less extreme than the individual response due to compensatory mechanisms associated with density dependence, but this cannot be taken for granted. For example, in honeybees, the impact on the colony of the loss of easily replaced foragers may have a much smaller effect on the population than the loss of brood.

As with individuals, the temporal pattern of stressor exposure is therefore an important factor in assessing the effect of PPPs at the population level. While there may be no obvious effect after a single exposure event, population-level effects are expressed gradually, increasing with the number of years of exposure events (Habel, Samways, et al., 2019). The cause of these long-term trends may have both spatial and non-spatial components. The non-spatial component is the best known and is often referred to as resilience (Ives, 1995). In a population, this is the result of the buffering capacity, which is a combination of the intrinsic rate of increase and mortality rates and is usually considered to be density-dependent. This means that when stressor-determined mortality is low, the population is able to compensate, effectively replacing the doomed surplus of density dependent mortality (Nicholson, 1933) with stressor mortality (compensatory mortality). Therefore, there is a balance point at which the natural variability of a population's normal operating range (NOR) (see, e.g., Vighi and Rico (2018)) will mask smaller population effects, although in the long-term stressor mortality may outweigh the population's ability to compensate. It is important to note that conducting a risk assessment without considering the mortality that contributes to reducing resilience capacity by exceeding the compensatory mortality threshold over time will underestimate impacts, potentially by a large margin (Topping et al., 2009).

The spatial component is simpler in that it relates to spatial differences in exposure. For example, if 5% of the habitat is exposed each year, the effect may be difficult to detect, especially if there is recolonisation from unexposed habitats and recovery is driven by reproduction. However, as with exceeding the compensatory mortality of the population, spatial mortality can build up slowly if the dispersal and reproductive capacity of the population is unable to fully compensate. In this case, the effect is to dynamically generate low and high population densities as the stressor moves around the landscape, eventually leading to local extinctions.

Phenology in relation to exposure is also an important factor to consider at the population level. For example, if exposure overlaps with important life history events such as the mating season (Larsen et al., 2020), the effects will be greater than if exposure occurs during a dormant period. Thus, to understand the effects of pesticide exposure at the population level, it is necessary to understand how a trait such as fecundity changes under stress conditions. These changes, together with effects on survival, will indeed lead to changes in population dynamics. There may also be indirect effects related to changes in phenological traits if developmental rates are altered. In this case, phenological synchrony with an organism's food source or host may be disrupted (Roubos et al., 2014).

A critical issue and weakness of the current ERA approach relates to the temporal scale of assessment for NTAs. In a study by Topping et al. (2015), the effect of pesticide exposure on a *Bembdion lampros* population was modelled over a ten-year period. The simulation clearly showed that the impact of pesticide exposure is not immediate, but changes over the years. The study also showed that if exposure is repeated year after year, the impact on the population is much greater, especially if the population does not have time to recover between pesticide applications.

Population effects due to indirect effects are also important. Herbicide use has been shown to cause a loss of NTA habitat by reducing the availability of host plants (Longley & Sotherton, 1997) and by altering the structural characteristics of spider habitat (Baines et al., 1998). Additional delayed effects may also occur, as the loss of important food sources may result in smaller and possibly less fertile adults, leading to the extinction of the local population (Dennis et al., 2004; Longley and Sotherton, 1997). A similar effect has also been shown in aquatic arthropods as a result of increasing exposure over time (Morrissey et al., 2015). All these studies show that repeated exposures to pesticides can have delayed effects on populations, so short-term tests may not detect long-term effects.

When considering population effects in space and time, sublethal effects of pesticides on individuals, as noted above, may also be important for populations. Changes in the physiology of NTAs and their ability to perform basic functions such as reproduction clearly have population consequences. These changes can be passed on to the next generation(s) and could mean that adults are unable to invest in their offspring (Muller, 2018). For example, long-term effects have been observed in ladybirds (*Harmonia axyridis*) exposed to insecticide-treated plants. The insecticide was applied to the seeds of cotton plants. The parental generation of ladybirds exposed to the plants showed no effects. However, there was a measurable effect on the offspring (first generation) larvae and pupae, which showed a shortened development time and a higher mortality rate. When the first generation became adults, they were smaller and their eggs had a lower viability (Oliveira et al., 2019).

Overall, population-level effects are affected by most of the same factors that affect individuals. However, they add further complications in terms of spatial patterns of exposure and population feedback mechanisms. These factors are the basis for driving spatial dynamic effects.

2.3 Spatial dynamics

When considering spatial dynamics in the context of environmental risk assessment of NTAs, the movement of NTAs needs to be considered alongside the spatial and temporal dynamics of stressors. There are many aspects to this, including species and environmental characteristics, the spatial scale considered, the landscape structure, and the level of detail at which the landscape and landscape management are represented. Although the focus of ERA for NTAs is usually on exposure mortality at the site of application, it is also possible for distant effects to occur when an organism exposed to pesticides migrates to an area where there has been no exposure, but then triggers indirect effects. This could happen, for example, if PPP-contaminated prey moves and are then eaten by predators that would not otherwise have been exposed to the PPP (Sharma et al., 2018).

The importance of spatial dynamics in the long-term survival of populations has been recognised for some time. Johnson (1960) noted that dispersal in insects often occurred after the emergence of adults, and later described the concept that dispersal could ensure the survival of insect populations in ephemeral or unstable habitats by providing the potential to colonise new habitats (Johnson, 1969). These ideas contributed to what became metapopulation dynamics (Levins, 1969), where the dynamics of subpopulations of organisms were considered rather than the dynamics of the organisms themselves, leading to source-sink dynamics (Pulliam, 1988), where the rate of exchange between populations and density effects are considered. These theoretical approaches all relate to populations distributed across habitat patches.

However, this can be quite misleading when applied to most NTAs in agroecosystems. It is important to note that metapopulation dynamics is a specific term associated with derivatives of the Levins' approach and is not synonymous with the dynamics of a metapopulation composed of subpopulations, i.e., it is a subset of specific dynamics. This leads to some confusion in terminology.

For NTAs, a significant body of work on population survival and spatial dynamics was produced by P. J. Den Boer but was generally disconnected from the main developments in spatial dynamics and ecology. The fact that carabid populations in agricultural systems must survive in a system with changing conditions and that there must be a balance in spatial dynamics mediated by dispersal was noted early (DenBoer, 1968). Later he pointed out that some carabid populations occupy large areas consisting of many relatively sparse local groups linked by high rates of dispersal exchange (DenBoer, 1971). This suggests a different structure from the more familiar patch-based approaches. Later, Den Boer used long-term observations of 64 carabid species to assess the role of dispersal in the survival of carabid populations. Although he initially adopted an 'overflow paradigm', in which dispersers were considered to be individuals in excess of the local population, he later changed his focus when he observed that many species were obligate dispersers. A key observation was that modern agriculture was changing the ratio of suitable to hostile habitat and that this could be detrimental to the long-term survival of populations (DenBoer, 1990). In effect, he was discussing over-dispersal of populations, where the chance of dispersal into hostile environments outweighs the benefit of the chance of finding new habitats. This was described in models by Bascompte and Sole (1996) and further developed using models based on random walks (Barton et al., 2009). Given the trends in agricultural intensification over the past 30 years since Den Boer identified the potential for over-dispersal, it is perhaps not surprising that we have lost so much terrestrial biodiversity (van Klink et al., 2020).

It is worth noting that the opposite of over-dispersal is the better known 'risk-spreading' (Hopper, 1999), whereby the risks of extinction are mitigated by dispersing to other locations. This is known to be favoured by organisms in unstable environments, but as noted above, there is a tipping point where the risks of dispersal outweigh the benefits of the potential to establish new local populations (Bascompte and Sole, 1996).

2.3.1 Source-sink dynamics theory

This is also a theory of patch dynamics but differs from Levins' metapopulation dynamics in that it focuses on the characteristics of patches, which are inherently different. Dispersal and habitat selection are thought to form the basis of source-sink dynamics in heterogeneous landscapes, as these factors control the movement of individuals between habitats, thereby controlling birth and death rates, as well as local densities (Heinrichs et al., 2016). Sink populations are subpopulations that have a negative growth rate and depend on immigration for their existence. Immigration comes from source populations that produce enough offspring to support sink populations (Heinrichs et al., 2016). It is important to maintain movement between subpopulations as it stabilises the overall population at a regional scale (Heinrichs et al., 2016). Factors that could influence source-sink dynamics are demographic traits and habitat characteristics. Demographic traits include fecundity, mortality, age structure and dispersal ability. Habitat characteristics include patch size, habitat quality and proximity to refugia (Heinrichs et al., 2016).

Source-sink dynamics is relevant to ERA because it provides an explanation for 'action at a distance', but it is not a perfect description because it is based on patch dynamics, whereas NTA populations may be better described as widely and unevenly distributed in fragmented and unstable landscapes. The latter situation is much more difficult to describe in simple mathematical terms, although it can be represented by simulation (e.g., Thorbek & Topping, 2005). However, even when describing the system mathematically, we are considering reproduction and mortality rates that change dynamically in space and time. There is therefore a strong interaction between species and environmental characteristics and the resulting population dynamics.

2.3.2 Species traits

For source-sink dynamics, the immigration potential of a species is a particularly important factor, as it alters the impact of pesticides on the population and its recovery time. This effect was demonstrated in a study that modelled the impact of pesticides on the beetle *B. lampros* and the spider *Erigone atra* and how their dispersal ability changed. The two species have very different dispersal strategies, with *B. lampros* having a low seasonal dispersal ability and *E. atra* having a high dispersal ability over a longer period of time (Topping et al., 2014). The simulation by Topping et al. (2014) showed that *B. lampros* had a higher decline in abundance and slower recovery than *E. atra*, most likely due to *E. atra's* larger pool of potential recolonisers around the affected area, while *B. lampros'* low dispersal ability meant that new individuals were unable to recolonise the area before the next applications further depleted the local population.

As noted above, other species characteristics will interact with spatio-temporal dynamics and may increase or decrease ecological risk as a result. These include phenology and behaviour of vulnerable life stages, including habitat choice. The number of generations per year may have a large effect, as reproductive recovery will be faster in species with faster generation turnover. There is also an interaction with environmental structure. Field data show that species with low dispersal ability are more dependent on local refugia. For example, in spiders, locally dispersing *Oedothorax* species are more affected by the proximity of refugia than the more dispersive *Erigone* species (Lemke and Poehling, 2002; Thomas et al., 1990).

However, dispersal ability alone cannot explain all the effects of spatial dynamics, as it is also influenced by interactions with population dynamics. Different forms of dispersal can be identified. Dispersal can occur as natal dispersal, in which case it is a fixed part of the life cycle after the emergence of a particular stage (e.g. Yip et al., 2019 in spiders), as a consequence of changes in local conditions that confer an individual advantage (e.g. leaving a crowded patch) (Benton and Grant, 2000), or as a mixed strategy (e.g. Topping and Sunderland, 1998). The consequences of different dispersal modes for individuals and populations will vary and will interact with the landscape in which they disperse. Local density-dependent dispersal will favour population stability in source habitats, in which case there would be little impact in terms of distance effects, whereas 'obligate' dispersal, whether natal or not, can lead to unstable dynamics (Hidalgo et al., 2016). In the case of *Leptyphantes tenuis* (now *Tenuiphantes tenuis*, Blackwall, 1852), the dispersal strategy was postulated to be mixed, with spiders leaving unfavourable conditions, but also with opportunistic dispersal for adult females that could immediately colonise new habitat opportunities (Topping and Sunderland, 1998).

2.3.3 Environmental factors

Unfortunately, the precise effect of a combination of pesticide, landscape and agricultural practice dynamics is difficult to determine in advance, even for a single species. In the long-term simulations for *Bembidion* and *Erigone* species (Topping et al., 2014), the differences in effects caused by the different dispersal abilities of the two species disappeared as the environmental persistence of the PPP increased. When the DT50 was changed from 1 to 10 days, the difference between spider and beetle population effects almost disappeared; the explanation being that the spider immigrants were killed by the prolonged exposure when they entered the field, and the local source of colonisers was depleted. Thus, long-term persistence negated the benefit of dispersal. Therefore, pesticide persistence is an important factor to consider as it can create ecological traps (Topping et al., 2014).

2.3.4 In- and off field

Currently, the risk assessment of PPPs is carried out separately for in-field and off-field areas and in different ways (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015). This can provide a reliable assessment for those species that spend their entire life in the in-field area and do not disperse. However, few species spend their whole life in an in-field area and many species disperse between in-field and off-field areas. As a result, exposure models are not accurate and the same individual may be exposed via multiple pathways depending on its activity, life stage and phenology. Therefore, the current risk assessment methodology does not provide a good estimate of the impact of PPPs (EFSA Scientific Committee, 2016).

NTAs and most other species will use resources from both on and off-site areas, with their decision to move from one area to another based on the risk associated with the landscape type. Therefore, it is important to consider the spatial and temporal dynamics in a landscape when conducting a risk assessment (Topping et al., 2015). As mentioned above, this potential for over-dispersal has been recognised for some years in population dynamics and depends on a balance between dispersal and environmental hostility (Bascompte and Sole, 1994). However, the precise interaction will be very specific for species/environment combinations, depending on habitat choice, habitat quality, and dispersal ability and behaviour.

2.3.5 Landscape management/structure and sink-source dynamics

Agriculture plays an important role in changing landscape structure and management, and therefore the pattern of suitable and hostile habitats available for NTAs. Consequently, it is important for the spatial dynamics of NTAs and their ability to recover after pesticide exposure (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015).

Agricultural intensification has led to many changes in landscape structure, resulting in a simplification of the landscape (Kautz and Gardiner, 2019; Togni et al., 2019) from small fields intertwined with refuges such as forests, meadows, and lakes to large fields with little off-field area. Crop composition is also an important consideration - the landscape can be dominated by single-crop monocultures or have multiple crop types. Source-sink dynamics are directly linked to this habitat structure and therefore change over time. Thus, source populations depend on higher quality habitats to sustain their population growth, whereas sink populations live in the lower quality habitats and can only persist if the source populations maintain a positive growth rate (Heinrichs et al., 2016). If these high-quality patches are lost, the population growth rate may become negative, pushing the population towards extinction. Therefore, the overall landscape context and its dynamics are very important in the relationship between habitat and population density (Iles et al., 2018).

Conventional intensive agriculture often results in a homogeneous and simplified landscape structure. Populations in these agricultural landscapes are often fragmented and exposed to a variety of stressors, mostly in the form of PPPs, but also general agricultural management, e.g., soil management. This can lead to interesting spatial dynamics. For example, sink populations in a fragmented landscape can act as bridges between source populations, thereby enhancing the persistence of a species by facilitating dispersal between spatially structured populations (Heinrichs et al., 2015).

However, crops are not permanent habitats and go through a cycle of sowing and harvesting each year, so they are not able to sustain NTA populations continuously (Duflot et al., 2016; Togni et al., 2019). This may also contribute to movement between fields and source-sink dynamics (Duflot et al., 2016). Note here that, contrary to the usual assumptions about source-sink populations, the dynamic nature of crop rotation means that source and sink populations vary in location in both time and space.

In all cases, source populations in the landscape are essential to protect populations from extinction. In agricultural landscapes, it is therefore necessary to maintain high quality habitats (refugia), otherwise the source population and thus the sink populations in the landscape will be lost (EFSA Scientific Committee, 2016). This is because refugia can support a source population, which in turn can support sink populations, despite large losses, e.g., due to pesticide exposure. Without refuges, source populations will be lost, and the entire regional population will disappear (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015).

Different habitats can be considered as good refuges for NTAs, but it is important to ensure that the habitat type actually supports the species exposed to pesticides. In general, forests (Togni et al., 2019), semi-natural meadows and semi-natural grasslands are considered good refuges for arthropods as they provide flowering plants and host plants (Kalarus et al., 2019). However, most forest species will not venture into agricultural fields, and even grassland species may avoid cultivated areas. Therefore, a useful management to create refugia in landscapes lacking them is the establishment of 'buffer strips', as they can provide suitable habitat for many relevant NTA species (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015).

2.3.6 Spatial and temporal dynamics impact on NTAs

Agricultural landscapes are structured in many ways and can range from homogeneous to heterogeneous in both physical structure and crop composition. As landscape composition can strongly modify the effect of pesticides on NTA populations, it is necessary to look at the composition of in- and off-field areas and how they interact with NTA population dynamics to properly understand how NTA populations are affected (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015).

Structure and time are also important for aquatic habitats. In streams, exposure largely consists of a wide variety of individual stressors that last for short periods of time, but the high number of compounds can have a severe impact. In ponds, the situation is the opposite - NTAs are exposed to fewer pesticides because the pond water comes from a smaller area, but the exposure time is much longer. Most aquatic NTAs are less affected in flowing habitats than in standing ones, because the longer persistence time in standing water means a lower chance of recovery (EFSA Scientific Committee, 2016). Conversely, if the organism is highly mobile, recovery through colonisation may occur as long as there are sufficient source habitats to provide colonists.

The dispersal ability of NTAs has the greatest impact on their ability to respond to the composition of in- and off-field habitats in the landscape. Species that are highly mobile can use different landscape elements compared to those with low dispersal ability (Bianchi et al., 2006). Therefore, the impact of pesticides on highly mobile NTAs cannot be adequately assessed by in-field effects. To assess the population as a whole, off-field effects must be included. This makes it difficult to estimate the impact on the whole population, and because the in-field population can act as a sink, the impact on the off-field population can be underestimated (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015).

It is difficult to see experimentally how landscape dynamics affect the effects of pesticides on populations. However, this has been demonstrated by Topping et al. (2015), who modelled the beetle *B. lampros* in two different landscapes with annual pesticide applications over ten years. The model showed that the impact of pesticides was reduced when there was suitable overwintering and breeding habitat around fields, such as field boundaries. Similarly, the addition of field boundaries reduced impacts in both landscapes. Overall, the model showed that landscape structure modifies pesticide effects at the population level. In order to interpret the effects on populations in space and time, the study used the Abundance–Occupancy Relationship (AOR) index (Hoye et al., 2012). This describes changes in distribution (occupancy) and mean density where it occurs (abundance). In the first landscape, Herning, pesticide use had the greatest effect on abundance, while in the second landscape, Præstø, the greatest effect was on occupancy. This difference was caused by the different initial conditions in the two landscapes. In Herning, the in-field populations were small and supported by large off-field populations. Over time, as these source populations were depleted, but still supplied individuals to the fields, there was little range contraction but a large change in abundance. In Præstø, there were no large source habitats, so the impact from year to year resulted in a range contraction where local in-field populations could no longer survive.

The study by (Topping et al., 2015) also demonstrated the importance of grassy field boundaries, which provide food and refuge habitats. By adding these areas to the agricultural landscape, it should be possible to maintain sustainable local populations while continuing to use pesticides in moderation. This was confirmed by a recent study under Polish conditions using the same model species (Ziółkowska et al., 2021). A similar conclusion was reached under Dutch conditions, but it was found that reducing the toxicity of pesticides led to a wider distribution in the landscape, whereas supporting current population abundance was best managed by adding field boundaries (Ziółkowska et al., 2022). In this study, the addition of wider field boundaries improved population stability in Polish landscapes but was less effective than reducing pesticide toxicity. As in previous studies, the combination of landscape structure and management interacted with beetle ecology, resulting in different impacts and responses in different landscapes. In general, however, the effectiveness of mitigation measures depended strongly on landscape heterogeneity (Ziółkowska et al., 2022; Ziółkowska et al., 2021).

Clearly, suitable field boundaries are not a panacea, and even a complex landscape might not always guarantee recovery. Yang et al. (2019) looked at the pesticide impact on the ladybird

Harmonia axyridis in a complex landscape and found that though the ladybird possessed the traits which should mitigate the negative impact (high dispersal, good recolonization chances), its populations were not able to recover. To explain this Yang et al. (2019) suggested three hypotheses: i) the unexposed population in the off-field area was not large enough to make up for the lost individuals; ii) the timespan in which the ladybirds could recolonize the field was too short, as the wheat field had a short growing period; iii) the ladybird did not try to recolonize the field, as the off-field area provided better prey resources, as the prey in-field had been killed.

Nevertheless, it can be generally concluded that a more complex landscape helps NTA to mitigate the negative impacts of pesticides (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015). However, as shown by Topping et al. (2014), Topping et al. (2015), Yang et al. (2019) and Ziółkowska et al. (2021), if pesticide doses are too high or too frequent, the off-field population may not be able to recolonize the in-field areas and thereby will not compensate for the loss of individuals caused by pesticide exposure. The ultimate result is a consequence of the balance between dispersal, mortality, and the benefits of finding new habitats; this relates directly to the over-dispersal concept.

2.4 Recovery

Currently, the ERA allows for the recovery option for NTAs, whereby if a population can be shown to return to the normal pre-exposure operating range within a specified timeframe, then the effect is considered acceptable. This aspect is addressed in detail in the relevant EFSA outputs (Brock et al., 2018; EFSA Scientific Committee, 2016). It is inextricably linked to the issue of population and spatial dynamics and the pattern of stressor use.

When a species is exposed to pesticides or other stressors, its life history traits determine the extent to which it is affected, and these traits, together with landscape structure and the persistence of the stressor, determine whether and when an individual or population can recover. Species traits can be defined as related to recovery through time, and landscape structure as related to recovery through space. Recovery with time and recovery with space are also referred to as internal and external recovery, respectively (Brock et al., 2018; EFSA Panel on Plant Protection Products and their Residues (PPR), 2015; EFSA Scientific Committee, 2016). Species traits associated with internal recovery are generation time, reproductive rate, and life stage resilience. In addition, the external factor of stressor persistence is of great importance in determining the impact. If generation time is short, the population has a higher chance of recovery as the new generation replaces the stressor-affected generation; conversely, long generation time reduces the chance of reproductive events between exposures. Reproductive rate works in a similar way to generation time: the more offspring produced, the more can replace those lost, increasing the number of reproductive events between exposures. Resistance of life stages to pesticides can vary widely, so the effect of PPPs on a population will depend on which life stage was exposed, which is a micro-timing issue. The persistence of the stressor in turn determines the length of time the population is exposed to the stressor and ultimately controls its chances of recovery by increasing the impact with persistence. If the stressor persists over many generations, it will continue to affect new generations, further hindering the population's recovery.

External recovery with space is controlled by individual home range, habitat or food preferences, dispersal ability, refuge availability and spatial scale of exposure. If the home range is small, the entire home range may be exposed to the stressor and the population may not be able to escape. The importance of habitat or food preference stems from the fact that if a specialised species loses its habitat or food source due to pesticide exposure, it may be critical to its survival. In contrast, high dispersal ability gives the exposed population a greater chance of recolonisation from source populations. The availability of refugia, in turn, provides an opportunity to avoid exposure if part of the home range is exposed to a stressor and to survive until the stressor has disappeared. In addition, connectivity to refuges implies a higher probability of immigration from a source population (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015; EFSA Scientific Committee, 2016; Yang et al., 2019). Finally, the spatial scale of exposure is important because if the area exposed is very large, and even more so if it is synchronised in time, it may be impossible for the population to escape the stressor and their chances of recovery will be low (EFSA Panel on Plant Protection Products and their Residues (PPR), 2015; EFSA Scientific Committee, 2016).

For NTAs, simulation studies of the univoltine carabid beetle B. lampros (Topping et al., 2014; Topping and Lagisz, 2012) showed that both impacts, and recovery were dependent on application duration, treated area, spatial distribution of the stressor, beetle dispersal and underlying habitat suitability. Stressor effects were detected well beyond the application area, and the magnitude was influenced by beetle dispersal and landscape structure. The results show that modelled recovery was primarily influenced by reinvasion, which depleted surrounding areas, calling into question the validity of the recovery endpoint as assessed in field trials. To demonstrate this effect, a simulated recovery experiment was scaled up to represent the effects of the same assumptions used at the landscape scale (Topping et al., 2014). The results showed that at the temporal and spatial scale of the ERA, the overall assessment of population effects was very under-protective.

If the aim is to reduce the impact of pesticides and comply with the EC 91/414 Regulation, there should be no unacceptable impact on non-target species. Source populations are needed to replenish populations recovering from a stressor. In today's agricultural landscape, refuges can be a way of maintaining these source populations. To support this, we need a better understanding of the connectivity of habitats, resources, and environmental stressors in a dynamic landscape to assess the potential for external recovery (EFSA Scientific Committee, 2016).

2.5 Conclusion

Repeated exposure to pesticides that cause repeated mortality in a 'sink' area can, for some species, eventually lead to a decline in the source populations. This happens when the reproductive rate of the source population is not high enough to keep up with the losses in the sink populations (EFSA Scientific Committee, 2016). The situation where a source population that has not itself been exposed to pesticides starts to decline is the phenomenon of action at a distance (Brock et al., 2018; Uhl and Brühl, 2019).

This review shows that the spatial dynamics of NTA species are influenced by landscape structure, and that the interactions between dynamics and environment influence the risk associated with pesticide use. Landscape structure influences spatial dynamics by altering connectivity, dispersal mortality and dispersal distances, and local habitat conditions. At the same time, species ecology and behaviour will determine both the spatial movements and growth rate of local populations and their vulnerability to pesticide use.

Consequently, there is no simple answer to the question of the importance of spatial dynamics for the environmental risk assessment of pesticides for NTAs. Within the same species, different conditions of environmental structure and pesticide use will lead to different effects, and it will not be possible to generalise these results to all NTAs. Different species will respond differently to the same landscape configurations due to different habitat affinities and responses to habitat quality and stressor effects. Tipping points in population dynamics are likely to occur, but when they occur will depend on specific species/landscape/stressor combinations. Indeed, it has been suggested that local-scale drivers are likely to be responsible for many population trends associated with insect declines (van Klink et al., 2020).

If action is taken at a distance, it may ultimately control the extent to which the NTA population is affected. It may facilitate exposure in areas considered safe, and if it is not included in the assessment, unanticipated subpopulation effects could occur, eventually leading to tipping points and population collapse. The only way to do this is to include landscape-level risk assessments that include landscape characteristics such as configuration, connectivity, and refugia, in effect moving towards a landscape management system (Topping et al., 2015). However, this approach needs to be species-specific and the extent to which results can be extrapolated to other NTAs needs to be critically examined.

3 Methods

Simulations were performed using the ALMaSS system, being an open source project available on GitLab (https://gitlab.com/ALMaSS/) with online documentation (https://projects.au.dk/almass/documentation/) based on the ODdox (Overview Design doxygen) protocol (Topping et al., 2010). ALMaSS integrates agent-based models of selected species with a detailed description of an environment (landscape) from which the model individuals obtain the information needed for the simulation of their behaviour.

The methods are divided into three sections describing (i) the design of a landscape model in ALMaSS and its parameterisation for German landscapes, (ii) the landscapes studied and their characteristics, (iii) the species model used and its calibration to German climatic conditions, and (iv) scenario design and analysis to evaluate mitigation strategies and landscape impacts.

The generation of the ALMaSS landscape models for Germany and therefore the simulation runs were limited to the regions of Brandenburg and Lower Saxony due to the availability of agricultural and animal data from the Integrated Administration and Control System (IACS).

3.1 Parametrization of the ALMaSS landscape component for the German landscapes

3.1.1 Dynamic landscape model in ALMaSS

In ALMaSS, landscapes are modelled using a detailed spatiotemporal representation that provides a highly realistic, daily updated, dynamic environment for agent-based simulations of the focal species (Topping et al., 2016). This representation consists of two components, spatial and temporal. The spatial component is a detailed raster land cover map with full coverage and a spatial resolution of 1 m2. Each landscape element in this map is classified according to its type (e.g., natural, or permanent grassland, field in rotation, built-up area). Fine-scale landscape elements important for focal species, such as hedgerows or field margins, are also included. Agricultural land is modelled with particular care, with individual fields assigned to farm units (where a farm unit is defined as a group of fields managed by the same farmer) of different types, e.g., arable, vegetable or livestock. This allows information on farm management to be incorporated into the description of spatial heterogeneity at a given point in time (Topping et al., 2003, 2016). On the other hand, the temporal landscape component allows modelling changes in the pattern of crops and farming practices over space and time. It includes crop management plans, which describe crop-specific agricultural practices throughout the year, as well as the cropping system, understood as a multi-year crop rotation. Changes in the growth of modelled vegetation types and crops (height, green and total biomass) are tracked on a daily basis and respond to weather conditions (daily mean temperature, daily mean wind speed and daily sum of precipitation) (Topping et al., 2016).

3.1.2 'Capturing' the German agricultural system

All details of the ALMaSS landscape model generation for Germany are described in Appendix A, and an overview is provided here. The approach broadly followed the methodology described in Topping et al. (2016) and was based on previous experience with landscape model generation for Denmark (Topping et al., 2016), Poland (Ziółkowska et al., 2021) and the Netherlands (Ziółkowska et al., 2022). It was divided into the following subtasks: (i) spatial and non-spatial data collection and quality control, (ii) generation of ALMaSS landscape maps (spatial component), and (iii) incorporation of crop management and vegetation growth (dynamic component).

Four main types of data were collected and processed to obtain the necessary ALMaSS landscape inputs:

a) *Land cover / land use information.* The data were derived from the Digital Basic-Landscape model (Basis-DLM) for the year 2019, which is part of the Authorative Topographic-Cartographic Information System (ATKIS) of the Federal Republic of Germany (https://www.adv-online.de/Products/Geotopography/Digital-Landscape-Models/Basis-DLM/). Basis-DLM describes the topographic objects of the landscape and the relief of the Earth's surface in vector format and is available for the entire territory of Germany. Basis-DLM groups objects into several types including: settlements (residential areas, industrial and commercial areas, sports, leisure, and recreational areas, etc.), communications (roads, railways), vegetation (agriculture, forests, heath, etc), water (watercourses, canals, harbour basins, etc.), buildings and other facilities, and others. For more detailed mapping of buildings, the data from the Federal Agency for Cartography and Geodesy (BKG, 2016) were used. As Basis-DLM has limited data on some important landscape elements, such as hedges and rows of trees, these were supplemented with information available through the Land Parcel Identification System (LPIS; see below).

   Individual layers of land use/land cover information, together with information on agricultural fields (details below), were then combined into a single raster landscape map in a stepwise process. The use of layers from different data sources resulted in inconsistencies in the spatial alignment of features (overlaps or gaps between features). In addition, some objects were represented as points or lines and therefore had to be pre-processed to make them two-dimensional. This process also contributed to the number of inconsistencies in the combined layers map. Therefore, a special step-by-step procedure was applied to intelligently correct these inconsistencies in order to obtain a landscape raster map without information gaps (see details in Appendix A).

b) *Agricultural and animal data from the Integrated Administration and Control System (IACS).* IACS provides the highest spatial and temporal resolution for deriving crop information per field at farm level. LPIS is a part of IACS responsible for the agricultural reference parcels (geographically delimited areas with unique identification codes) in the EU Member States and serves as a control mechanism under the Common Agricultural Policy (CAP). In Germany, IACS/LPIS is managed at the level of the federal state. As this data is farm-related, it is not, or only partially, publicly available. However, it can be made available for scientific purposes within the framework of user agreements. In the present case, IACS/LPIS data for the year 2019 were acquired for two federal states: Lower Saxony and Brandenburg. From the IACS / LPIS data we used information on the type of crops grown on the reference parcels (from the register of direct payments), identification numbers of agricultural holdings, which allow the grouping of individual reference parcels into agricultural units. The system also records information on farm area, livestock, and farm type (conventional/organic). The field boundaries are provided in a vector format as a shapefile or geodatabase with corresponding attribute tables.

   The information on the number of animals and their share per farm, which is needed to define the types of farms in ALMaSS, is part of the LPIS dataset. For Brandenburg, the number of animals provided had to be converted into Livestock Units (LSU) on the basis of the EUROSTATS statistical glossary. The data for Lower Saxony were provided in both head and LSU values and the LSU coefficients were adjusted to the EUROSTAT coefficients.

   By combining crop and animal information it was possible to classify farms into nine main types such as pig, arable or cattle farms, which were further classified as either conventional or organic (18 types in total; see Annex A, Table A6). The rules used to classify the farms had to be very general because real farms tend not to fit exactly into pure farm type rules (e.g., many arable farms have some grazing animals for their own use, e.g., consumption). The rules we used are based on information on production on German farms by type of farming, based on data from the Farm Accountancy Data Network Public Database (FADN, 2018), and analysis of crop and animal data for 2018, and are described in Appendix A.

c) *Soil data.* The ALMaSS landscape simulator modifies the actual production on each field based on the dominant soil type. In addition, some operations carried out by farmers on the fields (e.g., type of tillage) may depend on the soil type. We used the 1:200,000 scale national soil map BUEK200 from the German Federal Institute for Geosciences and Natural Resources (BGR). In order to use the soil data, it was necessary to translate the national soil classification into an internationally used classification system of the FAO (2006), which is also used in the ALMaSS model for other countries (soil types according to e.g., "fine sand", "medium sand", "coarse sand", etc.).

d) *Up-to-date crop management plans.* These plans for the most important German field crops (asparagus, cabbage, carrots, annual grassland for silage, green fallow, perennial herbs, legumes, maize, maize for silage, peas, permanent grassland grazed, potatoes, potatoes for industry, spring barley, spring rye, strawberries, sugar beet, winter barley, winter rape, winter rye, winter triticale and winter wheat; under both conventional and organic management) including time windows and probabilities of occurrence of the main soil cultivation practices, as well as of the use of fertilizers and pesticides (together with information on the product used and its dosage) were provided by the Julius Kühn Institute (JKI) and derived from interviews with farmer advisors. Where necessary, additional information from the reports on methods of integrated plant production was included.

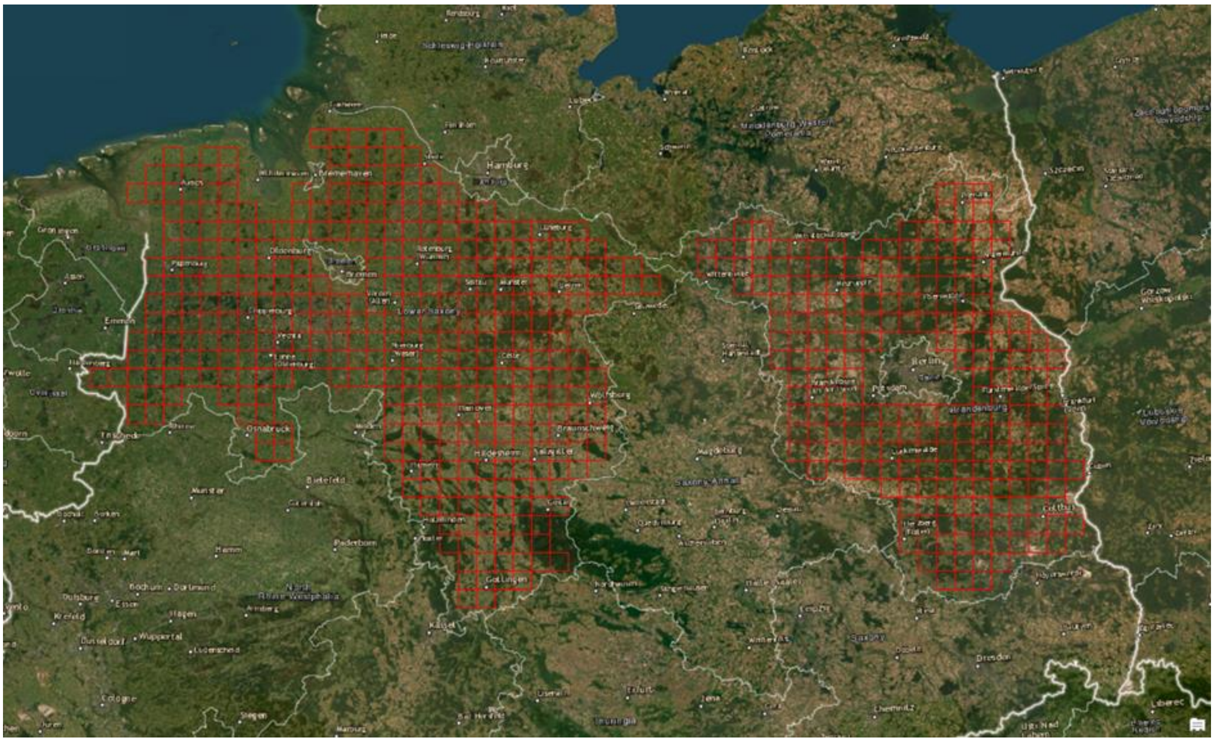
In ALMaSS each type of farm is associated with a crop rotation scheme. For the purpose of this project, 'artificial' rotation schemes were constructed based on the proportions of crops grown by the different farm types calculated from the IACS/LPIS data (Appendix A, Table A8). This means that each rotation scheme contained 100 crop entries, with the number of entries for each crop type corresponding to these pre-calculated proportions, i.e., one crop entry for every 1% of the area. At the start of each simulation, a random crop in the rotation was taken as the starting point for each arable field on a given farm, and the next crop in the list was assumed to be grown on the same field in the following year. The order of crops followed typical agronomic practices, and problems such as late harvest leading to impossible sowing conditions were handled by the built-in ALMaSS farm code. The result was a pattern of changing crops on a field that exactly matched the overall crop distribution pattern for that farm type over 100 seasons.

All spatial data handling and analysis was performed in Python 2.7 and the Python library arcpy for calling ArcGIS functions (ESRI, 2010), or directly in ArcGIS 10.4. Python scripts using the pandas tools (McKinney et al., 2010) were used to program the entire process of creating a German landscape model for ALMaSS. Any landscape in the regions of Brandenburg and Lower Saxony can be easily processed and used for simulation, as all procedures for generating German landscape models for ALMaSS are automated or semi-automated.

3.2 Study areas and their characteristics

For the modelling purposes, the regions of Lower Saxony and Brandenburg regions were divided into a regular grid of 611 non-overlapping study areas of 10x10 km each (see Figure 1). Each study area was characterised in terms of diversity, area, spatial arrangement of landscape elements, and farming intensity (Appendix B, Table B1). Landscape metrics were calculated at 1-m resolution using the GIS and the FRAGSTATS v4 software package (McGarigal et al. 2012).

Figure 1: Regular grids (red outlines) of 611 study areas of 10x10 km in the regions of Lower Saxony and Brandenburg.



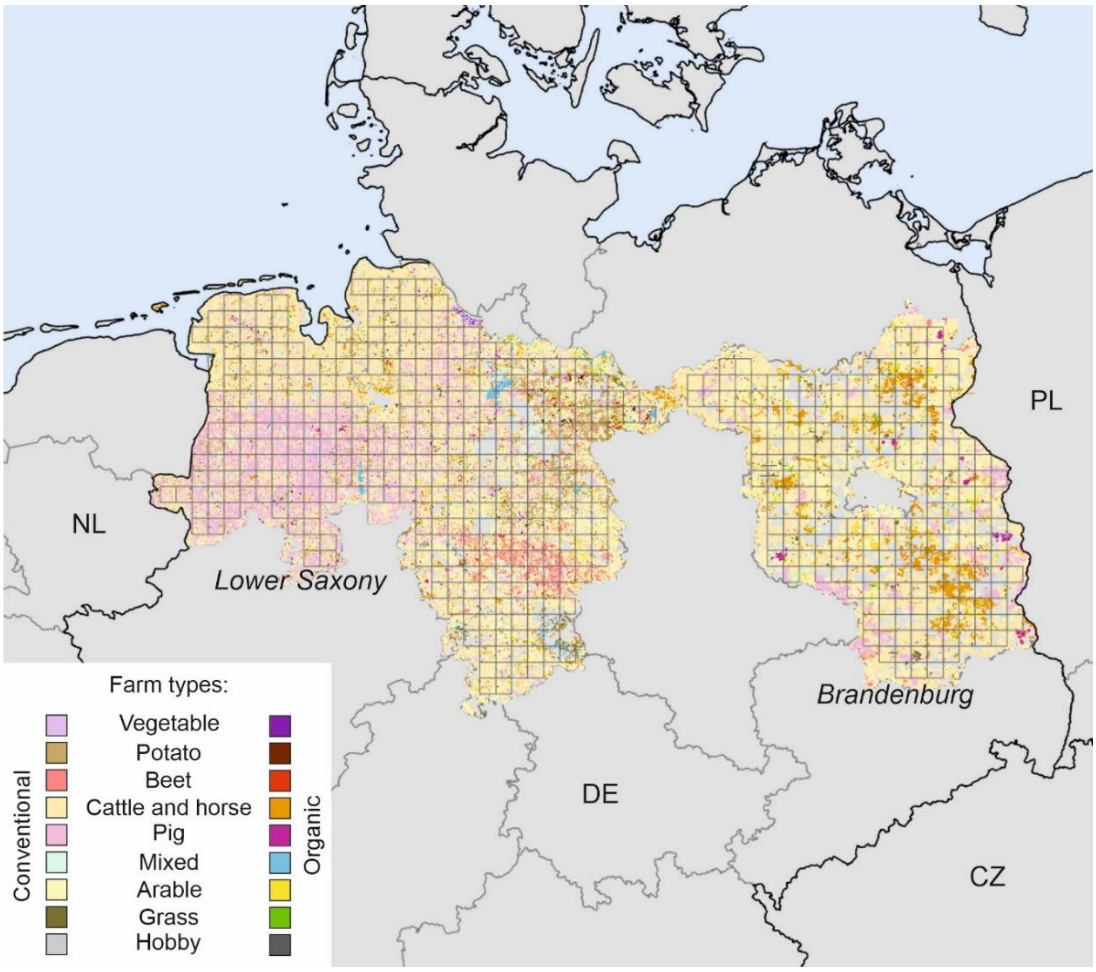
Source of background imagery: Sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.

The regions of Brandenburg and Lower Saxony differed considerably in terms of landscape and farmland heterogeneity (Figure 2, Figure 3 and Figure 4). In general, the study areas in the Brandenburg region represent relatively large-scale farming with a predominance of large fields (> 30% of the study areas have a mean field size of more than 10 ha). They are characterised by a low proportion of herbaceous semi-natural habitats (< 7% in all study areas), and a rather low proportion of permanent pastures (in 62% of the study areas the proportion of permanent pastures is less than 10%; Figure 4). Most of the study areas are dominated by conventional arable and cattle and horse farms. Organic farms (mainly cattle and horse) cover 12% of the agricultural area in Brandenburg (Figure 3). On the other hand, the study areas in Lower Saxony are dominated by medium and small fields (in all study areas the average field size was < 6 ha). They are characterised by a higher coverage of semi-natural herbaceous habitats and some of the study areas are dominated by permanent pastures (Figure 4). Although conventional arable farms dominate, there are visible sub-regions dominated by conventional pig farms (in the south-west) and conventional beet production (in the south-east). Cattle and horse farms also make a significant contribution. Organic farms (mainly cattle and horse) cover only 5% of the utilised agricultural area in the region of Lower Saxony (Figure 3).

Figure 2: Exemplary study areas from the regions of Brandenburg (left) and Lower Saxony (right). The difference in farming structure is clearly visible, with much larger fields present in Brandenburg compared to the more fine-scale farming in Lower Saxony.

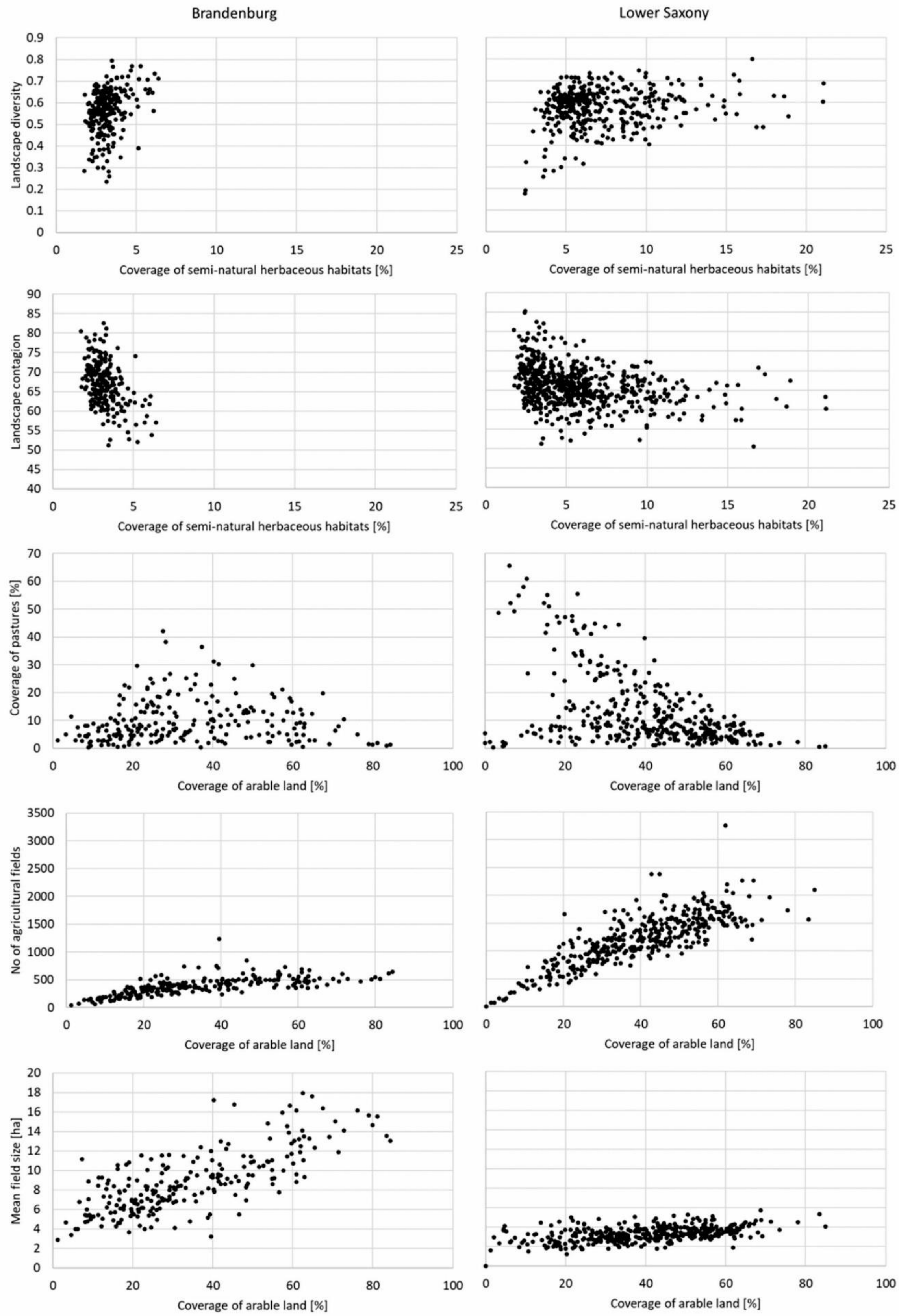
Source: Sources: Esri, DigitalGlobe, GeoEye, i-cubed, USDA FSA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community.

Figure 3: Types of farms delineated in the regions of Brandenburg and Lower Saxony.



Source: Authors' own.

Figure 4: Selected landscape metrics calculated for 230 study areas in the region of Brandenburg (left side) and 381 study areas in the region of Lower Saxony (right side).



Source: Authors' own.

3.2.1 Distinction of landscape types

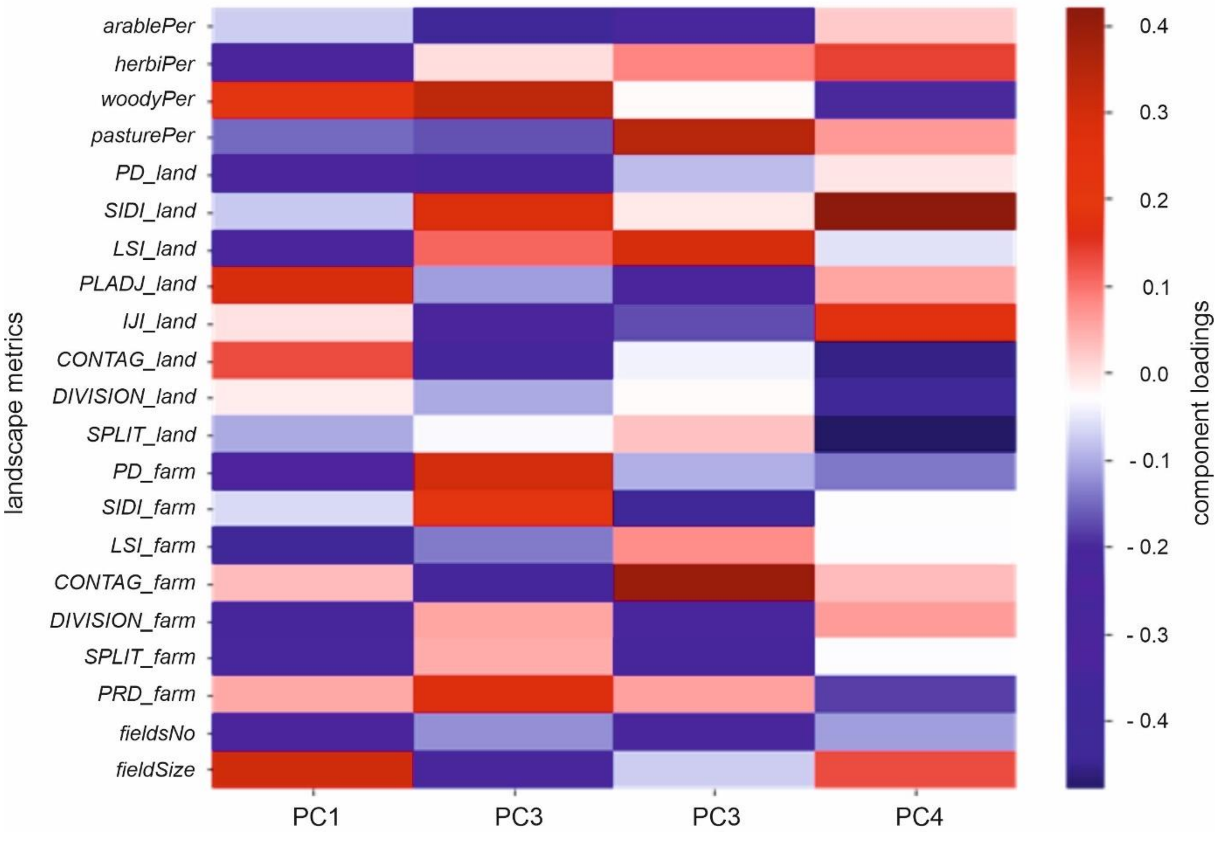
To divide the study areas into groups with similar landscape characteristics (i.e., to identify landscape types within the study areas), we combined principal component analysis (PCA) with unsupervised K-means clustering (Ding and He, 2004). K-means is a machine learning algorithm that assigns data points to clusters and attempts to minimise the variance within each cluster. Applying PCA prior to clustering aims to reduce noise in the input data and allows for improved clustering results.

We performed principal component analysis (PCA) on standardized landscape metrics (Appendix B, Table B1) to identify independent components of landscape and farmland structure that characterize our study areas. Metrics expressed as percentages were arc sin square root transformed prior to PCA. We applied the K-means clustering algorithm to four components, namely PC1, PC2, PC3 and PC4, which accounted for 31.0%, 16.7%, 14.9% and 10.9% of the total inertia in our data, respectively (73.5% of the total explained variance; Figure 5). PC1 was mainly driven by the spatial aggregation of farmland. It increased with decreasing subdivision and interspersion of farm types, as well as with decreasing number of fields and increasing size of fields. The configuration of landscape elements also affected PC1, as PC1 increased with increasing aggregation (both in terms of decreasing subdivision and interspersion) of landscape element types. In terms of landscape composition, PC1 was negatively correlated with the coverage of herbaceous semi-natural habitats. PC2 was mainly driven by landscape composition as it decreased with arable land coverage but increased with woody semi-natural habitat coverage. In addition, PC2 increased with increasing aggregation and diversity of landscape element types, and with decreasing aggregation of farm types. PC3 was mainly driven by the farmland diversity, but also by landscape composition. It increased with decreasing diversity of farm types and arable land coverage but increased with permanent pasture coverage. PC3 was also positively associated with the interspersion of landscape element types. PC4 was only driven by landscape (not farmland) configuration. It decreased with the diversity of landscape element types but increased with their fragmentation.

To determine the number of clusters in the K-means clustering algorithm, we ran the algorithm with different numbers of clusters (from 1 to 10) and determined the within-cluster sum of squares (WCSS), which is a measure of the variability of the observations within a cluster, for each solution. Based on the WCSS values and an approach known as the Elbow method, we decided to set the number of clusters to five.

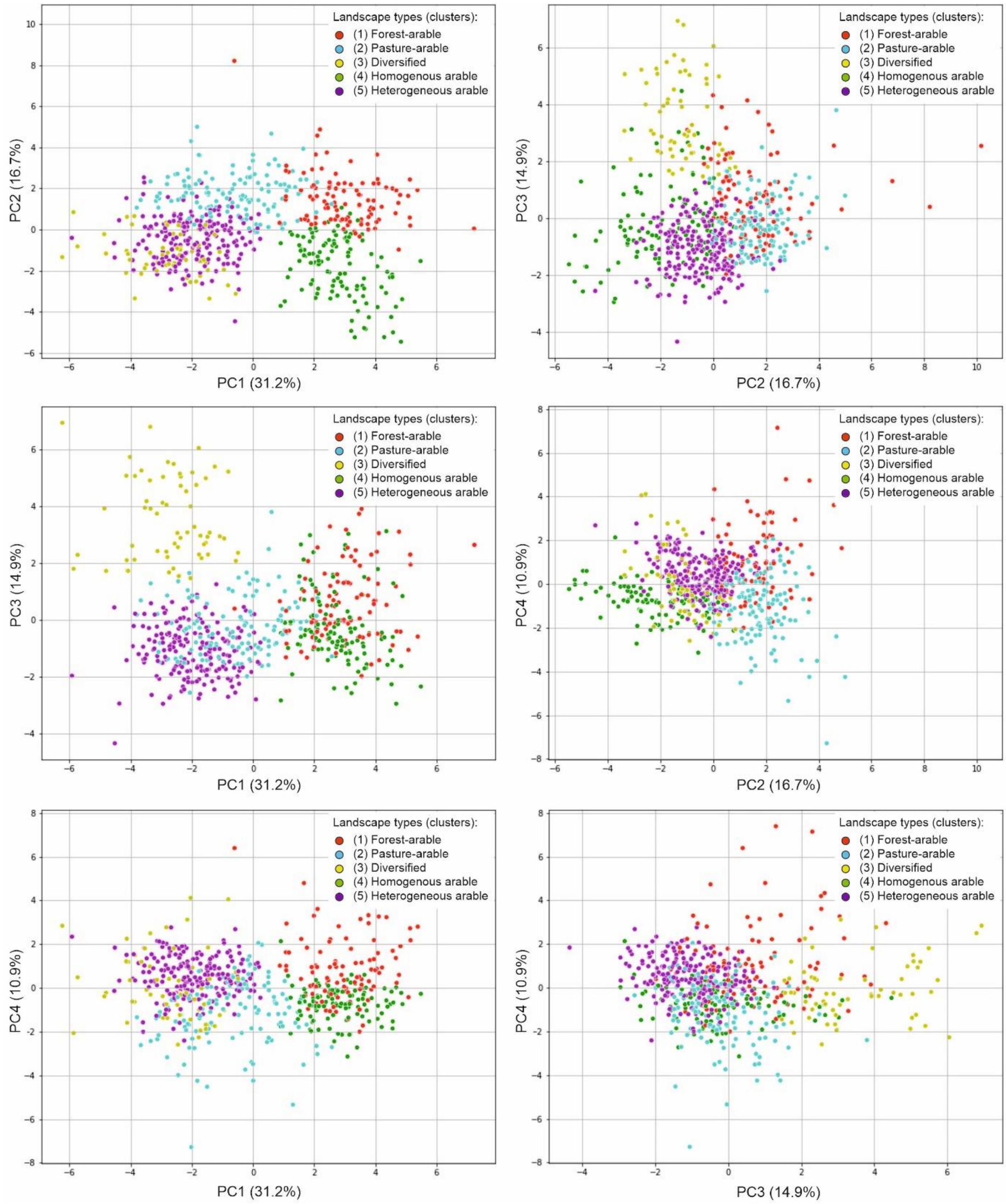
Based on the analysis of the delineated clusters in relation to the principal components of the landscape metrics (Figure 6), we distinguished the following types of landscapes within the study areas: (1) 'forest-arable', (2) 'pasture-arable', (3) 'diversified', (4) 'homogenous arable', and (5) 'heterogenous arable' (Table 1). The first type, 'forest-arable', is characterized by high coverage of woody semi-natural habitats (*woodyPer* > 40%) and low coverage of herbaceous semi-natural habitats (*herbiPer* < 5%). Arable land (*arablePer*) covers up to 40% and has a rather low fragmentation. The diversity of landscape element types varies in this landscape type, and landscape fragmentation could be from low to moderate. The second type, 'diversified', is characterized by a diverse structural composition and high landscape and farmland diversity with rather small or medium sized fields (2-10 ha). The third type, 'pasture-arable', has a low coverage of woody semi-natural areas (*woodyPer* < 20%) but a high coverage of pastures (*pasturePer* > 20%). As in 'forest-arable' landscape type, coverage of arable land does not exceed 40% but the fields are rather small (< 5 ha). The interspersion of both landscape element types (*LSI_land*) and of farm types (*LSI_farm*) is high in this landscape type. The fourth and fifth landscape types, 'homogenous arable' and 'heterogenous arable', are both characterized by a high coverage of arable land (*arablePer* > 40%) but differ greatly in terms of landscape and farmland heterogeneity. The ‘homogenous arable’ type is characterized by a small number of fields of rather medium to large size fields (5-20 ha) and a high aggregation of farm types (both in terms of low subdivision and low interspersion). In addition, the aggregation of landscape element types is moderate to high. The ‘heterogenous arable’ type, on the other hand, has a highly fragmented farmland, with a large number of small fields (2-5 ha) and a high diversity of farm types. The fragmentation of landscape element types is also high in this type, especially with regard to their subdivision.

Figure 5 Results of the principal component analysis (PCA) of study areas based on landscape metrics characterizing structural and farming heterogeneity: plot of correlation matrix for principal components (PC). Positive (red tones) and negative (blue tones) values in the component loadings reflect the positive and negative correlation of the variables with the PCs. Variables: *arablePer* – coverage of arable land, *herbiPer* – coverage of herbaceous semi-natural habitats, *woodyPer* – coverage of woody semi-natural habitats, *pasturePer* – coverage of permanent pastures, *PD_land* – patch density, *SIDI_land* – landscape diversity, *LSI_land* – landscape shape index, *PLADJ_land* – percentage of like adjacencies, *IJI_land* – interspersion and juxtaposition index, *CONTAG_land* – landscape contagion, *DIVISION_land* – landscape division, *SPLIT_land* – landscape splitting, *PD_farm* – farm type density, *SIDI_farm* – farming diversity, *LSI_farm* – farm shape index, *CONTAG_farm* – farm contagion, *DIVISION_farm* – farm division, *SPLIT_farm* – farm splitting, *PRD_farm* – farm richness density, *fieldsNo* – number of fields, *fieldSize* – mean field size. Description of landscape metrics is provided in Appendix B, Table B1.



Source: Authors’ own.

Figure 6 **Results of K-means clustering with principal component analysis of study areas based on landscape metrics characterizing structural and farming heterogeneity. Data points representing the study areas are plotted by principal components (PC) with assigned landscape types (clusters) marked by different colors. The following five landscape types (clusters) were delineated: (1) forest-arable, (2) pasture-arable, (3) diversified, (4) homogeneous arable and (5) heterogeneous arable. The characteristics of the different landscape types (clusters) are presented in Table 1.**



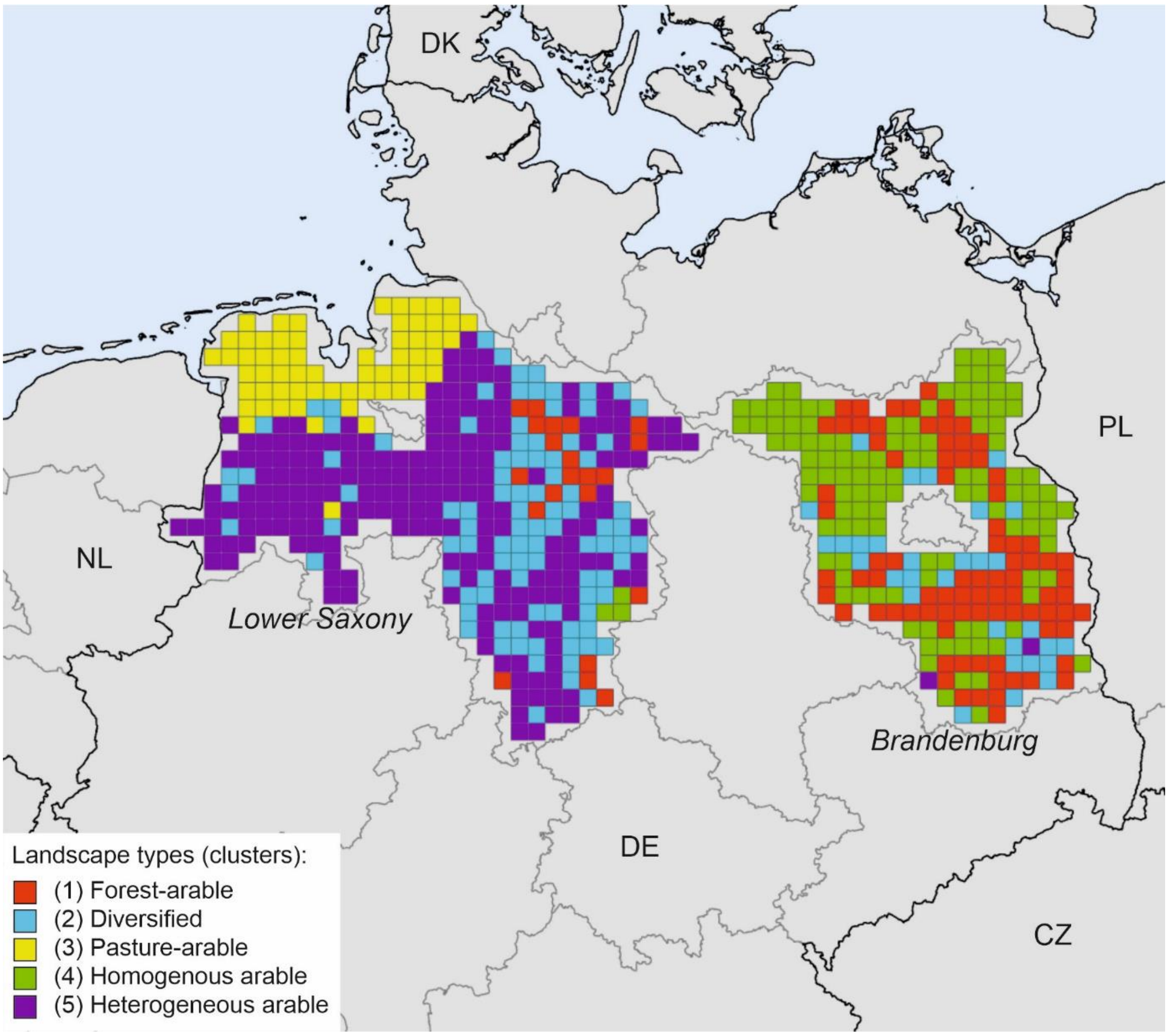
Source: Authors' own.

Table 1: Summary of landscape characteristics of designated landscape types (clusters) in the regions of Brandeburg and Lower Saxony: (1) forest-arable, (2) pasture-arable, (3) diversified, (4) homogeneous arable, and (5) heterogeneous arable. Variables: arablePer – coverage of arable land, herbiPer – coverage of herbaceous semi-natural habitats, woodyPer – coverage of woody semi-natural habitats, pasturePer – coverage of permanent pastures, PD_land – patch density, SIDI_land – landscape diversity, LSI_land – landscape shape index, PLADJ_land – percentage of like adjacencies, IJI_land – interspersion and juxtaposition index, CONTAG_land – landscape contagion, DIVISION_land – landscape division, SPLIT_land – landscape splitting, PD_farm – farm type density, SIDI_farm – farming diversity, LSI_farm – farm shape index, CONTAG_farm – farm contagion, DIVISION_farm – farm division, SPLIT_farm – farm splitting, PRD_farm – farm richness density, fieldsNo – number of fields, fieldSize – mean field size. Description of landscape metrics is provided in Appendix B, Table B1.

	COMPONENTS OF LANDSCAPE STRUCTURE	VARIABLE	LANDSCAPE TYPES (CLUSTERS) (1)	(2)	(3)	(4)	(5)
LANDSCAPE COMPOSITION		*arablePer*	< 40%	diverse	< 40%	> 40%	> 40%
		herbiPer	< 5%		diverse	< 5%	diverse
		woodyPer	> 40%		< 20%	0-50%	0-50%
		pasturePer	< 20%		> 20%	< 20%	< 20%
LANDSCAPE CONFIGURATION	LAND DIVERSITY	*SIDI_land* *CONTAG_land*	diverse	high	diverse	diverse	medium
	LAND AGGREGATION - SUBDIVISION	*PD_land* *DIVISION_land* *SPLIT_land*	small	medium	diverse	medium	high
	LAND AGGREGATION - INTERSPERSION	*LSI_land* *PLADJ_land* *IJI_land*	medium	medium	high	low	medium
	FARM DIVERSITY	*SIDI_farm* *CONTAG_farm* *PRD_farm*	diverse	high	diverse	diverse	high
	FARM AGGREGATION - SUBDIVISION	*PD_farm* *DIVISION_farm* *SPLIT_farm*	low	diverse	low to medium	low	diverse
	FIELDS AGGREGATION - SUBDIVISION	*fieldsNo*	< 500	< 1500	< 1500	200-700	> 1000
		fieldSize	diverse	2-10 ha	2-5 ha	5-20 ha	2-5 ha
	FARM AGGREGATION - INTERSPERSION	*LSI_farm*	low	medium	high	low	medium

The landscape types are not evenly distributed within the studied regions (Figure 7). In the Lower Saxony region 'heterogenous arable' type dominates (52% of the study areas belong to this type), followed by the 'diversified' type (25% of the study areas). The 'homogenous arable' type is almost absent in the Lower Saxony region (only three study areas were assigned to this type), whereas it dominates in the Brandenburg region (49% of study areas belong to this type). The 'forest-arable' type is the second dominant landscape type in the Brandeburg region (37% of study areas). The 'pasture-arable' type only occurs in the Lower Saxony region and is concentrated in its north-western part.

Figure 7 Distribution of delineated landscape types (clusters) within the regions of Brandenburg and Lower Saxony.



Source: Authors' own.

3.3 Overview of the carabid beetle model

Our model species was a small (~3-4 mm), univoltine, spring-breeding carabid beetle *Bembidion lampros*, a common species in temperate European agricultural landscapes. This species is considered to be a useful natural enemy of pests in agricultural fields, and relevant for risk assessment of pesticides according to the EFSA Scientific Opinion addressing the state of the science on risk assessment of plant protection products for non-target arthropods (EFSA 2015).

The original ALMaSS model for the carabid beetle *B. lampros* was described by Bilde and Topping (2004), and the online ODdox documentation is provided at https://sess_ac.gitlab.io/a1mass/almass_stable_oddox/_bembidion_page.html. The phenology of the species was calibrated for the German climatic conditions.

The *B. lampros* model represents four life stages: eggs, larvae, pupae, and adult females (males are not modelled as they do not limit the population size) as separately defined entities in the model. Due to the very high number of beetles in the real world, the model uses the concept of super individuals, meaning that each beetle agent in the model represents 100 real-world beetles (Topping et al., 2015). Beetles overwinter as adults in aggregations and begin dispersing to agricultural fields and other open areas from mid/end March (depending on weather conditions), with peak reproduction in mid-summer (Wallin et al., 1992). The new generation of adults appears from late summer to early autumn and begins its autumn migration to overwintering sites (grassy field boundaries and hedgerows) in early October. The behaviour of the beetles is modelled on a daily basis. The developmental rates of eggs, larvae and pupae are temperature dependent (defined according to Boye Jensen, 1990 and Bilde et al., 2000). Adult females interact with the environment (landscape) in various ways, e.g., they may die in response to agricultural activities in the field (e.g., tillage or harvesting; Thorbek and Bilde, 2004) or due to unfavourable temperatures and conditions during overwintering (Petersen, 1996). At high densities, the model invokes density dependence via intraspecific predation.

The response to the pesticide is incorporated into the model through the assumption of a threshold environmental concentration above which there is a daily probability of mortality (p). The following equation is used to calculate this probability:

$$(1-m) = (1-p)^d, \qquad \text{Equation [1]}$$

where m is the proportion of beetles assumed to die (e.g., 0.8 for 80% mortality over the test period) and d is the number of days over which the test was carried out. This means that a beetle in a given 1 m^2 grid cell of a landscape is assumed to die with probability p if an environmental concentration in that location is above a trigger threshold. The maximum mortality rate is set as m over d days, as no dose-response is assumed.

3.4 Simulation scenarios

3.4.1 Application of pesticides

Exposure in the model is determined based on the predicted environmental concentration at the location of an individual beetle over time. The concentration is based on the implementation of a detailed pesticide application model as described in the EFSA NTA SO recommendations. This approach divides the applied pesticide into soil and vegetation compartments and models the degradation of the pesticide in these compartments over time. The exposure pattern therefore integrates the application schedule in space and time with the location and life stage of the NTA and environmental degradation as determined by weather conditions. The exposure model runs at a very fine resolution (1 m) and can therefore represent fine-scale distributions of the pesticide that may be relevant to field boundary conditions.

3.4.1.1 Pesticide toxicity levels

The pesticide properties were chosen both to highlight the issues to be addressed and to be realistic. We assumed that normal fungicide and herbicide applications would have no effect on carabid beetles. Insecticides were applied to all crops according to normal practice in the region (according to crop management plans; Table 2).

For the insecticides, we chose a single toxicity level defined as an insecticide-driven beetle field lethality rate (LR) of 80%, measured for a foliar insecticide spray application over 10 days. This gives a daily beetle mortality probability p of 0.1489.

3.4.1.2 Environmental decay values

We used one environmental decay value (DT_{50}) at 20°C of 10 days.

The temperature dependence of the DT_{50} value in ALMaSS was defined as follows (EFSA 2007):

$$DT_{50}(t) = DT50(20°) \times \exp[0.094779 \times (20°-t)] \qquad \text{Equation [2]}$$

where *t* is a given mean daily temperature.

An application rate of twice the trigger concentration was used for all crops to ensure that beetles could be exposed above the trigger threshold for at least the period defined by DT_{50}=10 days, with an LR of 80%.

In all scenarios, spray drift up to 12 m from the edge of each sprayed field was considered, following the equation of Rautmann et al. (2001) with a reduction of 90% (a reduction of 50% is considered to be the minimum requirement for sprayers in field crops using modern sprayers) (JKI, 2020).

Table 2: Summary of main crops with insecticide applications defined according to the crop management plans provided by the Julius Kühn Institute (JKI) based on interviews with farmer advisors.

Crop	Brandeburg		Lower Saxony		Assumed probability in model runs	
	Cropped area in 2019 rounded (in 1000 ha)	% of arable land reported in LPIS (i.e., w/o permanent crops)	Cropped area in 2019 rounded (in 1000 ha)	% of arable land reported in LPIS (i.e., w/o permanent crops)	Timing	Application probability (% of farmers applying)
Wheat	1761	18.1	4115	21.4	Autumn	0.05
					Spring	0.50
					Summer	0.25
Barley	1092	11.2	2076	10.8	Autumn	0.10
					Spring	0.10
Maize	2293	23.5	6177	32.0	-	0
Winter oilseed rape	66	6.8	71	3.7	Autumn I	0.90
					Autumn II	0.10
					Autumn III	0.05
					Spring I	0.90
					Spring II	0.80
Potatoes	114	1.3	1318	6.8	Spring / Summer	0.75
Sugar beet	8	0.8	106	5.5	Spring	0.50
					Summer	0.05

Brandenburg:
[1] Wheat = summer durum wheat (64 ha), winter wheat (173621 ha), summer wheat (2447 ha), winter emmer wheat (4 ha), summer emmer wheat (15 ha)
[2] Barley = winter barley (103807 ha) + summer barley (5620 ha)
[3] Maize = maize (22966 ha) + maize for biogas (48898 ha) + silage maize (157590 ha)
[4] Potatoes = starch potatoes (8719 ha) + potatoes for consumption (1961 ha) + seed potatoes (550 ha) + other potatoes (1242 ha) + silage potatoes (15 ha)
Lower Saxony:
[5] Wheat = winter durum wheat (12179 ha) + summer durum wheat (266 ha), winter wheat (394924 ha), summer wheat (3898 ha), winter emmer wheat (21 ha), summer emmer wheat (1 ha)
[6] Barley = winter barley (162595 ha) + summer barley (44605 ha)
[7] Maize = maize (75302 ha) + maize for biogas (126267 ha) + silage maize (415112 ha)
[8] Potatoes = starch potatoes (84164 ha) + potatoes for consumption (39426 ha) + seed potatoes (7347 ha) + other potatoes (227 ha) + silage potatoes (2 ha)

3.4.2 Landscape-related mitigation measures

The ALMaSS landscape model for each study area of 10x10 km2 ('Regular') was used in two artificially manipulated forms to reduce the risk of pesticide use. The first was the creation of grassy field boundaries in the field around the crops (landscape-related scenario 'FB'). These are strips created in the field and managed as permanent grass strips. They are not subject to the same agricultural practices as the crop itself, such as soil cultivation, harvesting or pesticide application. The second was to leave parts of the crop untreated, i.e., to create within-field no-spray strips. These unsprayed field margins would be managed in the same way as the crop but would not be exposed to pesticides (landscape-related scenario 'UM'). To investigate the effectiveness of these mitigation measures, grassy field boundaries and unsprayed field margins of 10 m width were applied to all fields larger than 1 ha and wider than 40 m. Grassy field boundaries were not added where the field already bordered a grass field boundary or other herbaceous habitat, such as managed or unmanaged grassland.

3.5 Other settings and replicates

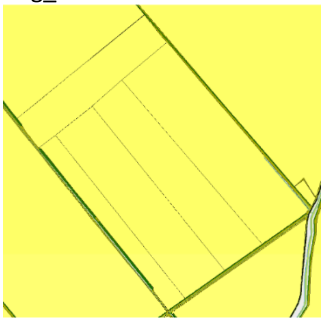
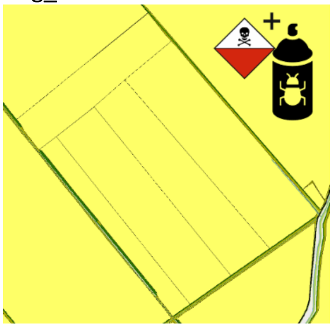
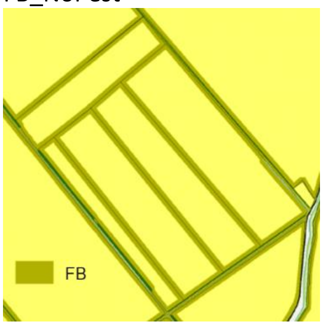
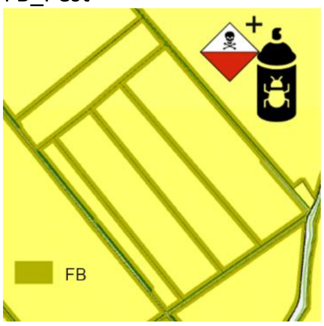
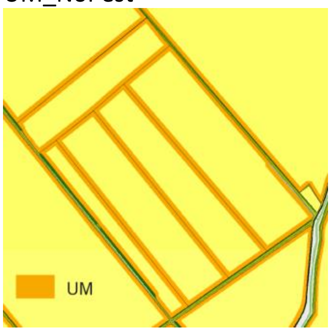
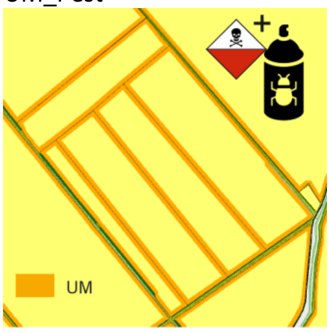
We run a fully factorial experiment combining all study areas and scenarios (Table 3). It should be noted, however, that for the species analysed, the 'UM_NoPest' scenario gives the same results as the 'Reg_NoPest' scenario (because unsprayed field margins are still subject to normal agricultural practices, including soil cultivation, which affects beetle mortality). Therefore, the 'UM_NoPest' and 'Reg_NoPest' scenarios were not compared.

In addition, for two exemplary landscapes (study area no. 113 from the region of Brandenburg and study area no. 534 from the region of Lower Saxony) with an arable land coverage of 84-85%, the same factorial experiment was carried out, but with the assumption of a winter wheat monoculture and a modified pesticide scenario. Both normal pesticide application (5% of farmers applying insecticide after sowing, 50% of farmers applying insecticide in May and 25% of farmers applying insecticide in June) and forcing 100% probability of all three applications were tested. The results allowed us to investigate the impact of pesticides and the effectiveness of mitigation measures in an extreme scenario (where arable land covers most of the study area and all fields are treated with pesticides) and compare it with the realistic scenario of pesticide use presented above.

All simulation runs were performed over 30 simulation years with no burn-in period. Due to the large number of study areas processed (611), the number of replicates for each scenario combination (see Table 3) was limited to two replicates. We believe that this is a sufficient number of replicates, as Tooping et al. (2015) showed that the variability between replicates is very low in the case of the Bembidion model. In addition, for ten selected landscapes, all scenario combinations were replicated five times and within-subject coefficient of variation for the analysed endpoints (see below) was reported. Each simulation started with the same number of super-individuals (200 000 per 100 km^2), with beetles randomly distributed over suitable habitats within the study area. Although the initial number of super-individuals was always the same, beetle populations approached densities that were independent of the initial population size after a few years of simulation runs.

Weather conditions were chosen to represent the period 2009-2019 and were defined individually for each of the 10x10 km2 study areas using the ERA5-Land dataset (Muñoz Sabater 2021).

Table 3: Summary of applied simulation scenarios.

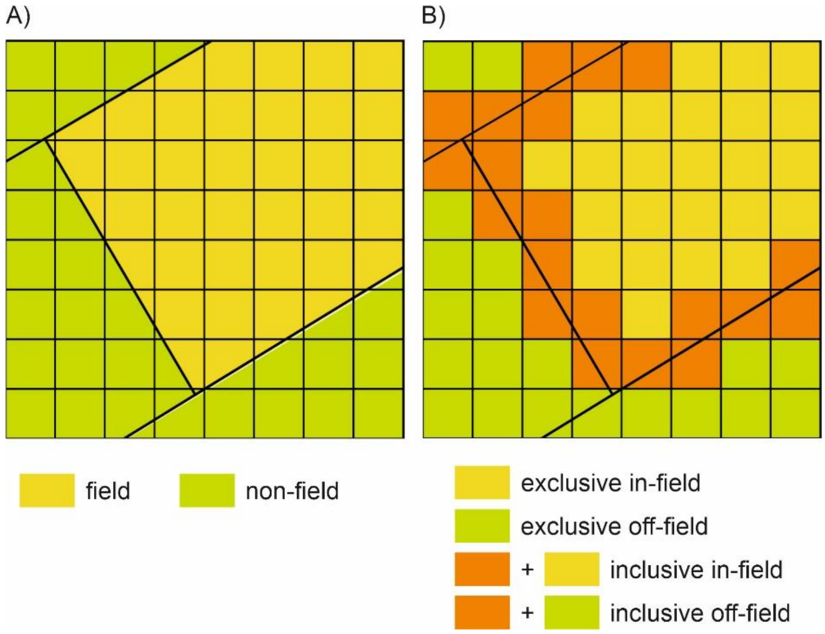
Landscape \ insecticide-related scenarios	Without insecticides ('NoPest')	With insecticides ('Pest')
Without changes ('Regular')	Reg_NoPest = BASELINE 	Reg_Pest 
With added grassy field boundaries ('FB')	FB_NoPest 	FB_Pest 
With added unsprayed crop margins ('UM')	UM_NoPest 	UM_Pest 

Source: Authors' own.

3.6 Simulation outputs and data analysis

From each simulation, three endpoints (*SE*) were analysed: (*SE1*) overall beetle population density (i.e., total number of adult female beetles divided by the landscape area, i.e. 100 km^2), (*SE2*) occupancy (i.e., beetle distribution defined as the proportion of grid cells in the landscape with at least 100 adult female beetles), and (*SE3*) abundance (mean density of adult females in the occupied areas). The latter two endpoints were presented as Abundance-Occupancy Relationship (AOR) plots (Høye et al., 2012). Although the spatial resolution of the landscape model in ALMaSS is 1 m^2, grid cells of 50 m^2 were used for the calculation of occupancy and abundance. Overall beetle population density and beetle abundance and occupancy were measured on day 185 of each year (4th July) of each simulation, and then averaged over the last 10 years of the simulations. The 4th of July was chosen to ensure a high number of adult beetles in the landscape (second generation) and to ensure that beetles were present both in and out of field areas. Simulation endpoints were averaged across replicate runs for each scenario. They were measured for the whole study area and within the in-field and off-field areas. In-field and off-field areas were delineated in two ways: (1) inclusive, i.e. all grid cells within fields or crossing the field boundary (inclusive in-field) or within non-arable land or crossing the boundary or non-arable land (inclusive off-field); or (2) exclusive, i.e. all grid cells completely within fields (exclusive in-field) or completely within non-arable land (exclusive off-field; Figure 8).

Figure 8: Definition of inclusive and exclusive in-field and off-field areas: (A) a grid of 50x50 m cells superimposed on the study area, (B) all the grid cells completely within the field / non-field area are defined as 'exclusive', and all the grid cells within the field / non-field area or crossing its border are defined as 'inclusive'.



Source: Authors' own.

The impact of each scenario *S* relative to the baseline was used and compared over time, separately for each of the study areas ($SA_{i=1…611}$), i.e., a relative change in each of the simulation endpoints ($SE_{j=1,2,3}$) to the baseline was calculated as:

*relative change of $SE_{j=1,2,3}$ in $SA_{i=1…611}$ = (endpoint $SE_{j=1,2,3}$ value in scenario S – endpoint $SE_{j=1,2,3}$ value in baseline)/ endpoint $SE_{j=1,2,3}$ value in baseline * 100 [%] Equation [3]*

The 'baseline' conditions were set to the scenario with no pesticide application and no changes in landscape structure (scenario 'Reg_NoPest', see Table 3).

In addition, the effectiveness of tested mitigation measures (grassy field boundaries and unsprayed field margins) was calculated as the reduction in the negative impact of pesticide use after application of the measure, i.e., the difference in the relative change in the simulation endpoints between 'Reg_Pest' and 'FB_Pest'/'UM_Pest'.

Importantly, only study areas with more than 30% arable land coverage (*n* = 392 out of 611) were included in the analysis of the impact of pesticide use on beetle populations ('Reg_Pest' scenario compared to baseline) and the effectiveness of the tested mitigation measures. This was due to the fact that in study areas with low arable land coverage, only a very small area was subject to pesticide spraying and therefore the impact on beetles was negligible.

The influence of metrics describing landscape and farmland heterogeneity (Appendix B, Table B1) on (1) simulation endpoints in the baseline scenario ('Reg_NoPest' scenario), and (2) changes in simulation endpoints in response to applied pesticides (scenario 'Reg_Pest' relative to 'Reg_NoPest'), and (3) changes in simulation endpoints in response to applied landscape-related mitigation measures (scenarios 'FB_Pest' and 'UM_Pest' relative to 'Reg_NoPest') was tested with multiple regression models. Thus, separate regression models were constructed for each of the simulation endpoints in the baseline scenario (to investigate factors driving beetle populations in landscapes without the added stressor of pesticides), as well as for relative changes in the simulation endpoints when comparing each of the applied scenarios to the baseline (to investigate factors favouring or disfavouring the observed changes). In the latter case, regression models were constructed both for all study areas analysed (i.e., all those with more than 30% arable land, n = 392 out of 611; see above) and for a subset of study areas with more than 60% arable land (n = 69). This was done to investigate how the effect of landscape metrics on the outcome of the population impact assessment depended on the range of landscapes considered.

Metrics of landscape and farmland heterogeneity were first checked for correlations (Appendix B, Table B2), and from each pair of highly correlated metrics (i.e., with a Pearson correlation coefficient $\geq |0.7|$), one metric was removed from the analysis. The decision on which metric to discard was guided by the ease of interpretation of the metric's properties. As a result, the following 13 metrics were used as explanatory variables in the regression analysis: coverage of arable land (*arablePer*), coverage of herbaceous semi-natural habitats (*herbiPer*), coverage of woody semi-natural habitats (*woodyPer*), coverage of permanent pastures (*pasturePer*), landscape diversity (*SIDI_land*), landscape shape index (*LSI_land*), interspersion and juxtaposition index (*IJI_land*), landscape division (*DIVISION_land*), landscape splitting (*SPLIT_land*), farm type density (*PRD_farm*), farming diversity (*SIDI_farm*), number of fields (*fieldsNo*), and mean field size (*fieldSize*).

Regression models were estimated using both non-standardised and standardised landscape variables. Models estimated using non-standardised variables can be used as predictors, while standardisation allows direct comparison of the importance (strength) of individual variables. After running the initial models, a backward stepwise selection procedure was used to remove non-significant variables, starting with those with the highest p-values, until only variables with $p \leq 0.05$ remained in the model, and the normal distribution of the residuals was formally tested using the Kolmogorov-Smirnov test. Dependent variables expressed as percentages (mean beetle occurrence) and proportions (ratio of 'off-field' to 'in-field' impacts) were transformed using the arcsine of the square root transformation (Zar, 1999). All statistical analyses were performed with Statgraphics 19.

4 Results

ALMaSS was used to simulate the effects of pesticides and the effectiveness of landscape-based mitigation measures (grassy field boundaries and unsprayed field margins) on *B. lampros* populations in 611 study areas with different landscape and farmland characteristics. Within-subject coefficients of variation calculated for simulation endpoints based on five replicates for the selected 10 study areas varied between simulation scenarios but were not greater than 2.6% for mean overall beetle population density, 1.4% for mean beetle abundance and 0.7% for mean beetle occupancy. This confirms that simulation replicates for the ALMaSS model of *B. lampros* are generally very similar and that a low number of replicates is sufficient.

4.1 Beetle populations under the baseline scenario

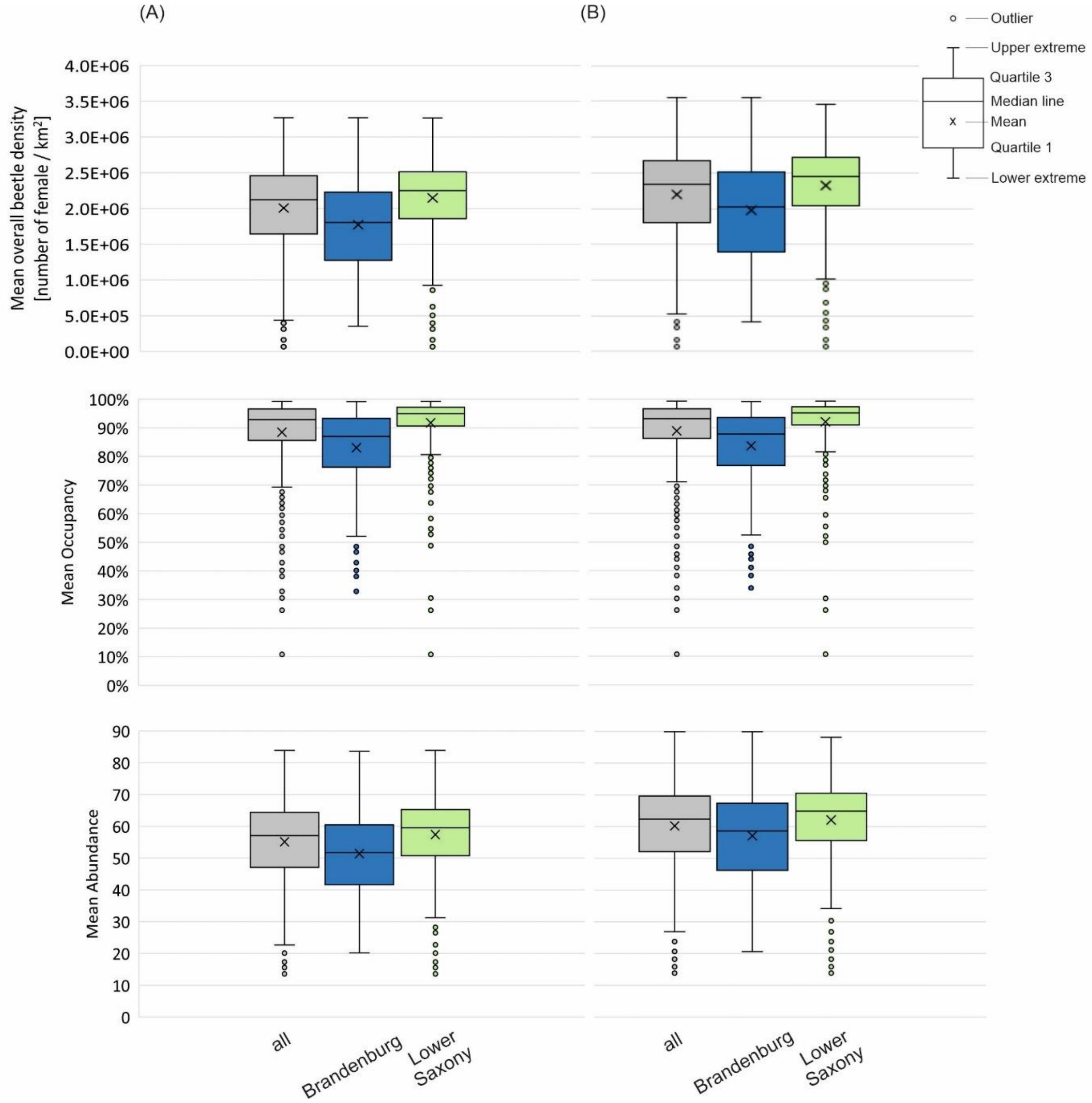
The beetle populations in the baseline scenario 'Reg_NoPest' varied considerably across selected study areas in both the Brandenburg and Lower Saxony regions (Figure 9), strongly depending on the landscape characteristics.

The final fitted regression model describing the relationship between the mean overall beetle density and landscape characteristics included 7 out of 13 input measures and explained 84.0% of the variability in the mean overall beetle density across studied landscapes (Appendix C, Table C1). The mean overall beetle density increased with the coverage of arable land (*arablePer*; $p < 0.001$) and permanent pastures (*pasturePer*; $p < 0.001$), as well as landscape diversity (*SIDI_land*; $p < 0.001$); and decreased with the coverage of the woody semi-natural habitats (*woodyPer*; $p < 0.001$), and landscape shape index (*LSI_land*; $p < 0.001$). The farmland heterogeneity also influenced beetle populations, i.e., populations were larger in study areas with higher farmland heterogeneity (*SIDI_farm*; $p = 0.028$) and consisting of rather small fields (*fieldSize*; $p < 0.001$; Figure 10). The beetle numbers were, however, manly driven by the share of arable land and pastures in the landscape, even if study areas with low coverage of arable land were excluded from the analysis (Appendix C, Table C1).

The final fitted regression model describing the relationship between the mean beetle Occupancy and landscape characteristics included 8 out of 13 input measures and explained 82.6% of the variability in the mean beetle Occupancy across studied landscapes. The mean beetle Occupancy increased with the coverage of the arable land (*arablePer*; $p < 0.001$), herbaceous semi-natural habitats (*herbiPer*; $p < 0.001$) and permanent pastures (*pasturePer*; $p < 0.001$), as well as landscape diversity (*SIDI_land*; $p < 0.001$) and landscape splitting (*SPLIT_land*; $p < 0.001$); and decreased with the coverage of the woody semi-natural habitats (*woodyPer*; $p = 0.005$), landscape aggregation (*IJI_land*; $p = 0.001$), and number of fields in the study area (*fieldsNo*; $p < 0.001$). The beetle occupancy was, however, manly driven by the share of arable land and pastures in the landscape. When excluding study areas with low coverage of arable land (< 30%), then farm richness density became an important explanatory variable with positive impact on beetle occupancy (Appendix C, Table C1)

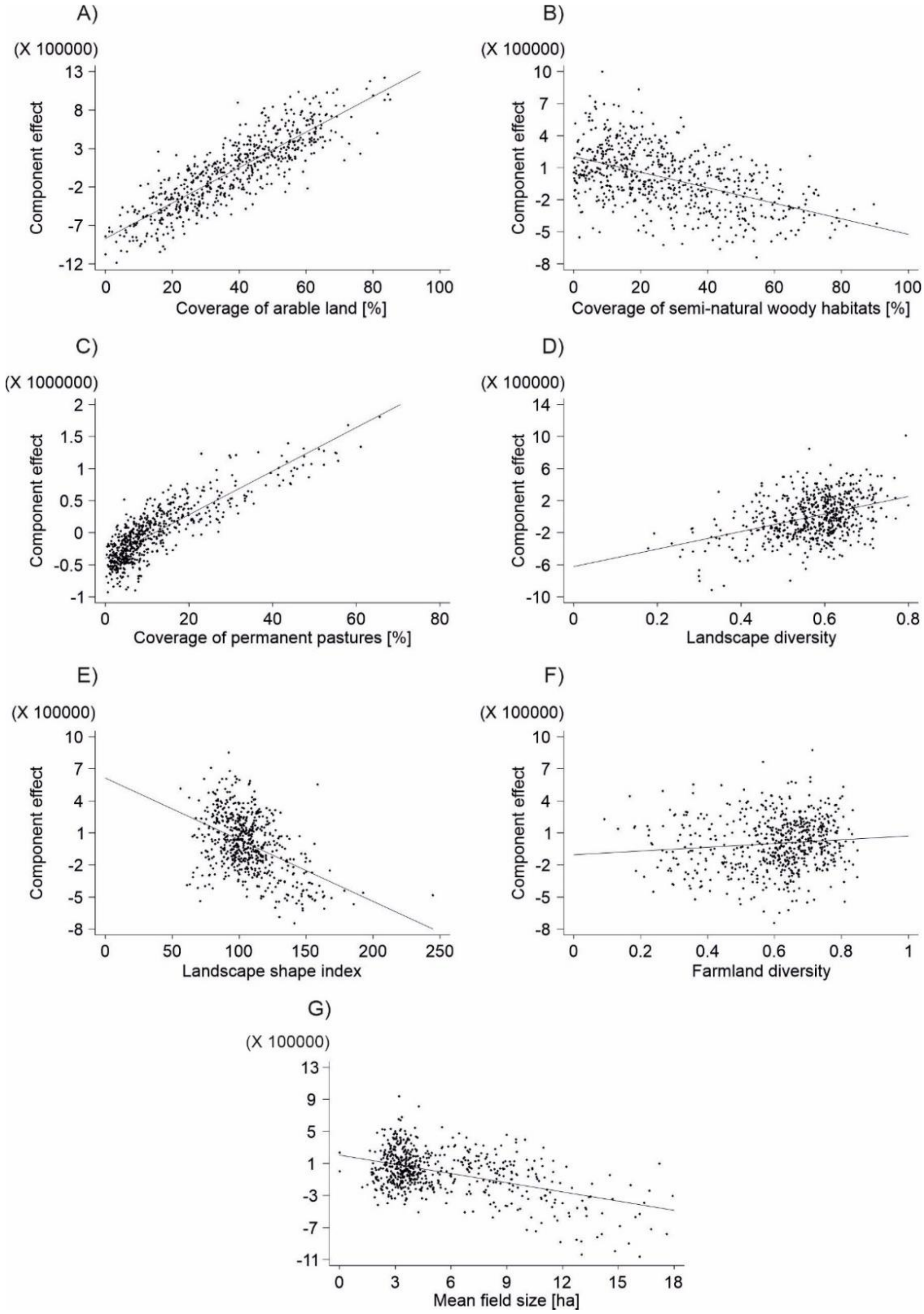
The final fitted regression model describing the relationship between the mean beetle Abundance and landscape characteristics included 8 out of 13 input measures and explained 79.1% of the variability in the mean beetle Abundance across studied landscapes. The mean beetle Abundance increased with the coverage of the arable land (*arablePer*; $p < 0.001$) and permanent pastures (*pasturePer*; $p < 0.001$), as well as landscape diversity (*SIDI_land*; $p < 0.001$) and landscape aggregation (*IJI_land*; $p = 0.025$); and decreased with the coverage of woody semi-natural habitats (*woodyPer*; $p = 0.002$), landscape division (*DIVISION_land*; $p = 0.012$) and landscape shape index (*LSI_land*; $p < 0.001$). The farmland heterogeneity also influenced mean beetle Abundance, i.e., abundance was higher in study areas consisting of smaller fields (*fieldSize*; $p < 0.001$). The beetle numbers were, however, manly driven by the share of arable land and pastures in the landscape, even if study areas with low coverage of arable land were excluded from the analysis (Appendix C, Table C1).

Figure 9: Variation in the mean beetle population density (no of female beetles / km2), Occupancy and Abundance in the study areas in the Brandenburg (n = 230) and Lower Saxony (n = 381) regions under the landscape-related scenarios: (A) baseline scenario 'Reg_NoPest', and (B) scenario with added grassy field boundaries 'FB_NoPest'. All study areas (n = 611) are included in the analysis.



Source: Authors' own.

Figure 10: Results of multiple regression analysis for the baseline ('Reg_NoPest') scenario: effects of (A) coverage of arable land (p < 0.001), (B) coverage of semi-natural woody habitats (p < 0.001), (C) coverage of permanent pastures (p < 0.001), (D) landscape diversity (p < 0.001), (E) landscape shape index (p < 0.001), (F) farmland diversity (p = 0.028), and (G) mean field size (p < 0.001) on the mean overall beetle density. The lines shows the relative change in the predicted values of mean overall beetle density that occurs when changing (A) coverage of arable land, (B) coverage of semi-natural woody habitats, (C) coverage of permanent pastures, (D) landscape diversity, (E) landscape shape index, (F) farmland diversity, and (G) mean field size over their observed ranges. The overall model including all these variables was significant at p < 0.001 and explained 84% of the variability.



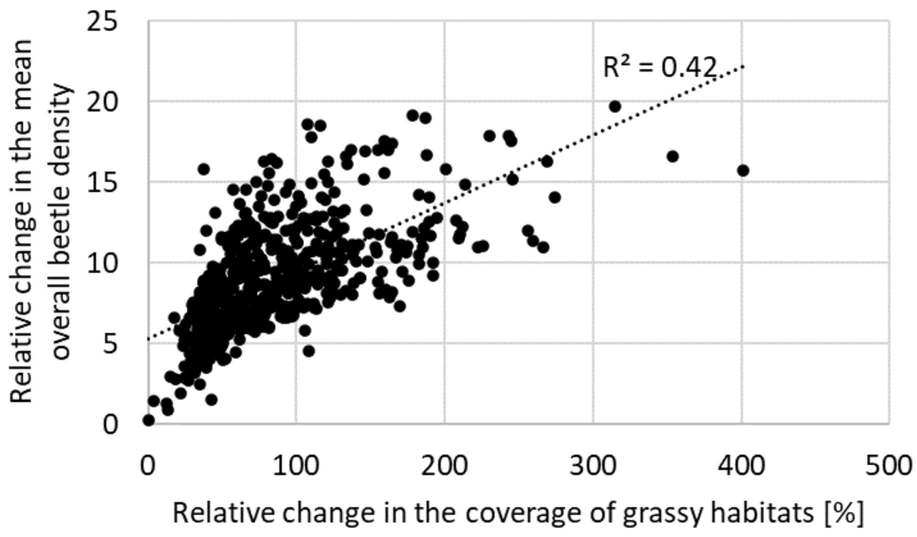
Source: Authors' own.

4.2 Impacts of grassy field boundaries on the beetle populations

Adding grassy field boundaries (scenario 'FB_NoPest) resulted in the increase of beetle populations in all the studied landscapes by on average 9.8% (maximum increase = 24.5%; Figure 9). Increase in beetle numbers was mainly due to an increase in the local beetle abundance, not the occupancy (Figure 9). As in most of the studied landscapes beetles already occupied most of the areas, changes in the occupancy were, on average, very low (< 1%). Only in four landscapes increase in beetle's occupancy exceeded 5% (study areas no. 29, 123, 225 and 548), but in all these study areas the initial beetle populations were very low and occupied < 50% of the area due to rather low coverage of arable land (~5-20%) and, at the same time, very low coverage of permanent pastures (< 1.5%) and herbaceous semi-natural habitats (< 2.5%). Additional grassy field boundaries added substantial proportion of habitats used for beetle's hibernation in these study areas.

The change in the mean overall beetle density due to including additional grassy field boundaries varied considerably among studied landscapes depending on the initial beetle numbers but also on composition and configuration of other landscape elements. In particular this change was related to the relative change in the coverage of grassy habitats (permanent pastures and herbaceous semi-natural habitats) (Figure 11).

Figure 11: Relative change in the mean overall beetle density in response to the relative change in the coverage of grassy habitats after including additional grassy field boundaries of 10-m width to all the fields in rotation larger than 10 ha and wider than 20 m.



Source: Authors' own.

4.3 Impacts of pesticide use on the beetle populations

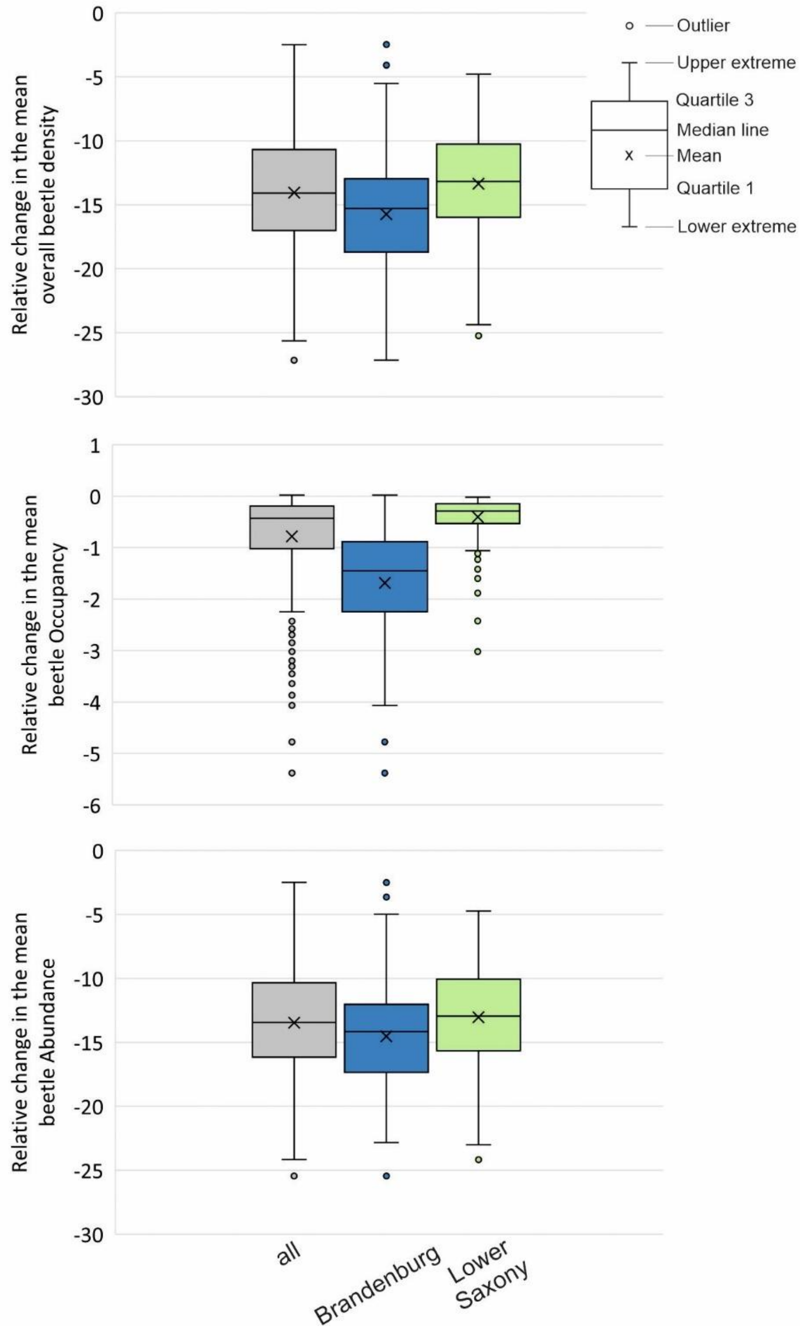
Under the pesticide scenario ('Reg_Pest'), beetle populations considerably decreased in all analysed study areas (the mean decrease was around 14.0%, slightly higher in the Brandenburg than the Lower Saxony region: 15.7% and 13.4% respectively), but the impacts varied across the study areas (from 2.5 to 27.2%; Figure 12). The decrease in beetle numbers was mainly due to a decrease in the local beetle abundance, not the occupancy, as the decrease in occupancy was on average lower than 1% (Figure 12).

The final fitted regression model describing the relationship between the relative change in the mean overall beetle density due to pesticide use and landscape characteristics included 6 out of 13 input measures and explained 70.0% of the variability in the relative change in the mean overall beetle density across studied landscapes. The negative impact of pesticide use on the mean overall beetle density increased with the coverage of arable land (*arablePer*; $p < 0.001$); and decreased with the coverage of herbaceous semi natural habitats (*herbiPer*; $p < 0.001$), coverage of permanent pastures (*pasturePer*; $p < 0.001$), landscape shape index (*LSI_land*, $p < 0.001$), interspersion and juxtaposition index (*IJI_land*; $p = 0.004$), and landscape splitting (*SPLIT_land*, $p < 0.001$) (Figure 13). The relative change in the beetle numbers was, however, manly driven by the share of arable land and pastures in the landscape. The positive impact of permanent pastures was more profound when study areas with more than 60% of arable land were analysed (Appendix C, Table C2). Interestingly, no significant relationship between farmland-related metrics and the relative change in mean overall beetle density was found.

The regression analysis for the relative change in the mean beetle Occupancy was only possible for the study areas with more than 60% of arable land (due to residuals not fulfilling the normal distribution condition in the regression analysis for the study areas with more than 30% of arable land). The final fitted regression model describing the relationship between the relative change in the mean beetle Occupancy due to pesticide use and landscape characteristics included 3 out of 13 input measures and explained only 82.8% of the variability in the relative change in the mean beetle Occupancy across studied landscapes. The negative impact of pesticide use on the mean beetle Occupancy increased with the mean field size (*fieldSize*; $p < 0.001$) and interspersion and juxtaposition index (*IJI_land*, $p = 0.034$); and decreased with the landscape division (*DIVISION_land*; $p = 0.003$) (Appendix C, Table C2).

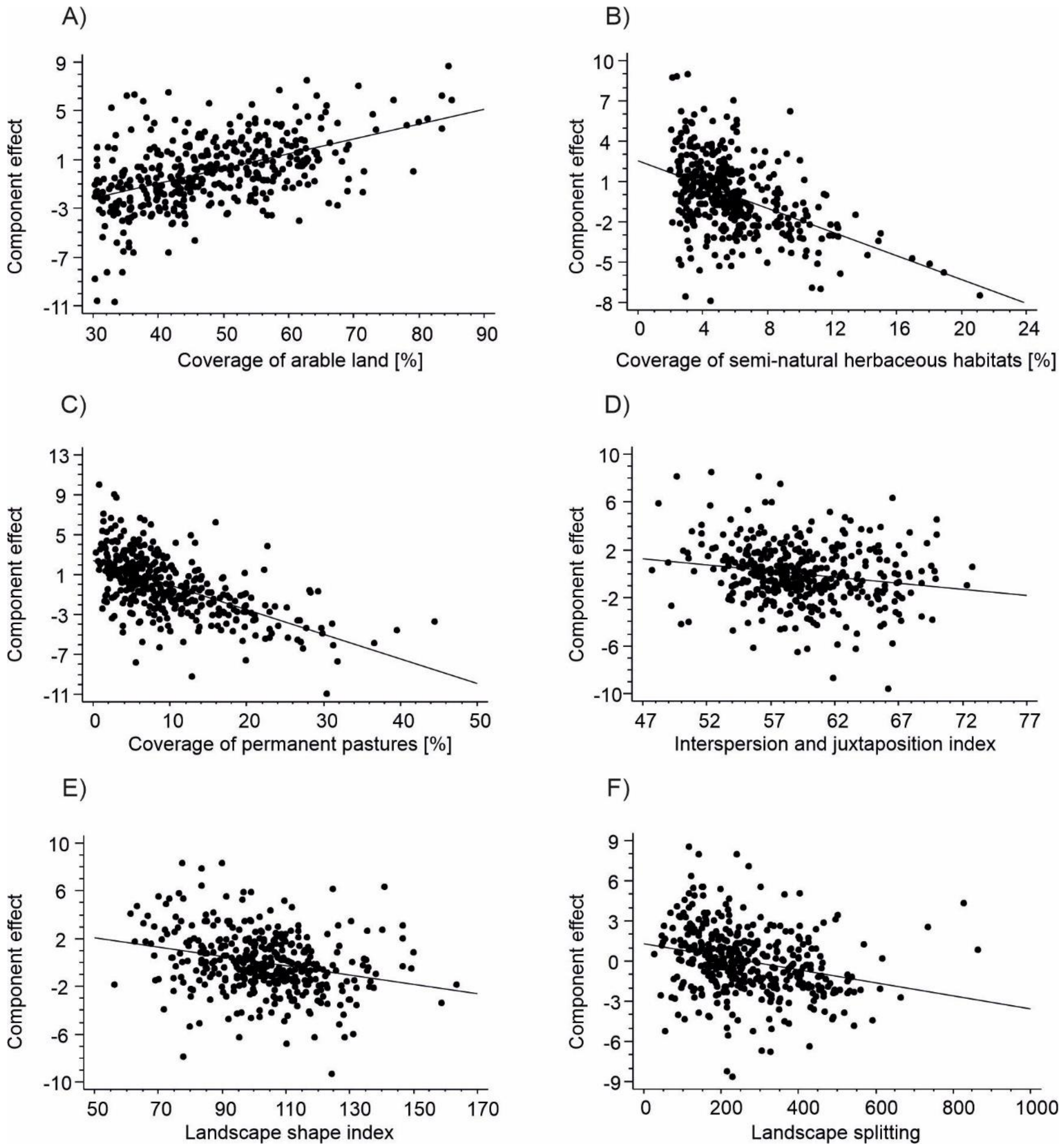
The final fitted regression model describing the relationship between the relative change in the mean beetle Abundance due to pesticide use and landscape characteristics included 7 out of 13 input measures and explained 70.4% of the variability in the relative change in the mean beetle Abundance across studied landscapes. The negative impact of pesticide use on the mean beetle Abundance increased with the coverage of arable land (*arablePer*; $p < 0.001$) and farm richness density (*PRD_farm*, $p = 0.049$); and decreased with the coverage of herbaceous semi natural habitats (*herbiPer*; $p < 0.001$), coverage of permanent pastures (*pasturePer*; $p < 0.001$), landscape shape index (*LSI_land*, $p = 0.005$), interspersion and juxtaposition index (*IJI_land*; $p = 0.002$) and landscape splitting (*SPLIT_land*, $p < 0.001$). The relative change in the beetle occupancy was, however, manly driven by the share of arable land and pastures in the landscape, and farm richness density. The positive impact of permanent pastures was more profound when study areas with more than 60% of arable land were analysed. At the same time, in study areas with high proportion of arable land, the impact of farm richness density became non-significant (Appendix C, Table C2).

Figure 12: Variation in the relative change in the mean beetle population density (no of female beetles / km2), mean Occupancy and mean Abundance after applying pesticides (scenario 'Reg_Pest' compared to 'Reg_NoPest'). Only study areas with coverage of arable land > 30% were included. That gives n = 115 study areas in the Brandenburg region, and n = 277 study areas in the Lower Saxony region.



Source: Authors' own.

Figure 13: Results of multiple regression analysis for the pesticide scenario ('Reg_Pest') scenario: effects of (A) coverage of arable land (*p* < 0.001), (B) coverage of semi-natural herbaceous habitats (*p* < 0.001), (C) coverage of permanent pastures (*p* < 0.001), (D) interspersion and juxtaposition index (*p* = 0.004), (E) landscape shape index (*p* < 0.001), and (F) landscape splitting (*p* < 0.001) on the relative change in the mean overall beetle density compared to the baseline scenario. The lines shows the relative change in the predicted values of relative change in the mean overall beetle density that occurs when changing (A) coverage of arable land, (B) coverage of semi-natural herbaceous habitats, (C) coverage of permanent pastures, (D) interspersion and juxtaposition index, (E) landscape shape index, and (F) landscape splitting over their observed ranges. The overall model including all these variables was significant at *p* < 0.001 and explained 70% of the variability.



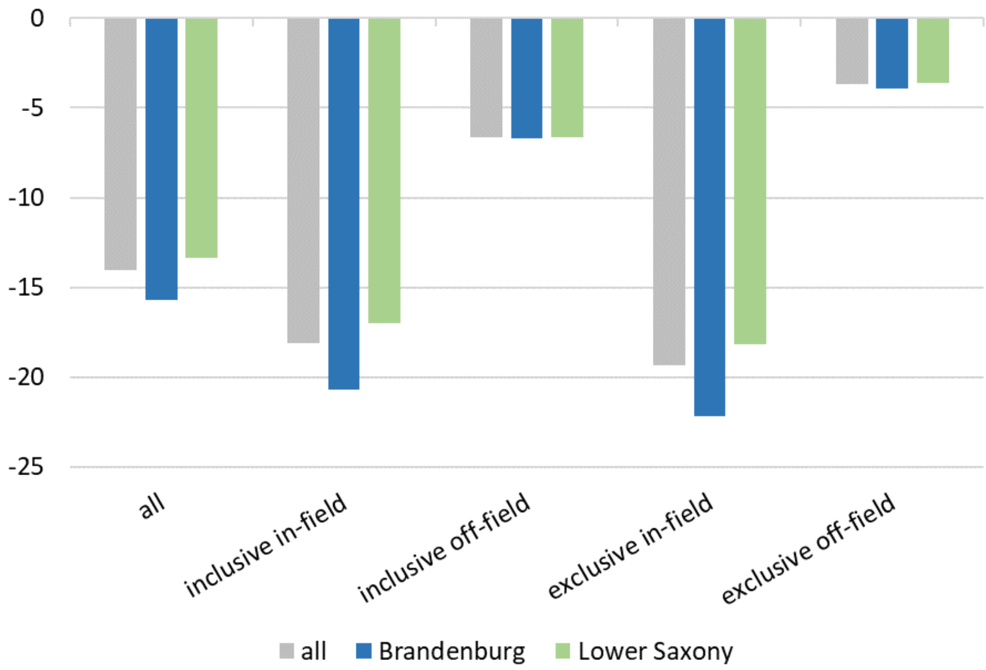
Source: Authors' own.

4.3.1 In-field and off-field impacts of pesticide use

Impacts of pesticide use on beetle populations was much higher in the in-field (mean decrease of 18.1%) than off-field areas (mean decrease of 6.7%; Figure 14). When analysing impacts in grid cells exclusively within the in-field and off-field areas, this difference even magnified (on average, 19.4% versus 3.7% decrease). Impacts of pesticide use noted in-field were larger in the Brandenburg than Lower Saxony region, while impacts in off-field areas were at the similar level (Figure 14). Importantly, the analysis showed that the level of impact varied considerably between the study areas (Figure 15, Figure 16). Although the decrease in the mean total beetle density in the exclusive off-field areas was less than 10% in most of the study areas, it reached extremely high values of 26% in some of them (Figure 15, Figure 16).

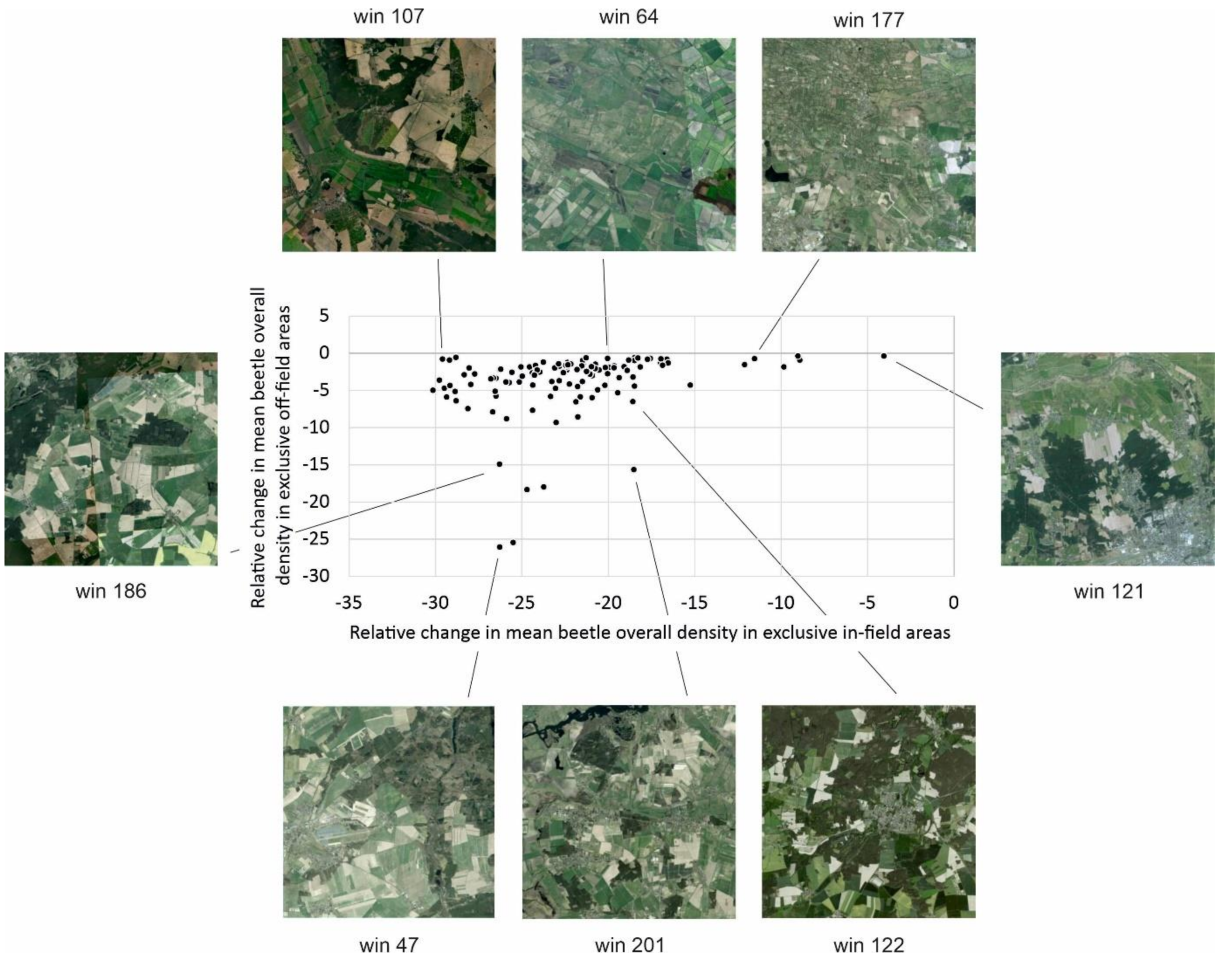
The impact ratio, i.e., ratio of off-field to in-field impacts of pesticide use on mean overall beetle density, differed among study areas (Figure 17). The regression analysis for the impact ratio was only possible for the study areas with more than 60% of arable land (due to residuals not fulfilling the normal distribution condition in the regression analysis for the study areas with more than 30% of arable land). Both ratio of inclusive and exclusive off-field to in-field impacts decreased with coverage of arable land (*arablePer*, $p < 0.001$), coverage of permanent pastures (*pasturePer*, $p < 0.001$) and landscape diversity (*SIDI_land*, $p < 0.001$). Ratio of inclusive off-field to in-field impacts increased with number of fields (*fieldsNo*, $p < 0.001$) while ratio of exclusive off-field to in-field impacts increased with farm type density (*PRD_farm*, $p < 0.001$). Regression analysis explained 65.7% and 38.4% of variability in ratio of inclusive and exclusive off-field to in-field impacts, respectively ($p < 0.001$).

Figure 14: Mean relative change [%] in the mean overall beetle density due to pesticide use in the studied landscapes: in-field versus off-field effects. Only study areas with more than 30% of arable land were taken into account.



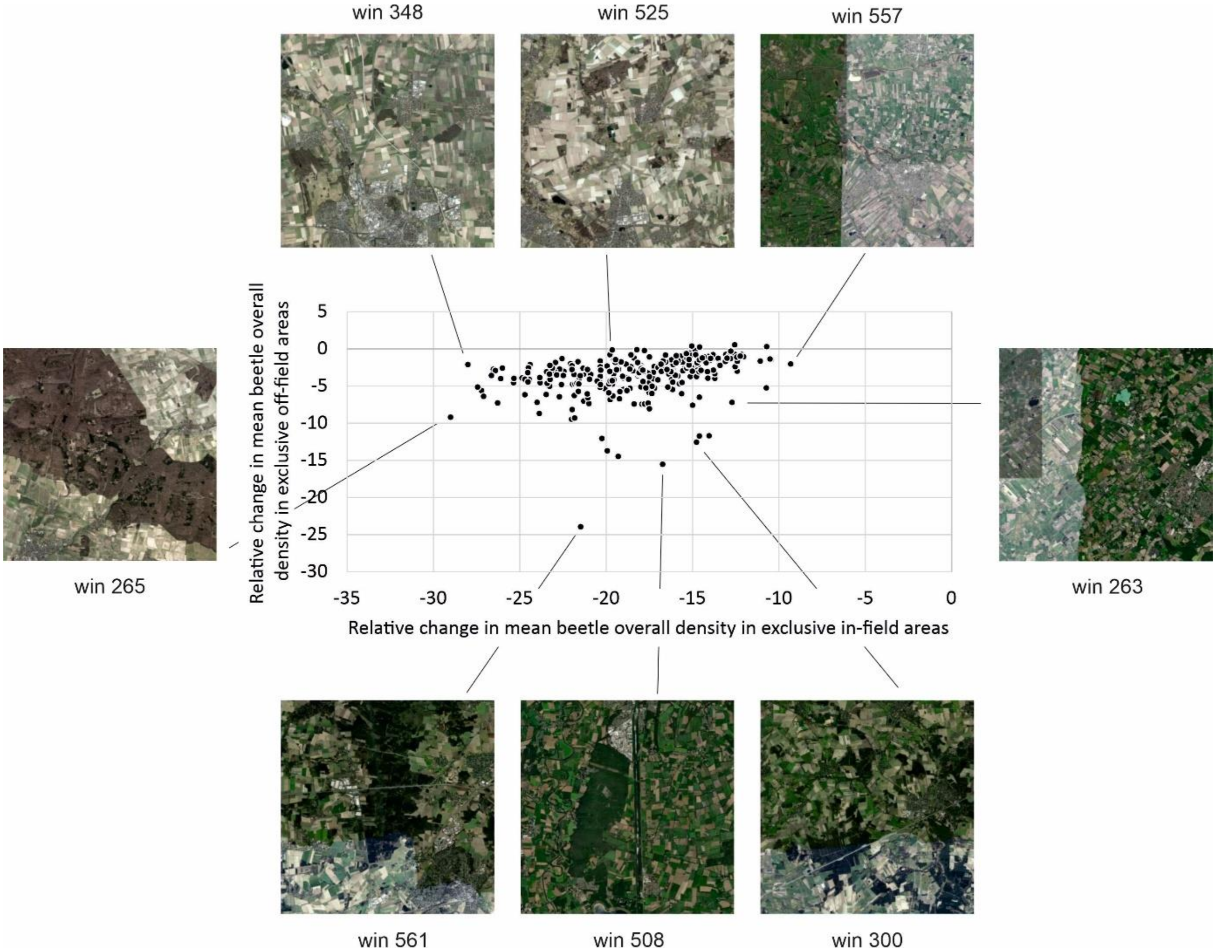
Source: Authors' own.

Figure 15: Relative change [%] in the mean overall beetle density due to pesticide use in the studied landscapes in the Brandenburg region: exclusive in-field versus exclusive off-field effects. Only study areas with more than 30% of arable land were taken into account.



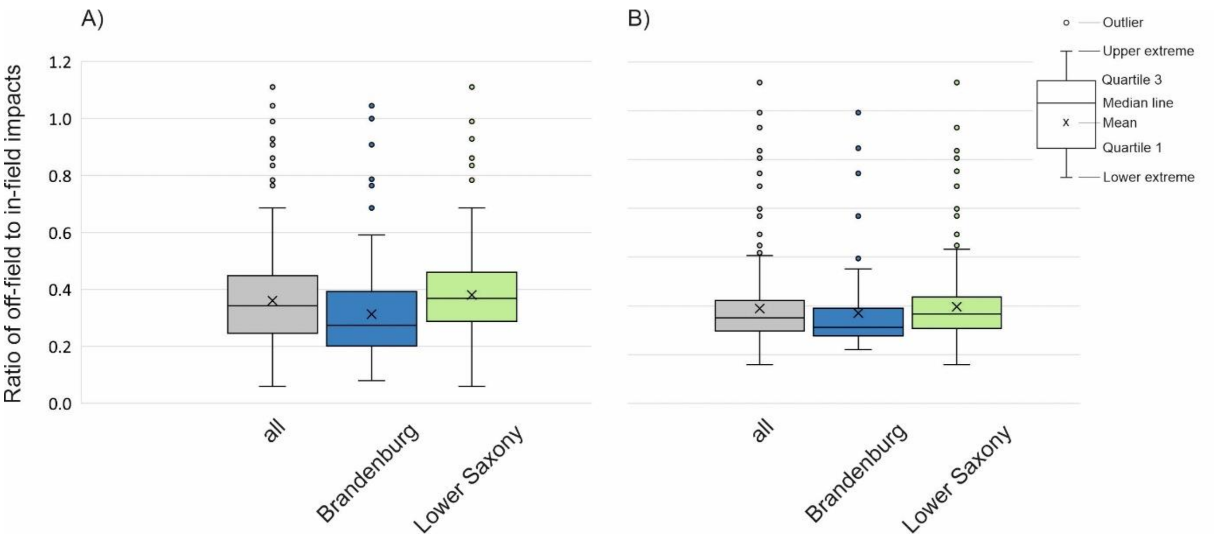
Source: Authors' own.

Figure 16: Relative change [%] in the mean overall beetle density due to pesticide use in the studied landscapes in the Lower Saxony region: exclusive in-field versus exclusive off-field effects. Only study areas with more than 30% of arable land were taken into account.



Source: Authors' own.

Figure 17: Ratio of (A) inclusive and (B) exclusive off-field to in-field impacts of pesticide use on mean overall beetle density. Only study areas with more than 30% of arable land were taken into account.



Source: Authors' own.

4.4 The effects of landscape-related mitigation measures

Grassy field boundaries were a more effective mitigation measure than unsprayed field margins, as they decreased the negative impacts of pesticide use on mean overall beetle density by on average 13.4% (the effect was slightly bigger in the Brandenburg than the Lower Saxony region: 16.0% and 12.3% respectively), while unsprayed field margins only by on average 2.7% (the effect was slightly smaller in the Brandenburg than the Lower Saxony region: 2.3% and 2.9% respectively; Figure 18). In both cases, the positive impact was mainly on mean beetle abundance, not on occupancy (the effect on mean beetle occupancy was < 1%). The effectiveness of both mitigation measures varied considerably among study areas (Figure 18).

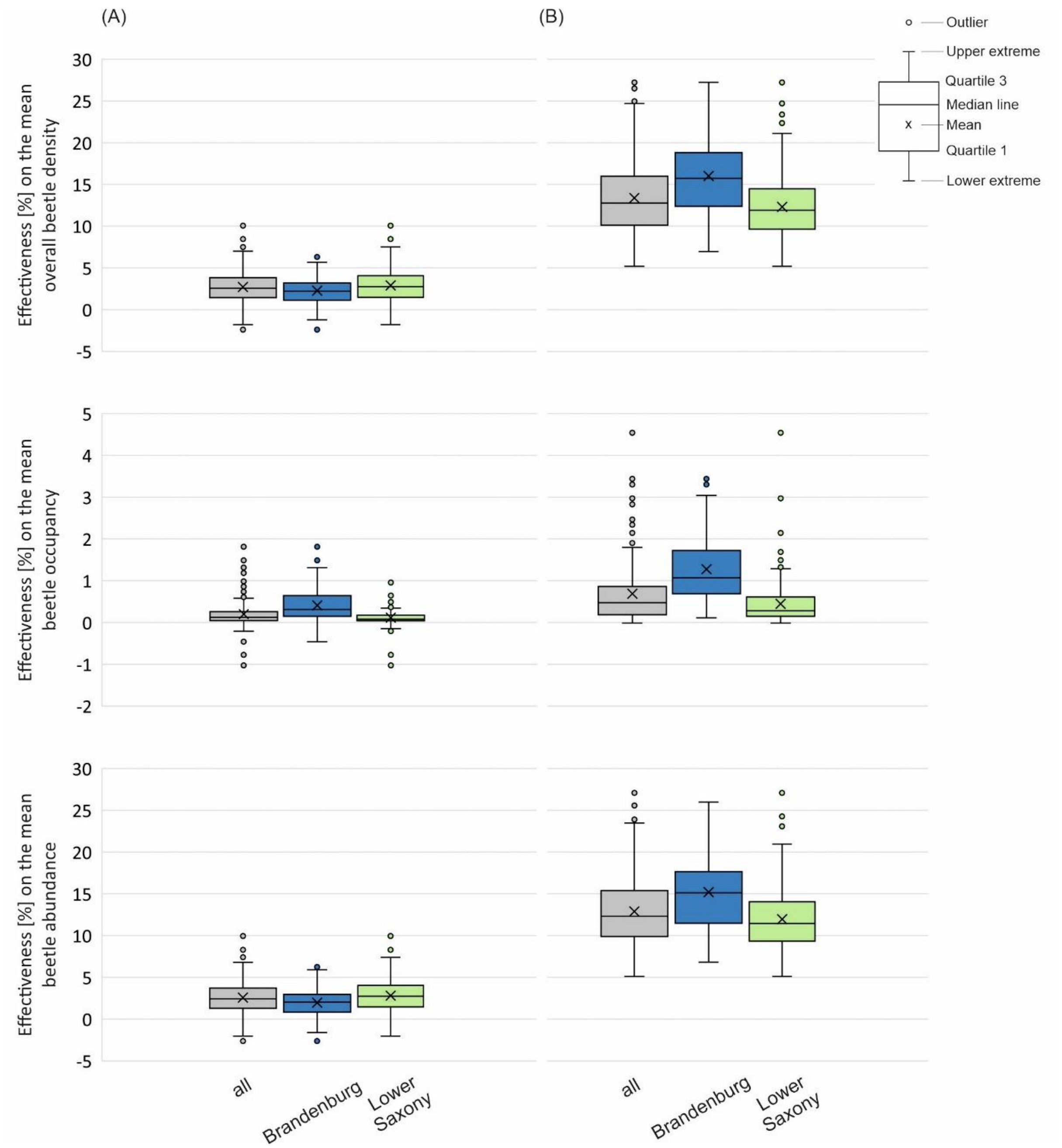
The final fitted regression model describing the relationship between the effectiveness of grassy field boundaries on the mean overall beetle density and landscape characteristics included 7 out of 13 input measures and explained 70.0% of the observed variability ($p < 0.001$; Appendix C, Table C3). The effectiveness of grassy field boundaries on the mean overall beetle density increased with the percentage of study area impacted by the mitigation measure ($p < 0.001$). It decreased with the coverage of semi-natural herbaceous habitats (*herbiPer*, $p < 0.001$), coverage of permanent pastures (*pasturePer*, $p < 0.001$), landscape diversity (*SIDI_land*, $p < 0.001$), landscape shape index (*LSI_land*, $p < 0.001$), interspersion and juxtaposition index (*IJI_land*, $p = 0.034$), splitting index (*SPLIT_land*, $p < 0.001$) and number of fields (*fieldsNo*, $p < 0.001$). The effectiveness of grassy field boundaries was mainly driven by the percentage of study area impacted by the mitigation measure and coverage of permanent pastures (Figure 19). However, when analysing only study areas with more than 60% of arable land, the coverage of permanent pastures became more important, and the percentage of study area impacted by the measure became non-significant (Appendix C, Table C3).

The final fitted regression model describing the relationship between the effectiveness of unsprayed field margins on the mean overall beetle density and landscape characteristics included 5 out of 13 input measures and explained only 12.4% of the observed variability

($p < 0.001$; Appendix C, Table C4). The effectiveness of unsprayed field margins on the mean overall beetle density decreased with the coverage of semi-natural herbaceous habitats (*herbiPer*, $p < 0.001$), coverage of woody semi-natural habitat (*woodyPer*, $p = 0.005$), coverage of permanent pastures (*pasturePer*, $p < 0.001$), landscape splitting (*SPLIT_land*, $p = 0.032$), and mean field size (*fieldsNo*, $p < 0.001$) (Figure 20). The model became non-significant when analysing only study areas with more than 60% of arable land (Appendix C, Table C4).

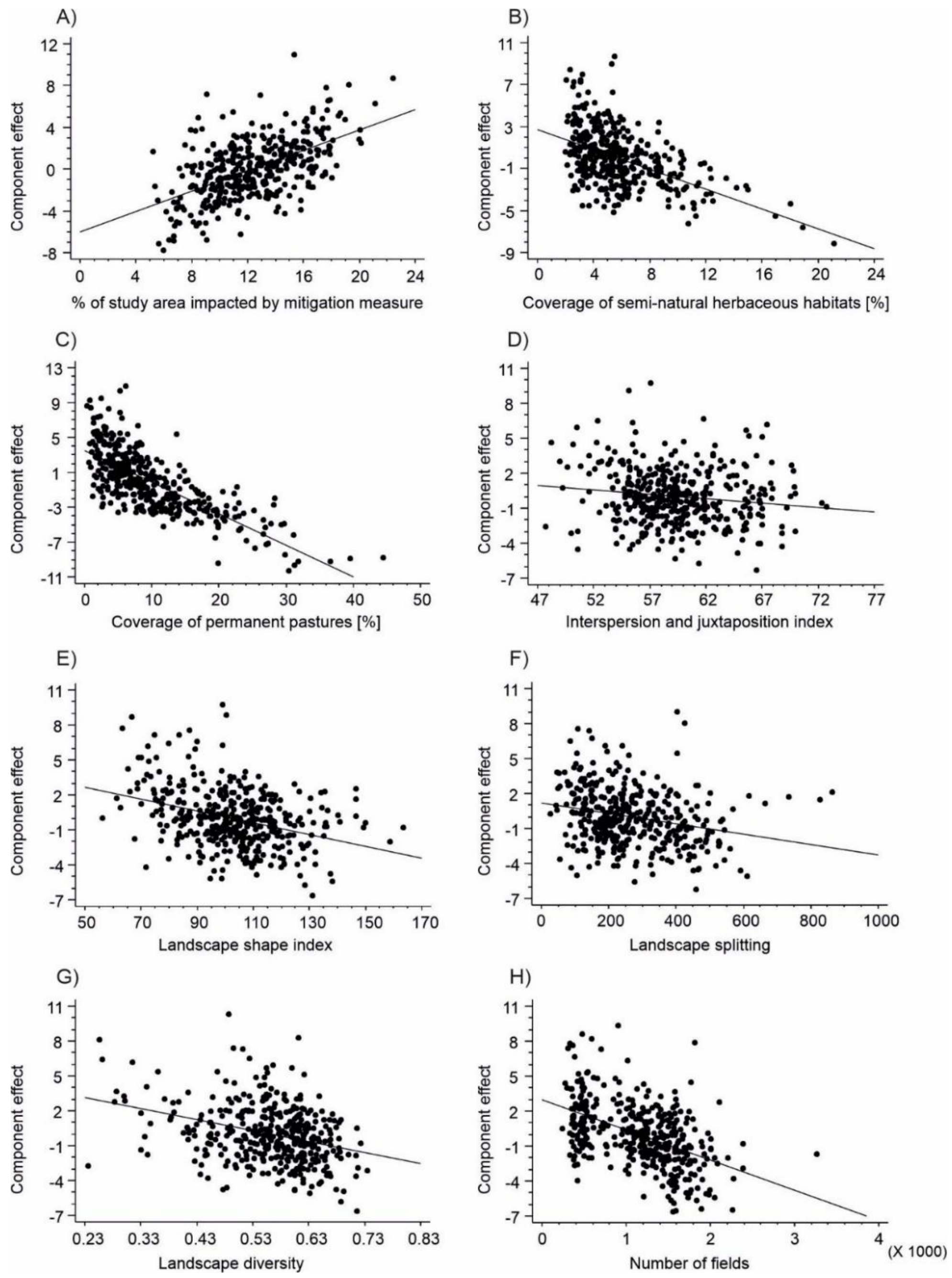
The difference in effectiveness between landscape-related mitigation measures on mean overall beetle density also varied considerably among study areas. Landscape and farmland metrics explained this variability in 68.3% ($p < 0.001$; Appendix C, Table C5). The difference in the effectiveness of grassy field boundaries and unsprayed field margins increased with the percentage of study area impacted by the measures ($p < 0.001$) and mean field size (*meanFieldSize*, $p < 0.001$). It decreased with the coverage of semi-natural herbaceous habitats (*herbiPer*, $p < 0.001$), coverage of permanent pastures (pasturePer, $p < 0.001$), landscape diversity (SIDI_land, $p < 0.001$), landscape shape index (*LSI_land*, $p = 0.003$), interspersion and juxtaposition index (*IJI_land*, $p = 0.010$), and number of fields (*fieldsNo*, $p < 0.001$). The magnitude of differences in the effectiveness of mitigation measures was mainly driven by the percentage of study area impacted by the measures and coverage of permanent pastures. However, these variables became non-significant when analysing only study areas with more than 60% of arable land. For such set of study areas, the differences in the effectiveness of mitigation measures increased with the coverage of arable land (*arablePer*, $p < 0.001$) and landscape diversity (*SIDI_land*, $p < 0.001$), and decreased with the landscape shape index (*LSI_land*, $p < 0.001$) (Appendix C, Table C5).

Figure 18: Variation in the effectiveness [%] of applied mitigation measures, (A) unsprayed field margins, and (B) grassy field boundaries, on the mean beetle population density, mean Occupancy and mean Abundance. Only study areas with coverage of arable land > 30% were included. That gives *n* = 115 study areas in the Brandenburg region, and *n* = 277 study areas in the Lower Saxony region.



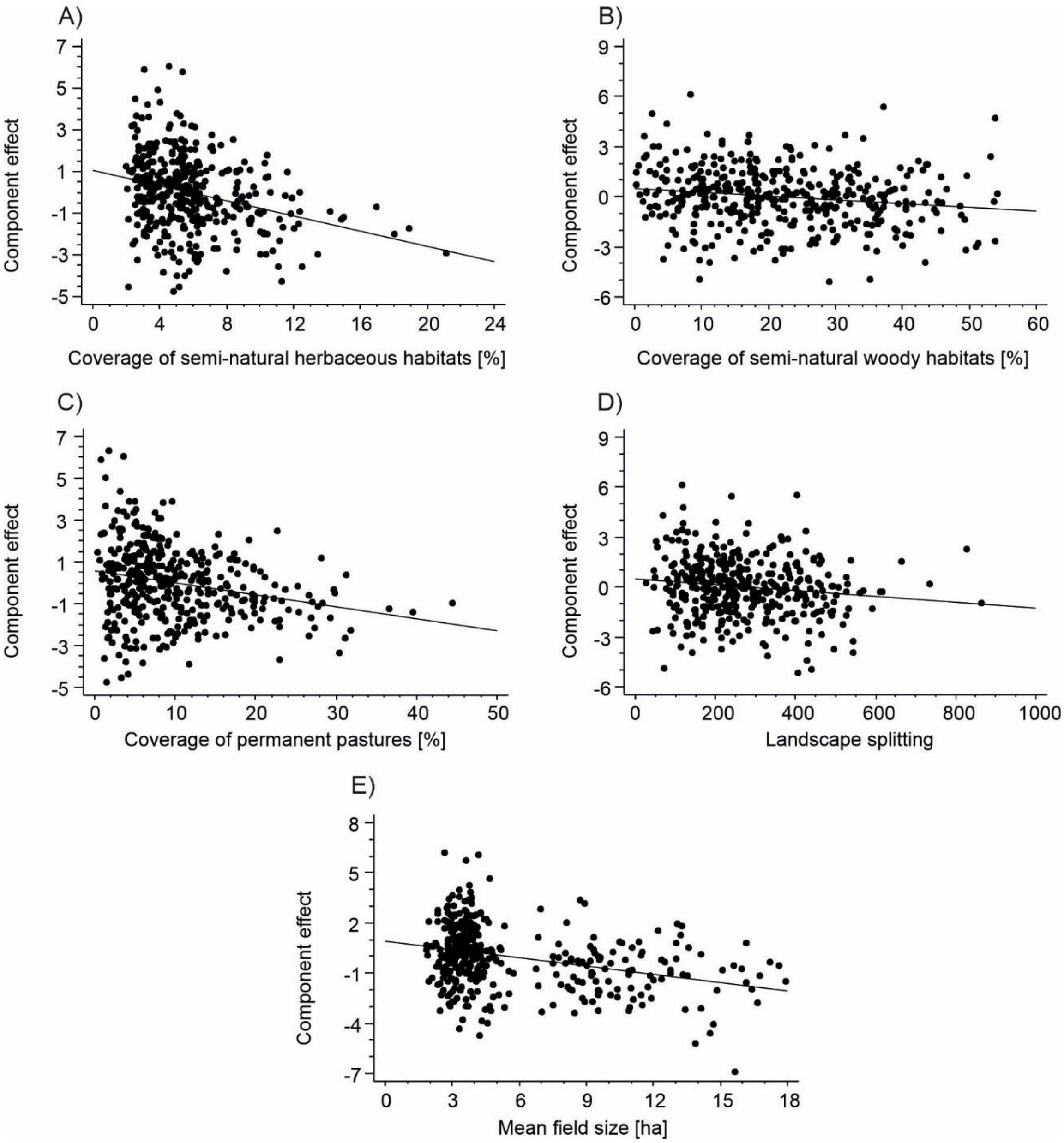
Source: Authors' own.

Figure 19: Results of multiple regression analysis for the scenario 'FB_Pest': effects of (A) % of study area impacted by the measure ($p < 0.001$), (B) coverage of semi-natural herbaceous habitats ($p < 0.001$), (C) coverage of permanent pastures ($p < 0.001$), (D) interspersion and juxtaposition index ($p = 0.034$), (E) landscape shape index ($p < 0.001$), and (F) landscape splitting ($p < 0.001$), (G) landscape diversity ($p < 0.001$) and (H) number of fields ($p < 0.001$) on the effectiveness of grassy field boundaries in mitigating negative impacts of pesticide use on mean overall beetle density. The lines show the effectiveness of grassy field boundaries when changing (A) % of the study area impacted by the measure, (B) coverage of semi-natural herbaceous habitats, (C) coverage of permanent pastures, (D) interspersion and juxtaposition index, (E) landscape shape index, (F) landscape splitting (G) landscape diversity and (H) number of fields over their observed ranges. The overall model, including all these variables, was significant at $p < 0.001$ and explained 70% of the variability.



Source: Authors' own.

Figure 20: Results of multiple regression analysis for the scenario 'UM_Pest': effects of (A) coverage of semi-natural herbaceous habitats (*p* < 0.001), (B) coverage of woody semi-natural habitats, (C) coverage of permanent pastures (*p* < 0.001), (D) landscape splitting (*p* < 0.001), and (E) mean field size (*p* < 0.001) on the effectiveness of unsprayed field margins in mitigating negative impacts of pesticide use on mean overall beetle density. The lines show the effectiveness of unsprayed field margins when changing (A) coverage of semi-natural herbaceous habitats, (B) coverage of woody semi-natural habitats, (C) coverage of permanent pastures, (D) landscape splitting and (E) mean field size over their observed ranges. The overall model, including all these variables, was significant at *p* < 0.001 and explained 12% of the variability.



Source: Authors' own.

4.5 The effects of pesticide use in 'extreme' scenarios

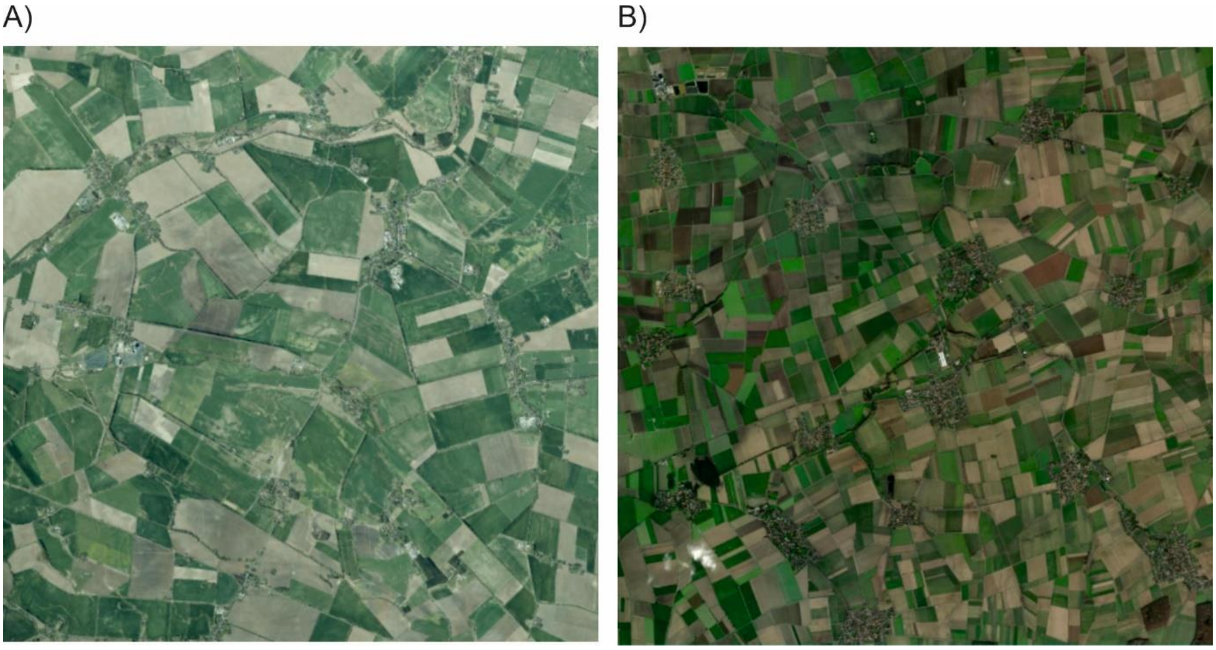
Extreme scenarios were tested for two exemplary landscapes (study area no. 113 from the Brandenburg region and study area no. 534 from the Lower Saxony region) with arable land coverage of 84-85% (Figure 21).

For regular landscapes and landscapes with unsprayed field margins, assuming normal pesticide application in wheat monoculture, the observed impacts on beetle populations were comparable to those obtained when crop rotations were applied. Only for landscapes with added grassy field boundaries, scenarios with wheat monoculture resulted in substantially bigger negative impacts on beetle populations than when crop rotations were applied. Increasing the probability of application to the point where all farmers applied pesticides in wheat monoculture had a pronounced effect in all landscape scenarios (Figure 22).

AOR plots showed that impacts on the more homogeneous landscape with intensive farming (study area no. 113) were much higher than on the more heterogeneous landscape dominated by small fields (study area no. 534) and included impacts on occupancy (Figure 23). Although mitigation measures had a positive effect, there were still large reductions in occupancy visible. There was no impact on occupancy in the more heterogeneous landscape until we assumed that all farmers were applying pesticides in the wheat monoculture (Figure 23 C2). When this threshold was reached, the impacts on occupancy could be only reduced by adding grassy field boundaries.

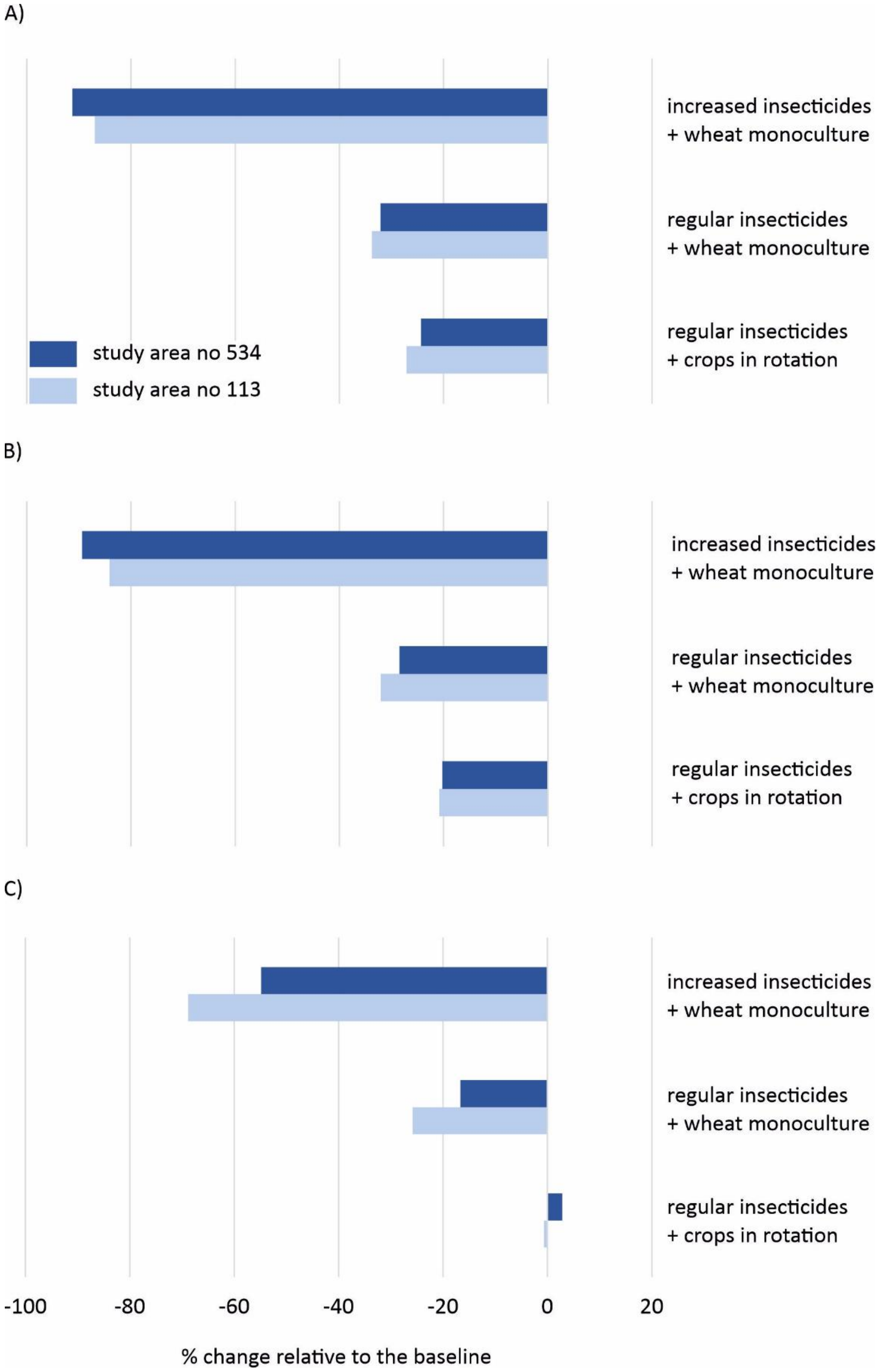
The impact of pesticide application on the beetle population in (both inclusive and exclusive) in-field areas was higher in the more homogeneous landscape with intensive farming (study area no. 113) than in the more heterogeneous landscape dominated by small fields (study area no. 534) under normal pesticide application in crop rotation and wheat monoculture scenarios (Figure 24 A&B). This trend was reversed when the probability of application was increased to the point where all farmers applied insecticides in wheat monoculture (Figure 24 C). When analysing the impacts in the inclusive off-field areas, they were lower in all scenarios in the more homogeneous landscape with intensive farming compared to the more heterogeneous landscape dominated by small fields. The opposite was true for the analysis of impacts in the exclusive off-field areas (Figure 24). Although the impact of pesticide use in the exclusive off-field areas was at a similar level under normal pesticide use in the crop rotation and wheat monoculture scenarios (Figure 24 A&B) (decrease in mean total beetle densities of 4-5%), it increased fourfold in the scenario where all farmers used insecticides in wheat monoculture (Figure 24 C).

Figure 21: Landscapes used for testing of extreme pesticide scenarios: (A) study area no. 113 in the Brandenburg region, and (B) study area no. 534 in the Lower saxony region.



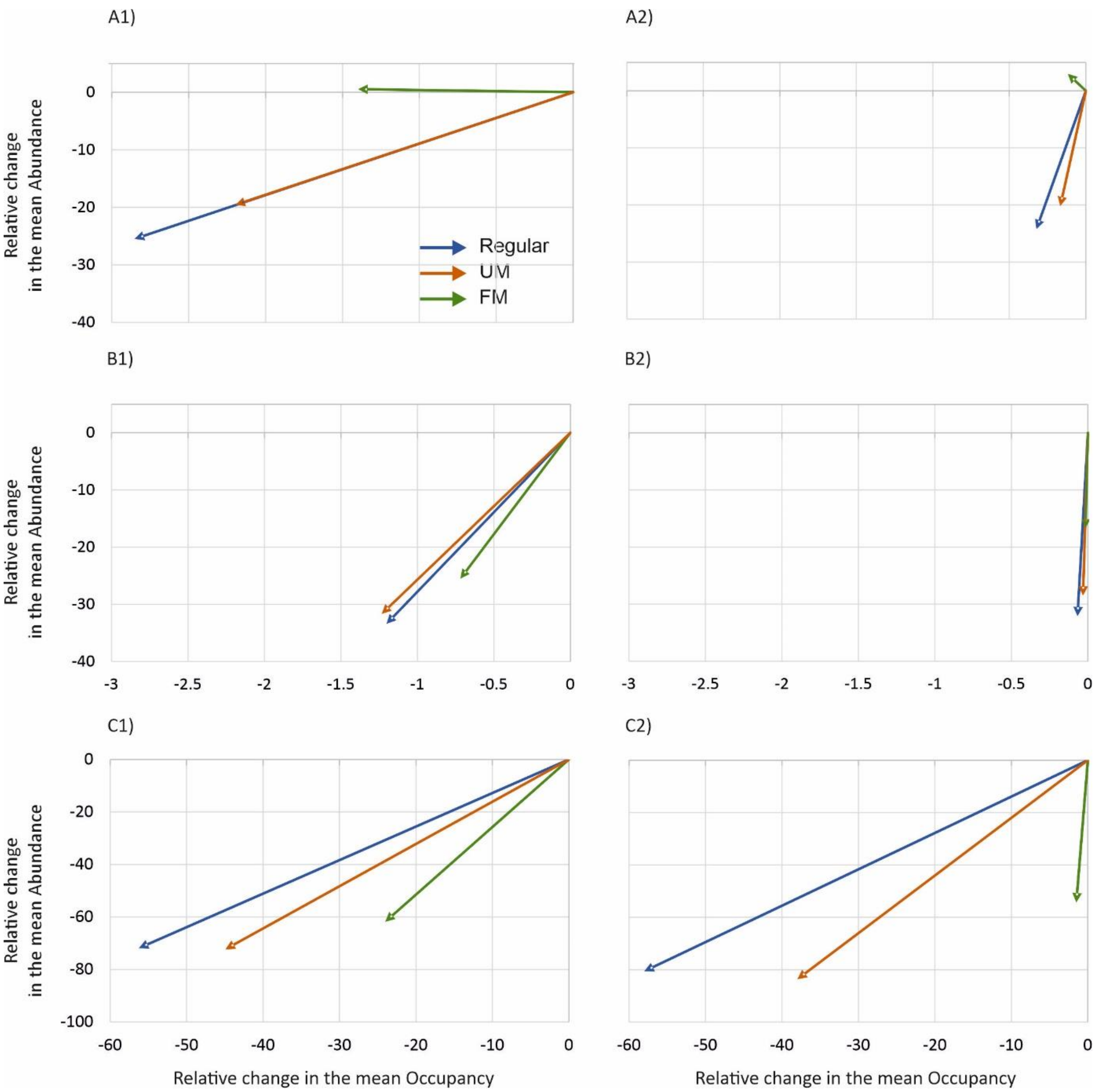
Source: Authors' own.

Figure 22: Mean relative change in the mean overall beetle density when comparing different pesticide scenarios for (A) regular landscape (scenario 'Regular'), (B) landscape with added unsprayed field margins (scenario 'UM'), and (C) landscape with added grassy field boundaries (scenario 'FB') to the baseline scenario.



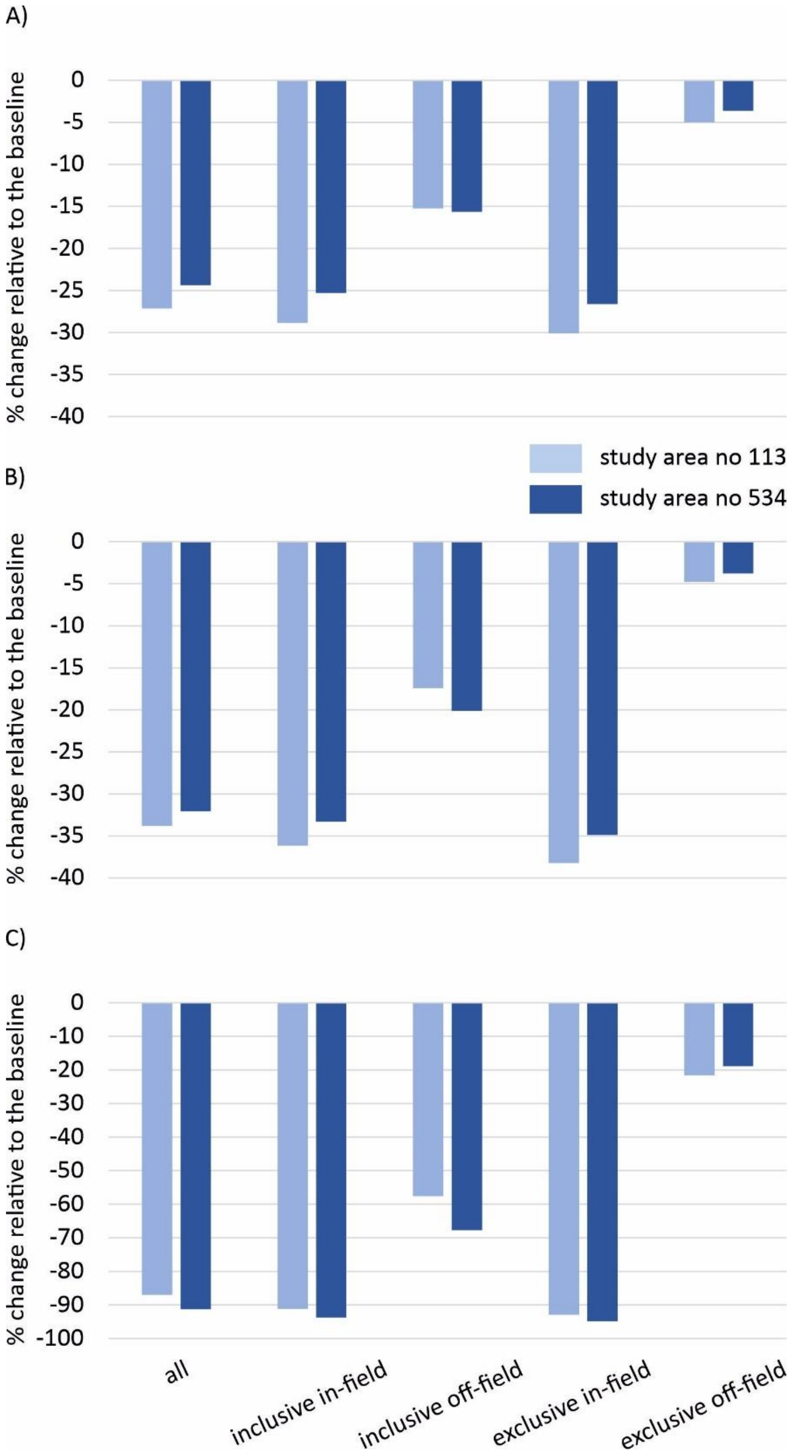
Source: Authors' own.

Figure 23: Relative change [%] in the mean beetle Abundance and Occupancy (AOR relationship) when comparing different pesticide scenarios: (A) regular insecticides + crops in rotation (B) regular insecticides + wheat monoculture, and (C) increased insecticides + wheat monoculture; and for two different study areas: (1) no 113, and (2) 534; to the baseline.



Source: Authors' own.

Figure 24: Relative change [%] in the mean overall beetle density due to pesticide use in the studied landscapes: in-field versus off-field effects when comparing different pesticide scenarios (A) regular insecticides + crops in rotation (B) regular insecticides + wheat monoculture, and (C) increased insecticides + wheat monoculture.



Source: Authors' own.

5 Discussion

In this study, by using a combination of high-resolution dynamic landscape models and a detailed spatially-explicit agent-based model, we could realistically simulate the behaviour and population dynamics of non-target arthropod species *B. lampros* in the various landscapes of the Brandenburg and Lower Saxony regions of Germany. The study areas differed considerably in their composition and configuration of landscape elements, providing a unique opportunity to investigate how the impacts of pesticide use and the effectiveness of mitigation measures (unsprayed field margins or grassy field boundaries) differ depending on the landscape context.

Simulated beetle populations under the baseline conditions (i.e., before application of pesticides; scenario 'Reg_NoPest') differed considerably between landscape and farming systems. The regression models explaining the variability of simulation endpoints (mean overall beetle density, mean Occupancy and mean Abundance) across study areas with landscape and farmland heterogeneity had high predictive power. This confirms the importance of landscape structure and landscape-scale patterns for carabid populations (Bertrand et al. 2016, Holland et al. 2000, Vanbergen et al. 2005, Vasseur et al. 2013). *B. lampros* populations were larger and distributed over larger areas in landscapes with a significant proportion of arable land and a high proportion of herbaceous semi-natural habitats and permanent pastures. *B. lampros* is a typical open area species, characteristic for agroecosystems, requiring arable fields for foraging and reproduction (Wallin et al. 1989). On the other hand, grassy habitats play an essential role for the species as overwintering sites and source habitats for the recolonization of fields (Saska et al. 2007). The importance of permanent pastures for beetle populations was even more pronounced when analyzing landscapes dominated by arable land, confirming that both overwintering habitats and open fields are essential to maintain beetle populations at high levels. Higher numbers and densities of beetles were also found in more diverse and heterogenous (also in terms of farmland) landscapes. Highly diverse landscapes have extended arable to non-arable boundaries supporting effective colonization of arable fields by beetles (where the mortality is increased due to soil cultivation) (Bianchi et al. 2003).

Beetle populations decreased on average by 14% under the pesticide scenario ('Reg_Pest') but the magnitude of impacts strongly depended on the landscape context. The negative impacts of pesticides mainly altered local beetle abundance, not the occupancy. They were higher in more homogenous landscapes with low initial beetle populations, high coverage of arable land, and low coverage of source habitats (semi-natural herbaceous habitats and permanent pastures). This is in line with the previous studies on *B. lampros* population in agricultural landscapes of Poland (Ziółkowska et al. 2021) and the Netherlands (Ziółkowska et al. 2022). The differences in the landscape structure explain the regional differences in observed impacts. More homogenous landscapes with a predominance of large fields and low coverage of beetle source habitats dominate the Brandenburg region. In contrast, Lower Saxony is dominated by more heterogeneous, diverse landscapes with small-scale farming.

It is important to realize that the effect of landscape metrics on the result of the population impact assessment depends on the range of landscapes considered. If landscape selection is restricted to those with high proportions of arable land, the contribution of factors related to heterogeneity increases. When analyzing study areas with a predominance (> 60%) of arable land, the coverage of permanent pastures became the most important variable reducing the negative impacts of pesticide use on beetle numbers and local density. Permanent pastures provide large areas free of insecticide spraying and soil cultivation. They are thus favorable for beetles, especially if embedded in a landscape with high-intensity use. In mixed farming systems, grasslands and croplands complement each other by providing continuous and different resources to the species throughout the year (Massaloux et al. 2020). We have, however, not considered in our simulations the intensity of grazing and its possible negative impacts on beetles (van Klink et al. 2015).

Our analysis indicates the impact of source-sink dynamics on the effect of pesticide application for the *B. lampros* populations. What is important is that beetles were also impacted in the exclusive off-field areas where the pesticide was neither applied nor drifted. The effect of pesticide use on off-field areas was reduced with the decreased density of field boundaries (i.e., in study areas with fewer and more aggregated fields) and increased area of suitable over-wintering and breeding habitats nearby (in this case, permanent pastures). Note that the first observation is due to the beetles being brought into contact with the pesticides through time where field boundaries are present, whereas pasture populations are physically distant from the pesticide application areas.

The study confirms that grassy field boundaries (scenario 'FB_Pest') are more effective than unsprayed field margins (scenario 'UM_Pest') in promoting and protecting beetle populations (Topping et al. 2015), but the difference in the effectiveness of these two measures varied across the study areas. In more heterogeneous landscapes, the increased effectiveness of grassy field boundaries compared to the unsprayed field margins was lower. This is probably because the baseline conditions for beetles were better in such landscapes; therefore, the addition of the grassy field boundaries had a lower relative impact on the beetle populations. In arable-dominated, more homogenous landscapes, the effect of field margins versus unsprayed margins was proportionally greater. This is due to the lack of buffering effect of other non-crop habitats in landscapes with a high coverage of arable land.

The baseline population used to compare the field margins differed from the population in the baseline for standard scenarios and unsprayed margins (which were identical). The higher beetle population in the baseline scenario should also be considered because it means that the actual landscape population in the field margin treated scenario differs more in absolute terms than would seem to be the case from the proportional change. These absolute numbers might be important if management's target was to maximize beetle numbers rather than reducing the impact of the pesticide as a proportion.

Additional tests showed that with worst-case monoculture assumptions, the population of beetles could be almost extirpated within the study area. This contrasts the scenarios where the more realistic pesticide use scenario was used, leading to a situation where population dispersion was barely altered. Assuming normal pesticide application in wheat monoculture, the observed impacts on beetle populations were comparable to those obtained when crop rotations were applied. This is due to the relatively low level of pesticide application normally used in this crop. However, increasing the application probability to the point where all farmers applied pesticides produced pronounced effects. This more extreme scenario demonstrates an important point. From Figure 21, where two contrasting landscapes are shown, it is clear that impacts on the more homogenous landscape with intensive farming are much higher than on the more heterogenous landscape dominated by small fields and include impacts on occupancy. Here, although mitigation had a positive effect, there were still large reductions in occupancy visible. There was no impact on occupancy in the more heterogenous landscape until we assumed that all farmers were applying pesticides in the wheat monoculture (Figure 23, graph C2). When this threshold was reached, the impacts on occupancy could be only reduced with grassy field boundaries. This indicates that there can be population tipping points at certain levels of stressor impact. The threshold between these two very different outcomes was not investigated but could be determined by gradually increasing pesticide use in crops until the beetle population crashes.

This clear effect of monoculture assumptions and the clear patterns of effects of landscape configuration suggest that for a particular species model, a matrix of landscape configuration types and effects could be constructed. This would have the advantage of covering the range of possibilities to be used as a look up table to make initial assessments of risk or determine the scale of mitigation that should be used in a particular 'use & landscape' case. This would ideally be done for a range of species and extensively for landscape and use combinations to reduce the need to run computationally demanding simulations using the original model.

The pesticide fate model used here only considers a single environmental compartment and thus is a worst-case exposure assumption. If a more complex model was used and the beetles were only exposed to the pesticide in the soil compartment (after interception by the crop canopy), then observed negative impacts of pesticide use would be expected to be lower. A further issue is that the spray drift model used here was based on the standard Ganzelmeier/Rautmann tables (Rautmann et al, 2001). This equation gives a very low percentage of drift in the first 1 m off-field and a relatively long tail. More recent Dutch studies (Stallinga et al. 2014, 2016) on a range of spray nozzles suggest that a more realistic pattern might be reduced distance effects, but higher concentration in the first 1 m. This could have an impact on the results if the difference leads to exceedance of the toxicological threshold in the first 1 m off-field, which currently it would not.

In addition to limits to the fate model, the pesticide impacts were assumed to be restricted to insecticides, and no impact of fungicides or herbicides was considered. This will underestimate the risks, since at least for fungicides, insecticidal activity is often reported (e.g., Zubrod et al, 2019). The impact of these pesticides could also be included in future applications and should be included if it is considered to be a significant factor. Future scenarios should also consider multiple chemicals with different properties, rather than assuming all pesticides have the same properties as was done here.

B. lampros was chosen for this study as it is one of the focal species for Coleoptera used in the environmental risk assessment (EFSA 2015). It is important for natural pest control and is widespread in the agricultural landscapes in central and northern Europe, including Germany. It is, however, not a good representative species for non-agricultural areas. Due to its rather low dispersal rates *B. lampros* can be expected to be a relatively sensitive species to disturbance. This is because larger movement ranges increase the probability of reaching the favorable habitat and thus positively impact population growth. For lower dispersal abilities, the magnitude of this effect increases with landscape and farmland heterogeneity, while higher model beetle dispersal rates (> 20 m per day) lead to disassociation of the population dynamics from landscape structure (Bilde et al. 2004, Topping and Lagisz 2012). This means that *B. lampros* is more exposed to pesticides in more homogenous landscapes with high-intensity farming where source habitats are more difficult to reach, and fields represent a barrier to gene flow (Marchi et al. 2013).

The migratory and aggregation behavior of *B. lampros* is not, however, typical for all carabid beetles of agricultural landscapes. For example, *Poecilus cupreus* and *P. melanarius* are examples of widespread carabids which do not aggregate in field boundaries and overwinters predominantly within open fields (Sotherton 1984). The spatial distribution of carabid beetles within agricultural landscapes varies due to their different preferences for overwintering sites (open field versus grassy habitats versus woodlots) and different abilities to penetrate in-field areas (Knapp et al. 2019, Saska et al. 2007). Thus, the impacts of pesticide use may vary for beetles with different ecology, including spring versus autumn breeders by altering exposure in time. Therefore, investigating a broader range of carabids with different habitat preferences and functional traits would allow for more in-depth evaluation of possible negative impacts of pesticides and their dependence on landscape structure.

6 Conclusions and recommendations

The important lesson from this study is that population responses to applied mitigation measures can be very complex and strongly depending on a landscape context. The decision on mitigation measures should be made in relation to farming system, policy aim, and landscape structure. Although the general effects of pesticide use could be predictable, the actual magnitude of these effects is highly variable and modified by various spatial dynamic factors (spatial distribution of source and sink habitats or underlying habitat suitability).

It is also important to clearly state the aim of the measures in any future model study. This study focuses on the effect of mitigation measures on the pesticide effects, but an alternative view could be to look at the health of the beetle populations in absolute terms (not done here). In this case a higher effect in heterogeneous landscapes might be acceptable. The scale of the assessment may also be important. The landscape metrics used in this study do not describe variability in pattern of pesticide loads across a landscape. This distribution might be important if the aim is to keep beetles in all fields. However, there was little reduction in landscape occupancy at the realistic levels of pesticide use simulated here, suggesting no substantial spatial effect.

Our analysis indicates the impact of source-sink dynamics on the effect of pesticide application for the *B. lampros* populations. We found significant exclusive off-field effects which to some extent persisted despite application of mitigation measures. As undisturbed semi-natural habitats and extensively managed field margins play a key role as overwintering sites and source habitats for many predatory arthropods (Pfiffner and Luka 2000), the landscape management in agroecosystems should be focus on their maintenance and protection, and on increasing landscape diversity especially in highly homogenous landscapes.

For future modelling studies, we recommend developing a standard set of scenarios from more realistic to more extreme in terms of pesticide application and landscape structure (intensive large-scale farming versus extensive small-scale farming, heterogenous and diverse landscapes versus homogenous ones), with a range of pesticide toxicity levels (expressed as, e.g., low to high insecticide-driven field lethality rates), and pesticide application probabilities. In this way the full range of resulting effects will be available and an estimation of how close a realistic scenario is to a tipping point can be made.

Together with the broad scenario set, a broader set of focal carabid beetles should be considered. Thus the environmental risk assessment can cover species representing different habitat preferences and functional traits (spring versus autumn breeders, short versus long dispersers, open field versus field-edge species etc.). This combination of scenarios and species will give the richest picture to understand the impacts of pesticides on carabid populations.

Whether the increased complexity of including modelling of more detailed pesticide compartments is warranted needs to be assessed. We recommend that a study is carried out to quantify the most important drivers of the impact and to focus attention on extra detail in those areas where the most significant return is found. Similarly, a more detailed or realistic model is possible for drift, but the added benefit of this should be investigated.

7 List of references

Alexander, A. C., Culp, J. M., Liber, K., & Cessna, A. J. (2007) Effects of insecticide exposure on feeding inhibition in mayflies and oligochaetes. Environmental toxicology and chemistry, 26(8), 1726-1732. https://doi.org/Doi 10.1897/07-015r.1

Alexander, A. C., Heard, K. S., & Culp, J. M. (2008) Emergent body size of mayfly survivors. Freshwater Biology, 53(1), 171-180. https://doi.org/10.1111/j.1365-2427.2007.01880.x

Almasi, A., Rasekh, A., Esfandiari, M., Seyahooei, M. A., & Ziaee, M. (2018) The prospect of using sub-lethal imidacloprid or pirimicarb and a parasitoid wasp, Lysiphlebus fabarum, simultaneously, to control Aphis gossypii on cucumber plants. Journal of Asia-Pacific Entomology, 21(1), 161-167. https://doi.org/10.1016/j.aspen.2017.11.016

Amarasekare, K. G., Shearer, P. W., & Mills, N. J. (2016) Testing the selectivity of pesticide effects on natural enemies in laboratory bioassays. Biological Control, 102, 7-16. https://doi.org/10.1016/j.biocontrol.2015.10.015

Baines, M., Hambler, C., Johnson, P. J., Macdonald, D. W., & Smith, H. (1998) The effects of arable field margin management on the abundance and species richness of Araneae (spiders). Ecography, 21(1), 74-86. https://doi.org/DOI 10.1111/j.1600-0587.1998.tb00395.x

Barton, K. A., Phillips, B. L., Morales, J. M., & Travis, J. M. J. (2009) The evolution of an 'intelligent' dispersal strategy: biased, correlated random walks in patchy landscapes. Oikos, 118(2), 309-319. https://doi.org/10.1111/j.1600-0706.2008.16936.x

Bascompte, J., & Sole, R. V. (1994) Spatially induced bifurcations in single-species population-dynamics. Journal of Animal Ecology, 63(2), 256-264. https://doi.org/10.2307/5544

Bascompte, J., & Sole, R. V. (1996) Habitat fragmentation and extinction thresholds in spatially explicit models. Journal of Animal Ecology, 65(4), 465-473. https://doi.org/10.2307/5781

Bayram, A., Salerno, G., Onofri, A., & Conti, E. (2010) Lethal and sublethal effects of preimaginal treatments with two pyrethroids on the life history of the egg parasitoid *Telenomus busseolae*. Biocontrol, 55(6), 697-710. https://doi.org/10.1007/s10526-010-9288-8

Beketov, M. A., & Liess, M. (2008) Acute and delayed effects of the neonicotinoid insecticide thiacloprid on seven freshwater arthropods. Environmental toxicology and chemistry, 27(2), 461-470. https://doi.org/Doi 10.1897/07-322r.1

Benton, T. G., & Grant, A. (2000) Evolutionary fitness in ecology: Comparing measures of fitness in stochastic, density-dependent environments. Evolutionary Ecology Research, 2(6), 769-789.

Bertrand, C., Burel, F., Baudry, J. (2016) Spatial and temporal heterogeneity of the crop mosaic influences carabid beetles in agricultural landscapes. Landsc Ecol., 31(2), 451–466. https://doi.org/10.1007/s10980-015-0259-4

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. Proceedings of the Royal Society B-Biological Sciences, 273(1595), 1715-1727. https://doi.org/10.1098/rspb.2006.3530

Bianchi, F.J.J.A., Van Der Werf, W. (2003) The Effect of the Area and Configuration of Hibernation Sites on the Control of Aphids by *Coccinella septempunctata* (Coleoptera: Coccinellidae) in Agricultural Landscapes: A Simulation Study. Environ Entomol., 32(6), 1290–1304. https://doi.org/10.1603/0046-225X-32.6.1290

Bilde, T., Topping, C. (2004) Life history traits interact with landscape composition to influence population dynamics of a terrestrial arthropod: A simulation study. Ecoscience, 11(1), 64–73. https://doi.org/10.1080/11956860.2004.11682810

BKG (2016) HU Hausumringe Bundesrepublik Deutschland, Vektordaten, ArcInfo-Shape-Format. Bundesamt für Kartographie und Geodäsie (BKG), https://gdz.bkg.bund.de/index.php/default/digitale-geodaten/sonstige-geodaten/amtliche-hausumringe-deutschland-hu-de.html

Boucias, D. G., Stokes, C., Storey, G., & Pendland, J. C. (1996) The effects of imidacloprid on the termite Reticulitermes flavipes and its interaction with the mycopathogen Beauveria bassiana. Pflanzenschutz-Nachrichten Bayer, 49, 109-144.

Brock, T., Bigler, F., Frampton, G., Hogstrand, C., Luttik, R., Martin-Laurent, F., Topping, C. J., van der Werf, W., & Rortais, A. (2018) Ecological Recovery and Resilience in Environmental Risk Assessments at the European Food Safety Authority. Integrated Environmental Assessment and Management, 14(5), 586-591. https://doi.org/10.1002/ieam.4079

Carvalheiro, L.G., Veldtman, R., Shenkute, A.G., Tesfay, G.B., Pirk, C.W.W., Donaldson, J.S., Nicolson, S.W. (2011) Natural and within-farmland biodiversity enhances crop productivity. Ecol Lett 14:251–259.

DenBoer, P. J. (1968) Spreading of risk and stabilization of animal numbers. Acta biotheoretica, 18, 165-194.

DenBoer, P. J. (1971) On the dispersal power of carabid beetles and its possible significance. Communication of the Biological Station, Wijster, 155, 119-137.

DenBoer, P. J. (1990. Density limits and survival of local-populations in 64 carabid species with different powers of dispersal. Journal of Evolutionary Biology, 3(1-2), 19-48. https://doi.org/10.1046/j.1420-9101.1990.3010019.x

Dennis, R. L. H., Hodgson, J. G., Grenyer, R., Shreeve, T. G., & Roy, D. B. (2004) Host plants and butterfly biology. Do host-plant strategies drive butterfly status? Ecological Entomology, 29(1), 12-26. https://doi.org/DOI 10.1111/j.1365-2311.2004.00572.x

Destatis (2020) Allgemeine und Repräsentative Erhebung über die Viehbestände. Code 41311. Online available: https://www-genesis.destatis.de/genesis//online?operation=table&code=41311-0003&bypass=true&levelindex=0&levelid=1619522347076#abreadcrumb. [2021-04-12]

Ding, C., & He, X. (2004) K-means clustering via principal component analysis. Proceedings of the twenty-first international conference on machine learning, p. 29.

Djoudi, E., Marie, A., Mangenot, A., Puech, C., Aviron, S., Plantegenest, M., & Petillon, J. (2018) Farming system and landscape characteristics differentially affect two dominant taxa of predatory arthropods. Agriculture Ecosystems & Environment, 259, 98-110. https://doi.org/10.1016/j.agee.2018.02.031

Djoudi, E., Plantegenest, M., Aviron, S., & Petillon, J. (2019) Local vs. landscape characteristics differentially shape emerging and circulating assemblages of carabid beetles in agroecosystems. Agriculture Ecosystems & Environment, 270, 149-158. https://doi.org/10.1016/j.agee.2018.10.022

Duflot, R., Ernoult, A., Burel, F., & Aviron, S. (2016) Landscape level processes driving carabid crop assemblage in dynamic farmlands. Population Ecology, 58(2), 265-275. https://doi.org/10.1007/s10144-015-0534-x

EFSA Panel on Plant Protection Products and their Residues (PPR) (2015) Scientific opinion addressing the state of the science on risk assessment of plant protection products for non-target arthropods. EFSA Journal, 13(2), 3996 [3212pp.]. https://doi.org/10.2903/j.efsa.2014.3996

EFSA Scientific Committee (2016) Recovery in environmental risk assessments at EFSA. EFSA Journal, 14(2), 4313 [4385pp.], Article 4313. https://doi.org/10.2903/j.efsa.2016.4313

FAO (2006) Guidelines for soil description. Rom: Food and Agriculture organization of the United Nations (FAO), http://www.fao.org/3/a0541e/a0541e.pdf

Galle, R., Happe, A. K., Baillod, A. B., Tscharntke, T., & Batary, P. (2019) Landscape configuration, organic management, and within-field position drive functional diversity of spiders and carabids. Journal of Applied Ecology, 56(1), 63-72. https://doi.org/10.1111/1365-2664.13257

Gibson, C. W. D., Hambler, C., & Brown, V. K. (1992) Changes in Spider (Araneae) Assemblages in Relation to Succession and Grazing Management. Journal of Applied Ecology, 29(1), 132-142. https://doi.org/Doi 10.2307/2404356

Gill, R. J., & Raine, N. E. (2014) Chronic impairment of bumblebee natural foraging behaviour induced by sublethal pesticide exposure. Functional Ecology, 28(6), 1459-1471. https://doi.org/https://doi.org/10.1111/1365-2435.12292

Habel, J. C., Samways, M. J., & Schmitt, T. (2019) Mitigating the precipitous decline of terrestrial European insects: Requirements for a new strategy. Biodiversity and Conservation, 28(6), 1343-1360. https://doi.org/10.1007/s10531-019-01741-8

Habel, J. C., Ulrich, W., Biburger, N., Seibold, S., & Schmitt, T. (2019) Agricultural intensification drives butterfly decline. Insect Conservation and Diversity, 12(4), 289-295. https://doi.org/10.1111/icad.12343

Heinrichs, J. A., Lawler, J. J., & Schumaker, N. H. (2016) Intrinsic and extrinsic drivers of source-sink dynamics. Ecology and Evolution, 6(4), 892-904. https://doi.org/10.1002/ece3.2029

Heinrichs, J. A., Lawler, J. J., Schumaker, N. H., Wilsey, C. B., & Bender, D. J. (2015) Divergence in sink contributions to population persistence. Conservation Biology, 29(6), 1674-1683. https://doi.org/10.1111/cobi.12540

Hidalgo, J., de Casas, R. R., & Munoz, M. A. (2016) Environmental unpredictability and inbreeding depression select for mixed dispersal syndromes. Bmc Evolutionary Biology, 16, Article 71. https://doi.org/10.1186/s12862-016-0638-8

Holland, J. M., Luff, M. L. (2000) The effects of agricultural practices on Carabidae in temperate agroecosystems. Integr Pest Manag Rev., 5, 109–129. https://doi.org/10.1023/A:1009619309424

Hopper, K. R. (1999) Risk-spreading and bet-hedging in insect population biology. Annual Review of Entomology, 44, 535-560. https://doi.org/10.1146/annurev.ento.44.1.535

Hoye, T. T., Skov, F., & Topping, C. J. (2012) Interpreting outputs of agent-based models using abundance-occupancy relationships. Ecological Indicators, 20, 221-227. https://doi.org/DOI 10.1016/j.ecolind.2012.01.017

Iles, D. T., Williams, N. M., & Crone, E. E. (2018) Source-sink dynamics of bumblebees in rapidly changing landscapes. Journal of Applied Ecology, 55(6), 2802-2811. https://doi.org/10.1111/1365-2664.13175

Ives, A. R. (1995) Measuring resilience in stochastic-systems. Ecological Monographs, 65(2), 217-233. https://doi.org/10.2307/2937138

Johnson, C. G. (1960) Basis for a general system of insect migration and dispersal by flight. Nature, 186(4722), 348-350. https://doi.org/10.1038/186348a0

Johnson, C. G. (1969). Migration and dispersal of insects by flight. Methuen.

Kalarus, K., Halecki, W., & Skalski, T. (2019) Both semi-natural and ruderal habitats matter for supporting insect functional diversity in an abandoned quarry in the city of Krakow (S Poland). Urban Ecosystems, 22(5), 943-953. https://doi.org/10.1007/s11252-019-00869-3

Kautz, A. R., & Gardiner, M. M. (2019) Agricultural intensification may create an attractive sink for Dolichopodidae, a ubiquitous but understudied predatory fly family. Journal of Insect Conservation, 23(3), 453-465. https://doi.org/10.1007/s10841-018-0116-2

Knapp, M., Seidl, M., Knappova, J., Macek, M., Saska, P. (2019) Temporal changes in the spatial distribution of carabid beetles around arable field-woodlot boundaries. Scientific reports, 9, 8967.

Larsen, A. E., Farrant, D. N., & MacDonald, A. J. (2020) Spatiotemporal overlap of pesticide use and species richness hotspots in California. Agriculture Ecosystems & Environment, 289. https://doi.org/UNSP 106741

Lemke, A., & Poehling, H. M. (2002) Sown weed strips in cereal fields: overwintering site and "source" habitat for Oedothorax apicatus (Blackwall) and Erigone atra (Blackwall) (Araneae : Erigonidae). Agriculture Ecosystems & Environment, 90(1), 67-80, Article Pii s0167-8809(01)00173-6. https://doi.org/10.1016/s0167-8809(01)00173-6

Levins, R. (1969) Some demographic and genetic consequences of environmental heterogeneity for biological control. Bulletin of the Entomological Society of America, 15(3), 4.

Longley, M., & Sotherton, N. W. (1997) Factors determining the effects of pesticides upon butterflies inhabiting arable farmland. Agriculture Ecosystems & Environment, 61(1), 1-12. https://doi.org/10.1016/S0167-8809(96)01094-8

Marchi, C., Andersen, L.W., Loeschcke, V. (2013) Effects of Land Management Strategies on the Dispersal Pattern of a Beneficial Arthropod. PLoS ONE, 8(6), e66208. https://doi.org/10.1371/journal.pone.0066208

Massaloux, D., Sarrazin, B., Roume, A., Tolon, V., Wezel, A. (2020) Complementarity of grasslands and cereal fields ensures carabid regional diversity in French farmlands. Biodivers Conserv., 29(9–10), 2861–2882. https://doi.org/10.1007/s10531-020-02002-9

Morrissey, C. A., Mineau, P., Devries, J. H., Sanchez-Bayo, F., Liess, M., Cavallaro, M. C., & Liber, K. (2015) Neonicotinoid contamination of global surface waters and associated risk to aquatic invertebrates: A review. Environment International, 74, 291-303. https://doi.org/10.1016/j.envint.2014.10.024

Muller, C. (2018) Impacts of sublethal insecticide exposure on insects - Facts and knowledge gaps. Basic and Applied Ecology, 30, 1-10. https://doi.org/10.1016/j.baae.2018.05.001

Navarro-Roldan, M. A., & Gemeno, C. (2017) Sublethal Effects of Neonicotinoid Insecticide on Calling Behavior and Pheromone Production of Tortricid Moths. Journal of Chemical Ecology, 43(9), 881-890. https://doi.org/10.1007/s10886-017-0883-3

Nicholson, A. J. (1933) The balance of animal populations [Article]. Journal of Animal Ecology, 2, 132-178.

Oliveira, R. L., Gontijo, P. C., Samia, R. R., & Carvalho, G. A. (2019) Long-term effects of chlorantraniliprole reduced risk insecticide applied as seed treatment on lady beetle Harmonia axyridis (Coleoptera: Coccinellidae). Chemosphere, 219, 678-683. https://doi.org/10.1016/j.chemosphere.2018.12.058

Pfiffner, L., luka, H. (2000) Overwintering of arthropods in soils of arable fields and adjacent semi-natural habitats. Agriculture, Ecosystems & Environment, 78(3), 215-222.

Potts, S.G., Biesmeijer, J.C., Kremen, C., Neumann, P., Schweiger, O., Kunin, W.K. (2010) Global pollinator declines: trends, impacts and drivers. Trends Ecol Evol, 25, 345–353.

Pulliam, H. R. (1988) Sources, Sinks, and Population Regulation. American Naturalist, 132(5), 652-661. https://doi.org/Doi 10.1086/284880

Raven, P. H., & Wagner, D. L. (2021) Agricultural intensification and climate change are rapidly decreasing insect biodiversity. Proceedings of the National Academy of Sciences, 118(2), e2002548117. https://doi.org/10.1073/pnas.2002548117

Roubos, C. R., Rodriguez-Saona, C., & Isaacs, R. (2014) Mitigating the effects of insecticides on arthropod biological control at field and landscape scales. Biological Control, 75, 28-38. https://doi.org/10.1016/j.biocontrol.2014.01.006

Saska, P., Vodde, M., heijerman, T., Weserman, P., van der werf, W. (2007) The significance of a grassy field boundary for the spatial distribution of carabids within two cereal fields. Agriculture, Ecosystems & Environment, 122(4), 427-434.

Schafer, R. B., von der Ohe, P. C., Rasmussen, J., Kefford, B. J., Beketov, M. A., Schulz, R., & Liess, M. (2012) Thresholds for the Effects of Pesticides on Invertebrate Communities and Leaf Breakdown in Stream Ecosystems. Environmental Science & Technology, 46(9), 5134-5142. https://doi.org/10.1021/es2039882

Seibold, S., Gossner, M. M., Simons, N. K., Bluthgen, N., Muller, J., Ambarli, D., Ammer, C., Bauhus, J., Fischer, M., Habel, J. C., Linsenmair, K. E., Nauss, T., Penone, C., Prati, D., Schall, P., Schulze, E. D., Vogt, J., Wollauer, S., & Weisser, W. W. (2019) Arthropod decline in grasslands and forests is associated with landscape-level drivers. Nature, 574(7780), 671-+. https://doi.org/10.1038/s41586-019-1684-3

Sharma, A., Jha, P., & Reddy, G. V. P. (2018) Multidimensional relationships of herbicides with insect-crop food webs. Science of the Total Environment, 643, 1522-1532. https://doi.org/10.1016/j.scitotenv.2018.06.312

Sotherton, N.W. (1984) The distribution and abundance of predatory arthropods overwintering on farmland. Annals of Applied Biology, 105, 423–429.

Stallinga, H., van de Zande, J.C., Michielsen, J.G.P., van Velde, P. (2014) Enkeldops validatiemetingen driftreducerende spuitdoppen en rijsnelheid : veldmetingen 2011-2012. https://www.wur.nl/nl/Publicatie-details.htm?publicationId=publication-way-343835363433

Stallinga, H., van de Zande, J.C., Michielsen, J.G.P., van Velde, P. (2016) Single nozzle spray drift measurements of drift reducing nozzles at two forward speeds. Aspects of Applied ecology, 132, 183-190.

Stark, J. D., Chen, X. D., & Johnson, C. S. (2012) Effects of herbicides on Behr's metalmark butterfly, a surrogate species for the endangered butterfly, Lange's metalmark. Environmental Pollution, 164, 24-27. https://doi.org/10.1016/j.envpol.2012.01.011

Statistische Ämter des Bundes und der Länder (2011) Agrarstrukturen in Deutschland – Einheit in Vielfalt. Regionale Ergebnisse der Landwirtschaftszählung 2010. Online available: https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Landwirtschaft-Forstwirtschaft-Fischerei/Landwirtschaftliche-Betriebe/Publikationen/Downloads-Landwirtschaftliche-Betriebe/agrarstrukturen-in-deutschland-5411203109004.pdf?__blob=publicationFile [2021-03-21]

Statistisches Bundesamt (Destatis) (2017) Agrarstrukturerhebung 2016. Online available: https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Landwirtschaft-Forstwirtschaft-Fischerei/Tiere-Tierische-Erzeugung/Publikationen/Downloads-Tiere-und-tierische-Erzeugung/viehhaltung-2030213169004.pdf?__blob=publicationFile [2021-03-21]

Statistisches Bundesamt (Destatis) (2019) Bodennutzung der Betriebe 2019. Fachserie 3, Reihe 3.1.2. Online available: https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Landwirtschaft-Forstwirtschaft-Fischerei/Publikationen/Bodennutzung/landwirtschaftliche-nutzflaeche-2030312197004.pdf?__blob=publicationFile [2021-03-21]

Tappert, L., Pokorny, T., Hofferberth, J., & Ruther, J. (2017) Sublethal doses of imidacloprid disrupt sexual communication and host finding in a parasitoid wasp. Scientific Reports, 7. https://doi.org/ARTN 42756

Tennekes, H. A. (2010) The significance of the Druckrey-Kupfmuller equation for risk assessment-The toxicity of neonicotinoid insecticides to arthropods is reinforced by exposure time. Toxicology, 276(1), 1-4. https://doi.org/10.1016/j.tox.2010.07.005

Thomas, C. F. G., Hol, E. H. A., & Everts, J. W. (1990) Modeling the diffusion component of dispersal during recovery of a population of linyphiid spiders from exposure to an insecticide. Functional Ecology, 4(3), 357-368. https://doi.org/10.2307/2389597

Thorbek, P., & Topping, C. J. (2005) The influence of landscape diversity and heterogeneity on spatial dynamics of agrobiont linyphiid spiders: An individual-based model. Biocontrol, 50(1), 1-33.

Togni, P. H. B., Venzon, M., Souza, L. M., Sousa, A. A. T. C., Harterreiten-Souza, S., Pires, C. S. S., & Sujii, E. R. (2019) Dynamics of predatory and herbivorous insects at the farm scale: the role of cropped and noncropped habitats. Agricultural and Forest Entomology, 21(4), 351-362. https://doi.org/10.1111/afe.12337

Tooming, E., Merivee, E., Must, A., Sibul, I., & Williams, I. (2014) Sub-lethal effects of the neurotoxic pyrethroid insecticide Fastac 50EC on the general motor and locomotor activities of the non-targeted beneficial carabid beetle Platynus assimilis (Coleoptera: Carabidae). Pest Management Science, 70(6), 959-966. https://doi.org/10.1002/ps.3636

Topping, C. J., & Lagisz, M. (2012) Spatial Dynamic Factors Affecting Population-Level Risk Assessment for a Terrestrial Arthropod: An Agent-Based Modeling Approach. Human and Ecological Risk Assessment, 18(1), 168-180. https://doi.org/10.1080/10807039.2012.632292

Topping, C. J., & Sunderland, K. D. (1998) Population dynamics and dispersal of Lepthyphantes tenuis in an ephemeral habitat. Entomologia Experimentalis Et Applicata, 87(1), 29-41.

Topping, C. J., Craig, P. S., de Jong, F., Klein, M., Laskowski, R., Manachini, B., Pieper, S., Smith, R., Sousa, J. P., Streissl, F., Swarowsky, K., Tiktak, A., & van der Linden, T. (2015) Towards a landscape scale management of pesticides: ERA using changes in modelled occupancy and abundance to assess long-term population impacts of pesticides. Science of the Total Environment, 537, 159-169. https://doi.org/10.1016/j.scitotenv.2015.07.152

Topping, C. J., Dalkvist, T., Forbes, V. E., Grimm, V., & Sibly, R. M. (2009) The potential for the use of agent-based models in ecotoxicology. In J. Devillers (Ed.), Ecotoxicology Modeling (pp. 205-235). Springer.

Topping, C. J., Kjaer, L. J., Hommen, U., Hoye, T. T., Preuss, T. G., Sibly, R. M., & van Vliet, P. (2014) Recovery Based on Plot Experiments Is a Poor Predictor of Landscape-Level Population Impacts of Agricultural Pesticides. Environmental toxicology and chemistry, 33(7), 1499-1507. https://doi.org/10.1002/etc.2388

Topping, C. J., Craig, P.S., de Jong, F., Klein, M., Laskowski, R., Manachini, B., Pieper, S., Smith, R., Sousa, J.P., Streissl, F., Swarowsky, K., Tiktak, A., van der Linden, T. (2015) Towards a landscape scale management of pesticides: ERA using changes in modelled occupancy and abundance to assess long-term population impacts of pesticides. Science of the Total Environment, 537, 159-169.

Topping, C.J., Dalby, L., Skov, F. (2016) Landscape structure and management alter the outcome of a pesticide ERA: Evaluating impacts of endocrine disruption using the ALMaSS European Brown Hare model. Science of the Total Environment, 541, 1477-1488.

Uhl, P., & Brühl, C. A. (2019) The Impact of Pesticides on Flower-Visiting Insects: A Review with Regard to European Risk Assessment. Environmental toxicology and chemistry, 38(11), 2355-2370. https://doi.org/10.1002/etc.4572

Wallin, H. (1989) Habitat Selection, Reproduction and Survival of Two Small Carabid Species on Arable Land: A Comparison between Trechus secalis and Bembidion lampros. Holarctic Ecology, 12(3), 193–200.

van Klink, R., Bowler, D. E., Gongalsky, K. B., Swengel, A. B., Gentile, A., & Chase, J. M. (2020) Meta-analysis reveals declines in terrestrial but increases in freshwater insect abundances. Science, 368, 417-420. https://doi.org/10.1126/science.aax9931

Vanbergen, A. J., Woodcock, B. A., Watt, A. D., Niemelä, J. (2005) Effect of land-use heterogeneity on carabid communities at the landscape scale. Ecography, 28(1), 3–16. https://www.jstor.org/stable/3683443

Vasseur, C., Joannon, A., Aviron, S., Burel, F., Meynard, J.-M., Baudry, J. (2013) The cropping systems mosaic: How does the hidden heterogeneity of agricultural landscapes drive arthropod populations? Agr. Ecosyst. Environ., 166, 3–14.

Vighi, M., & Rico, A. (2018) The Concept of Resilience in Ecological Risk Assessment: Scientific and Regulatory Issues [Editorial Material]. Integrated environmental assessment and management, 14(5), 581-585. https://doi.org/10.1002/ieam.4080

Yang, L., Zhang, Q., Liu, B., Zeng, Y. D., Pan, Y. F., Li, M. L., & Lu, Y. H. (2019). Mixed effects of landscape complexity and insecticide use on ladybeetle abundance in wheat fields. Pest Management Science, 75(6), 1638-1645. https://doi.org/10.1002/ps.5281

Yip, E. C., Rao, D., Smith, D. R., & Lubin, Y. (2019) Interacting maternal and spatial cues influence natal - dispersal out of social groups. Oikos, 128(12), 1793-1804. https://doi.org/10.1111/oik.06531

Zar, J.H. (1999) Biostatistical Analysis. 4th edition. Prentice Hill.

Ziółkowska, E., Tiktak, A., & Topping, C. J. (2022) Is the effectiveness of policy-driven mitigation measures on carabid populations driven by landscape and farmland heterogeneity? Applying a modelling approach in the Dutch agroecosystems. Plos One, 17(12), e0279639. https://doi.org/10.1371/journal.pone.0279639

Ziółkowska, E., Topping, C. J., Bednarska, A. J., & Laskowski, R. (2021) Supporting non-target arthropods in agroecosystems: Modelling effects of insecticides and landscape structure on carabids in agricultural landscapes. Science of the Total Environment, 145746. https://doi.org/https://doi.org/10.1016/j.scitotenv.2021.145746

Zubrod, J. P., M. Bundschuh, G. Arts, C. A. Brühl, G. Imfeld, A. Knäbel, S. Payraudeau, J. J. Rasmussen, J. Rohr, A. Scharmüller, K. Smalling, S. Stehle, R. Schulz and R. B. Schäfer (2019). "Fungicides: An Overlooked Pesticide Class?" Environmental Science & Technology 53(7): 3347-3365.

A Appendix: Parametrization of the ALMaSS landscape model for the German landscapes

The approach used broadly follows the one presented by Topping et al. (2016) but required specific German conditions and datasets to be taken into account. We described in detail, first, the input data used (section A.1), and second, the process of generating a complete simulation landscape for ALMaSS divided into two main tasks: generation of landscape map as input for ALMaSS (section A.2), and farm classification (section A.3).

The developed protocols allow for automatic extraction of landscape data for landscape windows of given size (typically 10 x 10 km) and generation of necessary ALMaSS input files for simulation. Automatic extraction and collation of data for simulation means that scaling up can be applied by virtue of simulation of multiple areas within the Brandenburg & Lower Saxony regions using batch file processing on mainframe computers.

All handling and analysis of spatial data was done using Python 2.7 (https://docs.python.org/2.7/) and the Python library arcpy to access ArcGIS features (ESRI 2010), or directly in ArcGIS 10.7 (migration to Python 3 and ArcGIS Pro is underway). The entire process of producing landscape model for ALMaSS has been programmed in Python scripts with Pandas library (https://pandas.pydata.org/). The scripts are available in the GitLab repository: https://gitlab.com/ALMaSS/almassauxillary/-/tree/master/landscape_generation.

A.1 Input data

A.1.1 Land cover / land use information

The basis for the land use information is the Digital Basic-Landscape model (Basis-DLM) for the year 2019 being part of the Authorative Topographic-Cartographic Information System (ATKIS) of the Federal Republic of Germany. Basis-DLM describes the topographic objects of the landscape and the relief of the Earth's surface in vector format and is available for the entire area of Germany. Basis-DLM groups objects into several (feature) types including: settlements (residential areas, industrial and commercial areas, sport, leisure, and recreation areas, etc.), communication (roads, railways), vegetation (agriculture, forest, heath etc.), water (watercourses, channels, harbor basins, etc.), buildings and other facilities, and others. Types of objects (feature types) relevant for ALMaSS were selected based on the information provided in the documentation (Dokumentation zur Modellierung der Geoinformationen des amtlichen Vermessungswesens – GeoInfoDok) (Table A1). In addition, for more detailed mapping of buildings the data from the Federal Agency for Cartography and Geodesy (BKG, 2016) were used.

To define the protected areas, types of land use / land cover (arable area, grassland area, swamp, bog, heath, wasteland with vegetation, wasteland without vegetation) with protection status were defined. For this purpose, we used the NATURA2000 area maps of the Federal Agency for Nature Conservation (BfN) of 2018. At the moment these protected areas are not considered in the ALMaSS landscape models because the consequences for the actual application of plant protection products and the implementation of the regulation differs between the regions.

Since Basis-DLM has limited data on some important landscape elements such as hedgerows and tree rows, these were supplemented with information available via the Land Parcel Identification System (LPIS; see subchapter 1.2). Landscape elements in LPIS can have different codes in each federal state. Therefore, the selection of relevant landscape elements was done outside of the landscape generation scripts (see chapter A.2).

Table A1: Description of the individual layers used in the final landscape map for Brandenburg / Lower Saxony, the theme in which they are grouped, their data sources and original data type. "Code" stands for the numerical value assigned to different objects in the second section of the script. "Cut-off" stands for the cut-off value which was used to add buffers to point and line objects. "ALMaSS TOLE code" stands for the code of Type Of Landscape Element (TOLE) used by ALMaSS.

Layer	Description	Code	Theme	Type	Source	Cut-off [m]	ALMaSS TOLE code
	Water buffer zone	100	Water	Polygon		1.50	98
gew01_l	Small river (<=3m width)	112		Line	ATKIS	1.00	96
	Medium size river (>3m and <= 6m width)	113		Line	ATKIS	2.00	96
	Large river (> 6m and <= 12 m width)	114		Line	ATKIS	5.00	96
gew01_f	Stream	115		Polygon	ATKIS		207
	Lakes	121		Polygon	ATKIS		219
	Port	140		Polygon	ATKIS	1.50	5
	Road verges	210	Communication			1.00	13
ver02_l	Track or path for bikes and pedestrians	211		Line	ATKIS	0.50	123
	Unpaved or low-paved road	212		Line	ATKIS	0.50	123
	Small road	213		Line	ATKIS	1.00	122
ver01_l	Medium road	215		Line	ATKIS	2.00	121
	Large road	217		Line	ATKIS	5.00	121
ver03_l	Railway 1 track	221		Line	ATKIS	2.50	118
	Railway 2 tracks	222		Line	ATKIS	4.50	118
sie03_p	High voltage mast	231		Point	ATKIS	2.50	212
	Windmill	232		Point	ATKIS	2.50	211
ver05_f	Ship traffic area	241		Polygon	ATKIS		12
ver04_f	Air traffic area	242		Polygon	ATKIS		12

Layer	Description	Code	Theme	Type	Source	Cut-off [m]	ALMaSS TOLE code
ver03_f	Railway traffic area	243		Polygon	ATKIS		118
ver01_f	Road traffic area	244		Polygon	ATKIS	1.00	121
sie02_f	Golf course	311		Polygon	ATKIS		12
	Park, green area, zoo, game enclosure	312		Polygon	ATKIS		14
	Private gardens, allotments	313		Polygon	ATKIS		11
	Camping sites, holiday home complex	314		Polygon	ATKIS		12
	Sport facilities, recreational facilities, amusement park, pool	315		Polygon	ATKIS		14
	Graveyard	316		Polygon	ATKIS		204
sie03_f	Solar panels	317	Cultural	Polygon	ATKIS		304
veg04_l	Single tree	321		Point	ATKIS	2.00	213
	Hedgerow	322		Line	ATKIS	2.00	130
	Tree line, deciduous	323		Line	ATKIS	2.00	41
	Tree line, coniferous	324		Line	ATKIS	2.00	41
	Tree line, mixed	325		Line	ATKIS	2.00	41
	hedgerow (LPIS)	326		Polygon	LPIS		130
sie02_f	Tree line (LPIS)	327		Polygon	LPIS		41
sie02_f	Urban area (living)	411		Polygon	ATKIS		8
	Urban area (industry, mixed use)	412		Polygon	ATKIS		8
	Landfill site	413		Polygon	ATKIS		224
	Opencast mining, quarry	414		Polygon	ATKIS		115
ver01_f	Place, square	421	Built-up	Polygon	ATKIS		8
sie03_f	Buildings for industry and commerce	431		Polygon	ATKIS		5
	Other buildings, unspecified	432		Polygon	ATKIS		5
Hausumringe	Buildings	440		Polygon	BKG		5
veg02_f +	Coniferous Forest	511	Natural	Polygon	ATKIS		50
veg04_f	Deciduous Forest	512		Polygon	ATKIS		40

Layer	Description	Code	Theme	Type	Source	Cut-off [m]	ALMaSS TOLE code
	Mixed forest	513		Polygon	ATKIS		60
veg04_l	Forest aisle	514		Line	ATKIS	6.00	413
veg03_f	Heath protected	521		Polygon	ATKIS + Natura2000		94
	Heath	522		Polygon	ATKIS		95
veg04_l	Copse/ small wood protected	523		Polygon	ATKIS + Natura2000		41
	Copse/ small wood	524		Polygon	ATKIS		41
veg03_f	Wasteland without vegetation protected	525		Polygon	ATKIS + Natura2000		209
	Wasteland without vegetation	526		Polygon	ATKIS		209
	Wasteland with vegetation protected	527		Polygon	ATKIS + Natura2000		209
	Wasteland with vegetation	528		Polygon	ATKIS		209
	Riverside area	529		Polygon	ATKIS		98
	Bog protected	531		Polygon	ATKIS + Natura2000		205
	Bog	532		Polygon	ATKIS		205
	Swamp protected	533		Polygon	ATKIS + Natura2000		95
	Swamp	534		Polygon	ATKIS		95
	Grassland protected	551		Polygon	ATKIS + Natura2000		
veg01_f	Grassland	552		Polygon	ATKIS		
	Grassland	554					210
	Wasteland	570					209
	Field margin	900	Cultivable				160
veg01_f	Orchard	610		Polygon	ATKIS		56

Layer	Description	Code	Theme	Type	Source	Cut-off [m]	ALMaSS TOLE code
	Tree nursery	620		Polygon	ATKIS		214
	Other agricultural area	630		Polygon	ATKIS		
	Arable area protected	641		Polygon	ATKIS + Natura2000		210
	Arable area	642		Polygon	ATKIS		50

A.1.2 The Land parcel identification System (LPIS)

Generation of the ALMaSS landscape models for Germany was restricted by the availability of agricultural data. The data of the Integrated Administration and Control System (IACS) offers the highest spatial and temporal resolution for deriving the crop information per field at the farm level. LPIS is a part of IACS responsible for the agriculturally managed reference parcels (geographically delimited areas with unique identification codes) in the EU Member States and serves as a controlling mechanism under the Common Agricultural Policy (CAP). In Germany, IACS / LPIS is managed at the federal state level. Since this data is farm-related, it is not or only partially publicly accessible. However, it can be made available for the scientific purposes within the framework of user agreements. In the present case, IACS / LPIS data for the year 2019 was acquired for two federal states: Lower Saxony and Brandenburg. From IACS / LPIS data we used information on type of crops cultivated in reference parcels (from the register of direct payments), ID numbers of agricultural holdings enabling grouping of individual reference parcels into farm units. The system also records information on farm area, livestock, and farm type (conventional/organic). The field outlines are provided in a vector format as shapefile or geodatabase with corresponding attribute tables.

A.1.3 Animal information

The information about the livestock husbandry and share par farm, which is necessary to define farm types in ALMaSS is part of the LPIS data set. For Brandenburg the provided numbers of animals had to be translated into Livestock Units (LSU) based on the EUROSTATS statistical glossary. The Lower Saxonian data were provided both as numbers of animals and LSU values, and the LSU coefficients were adjusted to match the EUROSTAT coefficients.

A.1.4 Soil maps

The ALMaSS landscape simulator modifies the actual production on each field based on the dominant soil type. In addition, some operations performed by farmers on fields (e.g., type of soil cultivation) may depend on soil type.

We used the national soil map BUEK200 in scale 1:200,000 provided by the Federal Institute for Geosciences and Natural Resources (BGR). BUEK200 is organized in topographic legend units (TKLE). In each TLKE, from two to eight soil profiles were taken. The first of these profiles is always the leading main profile ("Leitbodenprofil"). The others are additional profiles for different land use types in the legend unit (forest, grassland, arable land). We took the main profile and chose the upper soil horizon (1), and here the soil texture type ("BOART"). The soil texture type includes the fine soil texture codes and additionally a code for the stony texture (>63 mm = "O"). In order to use the soil data, it was necessary to translate the national soil classification into an internationally used classification system of the FAO (2006), which is also used in the ALMaSS model for other countries (soil types according to e.g., "fine sand", "medium sand", "coarse sand", etc.) (Table A2).

Other freely accessible international soil maps are also available online, for example from the European Soil Database, but their spatial resolution is much coarser compared to the national soil maps.

Table A2: ALMaSS soil classification and its relation to the FAO classification.

Lp.	Agricultural Usage	ALMaSS soil type code	FAO texture code	Description
1	None	0	-	Water
2	None	1	S	Sand (unspecified)
3	Poor	2	LS	Loamy sand
4	Poor	3	SL	Sandy loam
5	Poor	4	SCL	Sandy clay loam
6	Average	5	SiL	Silt loam
7	Average	6	SiCL	Silty clay loam
8	Good	7	CL	Clay loam
9	Good	8	L	Loam
10	Good	9	Si	Silt
11	Good	10	SC	Sandy clay
12	Good	11	SiC	Silty clay
13	Good	12	C	Clay
14	Good	13	HC	Heavy clay
15	Good	14	O	Organic & peat

A.2 Generation of ALMaSS landscape map

The aim of this task is to generate a landscape raster map of 1-m spatial resolution with complete coverage; hence all cells must be classified in accordance with their landscape element type. This was done by combining individual layers of land use / land cover information together with information on agricultural fields into a single raster landscape map in a step-by-step process. As layers from different data sources were used, this resulted in inconsistencies related to spatial alignment of features (overlaps or gaps between features). In addition, some objects were represented as points or lines and therefore as dimensionless had to be pre-processed to change them into two-dimensional ones. However, this process increased the number of inconsistencies in the combined map even more, so a special step-by-step procedure was applied to be able to obtain a landscape raster map with no gaps in information and with removed sliver polygons.

The overall process to generate the ALMaSS landscape map consisted of the following steps:

a) Pre-processing of ATKIS feature layers.

b) Pre-processing of LPIS data.

c) Clipping of the input layers to test study area extent.

d) Converting the input vector data to raster format (with spatial resolution of 1 m), object class by object class.

e) Themes: Combining individual layers into thematic maps (e.g., transportation theme, built-up theme).

f) Stacking of thematic maps to generate raw landscape map.

g) Cleaning: Removing of inconsistencies in the landscape raw map (multi-stage process including quality-check and removal of non-classified areas/pixels in a step-by-step procedure).

h) Reclassification and regionalization of resulting landscape map.

i) Exporting results.

j) Generating reference files for ALMaSS.

All handling and analysis of spatial data were done using Python 2.7 (https://docs.python.org/2.7/) and the Python library arcpy to access ArcGIS features (ESRI 2010), or directly in ArcGIS 10.4. The entire process of producing German (Brandenburg / Lower Saxony) landscape model for ALMaSS has been programmed in Python scripts with Pandas library (https://pandas.pydata.org/):

Script *landscape_DE_part0_layer_preparation.py* covers point (a - b);

Script *landscape_DE_part1.py* covers points (c) – (f);

Script *landscape_DE_part2.py* covers points (g) - (i);

Script *ALMaSS_files_generation_DE.ipynb* covers point (j).

Scripts are available at:

https://gitlab.com/ALMaSS/almassauxillary/-/tree/master/landscape_generation/de.

A.2.1 Pre-processing of ATKIS feature layers

The feature layers from the ATKIS were first pre-processed to obtain one layer per landscape element type. For example, all road types were mapped within a single feature layer in ATKIS, so they were divided into classes, such as small, medium, and large roads. This process is described below for selected types of landscape elements, whenever additional explanation is needed.

Roads in ATKIS are mapped within a single feature layer as dimensionless line features. They were therefore divided into several main categories, and their dimension (width) was defined for each type separately, based on information provided in the attribute “BRF” = “Breite Fahrbahn”, if possible (Table A3). Unfortunately, only 27 % of roads (and only 9 % of road line features have information on width included. Therefore, the other transport line features were classified according to their type using attribute “FKT” = “Funktion” (can be “WegPfadSteig”, “Wirtschaftsweg”, etc.) or attribute “WDM” = “Widmung” (which can be “Autobahn”, “Bundesstrasse”, etc.) (see details in Table). This may lead to incorrect classification for the large roads because “Autobahn” shows a large variation in width.

Water courses in ATKIS are mapped within a single feature layer as dimensionless line features. There is no direct information on their width, however classes of width (see Table A4) are provided in the attribute ‘BRG’. We used this classification in the ALMaSS landscape generation process, although it may lead to over-generalization, especially for the small rivers.

Table A3: Classification of road types from the ATKIS dataset based on combination of information from different attributes. “Cut-off” stands for the cut-off value which was used to add buffers to point and line objects.

Type	Feature layer	Object type from OBJART attribute	Type from FKT attribute	Type from WDM attribute	Width class [m] from BRF attribute	Cut-off [m]
Track or path for bikes and pedestrians	ver02_l	53003	-	-	-	0.5
Unpaved or low-paved road	ver02_l	42008	5212	-	-	0.5
Small road	ver02_l	42008	5211	-	<= 3 m	1
Medium road	ver01_l	-	-	NOT 1301	< 3 –- <= 6 m	2
Large road	ver01_l	-	-	1301	> 6 m – 12 m	5

Table A4: Classification of river/stream types from the ATKIS. "Cut-off" stands for the cut-off value which was used to add buffers to point and line objects.

Type	Width class [m] according to BRG attribute	Cut-off [m]
small river	<= 3	1
medium size river	< 3 – <= 6	2
large river	> 6 – 12	5

A.2.2 Pre-processing of LPIS data

Before the inclusion of the field data all parcels were selected which are managed annually (at least partially) as agricultural. All landscape elements were filtered out and included in the cultural theme.

All permanent crop types were identified and fields with those crops were attributed with appropriate ALMaSS TOLE (type of landscape element) code, as indicated in Table A5. All other fields were considered as fields in rotation and attributed with ALMaSS TOLE code of 20.

Table A5: List of permanent crops with associated ALMaSS TOLE (Type Of Landscape Elements) codes.

Crop code (*Nutzcodes*)	German crop name	ALMaSS Crop allocation	ALMaSS TOLE no	
			within conventional farms	within organic farms
8	Spargel unter Folie	Asparagus	525	528
428	Wechselgrünland	PermanentGrassGrazed	35	514
441	Wiesen Grünlandneueinsaat im Rahmen von AUKM	PermanentGrassGrazed	35	514
444	DGL Neueinsaat als Ersatz für genehmigten DGL Umbruch	SetasidePermanent	33	33
451	Wiesen	PermanentGrassGrazed	35	514
452	Mähweiden	PermanentGrassGrazed	35	514
453	Weiden und Almen	PermanentGrassExtensive	26	515
454	Hutungen	PermanentGrassExtensive	26	515
458	Streuwiesen	PermanentGrassExtensive	26	515
459	Grünland	PermanentGrassGrazed	35	514

Crop code (*Nutzcodes*)	German crop name	ALMaSS Crop allocation	ALMaSS TOLE no	
			within conventional farms	within organic farms
462	beweidete Sandheiden	PermanentGrassExtensive	26	515
463	beweidete Moorheiden	PermanentGrassExtensive	26	515
464	beweidete Magerrasen	PermanentGrassGrazed	35	514
465	beweidete montane Wiesen	PermanentGrassExtensive	26	515
466	gemähte Magerrasen	PermanentGrassGrazed	35	514
467	gemähte montane Wiesen	PermanentGrassGrazed	35	514
480	Streuobstfläche mit Grünlandnutzung	OrchardCrop	56	503
492	Dauergrünland unter etablierten lokalen Praktiken Z.B. Heide	PermanentGrassExtensive	26	515
576	Schutzstreifen Erosion	SetasidePermanent	33	33
592	Dauergrünland aus der Erzeugung genommen	SetasidePermanent	33	33
593	Dauerkulturen aus der Erzeugung genommen iSd. Art. 4 Abs. 1 Buchst. c ii VO 1307 2013	SetasidePermanent	33	33
821	Pfirsiche in Vollanbau	OrchardCrop	56	503
822	Kirschen Ertragsanlagen	OrchardCrop	56	503
823	Pflaumen Ertragsanlagen	OrchardCrop	56	503
824	Haselnüsse	OrchardCrop	56	503
825	Walnüsse	OrchardCrop	56	503
826	sonstige Schalenfrüchte	OrchardCrop	56	503
827	Äpfel in Vollanbau	OrchardCrop	56	503
828	sonst. Steinobst ohne Kirschen Pflaumen	OrchardCrop	56	503
829	Sonstige Obstanlagen z.B. Holunder Aronia Maulbeeren	OrchardCrop	56	503

Crop code (*Nutzcodes*)	German crop name	ALMaSS Crop allocation	ALMaSS TOLE no	
			within conventional farms	within organic farms
830	Baumschulen nicht für Beerenobst	OrchardCrop	56	503
831	Beerenobst zur Vermehrung in Baumschulen	Strawberries	504	505
832	Pflaumen Ertragsanlagen	OrchardCrop	56	503
833	Haselnüsse	OrchardCrop	56	503
834	Walnüsse	OrchardCrop	56	503
836	Äpfel in Vollanbau	OrchardCrop	56	503
837	sonst. Steinobst ohne Kirschen Pflaumen	OrchardCrop	56	503
838	Baumschulen nicht für Beerenobst	OrchardCrop	56	503
839	Beerenobst zur Vermehrung in Baumschulen	OrchardCrop	56	503
841	KUP lt. Direktzahlungendurchführungsverordnung	SetasidePermanent	33	33
842	Rebland	OrchardsExtensive	56	503
843	Bestockte Rebfläche	OrchardCrop	56	503
850	Sonstige Dauerkulturen	OrchardCrop	56	503
851	Bestockte Rebfläche	OrchardCrop	56	503
852	Unbestockte Rebfläche	OrchardsExtensive	56	503
853	Rebschulfläche	OrchardCrop	56	503
854	Unterlagsrebfläche	OrchardsExtensive	56	503
860	Spargel	Asparagus	525	528
861	Artischocke	Asparagus	525	528
915	Ackerrandstreifen und Blühflächen	SetasidePermanent	33	33

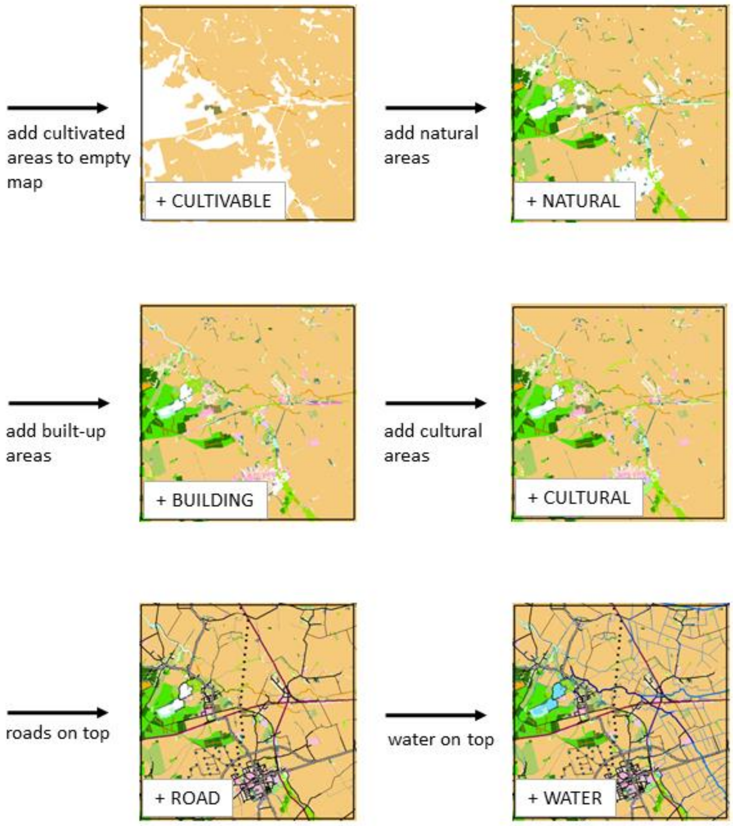
Crop code (*Nutzcodes*)	German crop name	ALMaSS Crop allocation	ALMaSS TOLE no	
			within conventional farms	within organic farms
918	Mehrjährige Blühstreifen und Blühflächen	SetasidePermanent	33	33
925	Biotope mit landwirtschaftlicher Nutzung	SetasidePermanent	33	33
928	Saum und Bandstrukturen	SetasidePermanent	33	33
966	Unkultivierte Heidefläche	SetasidePermanent	33	33
983	Weihnachtsbäume	OrchardsExtensive	56	503
995	Forstflächen Waldbodenflächen	OrchardsExtensive	56	503
998	Bodenschutzwald	OrchardsExtensive	56	503

A.2.3 Processing the raw landscape map

Steps (c) – (f) were programmed in the python script *landscape_DE_part1.py*. The first section of the script (Setup) describes the Python libraries, paths to input and output data, as well as processing environment. The second section of the script (Clipping) clips the necessary input data from the ATKIS and LPIS to the study area extent. The third section of the script (Conversion) deals with the conversion of the original vector data into raster format. For linear and point features (such as streams or single trees), first the Euclidian distance from the feature was calculated, and then the cut-off value was applied to add the buffer (dimension) to the feature. The cut-off values for different layers, as well as numeric values assigned to different objects (codes) are shown in Table.

The next section of the script (Themes) collects the raster layers into the following thematic maps: water, communication, cultural, built-up, nature and cultivable (Table A5). In cases where two or more of the layers in a theme overlap, the layer with the higher numeric value (code) is prioritized. The fourth section (Stack) stacks the thematic maps in a sequence such that the final landscape raw map shows the ecological meaningful layers on top (Figure A1). The order of thematic layer was as follows: fields (LPIS) first -> nature areas in empty space -> other cultivable areas (orchards, tree plantations etc.) on top -> built-up areas on top (without buildings) -> cultural features on top -> water on top -> communication areas on top -> buildings on top. After this process there was still number of cells without land cover type (i.e., ‘background’), as well as substantial number of ‘sliver’ polygons which needed to be removed. These steps were programmed in the python script *landscape_DE_part2.py*.

Figure A1: Stacking of thematic layers.



Source: Authors' own.

A.2.4 Removing of inconsistencies in the raw landscape map

The next step (g) was to get rid of sliver polygons and fill gaps (i.e., remove 'background' pixels with no landscape element type assigned) in order to generate landscape map with complete coverage. This was done in a multi-step process (programmed in script *landscape_DE_part2.py*) based on previous work done in Poland and the Netherlands.

A.2.5 Reclassification and regionalization, exporting results

Step (h) is finalizing the landscape as a final input map for ALMaSS. The landscape map contains more details than are used in ALMaSS. Therefore, to be consistent with landscape element types used in ALMaSS we used simple reclassification based on a text file (Table A5). All features in the ALMaSS landscape map, consisting both of single and multiple raster cells, have a unique value that is common to all cells within the feature. This was achieved by regionalizing the raster before exporting the map as a final ASCII file. Besides that, in this part of the script, attribute tables of landscape elements and agriculturally managed areas (including individual fields and permanent crops) are exported (step i) to be further processed in step (j).

A.2.6 Generating reference files for ALMaSS

Script ALMaSS_files_generation_DE.ipynb was used to generate the ALMaSS input files: polygon and farm reference text files, and landscape raster map in .lsb format.

As each polygon of the final ALMaSS landscape raster only contains the value that is the unique ID of the polygon, all additional information on the polygons needs to be described in separate reference files. The polygon reference file is a text file containing as the key to its set of rows the unique ID on each of the polygons in the landscape. Together with that, each row comprises information of the landscape element type, the number of cells, a reference number to a farm owner/holding, and optionally the soil type, mean elevation, slope, and aspect, as well as habitat type (for modelling of flowering resources available for pollinators) of polygon. The farm reference file is a 2-column text file relating the reference number to a farm owner/holding to farm types (see section A.3).

To create the polygon reference file, the attribute table from the final polygon map needs to be exported from ArcGIS. With this, the attribute table and information about farm ownership (which farm owns which fields) a minimal polygon reference file can be made. The task is to merge these pieces of information together. This is now done in a Python script that uses functions in the PANDAS package, building upon the former implementation that used R and functions in the R packages ralmass (Dalby 2015), devtools (Wickham & Chang, 2015) and data.table (Dowle et al. 2014).

A.3 Farm classification

By combining crop and animal information it was possible to identify nine major farm types such as pig, arable, or cattle farms, further being classified as either conventional or organic (18 farm types in total, see Table A6). Rules used to classify farms needed to be very general because real farms tend not to fit neatly into pure farm type rules (e.g., many arable farms have grazing because they have some animals e.g., a few animals for their own consumption). The rules we used were based on information on production in German farms according to type of farming based on data from the Farm Accountancy Data Network Public Database (FADN, 2018[1]) and on analyzes on crops and animal data for 2018. These are described below.

A.3.1 Types of farms

Nine major farm types were distinguished (Table A6):

a) *Vegetable farms*. In Germany, the mean share of vegetable acreage in vegetable farms is 52% (FADN, 2018). So, the farms with ≥ 50% vegetable area and a farm area >20 ha are defined as Vegetable farms. Farms with more than 20% potato area AND ≥ 50% vegetable area are also included in that group.

b) *Potato farms*. In Germany, 27060 farms will grow potatoes on a total of 271,600 ha in 2019, resulting in an average cultivated area per farm of 10.04 ha. Thus, only farms with >= 10 ha potato acreage are included (Statistisches Bundesamt, 2019). For potatoes, a rotation break of 4-5 years is recommended, resulting in a maximum cultivation share of 20-25%. Accordingly, for this farm type only farms are included whose potato cultivation area covers ≥ 20% of the agricultural area, i.e., a crop rotation with 1/5 potatoes can be assumed.

[1] https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html

c) *Sugar beet farms*. In Germany 26070 farms cultivate sugar beet on a total of 408700 ha in 2019, resulting in an average cultivation area per farm of 15.7 ha. Thus, only farms with >= 16 ha of sugar beet cultivation area are included (Federal Statistical Office, 2019).

d) *Cattle and horse farms*. The German official statistic summarizes all grazing animals like cattle and horses and goats and sheep for the definition of grazing livestock farms. So, we included horses here. The mean LSU over all farms with cattle, horses, sheep and/or goats was 73.2 LSU in 2016 (Statistisches Bundesamt, 2017). So, the limit for cattle farms here is ≥ 20 LSU and 75% cattle or sheep or goat or horse.

e) *Pig and poultry farms*. In Germany, 7.6% of farms kept pigs in 2020 (Destatis, 2020). In our classification pig and poultry farms are farms with pig and/or poultry ≥ 20 LSU and 75% pig or poultry of all livestock of the farm.

f) *Mixed farms*. These are farms with two or more pillars and no clear focus on potato or sugar beet or livestock production alone (≥ 20 LSU, but not pig or cattle farms, i.e., less than 75% cattle or 26% pig). That includes also farms with more than ≥ 20 LSU AND ≥ 20% beet or ≥ 20% potato area per farm area. Also farms with < 20 LSU but with beet area > 20% AND potato area >20% are added to this group.

g) *Arable farms*. As arable farms we define farms with < 20 LSU, < 50% vegetable crops and farm area >20 ha.

h) *Grass farms*. To calculate the grazing area per farm area, we need to first define all the LPIS codes included in the category 'grazing area' (Table A7). Then, based on results, we defined grass farms as those which fulfil the following conditions:

- ≥ 20 LSU but no Cattle or Pig farm
- ≥ 20 LSU AND ≥ 16 ha beet area OR ≥ 20 LSU AND ≥ 10 ha potato area
- Farm area is >20 ha (no Hobby farms).

i) *Hobby farms*. In German official statistics the Hobby farms are defined depending to the farm income in which off-farm income is greater than income from the agricultural holding (Statistisches Bundesamt, 2017). To receive a numerous group boundary according to the farm size, we calculate the mean farm size of the farms which are defined as Hobby farms in the German statistic. This is 20.8 ha. So, Hobby farms here have a farm area ≤ 20 ha and < 20 LSU.

Table A6: Summary of defined farm types and associated classification rules. LSU = Livestock Unit.

Farm ID	Farmtype	Classification rules
1 / 11	Conv. / Org. Vegetable farm	≥ 50% vegetable area and farm area >20 ha
2 / 12	Conv. / Org. Potato farm	≥ 16 ha beet area AND beet area per farm area is ≥ 20% and farm area >20 ha
3 / 13	Conv. / Org. Beet farm	≥ 10 ha potato area AND potato area per farm area is ≥ 20% and farm area >20 ha
4 / 14	Conv. / Org. Cattle and horse farm	≥ 20 LSU and 75% cattle or sheep or goat or horse
5/ 15	Conv. / Org. Pig farm	≥ 20 LSU and 26% pig or poultry
6 / 16	Conv. / Org. Mixed farm	≥ 20 LSU, but not pig or cattle farms (less than 75% cattle or pig)
7 / 17	Conv. / Org. Arable farm	< 20 LSU, < 50% vegetable, farm area >20 ha,
8 / 18	Conv. / Org. Grass farm	grazing or fodder plants area ≥ 40% but LSU=0
9 / 19	Conv. / Org. Hobby farm	≤ 20 ha farm area and < 20 LSU

Table A7: LPIS categories included in the area calculation for 'grazing area'.

Code	LPIS code explanation (German)	English definition
441	Wiesen (Grünlandneueinsaat im Rahmen von AUKM)	Grassland (new grassland sowing in the frame of AUKM)
444	DGL Neueinsaat als Ersatz für genehmigten DGL Umbruch	Permanent grassland (compensation for ploughed up grassland)
451	Wiesen	Grassland
452	Mähweiden	Meadows
453	Weiden und Almen	Pasture and alpine pasture
454	Hutungen	Rough pasture
459	Grünland	Grassland
480	Streuobstfläche mit Grünlandnutzung	Orchards with grassland use
492	Dauergrünland unter etablierten lokalen Praktiken (z.B. Heide)	Permanent grassland
592	Dauergrünland aus der Erzeugung genommen iSd. Art. 4 Abs. 1 Buchst. c) ii) VO 1307/2013	Permanent grassland

A.3.2 Crop rotation schemes for farm types

Based on proportions of crops cultivated by farms of different types, crop rotation schemes were generated for each farm type individually. Only crops with more than 1% share of the area of a farm type were considered (Table A8). It was assumed that the rotation could be represented by 100 crops (1 crop for each 1%). The order of crops followed typical agronomic practices and issues such as late harvest leading to impossible sowing conditions were controlled by the built-in ALMaSS farm code. The result was a pattern of changing crops on a field that matches the overall crop distribution pattern for that farm type precisely over 100 seasons. If a specific crop, e.g., maize for silage, occurs 13 times out of 100 in the rotation, it will on average occur on 13% of all fields covered by that rotation at any point in time.

Table A8: Share of crops by type of farm (%) in the regions of Brandenburg and Lower Saxony.

ALMaSS crop	Farm type																	
	Conventional									Organic								
	Veg	Potato	Beet	Cattle and horse	Pig	Mixed	Arable	Grass	Hobby	Veg	Potato	Beet	Cattle and horse	Pig	Mixed	Arable	Grass	Hobby
	1	2	3	4	5	6	7	8	9	11	12	13	14	15	16	17	18	19
BRANDENBURG																		
Cabbage	46	5	0	0	0	2	0	0	1	31	0		0	0	1	0	0	8
Carrots	12	9	0	0	0	0	0	0	0	7	0		0	0	0	0	0	1
CerealLegume	0	0	0	0	0	0	0	0	0	0	0		1	4	8	2	0	1
CloverGrassGrazed	4	1	1	5	2	6	2	13	19	16	23		23	7	20	10	14	33
Herbs/flowers	3	3	2	2	2	2	1	1	2	5	0		3	1	2	5	1	10
Legumes	2	1	0	1	1	1	1	0	2	5	8		8	8	17	8	5	12
Lucerne	0	0	0	3	1	1	1	0	2	0	0		10	10	4	6	48	3
Maize	3	8	0	1	5	0	3	4	2	0	0		1	3	0	5	0	0
MaizeSilage	2	4	9	26	18	17	20	16	7	0	0		5	2	3	1	2	0
Oats	0	0	0	1	0	2	1	1	5	14	0		7	12	9	9	1	4
Peas	0	2	1	1	1	0	1	0	1	0	0		0	2	0	3	0	0
Potatoes	2	1	0	0	0	0	0	0	2	13	31		0	0	1	0	0	2

ALMaSS crop	Farm type																	
	Conventional									Organic								
	Veg	Potato	Beet	Cattle and horse	Pig	Mixed	Arable	Grass	Hobby	Veg	Potato	Beet	Cattle and horse	Pig	Mixed	Arable	Grass	Hobby
	1	2	3	4	5	6	7	8	9	11	12	13	14	15	16	17	18	19
PotatoesIndustry	6	46	0	1	1	0	1	0	0	7	0		0	2	0	0	0	0
SetAside	7	5	3	4	4	3	5	15	6	2	0		0	0	1	1	0	1
SetAsideAnnualFlowers	2	1	0	0	0	0	0	0	1	0	0		0	0	0	0	0	1
SpringBarley	2	0	6	0	0	0	0	4	2	0	39		2	3	1	2	0	0
SpringRye	0	0	0	0	0	0	0	0	1	0	0		2	1	0	3	4	1
SpringWheat	0	0	0	0	0	0	0	0	1	1	0		1	2	0	2	0	2
SugarBeet	1	0	17	0	1	0	1	0	0	0	0		0	0	0	0	0	0
Triticale	1	1	0	5	4	6	3	5	7	0	0		4	3	4	3	2	4
WinterBarley	1	3	11	11	12	9	11	6	4	0	0		3	6	2	4	0	0
WinterRape	0	1	17	6	8	7	9	5	2	0	0		0	0	0	0	0	0
WinterRye	5	6	1	19	17	27	17	21	17	0	0		25	22	23	26	19	12
WinterWheat	1	4	32	15	21	17	22	6	16	0	0		5	11	4	8	3	4
LOWER SAXONY																		
Cabbage	6	0	0	0	0	0	0	0	1	28	1	0	1	1	2	1	0	8

ALMaSS crop	**Farm type**																	
	Conventional									**Organic**								
	Veg	**Potato**	**Beet**	**Cattle and horse**	**Pig**	**Mixed**	**Arable**	**Grass**	**Hobby**	**Veg**	**Potato**	**Beet**	**Cattle and horse**	**Pig**	**Mixed**	**Arable**	**Grass**	**Hobby**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
Carrots	26	2	0	0	0	0	0	0	0	23	2	0	0	2	1	2	1	3
CerealLegume	0	0	0	0	0	0	0	1	0	1	0	0	2	2	2	2	6	1
CloverGrassGrazed	1	0	0	9	1	6	1	14	6	13	2	0	30	11	25	8	45	26
Herbs/flowers	5	0	0	0	0	1	1	1	1	9	1	0	1	1	2	1	1	3
Legumes	9	0	0	0	0	0	0	0	0	6	5	1	6	10	6	7	4	3
Lucerne	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1
Maize	2	1	1	1	9	2	2	3	8	4	4	0	3	10	5	7	10	6
MaizeSilage	7	12	8	48	28	20	19	48	27	2	5	5	13	9	4	6	9	2
Oats	1	0	0	1	0	1	1	1	1	1	2	0	3	1	4	3	0	2
Peas	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	1	0	0
Potatoes	1	11	0	1	2	1	1	0	2	3	18	0	2	6	4	3	0	7
PotatoesIndustry	17	29	1	2	7	2	1	0	3	1	11	0	1	2	2	1	0	1
SetAside	3	3	3	1	1	2	4	5	4	1	3	3	2	2	4	3	7	6
SetAsideAnnualFlowers	1	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0

ALMaSS crop	Farm type																	
	Conventional									Organic								
	Veg	Potato	Beet	Cattle and horse	Pig	Mixed	Arable	Grass	Hobby	Veg	Potato	Beet	Cattle and horse	Pig	Mixed	Arable	Grass	Hobby
	1	2	3	4	5	6	7	8	9	11	12	13	14	15	16	17	18	19
SpringBarley	1	8	1	2	2	3	3	2	3	0	5	0	2	2	4	3	2	2
SpringRye	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	1	0	0
SpringWheat	0	0	0	0	0	0	0	0	0	0	1	0	1	4	3	2	2	3
SugarBeet	2	8	25	2	3	5	8	1	2	0	7	26	1	2	0	4	2	0
Triticale	1	2	0	3	6	4	3	3	6	1	2	1	5	8	4	5	4	4
WinterBarley	2	5	7	7	11	13	9	3	9	0	9	8	3	4	1	5	1	2
WinterRape	1	1	4	2	3	5	7	1	2	0	1	8	1	0	0	2	0	0
WinterRye	4	6	1	7	9	8	6	7	8	5	6	0	7	6	16	7	4	9
WinterWheat	10	11	48	13	16	26	33	9	15	2	14	47	14	14	8	24	2	10

B Appendix: Structural and farming heterogeneity of studied landscapes

Table B1: Metrics used to characterise landscape and farmland heterogeneity of studied areas.

Metric	Abbreviation	Explanation	Range (min – max) in BB*	Range (min – max) in NI*
Coverage of arable land	arablePer	% of arable land (i.e., fields in rotation) in a landscape	1.2 – 84.4	0.0 – 85.0
Coverage of herbaceous semi-natural habitats	herbiPer	% of herbaceous semi-natural habitats in a landscape	1.8 – 6.4	2.4 – 21.1
Coverage of woody semi-natural habitats	woodyPer	% of woody semi-natural habitats in a landscape	0.4 – 78.6	0.1 – 90.4
Coverage of permanent pastures	pasturePer	% of permanent pastures (under both conventional and organic management) in a landscape	0.3 – 42.2	0.4 – 65.6
Patch density	PD_land	Number of patches per 100 ha of a landscape taking into account six landscape element type categories: arable land, herbaceous semi-natural habitats, woodland (woody semi-natural habitats), build-up areas, water and others.	38.4 – 413.9	26.2 – 482.0
Landscape diversity	SIDI_land	Simpson's diversity index (0-1) of landscape element types including six categories: arable land, herbaceous semi-natural habitats, woodland (woody semi-natural habitats), build-up areas, water, and others (as in PD). The value of Simpson's index represents the probability that any two cells selected at random would-be different patch types. Thus, the higher the value the greater the likelihood that any two randomly drawn cells would be different patch types. It can effectively describe the variance in the proportion of area covered by different land-cover categories.	0.23 – 0.79	0.18 – 0.80
Landscape shape index	LSI_land	Normalized ratio of edge (i.e., patch perimeters) to area (class or landscape) in which the total length of edge is compared to a landscape with a standard shape (square) of the same size and without any internal edge. Values greater	55.9 – 158.5	74.1 – 244.4

Metric	Abbreviation	Explanation	Range (min – max) in BB*	Range (min – max) in NI*
		than one indicate increasing levels of internal edge and corresponding decreasing aggregation of patch types. Calculated for six landscape element type categories (defined as in PD_land).		
Percentage of like adjacencies	PLADJ_land	The proportion of cell adjacencies involving the same class [%]. PLADJ_land equals 0 when the patch types are maximally disaggregated (i.e., every cell is a different patch type) and there are no like adjacencies. PLADJ_land = 100 when all patch types are maximally aggregated (i.e., when the landscape consists of single patch and all adjacencies are between the same class), and the landscape contains a border comprised entirely of the same class. Calculated for six landscape element type categories (defined as in PD_land).	96.8 – 98.9	95.1 – 98.5
Interspersion and juxtaposition index	IJI_land	The observed interspersion over the maximum possible interspersion for the given number of patch types [%]. IJI_land approaches 0 when the distribution of adjacencies among unique patch types becomes increasingly uneven. IJI_land = 100 when all patch types are equally adjacent to all other patch types (i.e., maximum interspersion and juxtaposition). Calculated for six landscape element type categories (defined as in PD_land).	19.4 – 72.8	35.7 – 67.8
Landscape contagion	CONTAG_land	Landscape contagion index [%] is affected by both the dispersion and interspersion of landscape element types and varies between 0 and 100. When approaches 0, patch types are maximally disaggregated and interspersed. When is equal to 100, all patch types are maximally aggregated. Calculated for six landscape element type categories (defined as in PD_land).	51.2 – 82.5	50.6 – 85.3
Landscape division	DIVISION_land	Landscape division index (0-1) is based on the cumulative patch area distribution and is interpreted as the probability that two randomly chosen pixels in the landscape are not situated in the same patch. DIVISION_land equals 0 when the landscape consists of a single patch and increases with the subdivision of a landscape (equals 1 when every cell is a	0.96 – 0.99	0.92 – 0.99

Metric	**Abbreviation**	**Explanation**	**Range (min – max) in BB***	**Range (min – max) in NI***
		separate patch). Calculated for six landscape element type categories (defined as in PD_land).		
Landscape splitting	SPLIT_land	Splitting index is based on the cumulative patch area distribution and is interpreted as the effective mesh number, or number of patches with a constant patch size when the landscape is subdivided into *n* patches, where *n* is the value of the splitting index. It equals 1 when the landscape consists of single patch and increases as the landscape is increasingly subdivided into smaller patches and achieves its maximum value when the landscape is maximally subdivided; that is, when every cell is a separate patch. Calculated for six landscape element type categories (defined as in PD_land).	24.3 – 455.9	12.4 – 861.5
Farm type density	PD_farm	Number of patches per 100 ha of a landscape taking into account farm type categories.	1.3 – 21.2	4.1 – 70.7
Farming diversity	SIDI_farm	Simpson's diversity index calculated for fields categorized into farm types.	0.09 – 0.81	0.19 – 0.85
Farm shape index	LSI_farm	Landscape shape index calculated for farm type categories.	12.2 – 58.2	6.4 – 73.9
Farm contagion	CONTAG_farm	Landscape contagion calculated for farm type categories.	56.8 – 92.7	56.0 – 87.5
Farm division	DIVISION_farm	Landscape division calculated for farm type categories.	0.81 – 0.99	0.81 – 0.99
Farm splitting	SPLIT_farm	Landscape splitting index calculated for farm type categories.	5.1 – 112.5	5.3 – 510.6
Farm richness density	PRD_farm	Patch richness density calculated for farm type categories. It equals the number of different farm types present within the landscape boundary divided by total landscape area.	0.07 – 1.04	0.07 – 8.12
Number of fields	fieldsNo	Number of fields in a landscape.	41 - 1235	0 – 3260
Mean field size	fieldSize	Mean field size in ha.	2.9 – 17.9	0 – 5.7

* BB – Brandenburg region, NI – Lower Saxony region

Table B2: Correlation matrix (with Pearson correlation coefficients) of landscape metrics calculated for the analysed study areas in the Brandenburg and Lower Saxony regions.

landscape metric	*arable Per*	*pasture Per*	*herbi Per*	*woody Per*	*fields No*	*field Size*	*PD _land*	*LSI _land*	*PLADJ _land*	*IJI _land*	*CONTAG _land*	*DIVISION _land*	*SPLIT _land*	*SIDI _land*	*PD _farm*	*LSI _farm*	*CONTAG _farm*	*DIVISION _farm*	*SPLIT _farm*	*PRD _farm*	*SIDI _farm*
arablePer	1.00																				
pasturePer	-0.27	1.00																			
herbiPer	-0.03	0.44	1.00																		
woodyPer	-0.59	-0.44	-0.49	1.00																	
fieldsNo	0.59	-0.05	0.42	-0.53	1.00																
fieldSize	0.21	-0.18	-0.55	0.10	-0.58	1.00															
PD_land	0.59	0.25	0.49	-0.75	0.80	-0.39	1.00														
LSI_land	-0.29	0.51	0.49	-0.29	0.33	-0.68	0.37	1.00													
PLADJ_land	0.29	-0.51	-0.49	0.29	-0.33	0.68	-0.37	-1.00	1.00												
IJI_land	0.48	0.10	0.03	-0.44	0.08	0.35	0.31	-0.32	0.32	1.00											
CONTAG_land	0.34	0.00	-0.32	0.06	-0.04	0.35	0.01	-0.32	0.32	-0.09	1.00										
DIVISION_land	0.09	0.07	-0.19	0.20	0.14	-0.05	0.09	-0.01	0.01	0.11	0.27	1.00									
SPLIT_land	0.00	0.13	-0.05	0.13	0.29	-0.33	0.16	0.25	-0.25	-0.11	0.27	0.55	1.00								
SIDI_land	-0.33	-0.12	0.18	0.11	-0.02	-0.26	-0.12	0.17	-0.17	0.03	-0.94	-0.21	-0.24	1.00							
PD_farm	-0.14	-0.13	0.39	0.05	0.48	-0.72	0.24	0.47	-0.47	-0.31	-0.27	-0.05	0.15	0.20	1.00						
LSI_farm	0.23	0.54	0.67	-0.66	0.73	-0.64	0.79	0.71	-0.71	0.11	-0.17	0.12	0.32	0.03	0.40	1.00					
CONTAG_farm	-0.03	0.41	0.05	-0.22	-0.12	0.12	0.11	0.14	-0.14	0.05	0.14	0.03	0.00	-0.19	-0.41	0.10	1.00				
DIVISION_farm	0.24	0.02	0.42	-0.35	0.57	-0.50	0.45	0.34	-0.34	0.07	-0.30	-0.02	0.11	0.23	0.48	0.54	-0.34	1.00			
SPLIT_farm	0.30	-0.07	0.44	-0.32	0.67	-0.51	0.53	0.25	-0.25	0.07	-0.21	0.04	0.18	0.15	0.60	0.55	-0.40	0.64	1.00		
PRD_farm	-0.33	-0.16	0.00	0.33	-0.20	-0.14	-0.30	0.05	-0.05	-0.31	0.04	-0.05	-0.02	-0.04	0.38	-0.26	-0.12	-0.16	-0.09	1.00	
SIDI_farm	0.17	-0.42	-0.01	0.12	0.22	-0.13	-0.01	-0.14	0.14	0.03	-0.12	-0.01	0.01	0.18	0.40	-0.02	-0.93	0.41	0.47	0.08	1.00

C Appendix: Results of regression analysis

Table C1. The results of fitting multiple regression analysis for the baseline scenario ('Reg_NoPest') to describe the relationship between simulation endpoints (mean overall beetle density, mean beetle Abundance and mean beetle Occupancy) and 13 independent variables (landscape and farmland metrics). The values of parameters *b, β* (for the model on standardized variables) and *p* for the variables included in the final model, i.e., the model with only significant explanatory variables (at p ≤ 0.05) after backward stepwise selection are presented together with R^2, R^2_{adj} and *p* values for the final model.

Study areas selection	Exponatory variable	Parameters	Independent variables: Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	Model's statistics: *p* value for the model	R^2	R^2_{adj}
All, *N*=611	Mean overall beetle density [x 10^{-5}]	*p*	<0.001		<0.001	<0.001	<0.001	<0.001					0.028		<0.001	<0.001	84.13	83.94
		b	0.23		-0.07	0.34	10.93	-0.06					1.74		-0.38			
		β	4.00		-1.41	3.78	1.04	-1.24					0.25		-1.28			
	Mean beetle Abundance	*p*	<0.001		0.002	<0.001	<0.001	<0.001	0.025	0.012					<0.001	<0.001	79.36	79.10
		b	0.44		-0.12	0.74	25.51	-0.17	0.14	-118.19					-0.98			
		β	7.65		-2.33	8.18	2.42	-3.64	0.78	-0.82					-3.26			
	Mean beetle Occupancy	*p*	<0.001	<0.001	0.005	<0.001	<0.001		0.001		<0.001			0.001		<0.001	82.86	82.63
		b	0.51	0.62	-0.07	0.41	27.11		-0.14		0.01			-0.002				
		β	8.87	1.98	-1.27	4.59	2.57		-0.76		1.95			-1.15				

Study areas selection	Exponatory variable	Parameters	Independent variables													Model's statistics		
			Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	p value for the model	R^2	R^2_{adj}
Arable land > 30%, N=392	Mean overall beetle density [x 10^{-5}]	p	<0.001	0.034	0.007	<0.001	<0.001	<0.001		0.027			0.002		<0.001	<0.001	57.08	55.73
		b	0.25	0.15	-0.08	0.41	14.36	-0.05		99.88			3.38		-0.29			
		β	4.41	0.47	-1.48	4.58	1.36	-1.15		0.69			0.48		-0.97			
	Mean beetle Abundance	p	<0.001		<0.001	<0.001	0.001	<0.001					0.008		<0.001	<0.001	58.78	58.03
		b	0.44		-0.21	0.87	31.54	-0.17					7.05		-0.90			
		β	7.58		-4.09	9.62	2.99	-3.60					1.01		-3.01			
	Mean beetle Occupancy	p	<0.001	<0.001	0.003	<0.001	0.001	<0.001			<0.001	<0.001		<0.001		<0.001	73.75	73.13
		b	0.70	0.72	0.10	0.64	17.39	0.08			0.01	16.52		-0.002				
		β	12.07	2.27	2.03	7.15	1.65	1.66			1.11	6.30		-1.30				
Arable land > 60%, N=69	Mean overall beetle density [x 10^{-5}]	p	< 0.001			0.001				0.010			0.005		0.004	<0.001	58.87	55.61
		b	0.19			0.25				288.85			8.33		-0.25			
		β	3.21			2.79				2.01			1.19		-0.82			
	Mean beetle Abundance	p	0.004			0.007							0.016		<0.001	<0.001	50.79	47.71
		b	0.32			0.50							17.83		-0.92			
		β	5.46			5.58							2.55		-3.07			

Study areas selection	**Exponatory variable**	**Parameters**	**Independent variables**													**Model's statistics**		
			Arable_per	**Herbi_per**	**Woody_per**	**Pasture_per**	**SIDI_land**	**LSI_land**	**IJI_land**	**DIVISION_land**	**SPLIT_land**	**PRD_farm**	**SIDI_farm**	**Fields_no**	**Mean_field_size**	***p* value for the model**	**R^2**	**R^2_{adj}**
	Mean beetle Occupancy	*p*	<0.001	0.005	<0.001	<0.001		0.001			0.001		0.013	0.001	0.039	<0.001	81.74	78.96
		b	0.71	0.57	0.24	0.66		0.12			0.01		6.14	-0.003	-0.24			
		β	12.34	1.79	4.68	7.35		2.65			1.03		0.88	-1.89	-0.82			

Table C2. The results of fitting multiple regression analysis for the pest scenario ('Reg_Pest') to describe the relationship between relative change in the simulation endpoints (mean overall beetle density, mean beetle Abundance and mean beetle Occupancy) to baseline values and 13 independent variables (landscape and farmland metrics). The values of parameters *b, β* (for the model on standardized variables) and *p* for the variables included in the final model, i.e., the model with only significant explanatory variables (at p ≤ 0.05) after backward stepwise selection are presented together with R^2, R^2_{adj} and *p* values for the final model.

Study areas selection	Exponatory variable	Parameters	Independent variables													Model's statistics		
			Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	*p* value for the model	R^2	R^2_{adj}
Arable land > 30%, *N*=392	Relative change in mean overall beetle density	*p*	<0.001	<0.001		<0.001		<0.001	0.004		<0.001					<0.001	70.71	70.25
		b	0.12	-0.44		-0.24		-0.04	-0.10		0.005							
		β	2.11	-1.40		-2.72		-0.84	-0.56		-0.66							
	Relative change in mean beetle Abundance	*p*	<0.001	<0.001		<0.001		0.005	0.002		<0.001	0.049				<0.001	70.90	70.37
		b	0.15	-0.38		-0.21		-0.03	-0.10		0.004	5.89						
		β	2.61	-1.21		-2.37		-0.58	-0.57		-0.60	2.25						
	Relative change in mean beetle Occupancy	*p*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		b	-	-	-	-	-	-	-	-	-	-	-	-	-			
		β	-	-	-	-	-	-	-	-	-	-	-	-	-			

Study areas selection	Exponatory variable	Parameters	Independent variables													Model's statistics		
			Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	*p* value for the model	R^2	R^2_{adj}
Arable land > 60%, *N*=69	Relative change in mean overall beetle density	*p*		0.003		<0.001	0.025				<0.001					<0.001	67.86	65.85
		b		-0.62		-0.48	-8.94				-0.01							
		β		-1.96		-5.28	-0.85				-1.39							
	Relative change in mean beetle Abundance	*p*	0.039	0.022		<0.001					<0.001					<0.001	63.67	61.40
		b	0.10	-0.45		-0.40					-0.01							
		β	1.70	-1.42		-4.48					-1.10							
	Relative change in mean beetle Occupancy	*p*							0.034	0.003					<0.001	<0.001	83.57	82.81
		b							0.04	-86.44					0.15			
		β							0.20	-0.60					0.51			

Table C3. **The results of fitting multiple regression analysis for the FB scenario (‘FB_Pest’) to describe the relationship between effectiveness of FB mitigation measure on simulation endpoints (mean overall beetle density, mean beetle Abundance and mean beetle Occupancy) and 13 independent variables (landscape and farmland metrics). The values of parameters b, β (for the model on standardized variables) and p for the variables included in the final model, i.e., the model with only significant explanatory variables (at p ≤ 0.05) after backward stepwise selection are presented together with R2, R2adj and p values for the final model.**

Study areas selection	Exponatory variable	Parameters	Independent variables														Model's statistics		
			% of study area impacted by the mitigation measure	Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	*p* value for the model	R^2	R^2_{adj}
Arable land > 30%, *N*=392	Effectiveness of FM on mean overall beetle density	*p*	<0.001		<0.001		<0.001	<0.001	<0.001	0.034		<0.001			<0.001		<0.001	70.64	70.03
		b	0.49		-0.47		-0.36	-9.42	-0.05	-0.07		-0.004			-0.003				
		β	2.33		-1.50		-4.03	-0.89	-1.09	-0.41		-0.62			-1.43				
	Effectiveness of FM on mean beetle Abundance	*p*	0.001	<0.001	<0.001		<0.001		<0.001	0.003		0.002			<0.001		<0.001	70.35	69.73
		b	0.43	0.10	-0.44		-0.26		-0.04	-0.10		-0.003			-0.003				
		β	2.08	1.71	-1.40		-2.87		-0.96	-0.58		-0.48			-1.46				
	Effectiveness of FM on mean beetle Occupancy	*p*	<0.001	<0.001	0.005		<0.001	<0.001	0.001			0.005				<0.001	<0.001	67.97	67.30
		b	0.12	-0.08	-0.03		-0.11	-5.42	-0.01			-0.001				0.13			
		β	0.58	-1.47	-0.10		-1.17	-0.51	-0.15			-0.08				0.45			

Study areas selection	Exponatory variable	Parameters	Independent variables: % of study area impacted by the mitigation measure	Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	Model's statistics: *p* value for the model	R^2	R^2_{adj}
Arable land > 60%, *N*=69	Effectiveness of FM on mean overall beetle density	p					<0.001		<0.001			0.003					<0.001	64.47	62.83
		b					-0.46		-0.11			-0.01							
		β					-5.15		-2.29			-1.38							
	Effectiveness of FM on mean beetle Abundance	p					<0.001		0.003			0.003					<0.001	62.58	60.85
		b					-0.47		-0.09			-0.01							
		β					-5.18		-1.99			-1.35							
	Effectiveness of FM on mean beetle Occupancy	p		0.006			0.027		0.008	0.023					0.013	<0.001	<0.001	75.64	73.29
		b		-0.03			-0.03		-0.02	0.04					0.001	0.13			
		β		-0.55			-0.37		-0.51	0.20					0.039	0.45			

Table C4. The results of fitting multiple regression analysis for the UM scenario ('UM_Pest') to describe the relationship between effectiveness of UM mitigation measure on simulation endpoints (mean overall beetle density, mean beetle Abundance and mean beetle Occupancy) and 13 independent variables (landscape and farmland metrics). The values of parameters b, β (for the model on standardized variables) and p for the variables included in the final model, i.e., the model with only significant explanatory variables (at p ≤ 0.05) after backward stepwise selection are presented together with R2, R2adj and p values for the final model.

Study areas selection	Exponatory variable	Parameters	Independent variables: % of study area impacted by the mitigation measure	Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	Model's statistics: *p* value for the model	R^2	R^2_{adj}
Arable land > 30%, *N*=392	Effectiveness of UM on mean overall beetle density	*p*			<0.001	0.005	<0.001					0.032				<0.001	<0.001	13.53	12.41
		b			-0.18	-0.02	-0.06					-0.001				-0.16			
		β			-0.57	-0.43	-0.64					-0.23				-0.55			
	Effectiveness of UM on mean beetle Abundance	*p*			<0.001	0.001	<0.001					0.033				<0.001	<0.001	14.88	13.78
		b			-0.18	-0.02	-0.06					-0.002				-0.19			
		β			-0.56	-0.47	-0.63					-0.23				-0.63			
	Effectiveness of UM on mean beetle Occupancy	*p*	<0.001	<0.001	0.013		<0.001	<0.001		0.019		0.005		0.004		<0.001	<0.001	30.97	29.34
		b	0.06	-0.02	-0.02		-0.03	-1.48		0.01		-0.0004		0.34		0.05			
		β	0.26	-0.42	-0.05		-0.34	-0.14		0.05		-0.05		0.005		0.17			

Study areas selection	Exponatory variable	Parameters	Independent variables: % of study area impacted by the mitigation measure	Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	Model's statistics: *p* value for the model	R^2	R^2_{adj}
Arable land > 60%, *N*=69	Effectiveness of UM on mean overall beetle density	*p*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		b	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
		β	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
	Effectiveness of UM on mean beetle Abundance	*p*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		b	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
		β	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
	Effectiveness of UM on mean beetle Occupancy	*p*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		b	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
		β	-	-	-	-	-	-	-	-	-	-	-	-	-	-			

Table C5. **The results of fitting multiple regression analysis to describe the relationship between difference in effectiveness of FB and UM mitigation measures on simulation endpoints (mean overall beetle density, mean beetle Abundance and mean beetle Occupancy) and 13 independent variables (landscape and farmland metrics). The values of parameters *b, β* (for the model on standardized variables) and *p* for the variables included in the final model, i.e., the model with only significant explanatory variables (at p ≤ 0.05) after backward stepwise selection are presented together with R^2, R^2_{adj} and *p* values for the final model.**

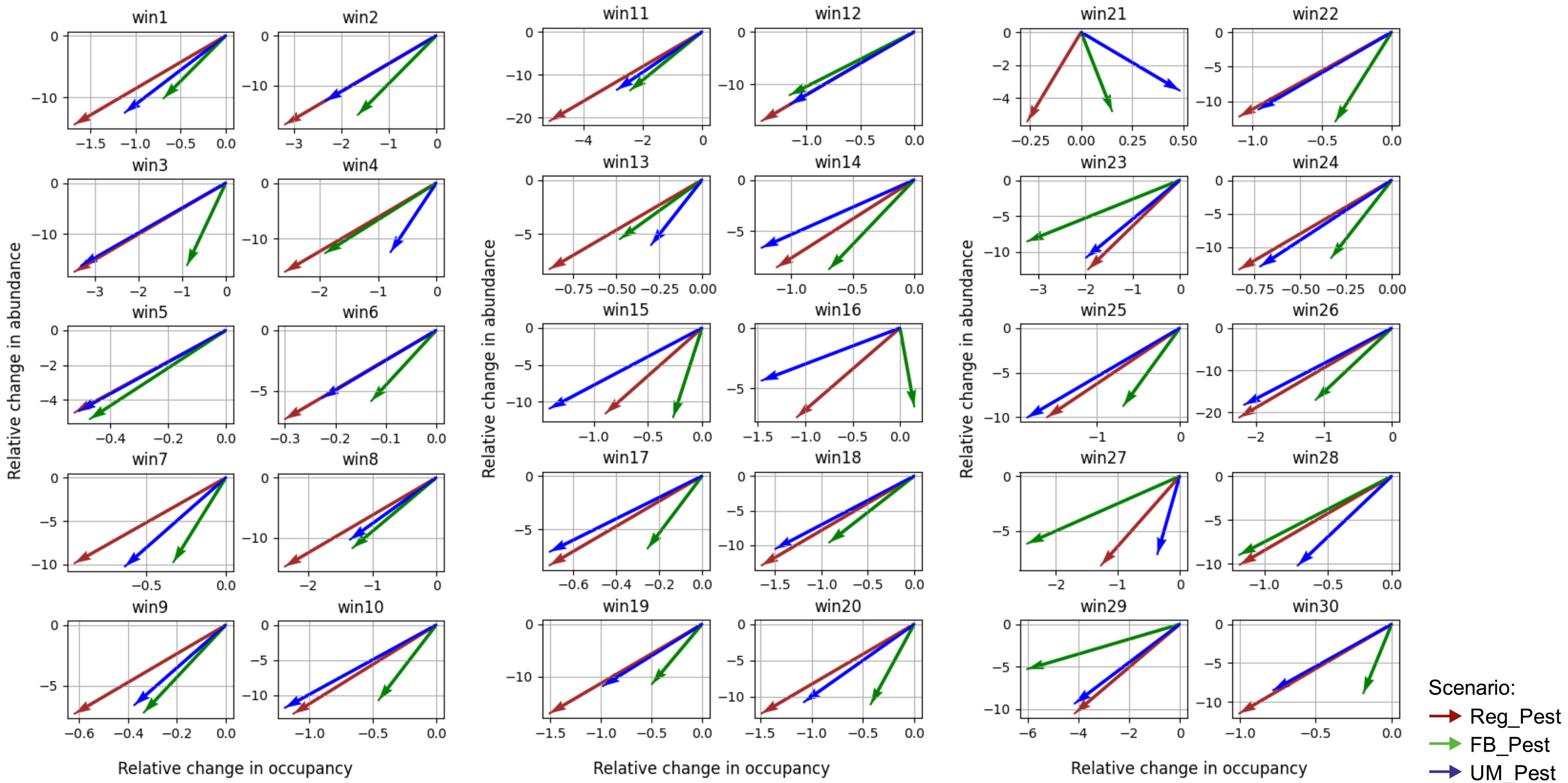
Study areas selection	Exponatory variable	Parameters	Independent variables														Model's statistics		
			% of study area impacted by the mitigation measure	Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	*p* value for the model	R^2	R^2_{adj}
Arable land > 30%, *N*=392	Effectiveness diff on mean overall beetle density	*p*	<0.001		<0.001		<0.001	0.031	0.003	0.010					<0.001	<0.001	<0.001	68.96	68.31
		b	0.47		-0.24		-0.32	-6.02	-0.04	-0.09					-0.003	0.34			
		β	2.24		-0.77		-3.56	-0.57	-0.78	-0.51					-1.42	1.13			
	Effectiveness diff on mean beetle Abundance	*p*	0.001	0.010	<0.001		<0.001		0.008	0.003					<0.001	0.002	<0.001	68.94	68.29
		b	0.43	0.07	-0.24		-0.24		-0.03	-0.10					-0.003	0.29			
		β	2.07	1.26	-0.75		-2.70		-0.68	-0.55					-1.53	0.97			
	Effectiveness diff on mean beetle Occupancy	*p*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		b	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
		β	-	-	-	-	-	-	-	-	-	-	-	-	-	-			

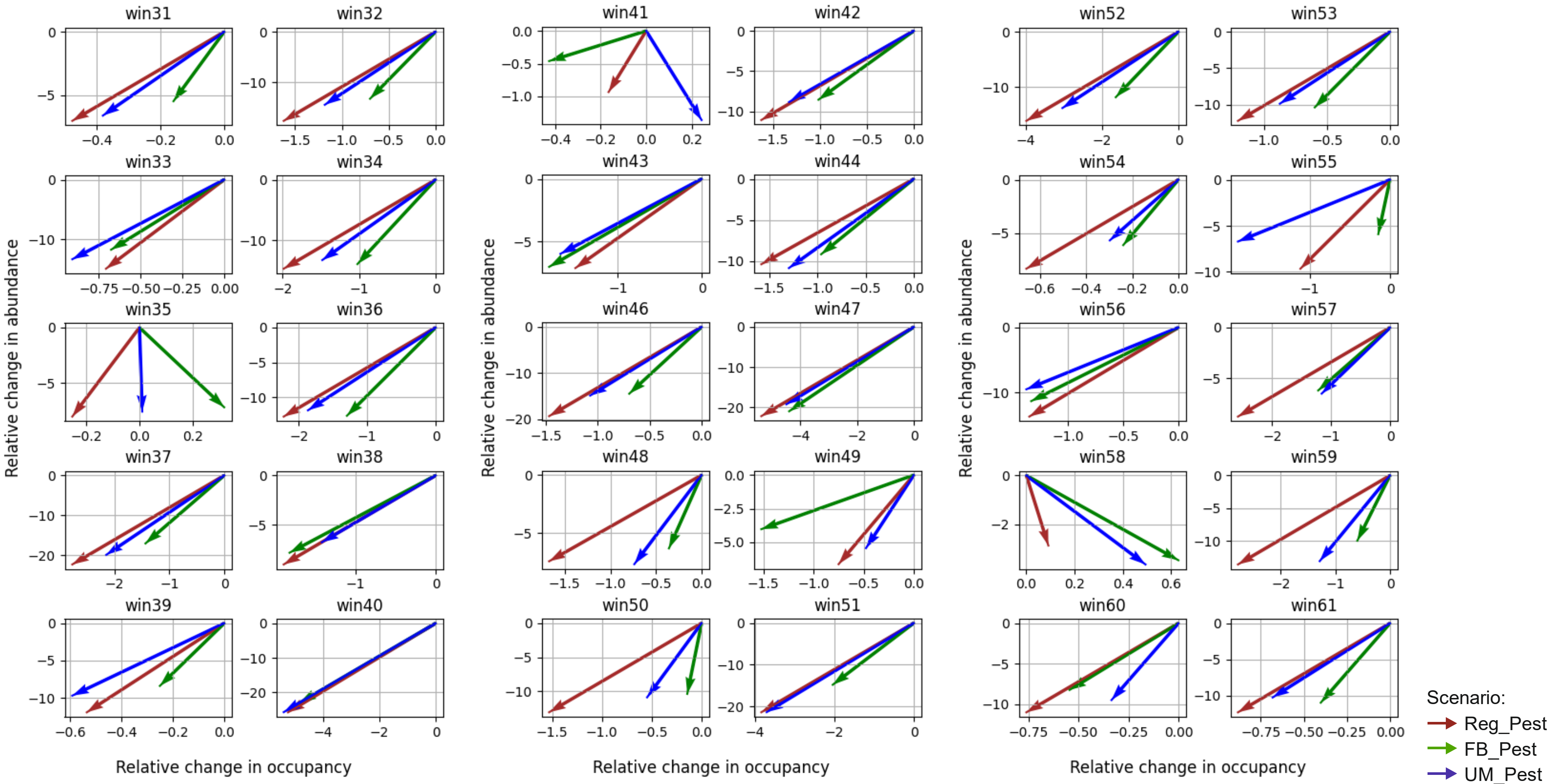
Study areas selection	Exponatory variable	Parameters	Independent variables														Model's statistics		
			% of study area impacted by the mitigation measure	Arable_per	Herbi_per	Woody_per	Pasture_per	SIDI_land	LSI_land	IJI_land	DIVISION_land	SPLIT_land	PRD_farm	SIDI_farm	Fields_no	Mean_field_size	*p* value for the model	R^2	R^2_{adj}
Arable land > 60%, *N*=69	Effectiveness diff on mean overall beetle density	*p*		<0.001				<0.001	<0.001								<0.001	61.08	59.29
		b		0.39				28.11	-0.18										
		β		6.78				2.66	-3.90										
	Effectiveness diff on mean beetle Abundance	*p*		<0.001				<0.001	0.001								<0.001	60.40	58.57
		b		0.40				27.07	-0.17										
		β		6.88				2.56	-3.65										
	Effectiveness diff on mean beetle Occupancy	*p*	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		b	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
		β	-	-	-	-	-	-	-	-	-	-	-	-	-	-			

D Appendix: AOR plots for analysed study areas

D.1 Impact of pesticide use on mean beetle occupancy and abundance in the studied landscapes.

Figure D1: Relative change in the mean beetle occupancy and abundance (plot of Abundance to Occupancy Relationship, AOR) due to pesticide use.

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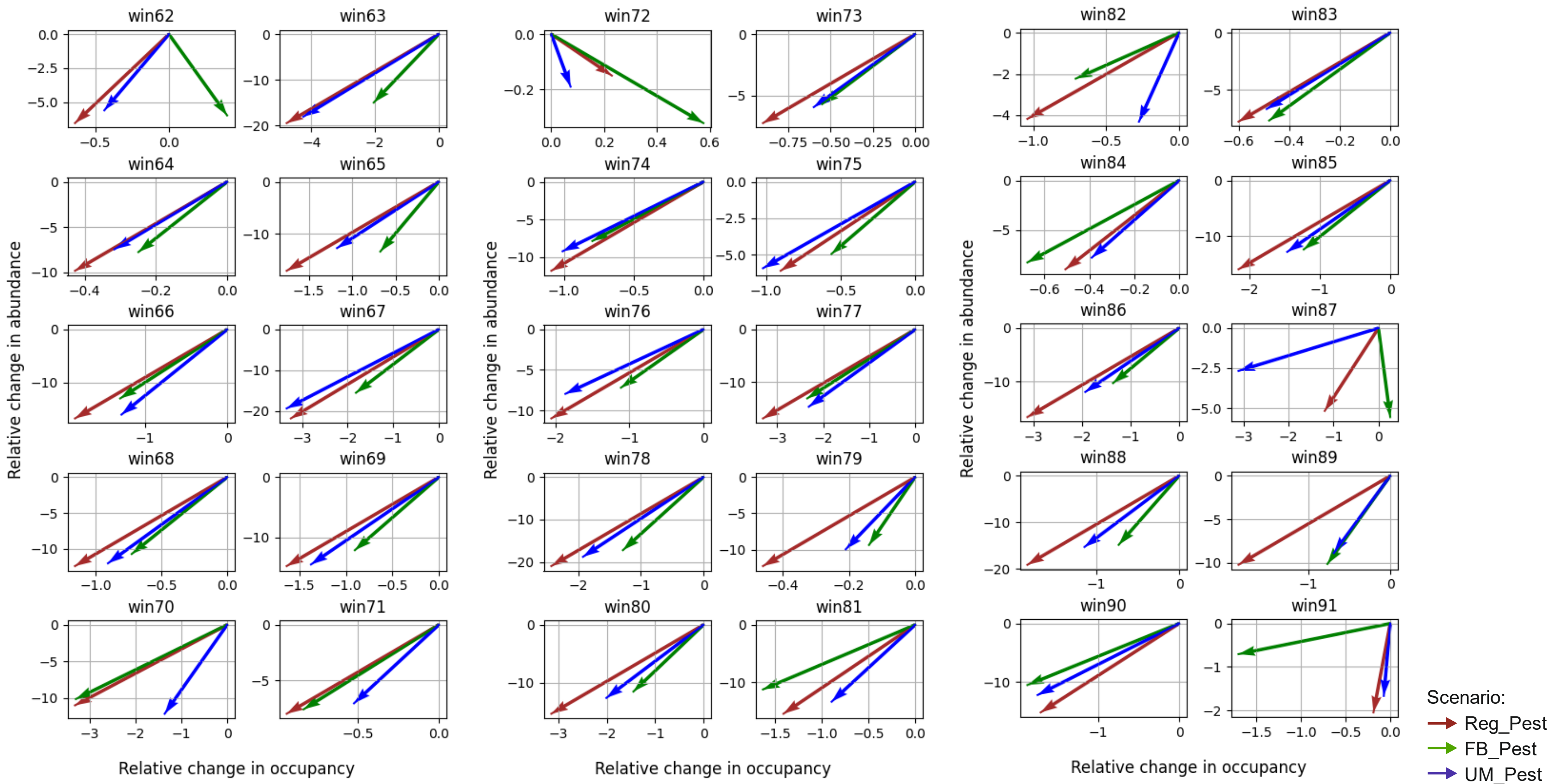
Relative change in abundance
Relative change in occupancy
Scenario:
Reg_Pest
FB_Pest
UM_Pest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Relative change in abundance
Relative change in occupancy
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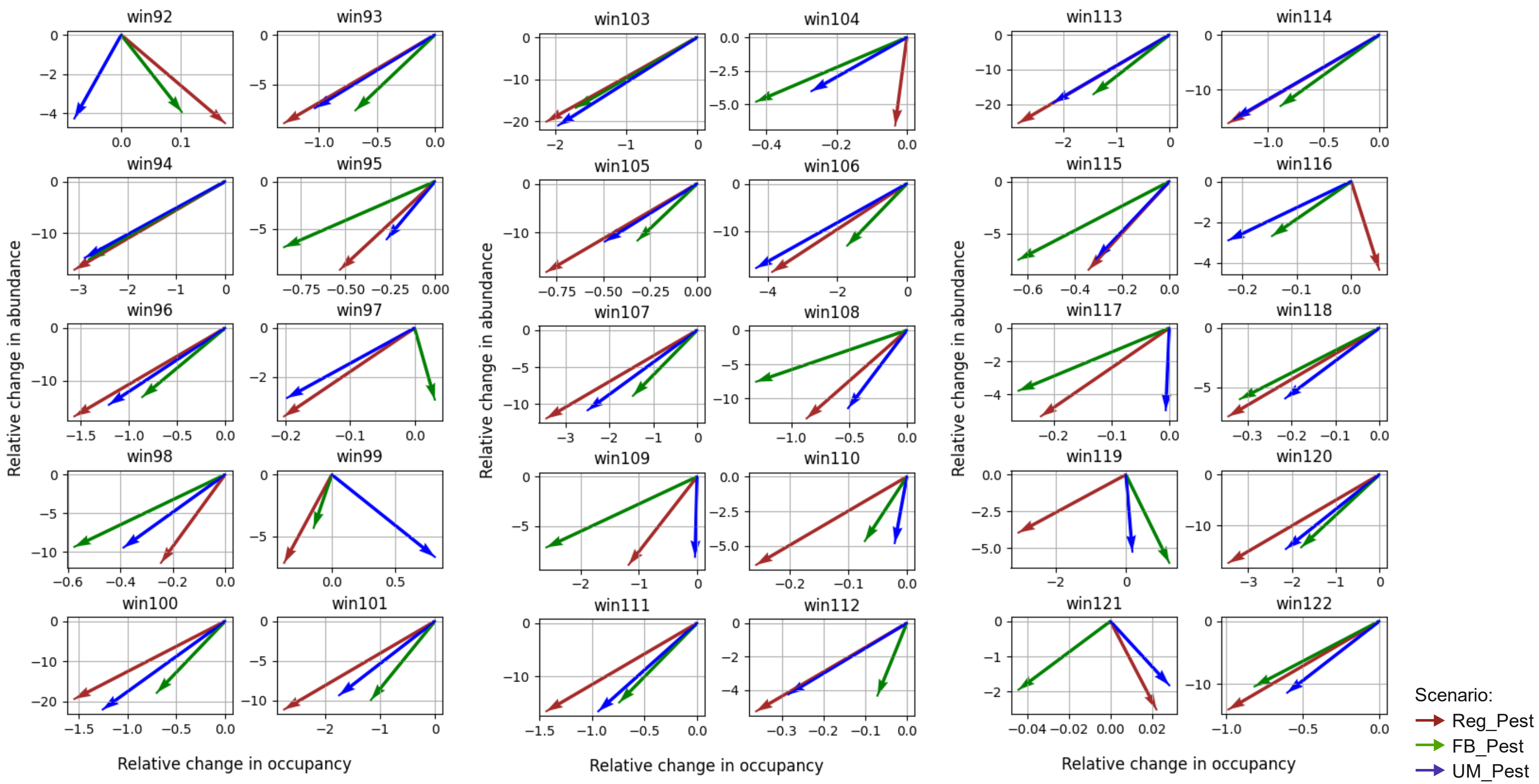
FB_Pest
UM_Pest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Relative change in abundance
Relative change in occupancy
Scenario:
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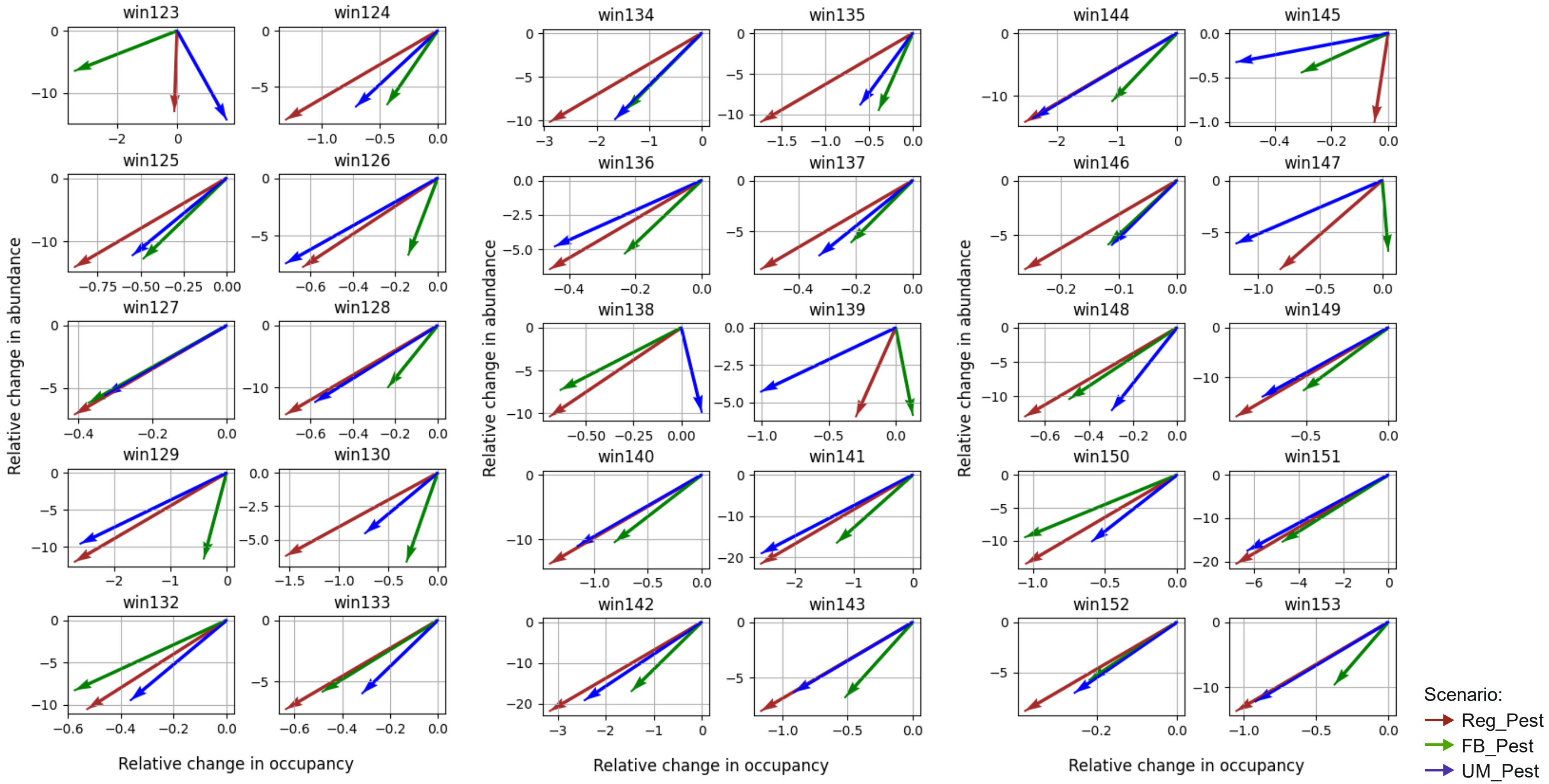
FB_Pest
UM_Pest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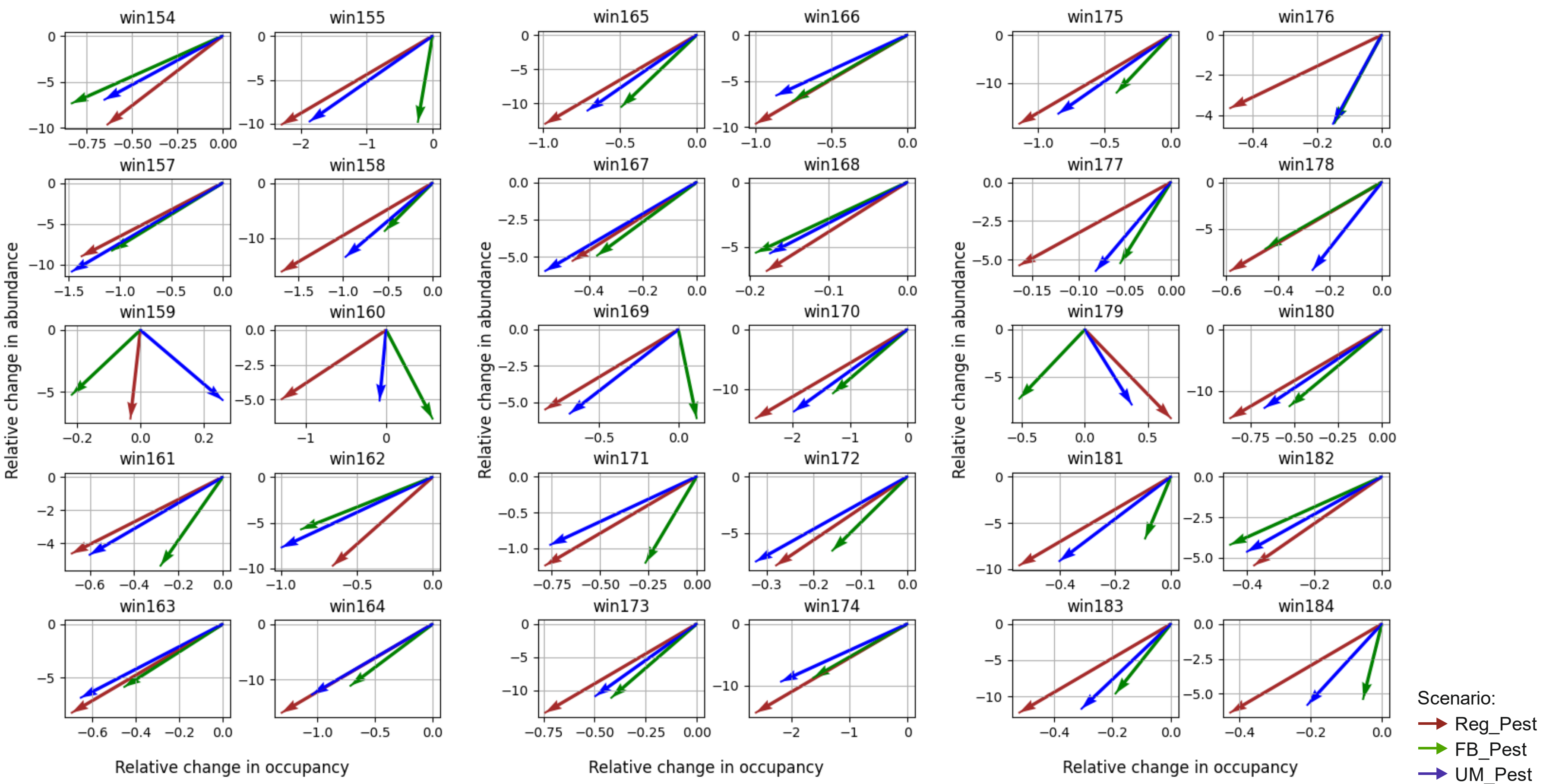
Relative change in abundance
Relative change in occupancy
Scenario:
Reg_Pest
FB_Pest
UM_Pest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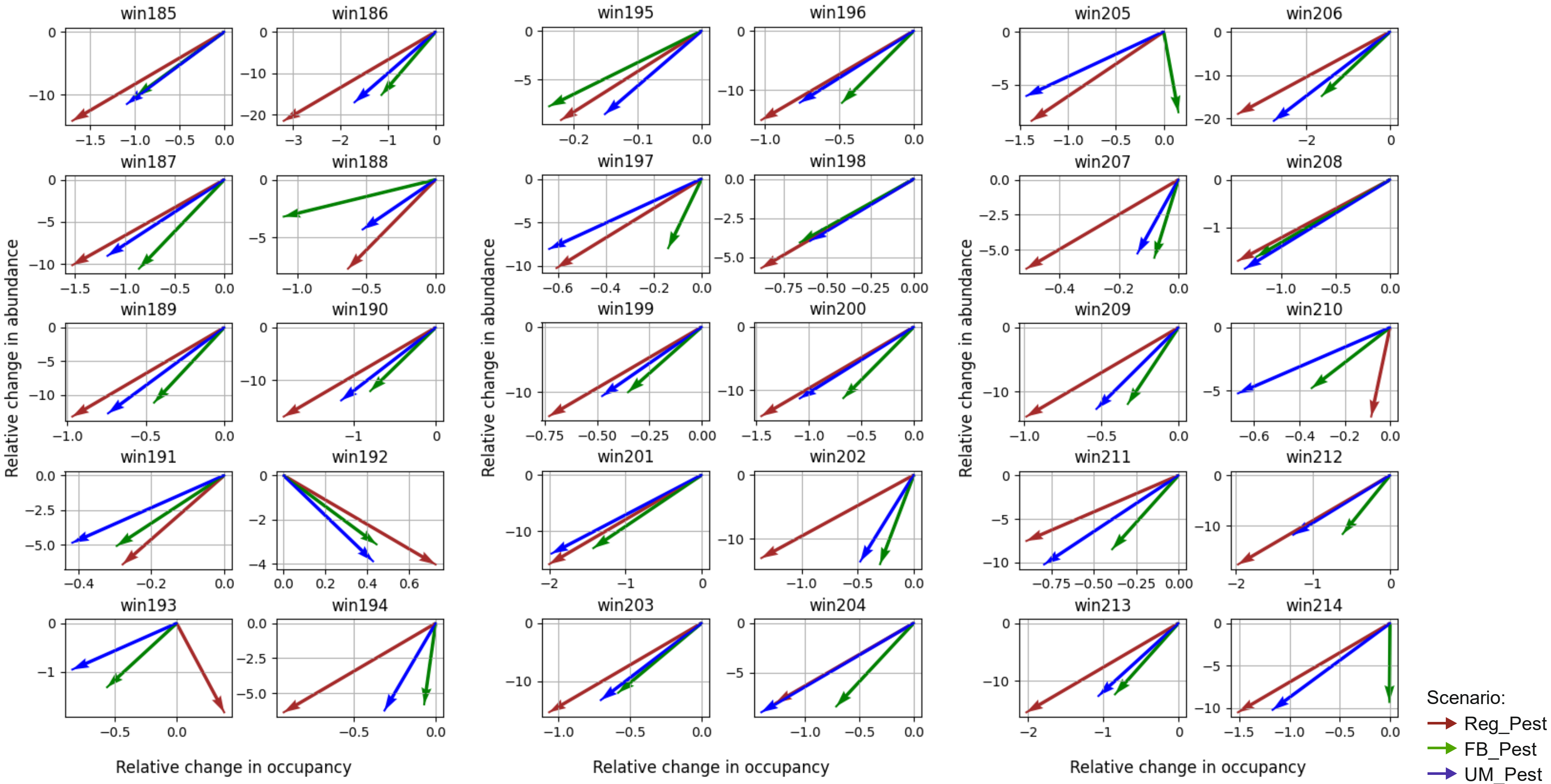
Relative change in abundance
Relative change in occupancy
Scenario:
Reg_Pest
FB_Pest
UM_Pest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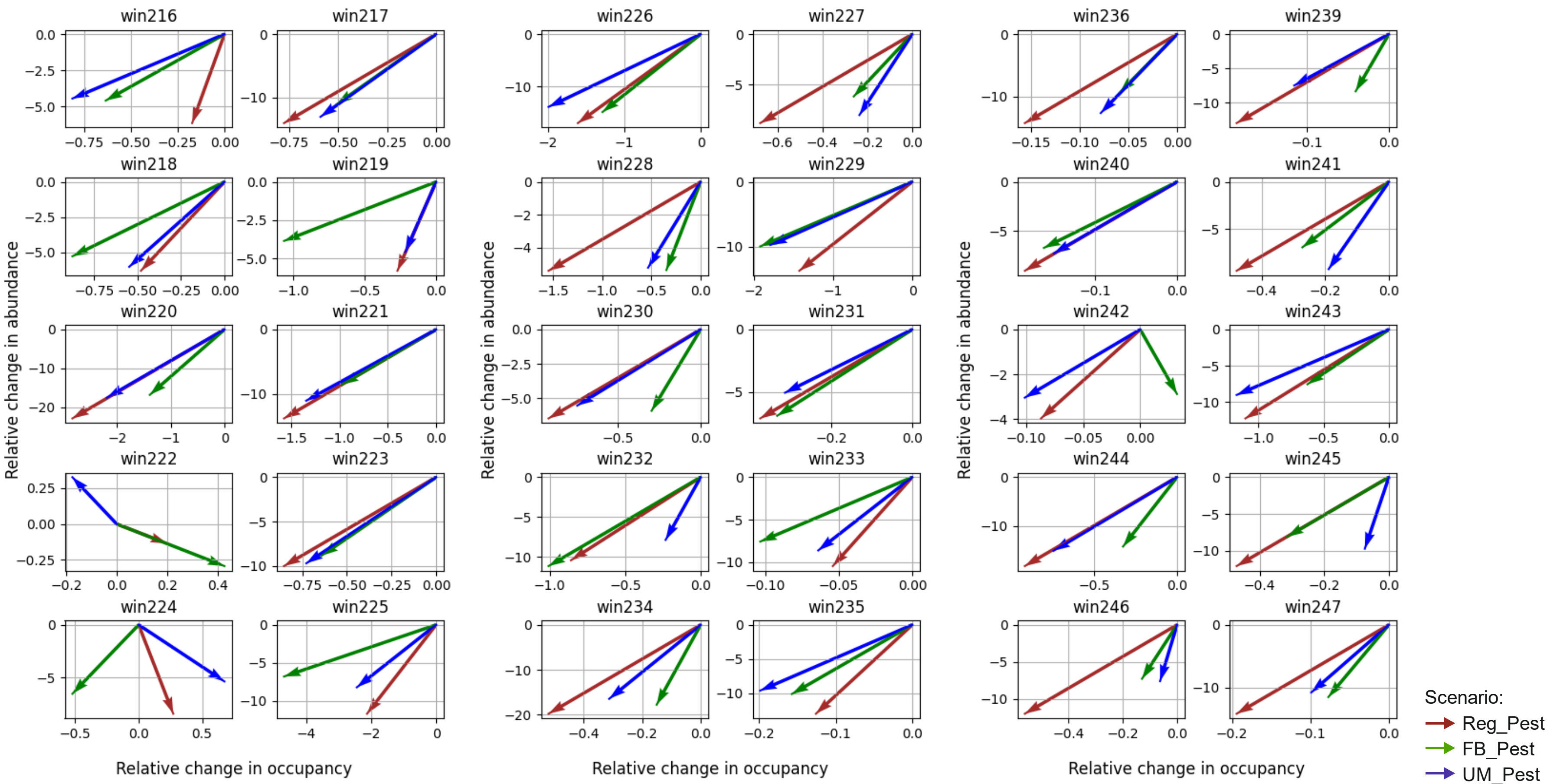
Relative change in abundance
Relative change in occupancy
Scenario:
Reg_Pest
FB_Pest
UM_Pest



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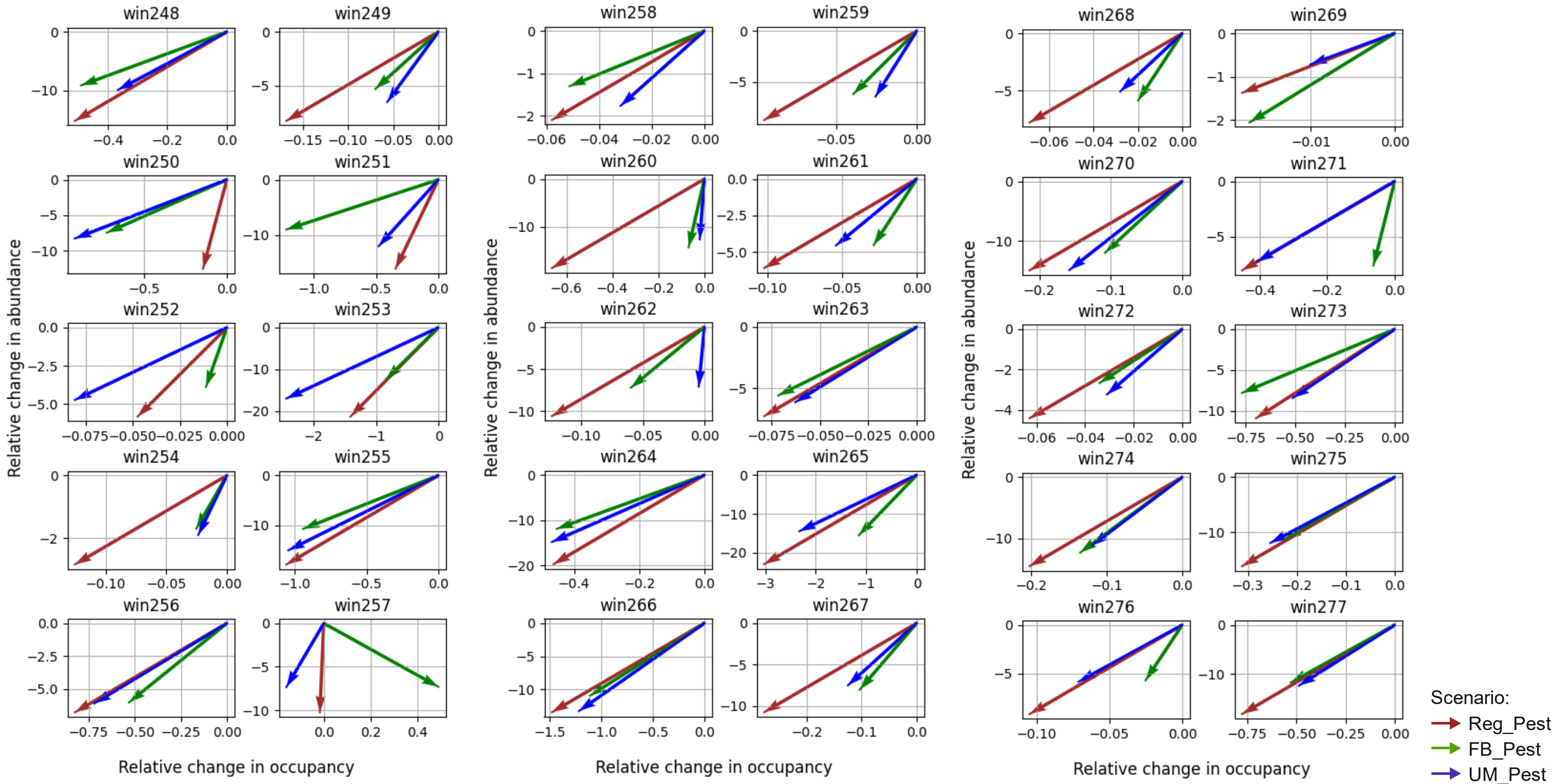
Relative change in abundance
Relative change in occupancy
Scenario:
Reg_Pest
FB_Pest
UM_Pest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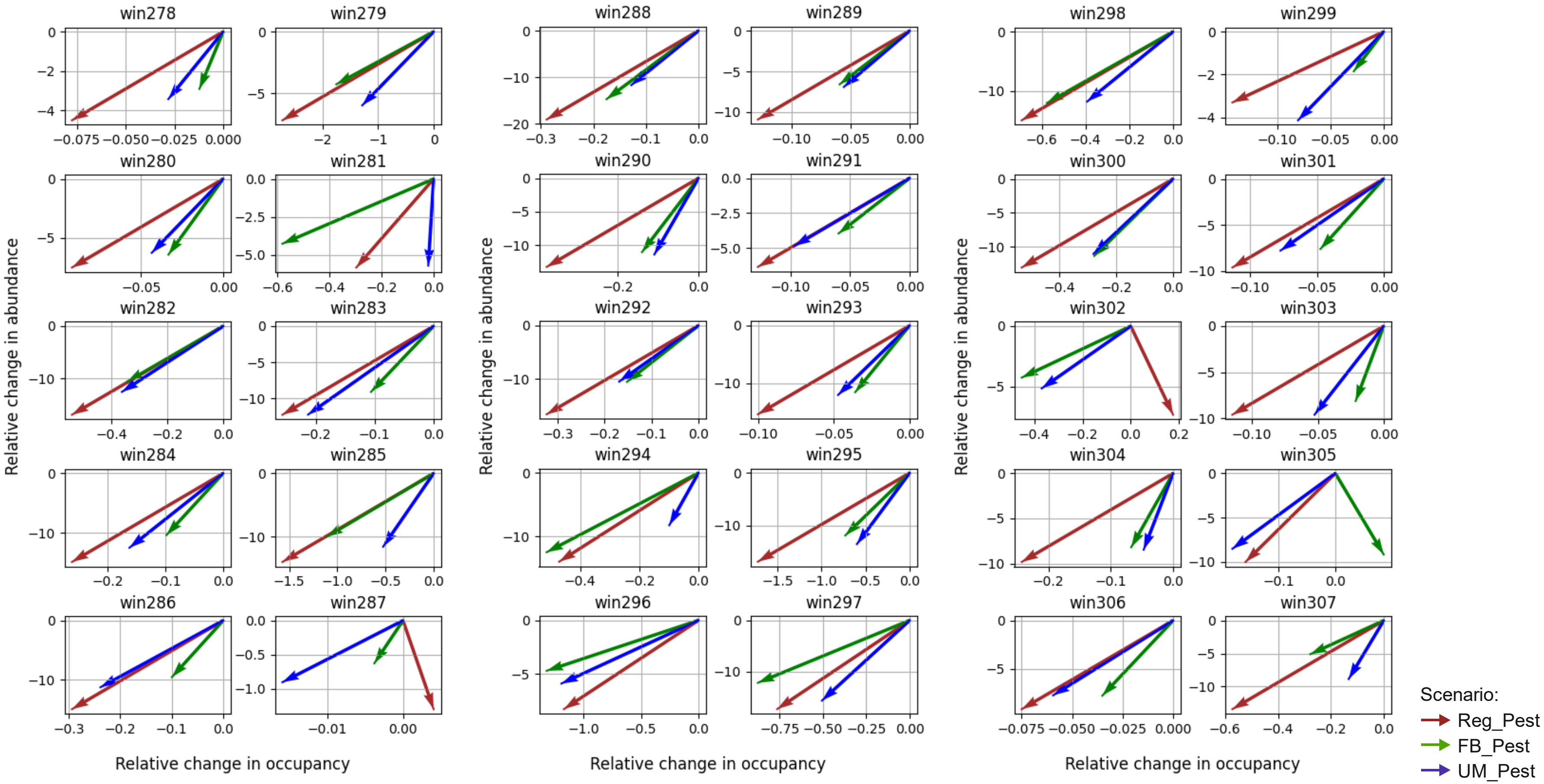
Relative change in abundance
Relative change in occupancy
Scenario:
Reg_Pest
FB_Pest
UM_Pest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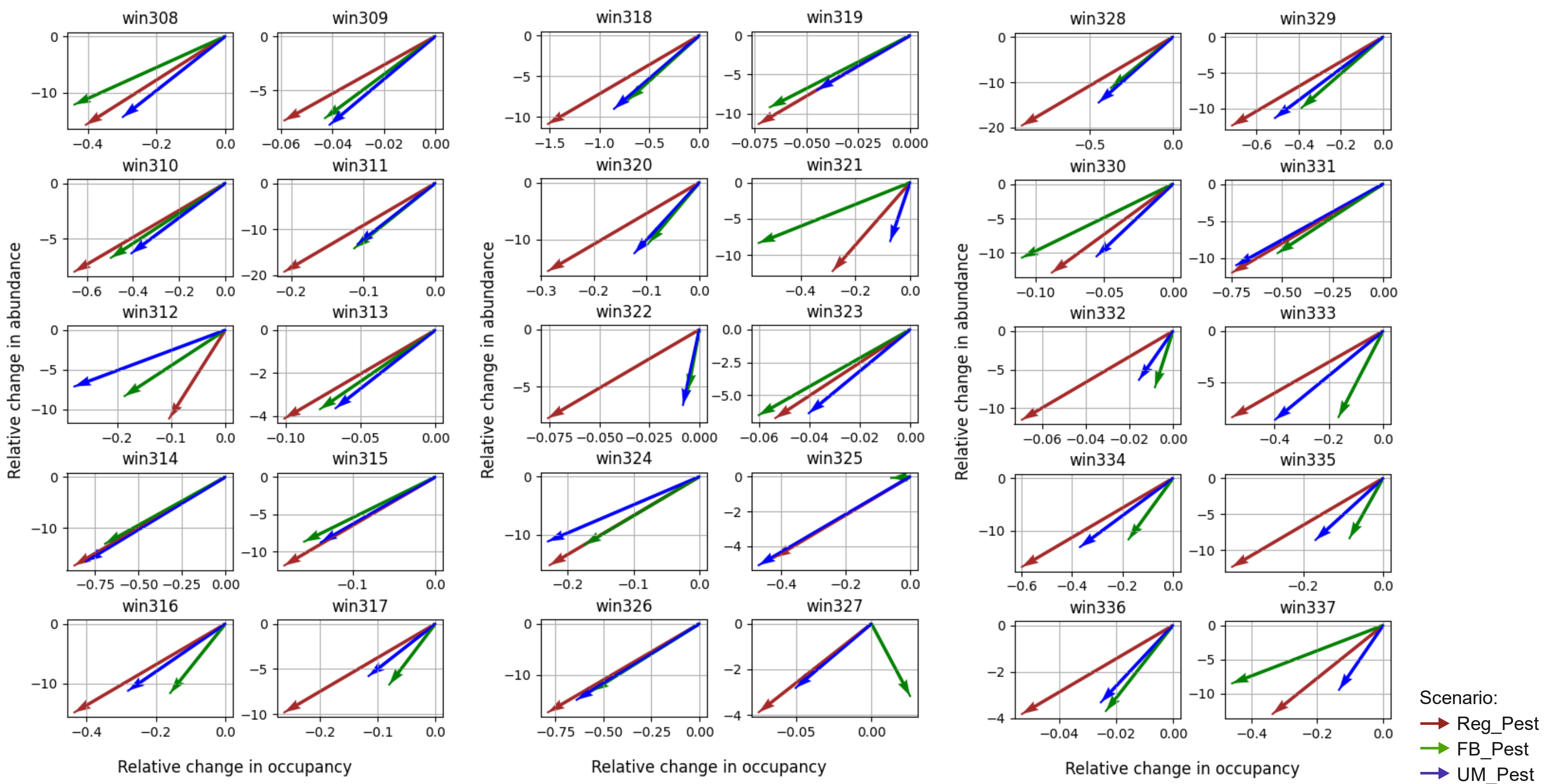
Relative change in abundance
Relative change in occupancy
Scenario:
Reg_Pest
FB_Pest
UM_Pest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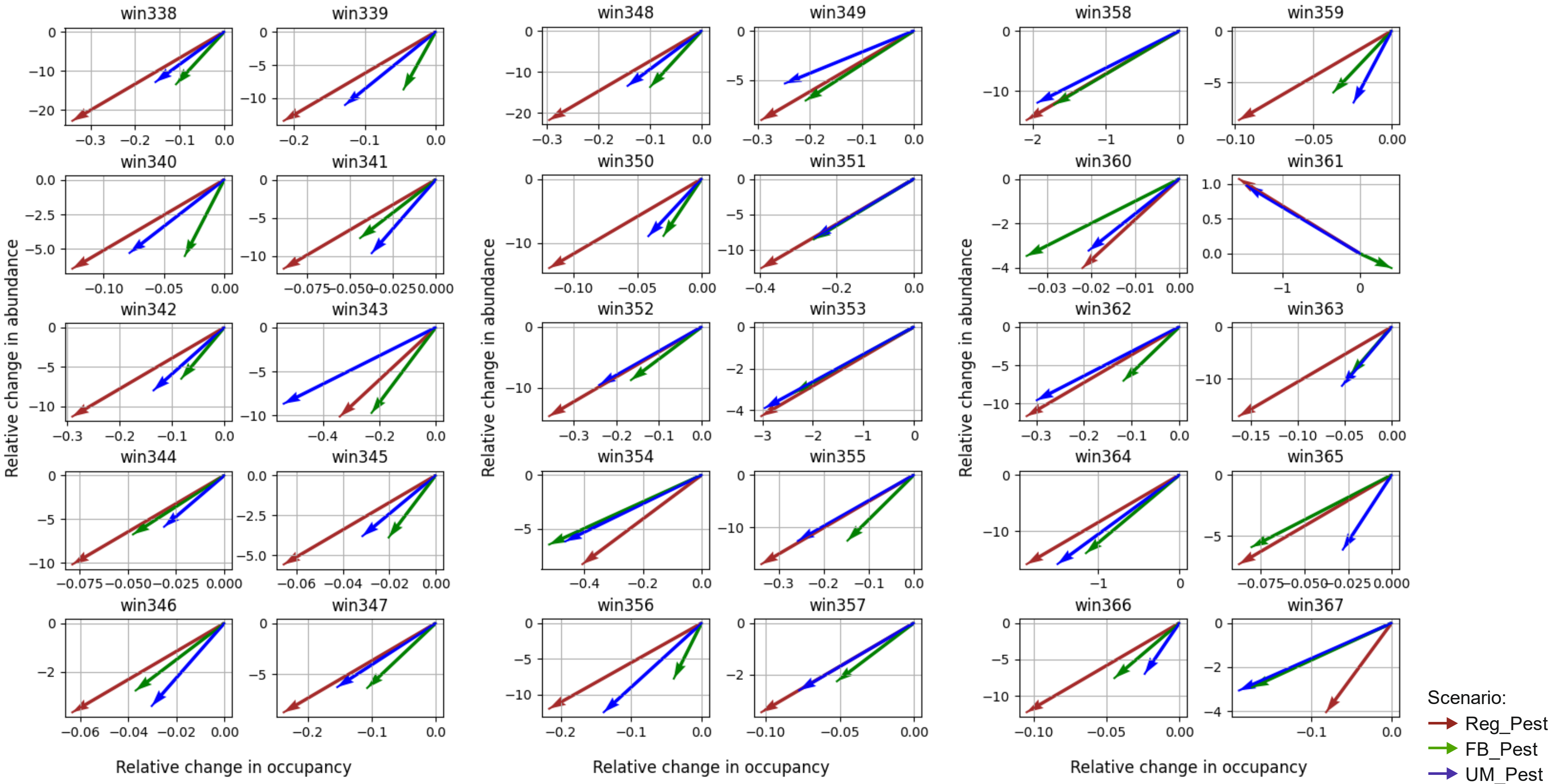
Relative change in abundance
Relative change in occupancy
Scenario:
Reg_Pest
FB_Pest
UM_Pest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Relative change in abundance
Relative change in occupancy
Scenario:
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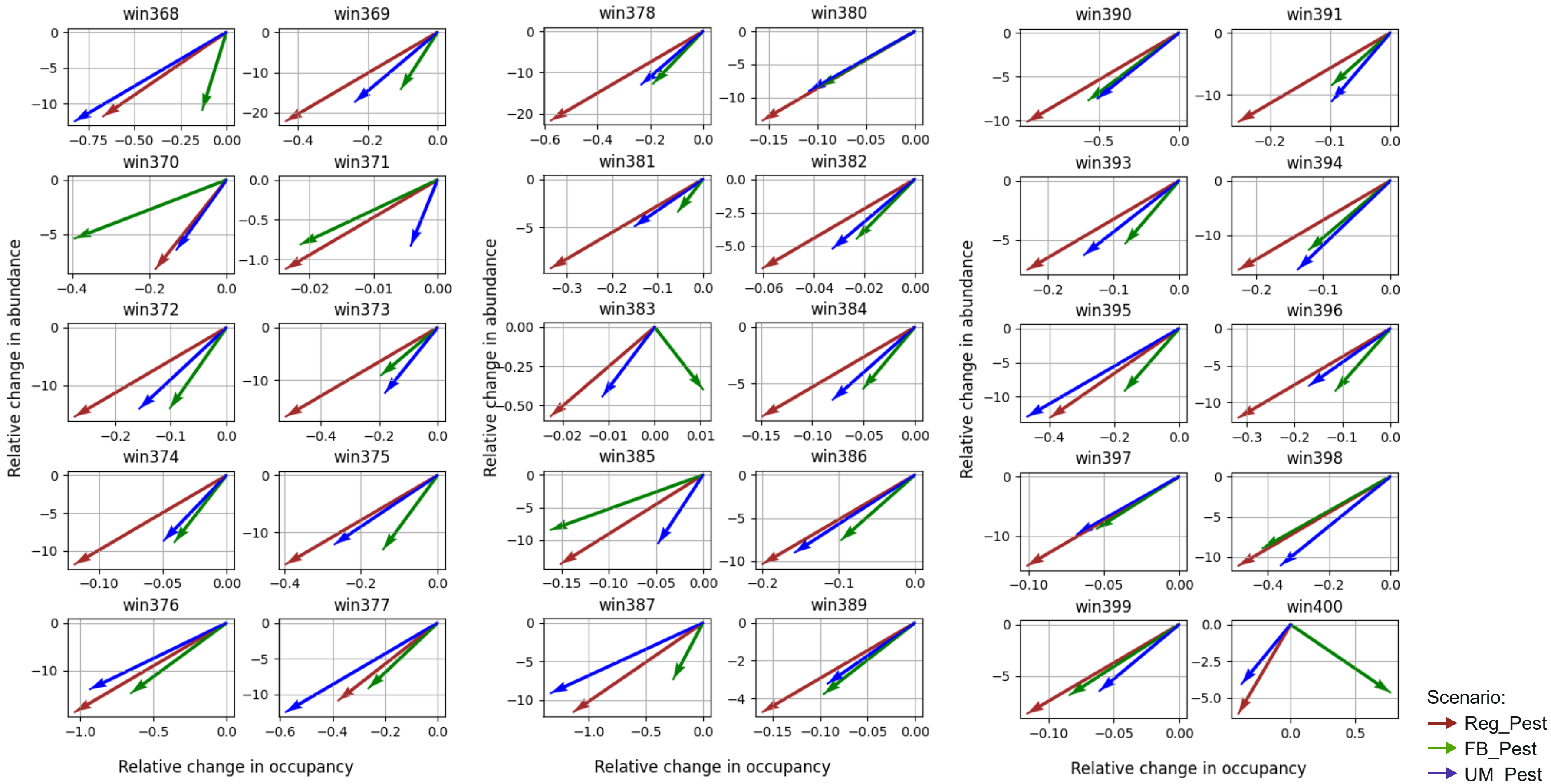
UM_Pest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Relative change in abundance
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Scenario:
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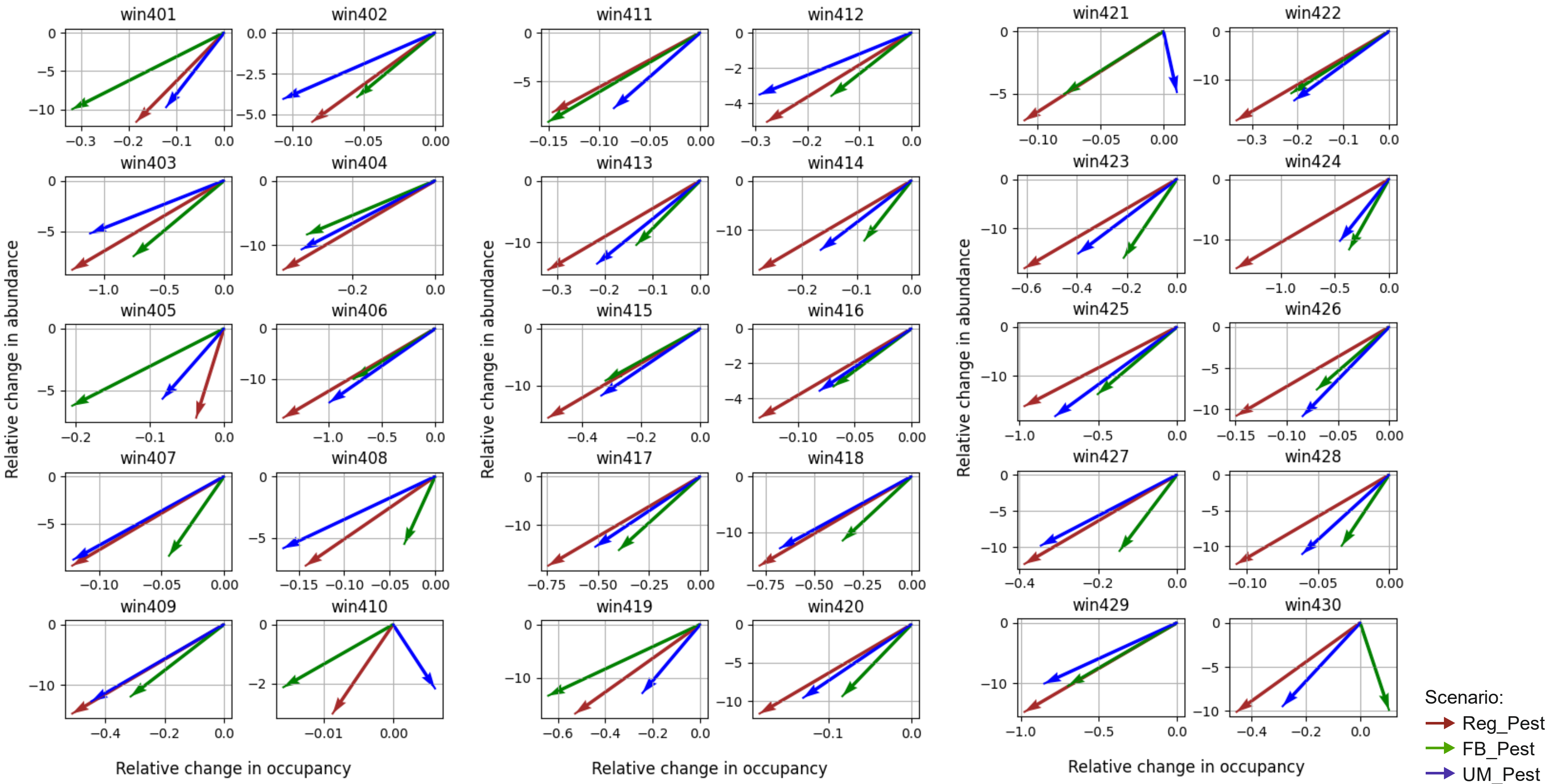
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Scenario:
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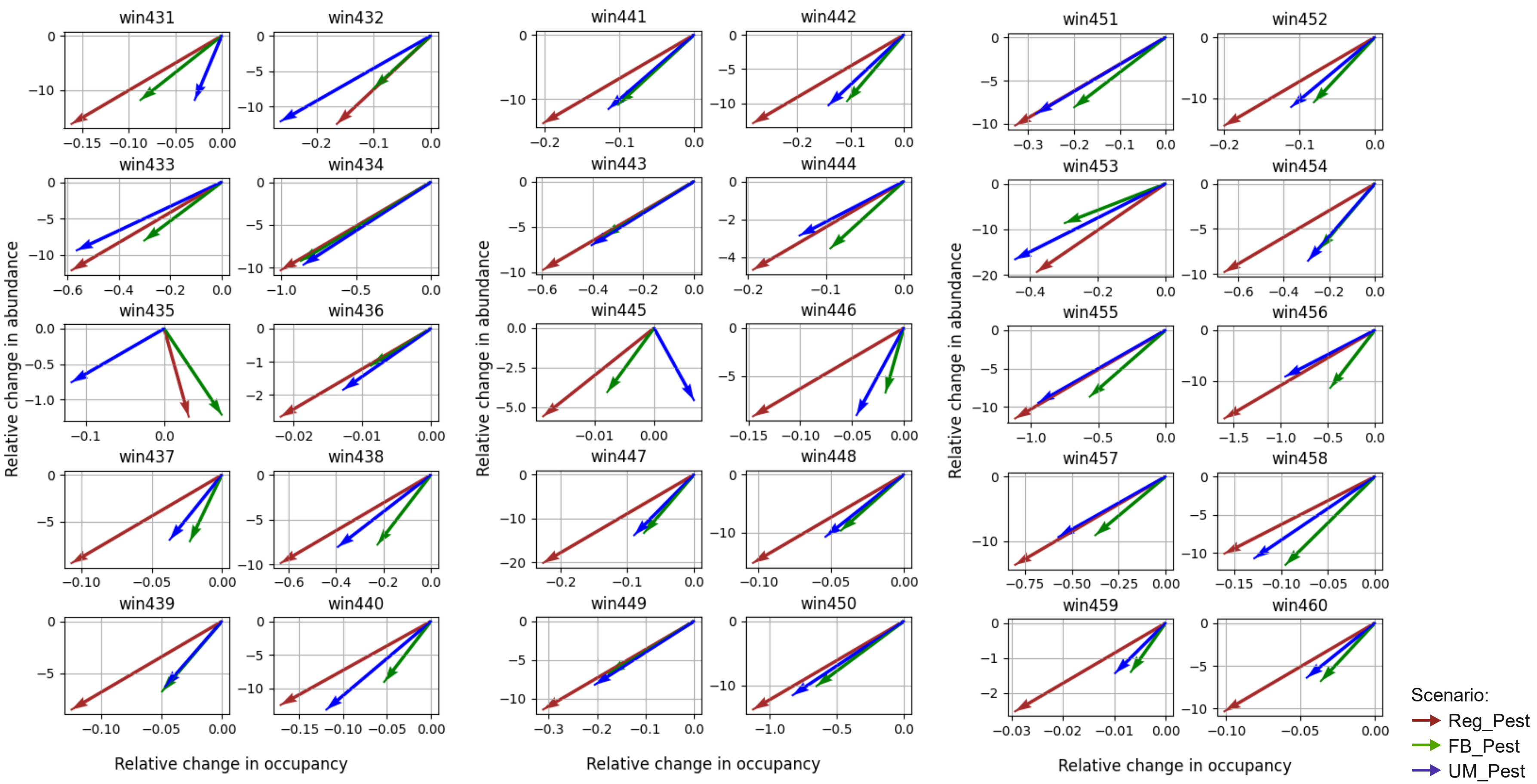
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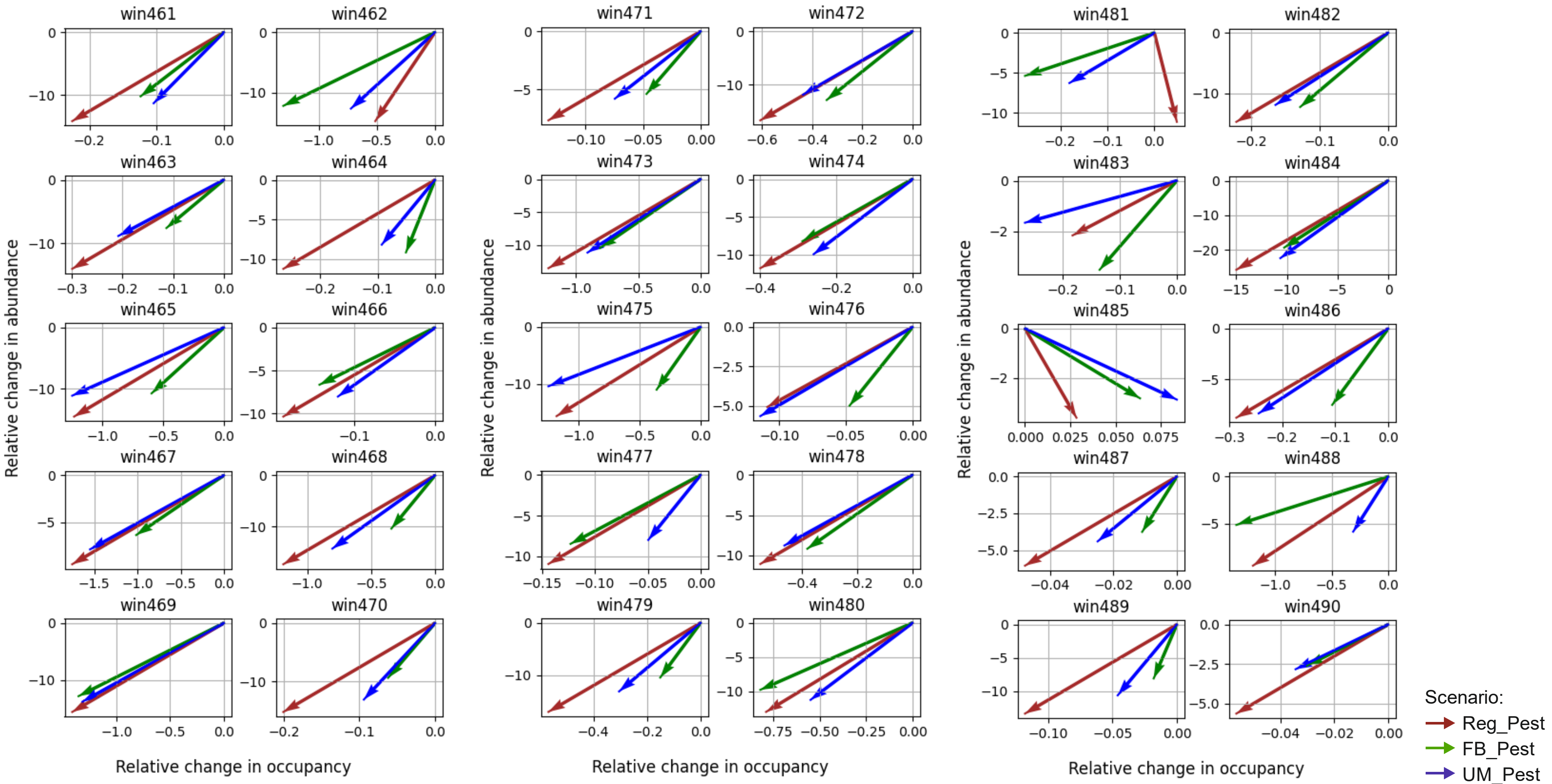
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Relative change in abundance
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Scenario:
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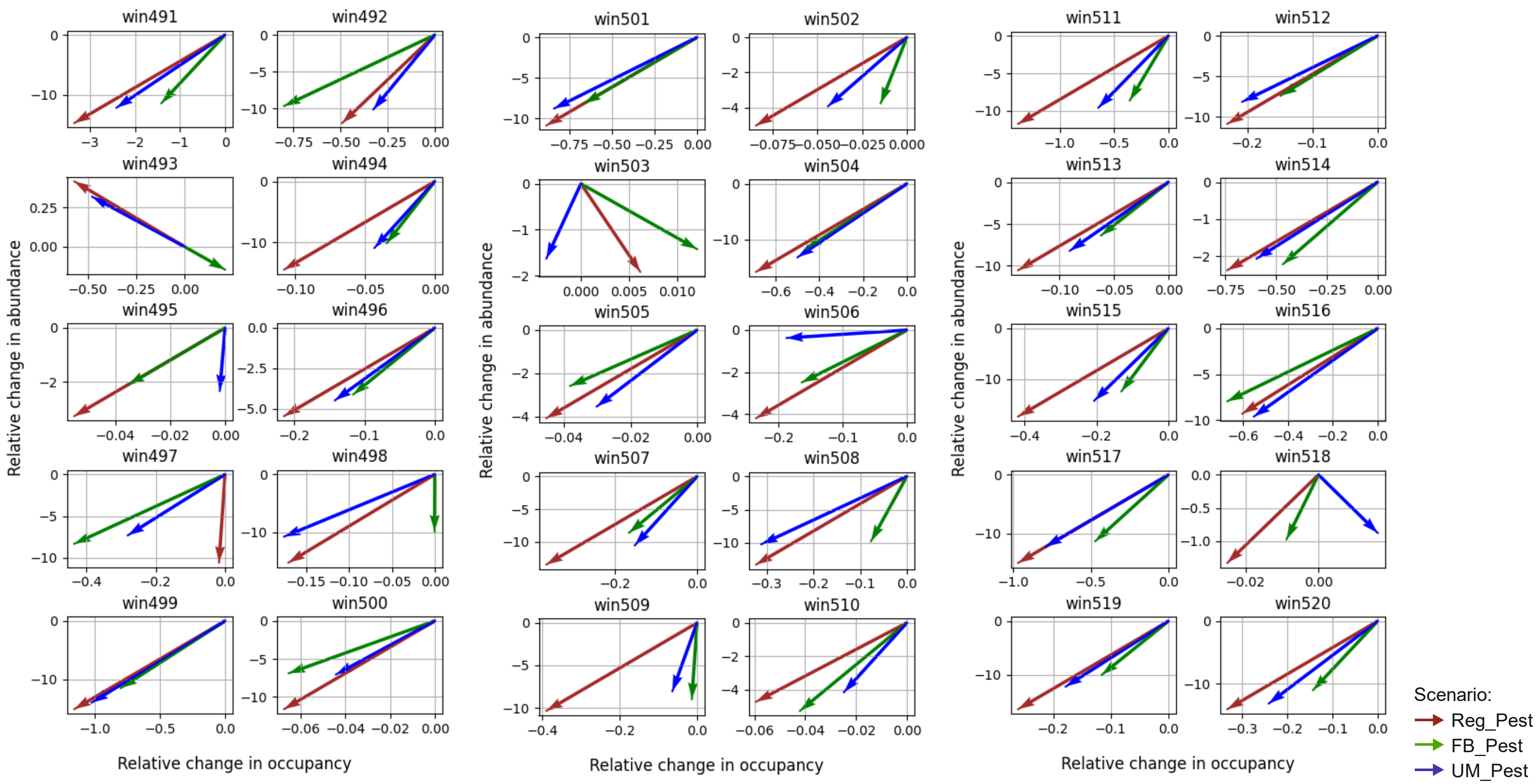
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Relative change in abundance
Relative change in occupancy
Scenario:
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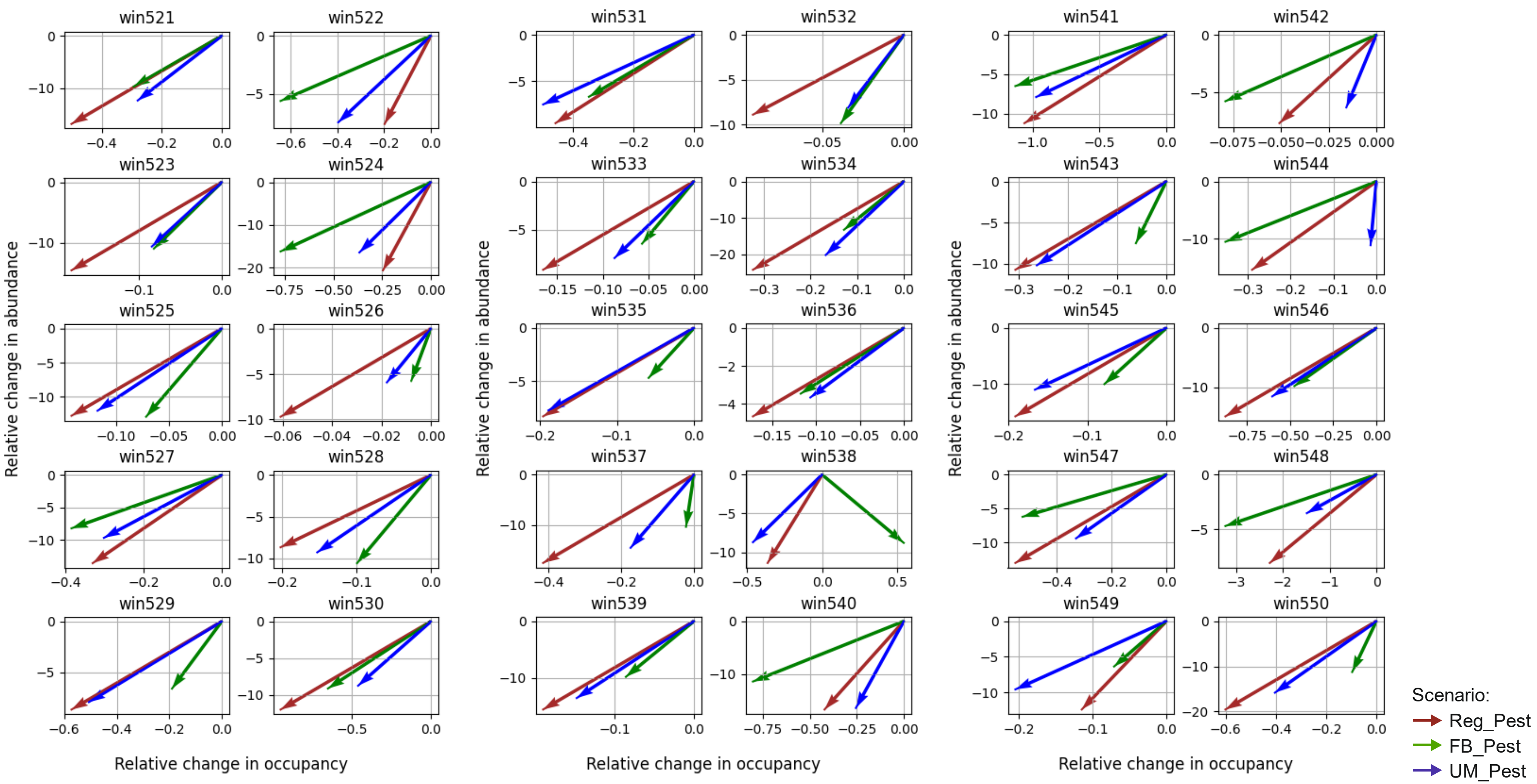
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Relative change in abundance
Relative change in occupancy
Scenario:
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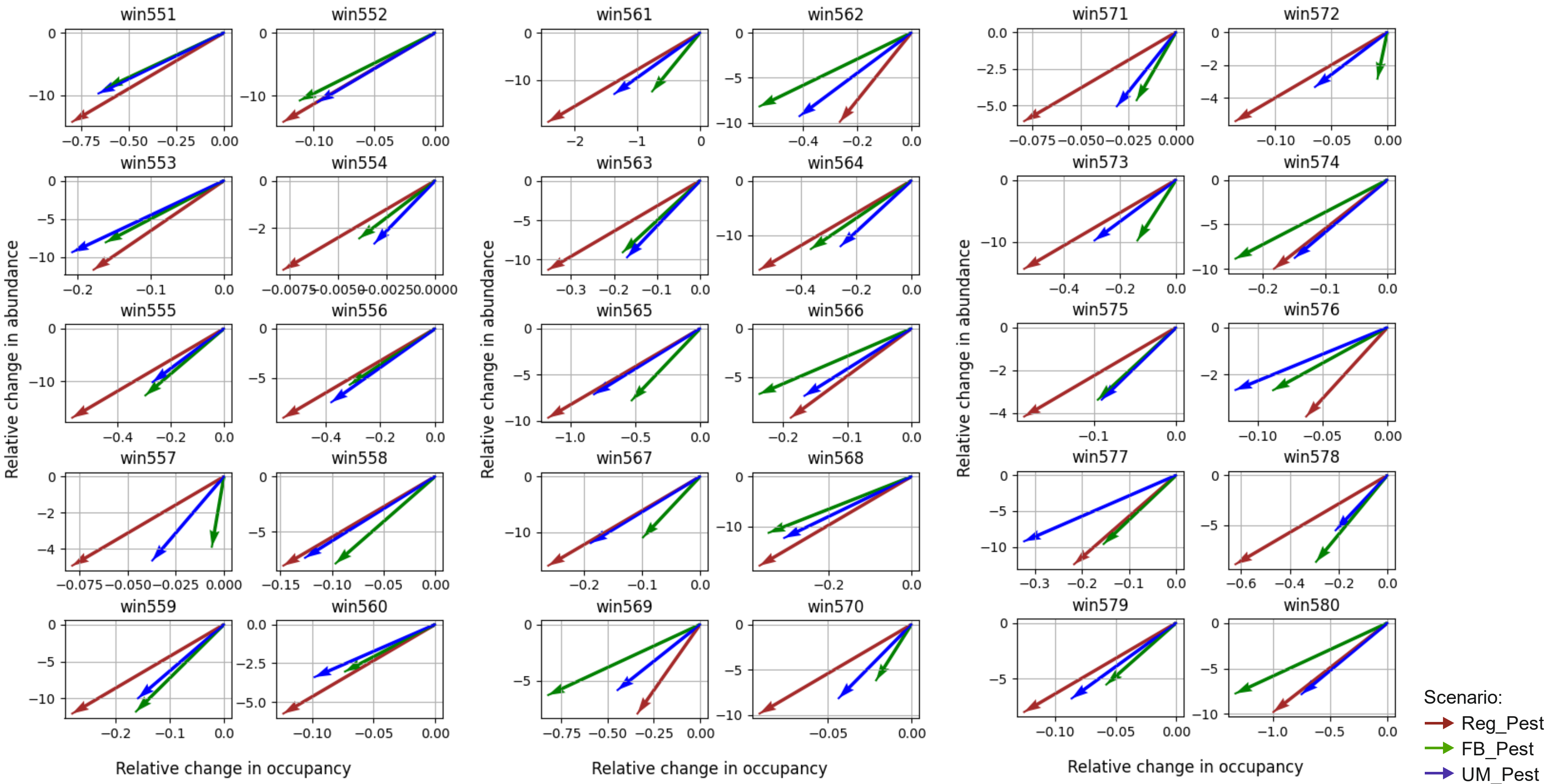
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Relative change in abundance
Relative change in occupancy
Scenario:
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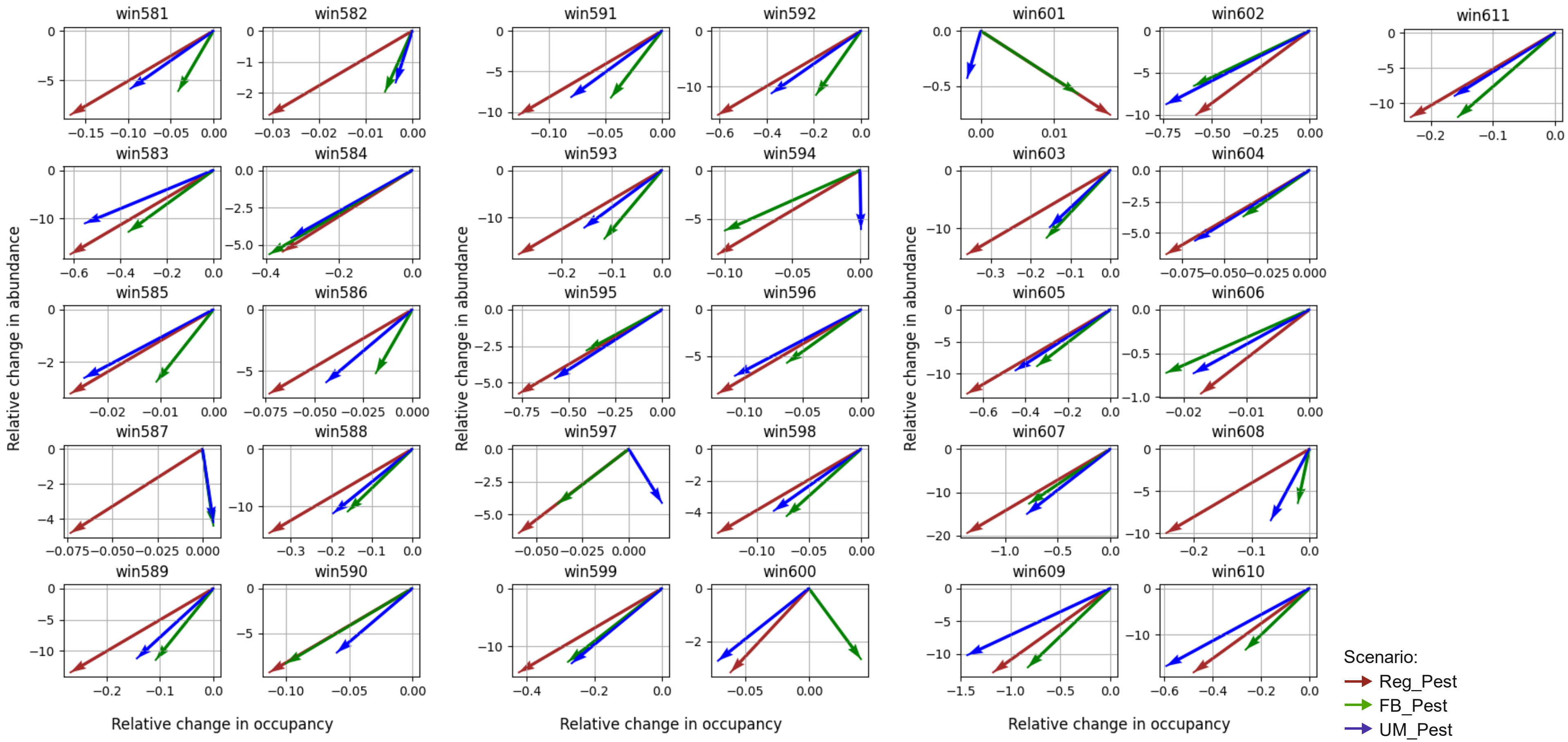

Source: Authors‘ own.