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Two decades of spatial and temporal pesticide risk to non-target invertebrates in England farmlands☆

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ABSTRACT

Pesticide impact assessment methods provide relevant approaches to quantifying risks to non-target terrestrial biodiversity in agricultural systems. Here we develop such an approach through combined analysis of pesticide usage, cropping patterns and ecotoxicological hazard datasets to generate a temporal series of maps (1994–2016) of the spatial risk of pesticides for invertebrates in England. Using data for 179 insecticides, fungicides and herbicides applied on arable crops, we assessed how pesticide risk for bees, earthworms, springtails, parasitic wasps and lacewings varied in space and time over two decades of usage shift. Change in the extent of risk associated with annual applied pesticide amounts differed depending on the organism examined. Organophosphates, pyrethroids, organochlorines and neonicotinoids all contributed to risk in bees. Insecticides, fungicides and herbicides all contributed to risk in springtails. Unexpectedly herbicides (particularly chlorotoluran) had the largest contribution to risk in lacewings, albeit with some uncertainty. Insecticides (particularly organophosphates) made the greatest contribution to risk in parasitic wasps. For earthworms, fungicides (particularly triazole fungicides and the diarylamine fluazinam) were important for risk. A noteworthy finding was that temporal risks linked to pesticide usage have changed only modestly from 1994 to 2016, despite the changes in approved authorisations and key policy such as the removal from use of most members of the neonicotinoid class of insecticides. We discuss how insights, particularly those relating to the magnitude of risk, should be considered in future studies, and how the provision of higher resolution usage data and better hazard information could improve past and future pesticide risk understanding.

1. Introduction

Plant protection products, commonly referred to as "pesticides" in the following text (reflecting the name used in the key databases used in our analysis), reduce crop losses by insect and other pests, control diseases and lower competition from weeds, thereby, increasing crop yield and quality (Damalas & Eleftherohorinos 2011). Concerns exist around the impacts of pesticides on beneficial non-target species, including those important for various ecosystem processes, such as pollinators, biocontrol, and as ecosystem engineers (Mancini et al., 2020; Wan et al., 2025). These considerations have led to the introduction of risk-based approval processes (European Food Safety Authority 2023) and a continued focus on Integrated Pest Management programs that are designed to reduce pesticide use in agriculture (Möhring et al., 2020). Depending on the ecotoxicological properties of different pesticides (e.g. taxon specific toxicity), decreasing the absolute weight of all pesticides applied to crops may not automatically decrease the extent of risk (Babut et al., 2013, Mancini et al., 2020). To understand how changes in pesticide use affect risks to non-target taxa, the nature of exposure and toxicological properties of the whole range of active ingredients used

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needs to be taken into account (Padovani et al., 2004, Mancini et al., 2020).

Although risk assessments are conducted for individual active ingredients, it is typical for crops to receive a range of applications to target different insects, fungi and weeds. Further, it is also common to use products with diverse modes of action to prevent the development of resistance (Kudsk et al., 2018). Under multiple application scenarios, unintentional mixtures can occur together in the environment, even though they were not intentionally combined by the users. Classical single substance assessments do not address unintentional pesticide mixture risks under these real application scenarios. A range of impact assessment tools and approaches have emerged through which the potential real-world risks and impacts of pesticide use can be assessed. These methods use a range of different underlying metrics (e.g., risk ratios, relative risk ranking, decision trees and fuzzy systems), each with its own benefits and limitations (Labite et al., 2011, Bockstaller et al., 2009). The risk ratio approach is based on calculating the extent of environmental exposure (e.g., as an environmental concentration/dose) compared to the substance's ecotoxicity potential (Linders et al., 1994). Risk ratio calculation represents one of the most established approaches for impact assessments (Padovani et al., 2004, Labite et al., 2011, Bockstaller et al., 2009). Insights gained from risk ratio analysis are relatively easy to interpret, making them effective for communicating risk under different treatment scenarios. Further, these approaches can also be applied to cases where multiple pesticides are used. This reflects a wider recognition that unintentional mixture effects need to be included for robust assessment of non-target impacts (EFSA et al., 2023, De Zwart & Posthuma 2005). Such mixture risks are normally estimated based on assumptions of additivity, a pattern reported in the majority of pesticide mixture studies (Cedergreen, 2014), although greater or lesser than additive effects have also been reported in a moderate number of cases (Cedergreen, 2014; Gill et al., 2012; Johnson and Sumpter, 2016; Robinson et al., 2017).

A known limitation with any approach to pesticide impact assessment is that any prediction of risk can only be developed for species for which ecotoxicity data are available. In general, this is the case for only a few species used as internationally recognised (e.g., in OECD protocols) standard test organisms. Examples include honeybee *Apis mellifera*, earthworm *Eisenia fetida*, springtail *Folsomia candida* and various non-target arthropods, which are all used within regulatory risk assessments conducted according to agreed guidelines (e.g., European Commission Regulation (EC) No 1107/2009, which remains the basis for Plant Protection Product risk assessment in the UK). Although the reliance on model test species is limiting, this constraint reflects a more generalised absence of wider information on the toxicity of different active ingredients across the range of biodiversity (species and taxa) commonly found in agroecosystems. As such, using model species to predict risk in pesticide impact assessments currently represents the most tractable approach (Mancini et al., 2020).

In this study, we present an integrated approach that uses information on pesticide usage (for the 179 insecticides, fungicides and herbicides most applied by weight in England between 1994 and 2016), cropping patterns, exposure information and ecotoxicity data to produce maps of pesticide risk, as risk ratios for the major model ecotoxicological test species. To conduct any such assessment for pesticides and unintentional mixtures, any potential approach needs to account for differences in exposure under the relevant usage regime, as well as the potency of the active ingredients (and their combined effects) on the different focal taxa (Mancini et al., 2020). To allow the direct comparison of exposure to toxicity, simple models exist that can translate application rates into organism-relevant exposure metrics expressed in the same units as the available ecotoxicity data (US Environmental Protection Agency 2014; European Food Safety Authority, 2015, 2023; Adriaanse et al., 2022). By applying our approach to different pesticide usage data sets across time, we provide an understanding of evolving pesticide risk trends to different non-target taxa (bees, earthworms, springtails, beneficial arthropods), as well as a national resource on the spatial and temporal patterns of mixture risk for the major pesticides used in arable agriculture. When combined with diversity information (e.g., species abundance data), our approach and derived datasets could support studies of the impacts of pesticide usage change (i.e., phasing out of some actives, introductions of others to the market) on species in England. Further in undertaking this analysis, we set out an overall approach that could potentially be operationalised to other regions/countries to contribute to pesticide risk analysis in research, chemical assessment and management actions in other locations and jurisdictions.

2. Materials and methods

Our approach uses available annual pesticide usage data, cropping patterns, early tier regulatory relevant exposure assessment models and the available ecotoxicity data to quantify the spatial patterns of risks for single substances and mixtures of pesticides at national scale.

2.1. Pesticide usage data collection and analysis

Our approach starts with the generation of national application maps from the available pesticide usage data and cropping information. The approach used for modelling application builds on that used to create the CEH Land Cover® Plus: Pesticides maps (Jarvis et al., 2020) and for the analysis of the ratio of agricultural input to wheat yield ratios (Bullock et al., 2024). Data on pesticide use on arable crops in England from 1994 to 2016 were obtained from the Pesticide Usage Survey (PUS; pusstats.fera.co.uk/home). The PUS data is not open access, and its provision comes at considerable cost. Unfortunately, due to budget constraints, we were not in a position to procure the most up to date datasets from the PUS team for our analysis. Instead, we used the data we were allowed to access at affordable cost. Moreover, the crop data used to model pesticide application is only available up to 2016 for England (agcensus.edina.ac.uk). The available pesticide usage data we could access were derived at a scale linked to EU NUTs designated regions in England of the Northeast, Northwest, Yorkshire and the Humber, East Midlands, West Midlands, South West, London and the South East and East. This resolution is higher than that in the current open access version of this dataset (South East, South West, Eastern, Midlands & Western and Northern). Ideally, we would have liked to go to a finer scale, however, resolution below this regional level proved problematic to obtain from the data holder due to UK General Data Protection Regulations.

To estimate patterns of use, we combined the PUS average application data for each NUTS region with data on arable crop cover. We used the agCensus data (agcensus.edina.ac.uk), which describes agricultural land use within 5 × 5 km grid squares for field beans, oilseed rape, potatoes, spring barley, winter barley, wheat, oats and sugar beet (but not horticulture, top or soft fruit or amenity/non-agricultural use of active ingredients). agCensus datasets were available for the following years: 1994, 1995, 1996, 1997, 2000, 2003, 2004, 2010 and 2016. We used linear interpolation where we had missing data between years and only included years that matched the PUS data. The weight per unit area of 179 pesticide active ingredients used on grown arable crops from 1994 to 2016 was calculated for all 5 × 5 km grid squares in England. For each crop grown within a given 5 × 5 km grid square, pesticide application was estimated as:

$$Mass\ applied\ AI\ \left(kgha^{-1}\right) = AI_x = \frac{\sum_{i=1}^{x,n} Application_{x,n} \times Area_n}{Total\ area} \tag{1}$$

Where: AI_x is the mass per unit area of active ingredient x applied in a 5 × 5 km grid square; *Application* $_{x,n}$ is the average predicted mass of active ingredient x (kg ha^{-1}) applied to crop n within a 5 × 5 km grid squares; *Area* $_n$ is the total area*proportion of area treated (ha) of crop n within the same grid square, and *Total area* is the grid square total area (ha).

For some regions in certain years, the PUS survey indicated no pesticide use for a specific crop, despite the agCensus data indicating that those crops were grown in that region (see below). As the PUS is not an exhaustive survey and is dependent on recipients responding, it is likely that these crops were grown and there was some degree of pesticide application, but this was not recorded in the PUS. Rather than assume no chemical use in the survey year for that crop in a particular region, we instead input the average value for the chemicals applied to that specific crop based on neighbouring regions. This approach will likely incorrectly assign pesticide use to areas under organic farming. However, such low input locations are a relatively small proportion (approximately ~50,000 of a UK total of ~3,000,000 ha of arable croplands) of the total land area. Further, because of the nature of the PUS survey data available to us at the county scale, such organic areas cannot be resolved to specific localities.

2.2. Ecotoxicological exposure assessment

To predict pesticide exposure for our focal species, we used equations taken from early tier pesticide exposure modelling to convert application rates as modelled usage per 5 × 5 km square to exposure values expressed in the same metrics as the available ecotoxicity data. The approach used varied by the species of interest.

i) Soil exposure of the earthworm Eisenia fetida and springtail Folsomia candida

Soil concentrations were calculated from application rates based on the assumption that the added pesticide per unit area enters evenly into the top 5 cm of a soil with a bulk density of 1.5 g/cm^3. These two values were taken as standard from the UK Health and Safety Executive Tier 1 PEC Soil.xlsx calculation tool (www.hse.gov.uk/pesticides/data-requirements-handbook/fate/environmental-fate-models.htm). The first assumption converts application rates from an area to volume metric, the second accounts for bulk density in calculating soil concentrations. Ultimately in combination their effect was to give a soil concentration in mg/kg (the same units in which ecotoxicity data for earthworms and springtails are mostly reported), as the product of the application rate (kg/ha)*1.33.

ii) Daily dietary (oral) exposure for bees

The approach for dietary exposure converts the area-based application rates into dietary exposures, based on the size of the bee species and their food consumption in μg/bee/day as needed to calculate the μg/bee dose metrics reported in toxicity tests, i.e., in regulatory authorisation dossiers. The conversion equation used depends on the pesticide application method and the bee species of interest. For actives with dominant application by downward spray and seed treatment, dietary exposure was calculated using the following Equation (2) from the European Food Safety Authority (2023) guidance:

$$\text{Application rate (kg/ha}^{-1}\text{)* Number of applications * (Constant B*1000)} \tag{2}$$

The number of applications was set to one, given as the modelled predictions of aggregated annual input per 5 x 5 km unit area. Constant B accounts for the size of the bee species and their food consumption. For the honeybees (*Apis mellifera*), constant B is 6.4 for spray and 1.08 for seed treatments; for bumble bees (*Bombus terrestris*), B is 10 for spray and 1.67 for seed treatments; for solitary bees (*Osmia* sp.), B is 0.7 for spray and 0.12 for seed treatments. The multiplication term (1000) is included to convert the application rate from kg/ha to g/ha.

For dominantly soil-applied active ingredients, acute adult dietary exposure in μg/bee/day for all bee species was calculated based on model input variables for honeybees. These parameters are based on the amount of nectar (292 mg/day) and pollen (0.041 mg/day) consumed (total consumption 292.041 mg) multiplied by the predicted pesticide concentration in these foods estimated from the substance log K_{ow} and KoC. Calculation is made following Equation (3) from the US Environmental Protection Agency (2014) Tier 1 honeybee Bee-REX xv1.0 exposure tool:

$$\text{Concentration [μg/mg]} = ((10\hat{}(0.95*\log K_{ow}-2.05) + 0.82)* ((-0.0648*\log K_{ow}\hat{}2) + 0.2431*\log K_{ow} + 0.5822)*(1.5/0.2 + 1.5*K_{oc}*0.01))*0.45*\text{Application\_Rate [kg/ha]})/1000*292.041 \tag{3}$$

Although EFSA et al., 2023 (section 5.3.5) have derived a range of food consumption values for different bee species to be considered for the risk assessments, they recognise that there are significant knowledge gaps regarding the food consumption of bees and bee larvae (section 5.5.5). In particular, further research is needed to reliably quantify pesticide exposure for bumble bees and solitary bees, as reliable food consumption rates are generally lacking for these species (Gradish et al., 2019; Sgolastra et al., 2018). In the absence of reliable species-specific information, daily nectar and pollen consumption for honeybees was used in the bumble bee and solitary bee exposure calculations. This approach is likely to underestimate exposure in bumble bees, while overestimating exposure in solitary bees.

iii) Daily contact exposure for bees

To calculate honeybee exposure via contact (e.g. on plant surfaces) expressed as μg/bee/day, as needed to calculate the μg/bee dose metric reported in ecotoxicological studies, we used the simplified Equation (4) taken from section 5.6 of the European Food Safety Authority (2023) guidance:

$$\text{Application rate (kg/ha}^{-1}\text{)*(Bsf *1000)} \tag{4}$$

where Bsf is a Body surface factor, which for honeybees is 0.0114 dm^2/bee, 0.0146 dm^2/bee for bumble bees and 0.00184 dm^2/bee for solitary bees. The multiplication term (1000) is included to convert the application rate from kg/ha to g/ha. This simplification does not include the contact exposure factor, EF_{co}, which accounts for the source of the exposure from the landscape. The parameters for EF_{co} are derived from deposition factors (where the deposition factor for the weed scenario is related to the crop interception and dependent on the growth stage of the crop and the deposition to the field margin is related to the spray drift/dust drift; section 5.2.2, EFSA et al., et al., . 2023). Our developed approach was taken because the modelled predictions are based on aggregated annual inputs per 5 x 5 km unit area.

iv) Acute oral + contact exposure for bees

To calculate combined oral and contact exposure, the calculation used depends on the dominant application method and bee species as detailed above. For each bee species, the final exposure term is the total via both routes expressed in μg/bee/day. This value is multiplied by 2 to estimate bee exposure dose in μg/bee over a 48 h period; the same duration as used for the honeybee acute test from which the vast majority of the ecotoxicity data are taken.

v) Contact exposure for Lacewing (Chrysoperla carnea) and Parasitic wasp (Aphidius rhopalosiphi)

For these two species the following exposure calculation is used:

$$\text{Application rate (kg/ha}^{-1}\text{)*1000} \tag{5}$$

This equation simply converts application rate in kg/ha to g/ha, the same area-based exposure metric used in the tests from which the vast majority of the ecotoxicity data are taken.

2.3. Ecotoxicological hazard

Ecotoxicological values were collected for six acute (i.e., LC_{50}, LD_{50}) values, relating to honeybees, earthworms, springtails, lacewings and parasitic wasps, and two chronic values (i.e. reproduction NOECs) relating to earthworms and springtails (Table 1). LC_{50}/LD_{50} values are the concentration (C) or dose (D) at which a substance is lethal for 50 % of the organisms tested. NOEC is the no observed effect concentration, which is the highest concentration of a chemical in a toxicity test where no statistically significant effects are observed in the test organism.

Table 1
Input parameters included in exposure and hazard calculations, detailing the number of active ingredients in each pesticide class with the maximum value for each input parameter (i.e., the minimum endpoint value that indicates the highest toxicity). Note the input parameters for honeybees were used to derive exposure estimates for 3 additional bee species *Bombus terrestris*, *Osmia bicornis* and *O. cornuta* using methods described by EFSA et al 2023. As such the input values shown for honeybees were therefore also used in risk calculations for these 3 bee species.

Group	Species and test method	Exposure unit	Fungicide PNECs	Herbicide PNECs	Insecticide PNECs	Molluscicide PNECs	Missing PNECs	Max value	Most potent pesticide
Pollinator	Honeybee – acute contact LD_{50} (48hr) – OECD, 1998, Test No. 214	µg/bee	67	76	27	2	7	0.0015	Deltamethrin
	Honeybee – acute oral LD_{50} (48hr) – OECD, 1998, Test No. 213	µg/bee						0.0037	Imidacloprid
Soil macro-organism	Earthworm – acute LC_{50} (14 days) – OECD, 1984, Test No. 207	mg/kg	65	78	28	2	6	0.565	Beta-cyfluthrin
	Earthworm – chronic NOEC for reproduction (28 days) – OECD, 2016, Test No. 222	mg/kg						0.084	Epoxiconazole
	Springtail – acute LC_{50} (28 days) – OECD, 2016, Test No. 232	mg/kg	35	29	14	2	99	0.101	Carfentrazone-ethyl
	Springtail – chronic NOEC for reproduction (28 days) – OECD, 2016, Test No. 232	mg/kg						0.065	Chlorpyrifos
Non-target (predatory) arthropod	Lacewing – acute LD_{50} (48hr) – Candolfi et al 2000, IOBC study guidelines	g/ha	22	26	11	0	120	1.5	Dimethoate
	Parasitic wasp – acute LD_{50} (48hr) – Candolfi et al 2000, IOBC; Mead-Briggs et al 2010	g/ha	54	61	17	1	46	0.014	Dimethoate

These values were initially collected from the University of Hertfordshire Pesticide Property Database (UoH-PPDB) (Lewis et al., 2016). This resource contains values for ecotoxicity (and other relevant information) reported in registration documents used for active ingredients submitted for authorisation under European Commission regulation No. 1107/2009. For the most commonly used (top 15 in each class) herbicides, fungicides and insecticides applied by weight in 2016, in cases where UoH-PPD gave unbounded values available for a species (e.g., where ecotoxicity is reported as a > value or < value), the UoH-PPDB data were supplemented by data from the scientific literature.

Our focal non-target invertebrates are all ecotoxicological models and standard test organisms. As such they are the species for which the greatest amount of ecotoxicity data is available. The species cover a range of taxonomic groups (Annelids, Collembola, Insects) and include both above and below ground species. Different model species have been used historically to lesser or larger extents in pesticide hazard assessment. For example, while honeybees have been widely used as a terrestrial insect model species for decades, this is not the case for other wild bee species, which have come into use only since the 2010s, as guidance has further developed (European Food Safety Authority 2023). For bee species, there is, therefore, a paucity of ecotoxicological values for available for non-honeybee species in the UoH-PPDB (Lewis et al., 2016) and wider scientific literature. Under revised guidance on the risk assessment of plant protection products for bees (*Apis mellifera*, *Bombus* spp. and solitary bees), methods have been proposed where toxicity data for honeybees are used to derive estimates of risk for bumble bees (*Bombus terrestris*) and two solitary bee species *Osmia bicornis* and *O. cornuta* using Toxicity extrapolation factors (Tef) (European Food Safety Authority 2023). Although the use of Tefs is not approved under current regulation and, therefore, should be used with caution, their use represents the best available approach for estimating risk to bumble bees (*Bombus terrestris*) and the two solitary bee species (*Osmia bicornis* and *O. cornuta*).

The ecotoxicity data available for our focal species represent a range of LD_{50}/LC_{50} and reproduction NOECs taken from experiments with different exposure durations. The differences in measured endpoints and test durations mean that for each taxon, hazard is quantified on a different basis. To provide a consistent hazard metric for risk mapping, a systematic approach was used to calculate species PNECs from the reported ecotoxicity data for each pesticide to provide a consistent metric (a predicted NOEC) for assessment:

- For this conversion, the inequality symbols (e.g., < and >) were removed from all unbounded values to change them into defined values.
- In those cases where the unbounded value was reported as a > value, the defined value was taken as 2x the unbounded value; when the unbounded value was reported as a < value, the defined value was taken as ½ the unbounded value.
- The complete set of defined values were then converted to a PNEC using a widely used generic approach that was consistent for all species that was based on the use of two assessment factors according to the tested endpoint (LD_{50}/LC_{50} or NOEC reproduction) and test duration (short term or long-term) following principles set out in an established risk assessment guidance (European Chemicals Agency 2008). First, when a reported metric was for an effect on survival (e.g., an LC/LD_{50}), this value was divided by a factor of 10 to convert from mortality to sub-lethal effects. Second for tests of short duration (defined as a test of <168 h), an additional assessment factor of 10 is included to account for the potential for greater effects under the longer exposure times that may be encountered in the field.
- In cases where a test measured both an effect on mortality and over a short-term exposure (e.g., 48hr), then the assessment factors were multiplied (e.g., PNEC = short term LC_{50}/LD_{50})/100).
- For those tests that assessed a sub-lethal effect over a longer duration exposure, then the NOEC for this study was taken as the PNEC, i.e., no division of the reported NOEC values by either assessment factor.
- For species for which both acute and chronic toxicity data were available (e.g., earthworms, springtails), the lowest of the two calculated PNECs was taken as the hazard value for the assessment. The lowest PNEC was used as this enables a more conservative assessment.

Table 1 shows the number of lowest PNEC values available for hazard calculations for fungicides, herbicides, insecticides and molluscicides.

2.4. Risk calculations for single pesticides and mixtures

The risk of each active ingredient for which a species specific PNEC was available was calculated by dividing the predicted exposure concentration, expressed in appropriate units (mg/kg soil, μg/bee, g/ha application rate) by the lowest PNEC value for the species expressed in the same units (i.e., Risk = PEQ/lowest PNEC). By calculating risk based on the exposure concentration predicted from pesticide usage data for each 5 km square, it was possible to map risk for each focal species. Further, by repeating this analysis for all usage datasets available from 1994 to 2016, a time-sliced view of the spatial patterns of risk could be generated (Supplementary file 1).

To calculate mixture risk, two potential models could potentially have been used: concentration addition and independent action. These two mixture models differ in their mechanistic assumptions, concentration addition being considered more relevant to similarly acting chemicals and independent action to dissimilarly acting substances (Van Gestel et al., 2010). The statistical calculation of both models are established and are discussed in full in (Van Gestel et al., 2010). In mixture studies with non-target species, applying these two models according to their mechanistic basis is often problematic due to uncertainties in mode of action assignment. Instead, other reasons can underpin choice. Here we chose to use concentration addition for two reasons. First, this model is often marginally more conservative than independent action. Such conservatism is seen as potentially beneficial in risk assessment studies, where failure to identify risk could lead to irrecoverable species-specific effects from co-exposure to chemical mixtures. Second, this model requires only a single hazard metric (i.e., a PNEC) to calculate individual pesticide contributions to a mixture effect, while independent action needs the full concentration response relationship; something not available in the UoH-PPDB. Finally, this model is recognised as a widely accepted default approach to predict mixture toxicities for human health as well as the environment (European Commission 2020).

To analyse trends in usage and risks to our focal species we used concentration addition to sum risk for all active ingredients, by major pesticide group (fungicides, insecticides, herbicides and molluscicides) and by pesticide class (Chloronitrile, Triazole, Carbamate, Morpholine, Strobilurin, Triazolinthione, Benzimidazole, Urea, Dinitroaniline, Organophosphate, Thiocarbamate, Aryloxyalkanoic acid, Chloroacetamide, Benzamide, Triazine, Oxyacetamide, Pyridine compound, Triazinone, Pyrethroid, Neonicotinoid and Organochlorine). Risks were mapped as raster stacks, where each layer contains the values of the risk metric per year for each 5 x 5 km square.

However, because many aspects of the test method, e.g., duration, endpoint, exposure method, test media etc., differ between the focal invertebrates, simple comparison of these quotients across species is not fully appropriate. Instead, we chose to compare predicted risk in space and time for each species. To allow temporal and spatial risk comparison, calculated mixture risk per species was plotted on a relative scale, with 1994 as the baseline. These plots give a snapshot of change over the longest duration possible with the available data. Visualising in this way does not capture the full trajectory of change for cases where risk is highest in the middle of the time series. Hence, for more detailed time resolved comparisons, maps of absolute risk for each time year modelled are provided in Supplementary File 1.

3. Results

3.1. Data availability

The use of 179 pesticides; 81 herbicides (75 spray, 6 soil application), 68 fungicides (53 spray, 12 seed dressing; 3 soil application), 28 insecticides (17 spray, 6 seed application, 5 soil application) and 2 molluscicides (both soil application) were mapped based on the PUS data available to us and cropping information in years from 1996 to 2016. Supplementary file 2 provides a summary of the substance identity and authorisation status information for each of the 179 pesticides collected from the University of Hertfordshire Pesticide Property Database (UoH-PPDB) (Lewis et al., 2016). The usage information for these pesticides was compared to extracted ecotoxicity values for eight non-target invertebrate species to allow spatial and temporal risk characterisation.

Despite using a comprehensive resource of regulatory ecotoxicity data, hazard data suitable to generate a PNEC for use in risk mapping was not available for all active ingredients. PNECs could be calculated for 172 of 179 pesticides in honeybees (and by following the methods described in European Food Safety Authority 2023 also for bumblebees and solitary bees), 173 of 179 for earthworms, 133 of 179 for parasitic wasps, 80 of 179 for springtails and 59 of 179 for lacewings. For further breakdown of the available PNEC by pesticide group and the most hazardous active for each species and endpoint (lowest LC/LD_{50} and NOEC values) see Table 1. In cases where a substance PNEC was missing for a species, these pesticides were excluded from the mixture risk assessment. Thus, especially for springtails and lacewings, mixture risk calculations do not include the contributions of a number of pesticides, including some insecticides, that lack ecotoxicity values for this species.

3.2. Change in risk between 1994 and 2016 for each non-target invertebrate species

Combining the pesticide use data, exposure models and PNEC values allowed bi-annual maps of combined pesticide risk to be generated for each focal species. Visualisation of trends in data suggested that the risk in England has decreased since 1994 for parasitic wasps, springtails and lacewings, but increased for all four bee species and earthworms (Fig. 1). The magnitude of decrease is greatest for parasitic wasps for which risk has decreased > 75 %. The greatest increase in risk is for solitary bees, with risk to earthworms also predicted to have increased > 2 fold.

3.3. Temporal trends in the contribution of different pesticide groups to risk

The contributions of broad pesticide classes (herbicides, insecticides, fungicides, molluscicides) and contributions of the different main classes of insecticides to risk varied between the focal species (Fig. 2). Insects are the main target pests for which insecticides are developed. As such, higher maximum values for insects compared to soil arthropods may be expected. In support of this, modelling of mixture risk indicated generally higher maximum values for bees, lacewings and parasitic wasps compared to the two soil invertebrates. Visualisation of trends suggests that insecticides make a contribution to modelled risk for all focal species, especially so for the four bees and parasitic wasps. For the remaining three species, there is a substantial contribution to mixture risk for either herbicides (for lacewings), fungicides (for earthworms) or both (for springtails). Across all non-target invertebrates, molluscicides make only a small contribution to risk, due to either low use or low hazard.

Bees and parasitic wasps – insecticides dominated risk: To visualise how different pesticide classes contribute to insecticide risk in all bees and the parasitic wasp, we plotted the time trends of risk for the carbamates, neonicotinoids, organochlorines, organophosphates, pyrethroids and 'other' (i.e., those not in the other five groups) classes. For parasitic wasps, organophosphates make the largest contribution to risk. The decline in the use of this class of insecticide accounts for the drop in mixture risk to this species (Fig. 3). The replacement of organophosphates with neonicotinoids might have been expected to retain, or even increase, risks in this taxon. However, the nature of the short-term contact test used for testing for parasitic wasps may underestimate

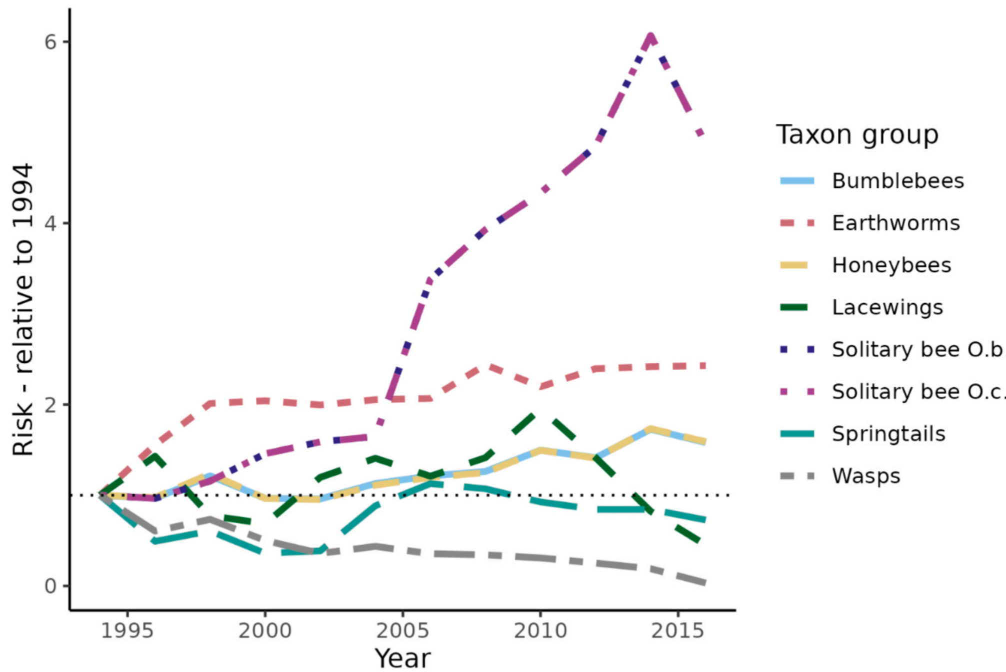

Fig. 1. Trends in the cumulative mixture risk relative to the baseline year of 1994 for eight focal invertebrate species. Lines show pattern of change in relative risk relative to the baseline, line for bumblebees are overlaid by that for honey bees and for *O. bicornis* by the trend of *O. cornuta*.

neonicotinoid risk as these compounds have low lipophilicity and so may be poorly adsorbed across the insect cuticle. As a result of this mechanism, the toxicity of neonicotinoids to this species may be underestimated, especially over the short exposure times used for testing (Sánchez-Bayo & Tennekes, 2020). For all four bees, and particularly the solitary species, insecticide risk was dominated by neonicotinoids (Fig. 3). In all cases, risk from neonicotinoids rose steeply in the 2000s before declining, especially near the end of the time series as the moratorium for use on mass flowering crops came into force in 2013 (with 2014 being the last year neonicotinoids were used in field).

Lacewings – herbicides dominated risk: Trends for pesticide class contributions for lacewings suggest that herbicides are the largest contributors to risk. This finding should, however, be treated with some caution, as it is based on a cumulative assessment for only the 63 actives for which PNECs are available for this species (Fig. 3). To visualise which of the included active ingredients within the herbicide class had the largest contribution to risk in lacewings, graphs were plotted for the classes: aryloxyalkanoic acid, benzamide, carbamate, chloroacetamide, dinitroaniline, organophosphate, oxyacetamide, pyridine compound, thiocarbamate, triazine, triazinone, urea and an ‘other’ category consisting of active ingredients not included in those classes and substances (e.g., glyphosate) that are the only member of their class. Visualisation of these classes suggest the ‘other’ class of herbicides was the largest contributor to risk (Fig. 3). Further investigation suggested that chlorotoluron, a phenylurea class herbicide in the ‘other’ class, was the dominant contributor. The reported LD_{50} for this herbicide at 2.5 g/ha is below those for the other herbicides and comparable to some insecticides (e.g. alpha-cypermethrin, 2.88 g/ha), indicating that this herbicide could indeed contribute to risk based on this potency. This finding indicates how a single active ingredient, even one from an unexpected class, can be identified as an important contributor to mixture risk, acting as a stimulus for further research into its potential field effects.

Earthworms – fungicides dominated risk: Visualisation of trends in data suggests that fungicides were the largest contributor to combined risk for earthworms (Fig. 2). To visualise which active ingredients most contribute, the fungicide risk was apportioned to the following classes; benzimidazole, carbamate, chloronitrile, morpholine, strobilurin, triazole, triaolinithione and ‘other’. The class assessment indicated that, although triazoles also had a significant contribution, the ‘other’ class was the largest contributor, with risks to earthworms due to both of these classes increasing over time (Fig. 3). Among the ‘other’ fungicides, the phenylpyridinamine fluazinam, had a large contribution to earthworm risk.

Springtails – multiple pesticide risk: Insecticides, fungicides and herbicides all make a substantive contribution to risk for springtails. In more recent modelled years, there has been a trend for a greater contribution from fungicides and less from insecticides (Fig. 2). Risks to springtails from herbicides was also observed to increase over time (Fig. 2). Among the insecticides, those in the organophosphate class were observed to have the largest contribution to risk in springtails in the years until 2010, although in latter times the contribution of risk from neonicotinoids increased (Fig. 3).

3.4. How has the spatial pattern of risk changed over time?

To assess how risk has varied in space and time, we calculated change maps to compare the overall modelled pesticide risk between 1994 and 2016. These change maps consider whether the most recent time period has higher or lower risk than the earlier year to provide a snapshot of change over the longest duration possible with the available data. For each bee species, a greater change in risk due to pesticides was indicated for areas in the southeast and west midlands of England. This pattern of change was particularly notable for solitary bee species (Fig. 4). These regions of England have the highest land use given to the growth of arable crops, and so the greatest potential to see changes in risk as trends in pesticide usage shift in time. Spatially, a lower change in risk was observed in urban areas for solitary bees and more widely for honeybees and bumble bees across years (Fig. 4). This lower change in risk is naturally linked to the absence of agriculture in these areas, although amenity and garden use may provide additional risk not captured in the underlying arable based PUS statistics.

The patterns of overall risk in the other taxonomic groups showed the greatest change in the southeast of England, matching the spatial profile of change for bees in these areas where there is high arable land use (Fig. 4). Earthworm risk showed a trend for increase, with the risk

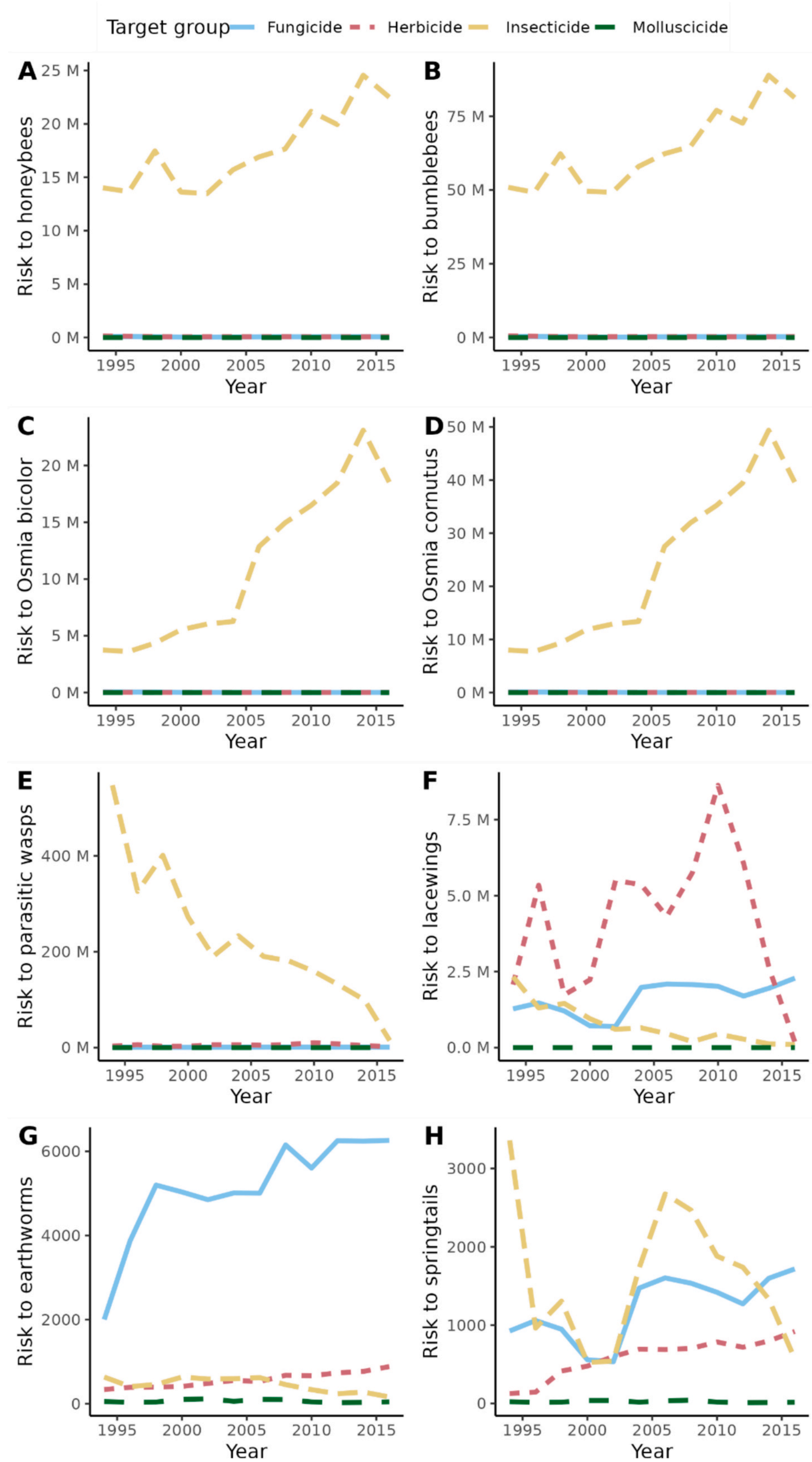

Fig. 2. Trends in the absolute risk of herbicides, fungicides, insecticides and molluscicides for (A) the honeybee *A. mellifera*, (B) the bumblebee *B. terrestris*, (C) the solitary bee *O. bicornis*, (D) the solitary bee *O. cornuta*, (E) the lacewing *C. carnea*, (F) the parasitic wasp *A. rhopalosiphi*, (G) the earthworm *E. fetida*, and (H) the springtail *F. candida* for biannual years from 1994 to 2016.

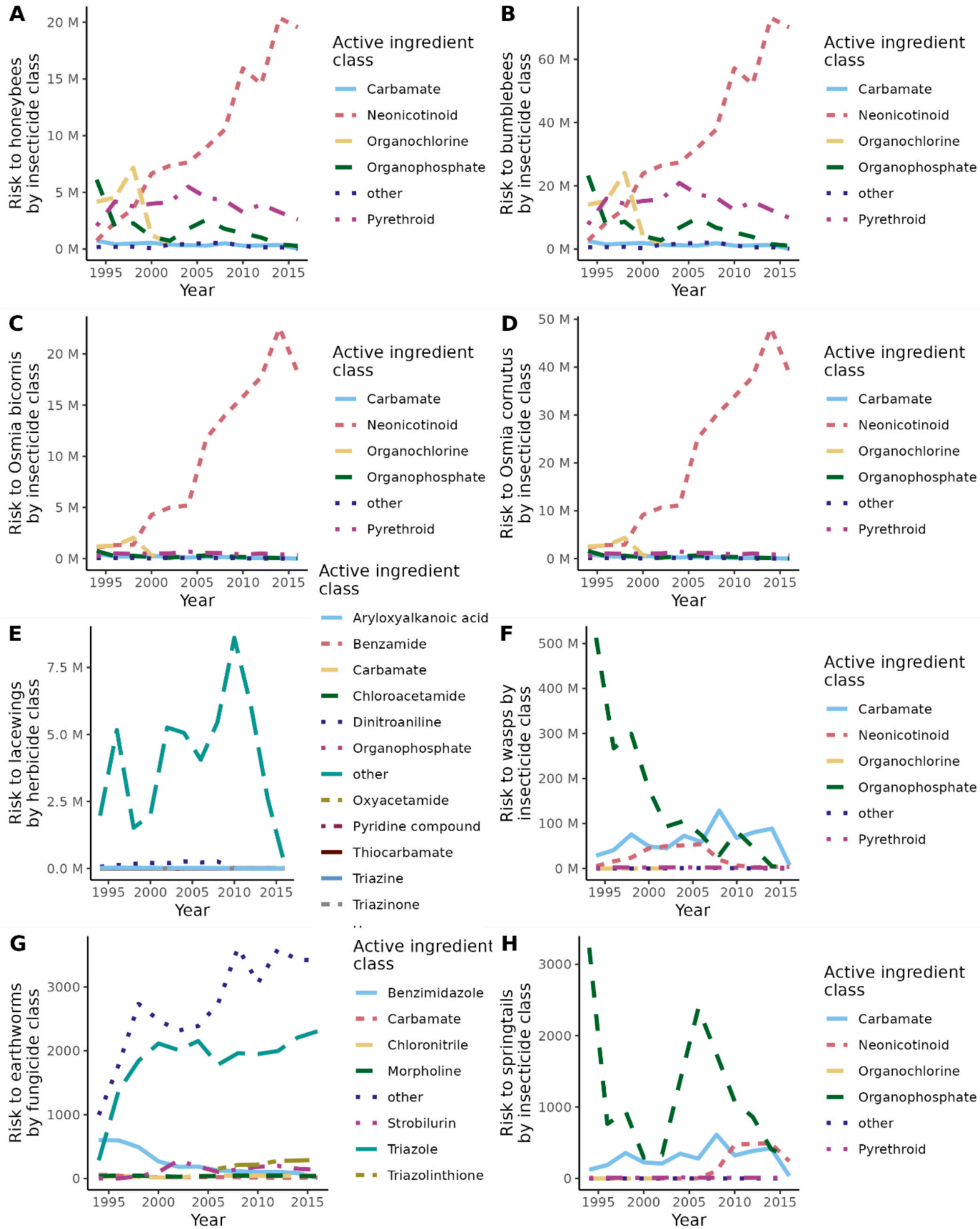

Fig. 3. Trends in the absolute risk of different insecticide classes for (A) the honeybee *A. mellifera*, (B) the bumblebee *B. terrestris*, (C) the solitary bee *O. bicornis*, (D) the solitary bee *O. cornuta*, (F) the parasitic wasp *A. rhopalosiphi*, (G), the springtail *F. candida*; herbicide classes to (E) the lacewing *C. carnea*; and fungicide classes to (H) the earthworm *E. fetida* for all for biannual years from 1994 to 2016.

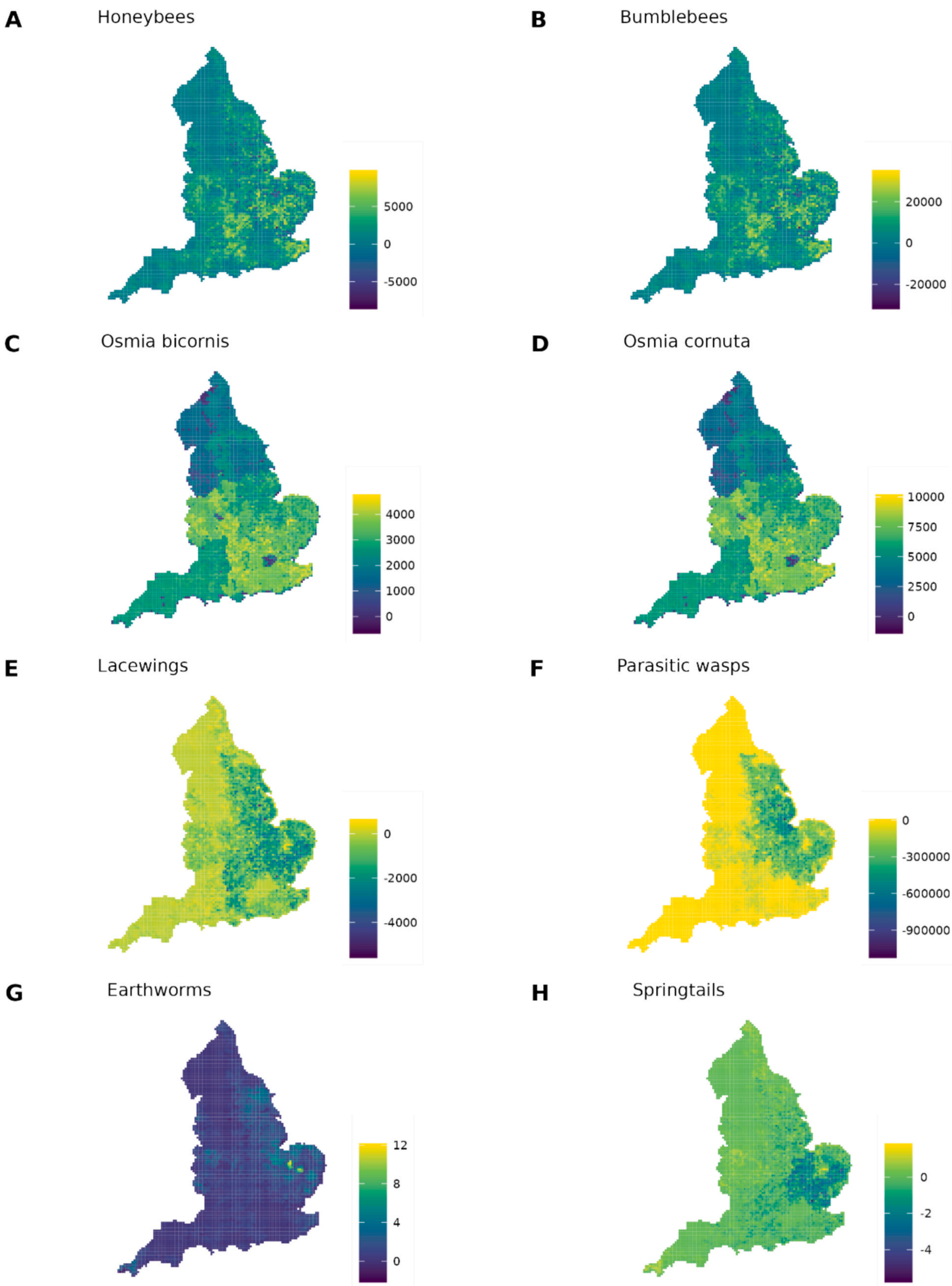

Fig. 4. Map, at 5 x 5 km resolution of the change from 1994 to 2016 in cumulative mixture risk due to pesticide exposure for A) the honeybee *A. mellifera*, (B) the bumblebee *B. terrestris*, (C) the solitary bee *O. bicornis*, (D) the solitary bee *O. cornuta*, (E) the parasitic wasp *A. rhopalosiphi*; (F) the lacewing *C. carnea*; (H) the earthworm *E. fetida* and (G) the springtail *F. candida*.

change largest in the regional area of East Anglia, specifically in counties (Cambridgeshire, Lincolnshire, Suffolk) known to be important for vegetable production in lowland peat soils (Fig. 4). For parasitic wasps, lacewings and springtails, there is an overall pattern of decrease in risk over the modelled time period.

4. Discussion

4.1. Visualising the spatial and temporal patterns of risk to non-target terrestrial invertebrates

Using a combination of pesticide usage, exposure prediction approaches and ecotoxicity data, we have produced a highly resolved picture of the temporal and spatial patterns in risks due to arable pesticide use for non-target terrestrial organisms in England. Our approach advances beyond the previous state of the art, which allowed only understanding of usage amounts by area. Overall, the spatial and temporal risk assessments suggest that risks linked to pesticide usage in England have changed only modestly from 1994 to 2016. Visualisation of the spatial distribution of risk identified a clear pattern with all non-target invertebrates having the highest change in southeast England, the region of the country with the greatest percentage of land given over to arable farming, the greatest pesticide use, and so the greatest potential to see changes in risk as usage shift patterns over the studied timeframe.

Over the period of the assessment, there has been a marked transition in the active ingredients used in England (Garthwaite et al., 1995, 2017). For example, pyrethroids are the most extensively used insecticide applied as sprays on arable farm crops (Garthwaite et al., et al., 1995, 2017). The Pesticide Usage Survey data available for our analysis reported an increase in pyrethroid use from 45 % of all sprayed insecticides in 1994 to 94 % in 2016 (Garthwaite et al., 1995, 2017). Conversely, organophosphate use declined from 35 % in 1994 to less than 1 % in 2016. Our results indicate that parasitic wasps are most at risk from the organophosphate class of insecticides, and the sensitivity of parasitic wasps to organophosphates explains the reduction in cumulative pesticide risk for this species as the usage of these products declined. Like organophosphates, carbamate use has also declined from 16 % in 1994 to 2 % in 2016 (Garthwaite et al., 1995, 2017). Neonicotinoid use was observed to be 2 % of the insecticide-treated area of arable farm crops grown in Great Britain by 2016 (Garthwaite et al., 2017). Nonetheless, this group still made a significant contribution to the risk to bees and to a lesser extent, to parasitic wasps (Fig. 2). For lacewings, a high contribution of herbicides and a reducing contribution of pesticide risk was indicated as the drivers of changes in risk to this taxon (Fig. 2).

For each individual non-target invertebrate, visualisation of trends indicated different patterns of risk change over the studied period. For parasitic wasps and springtails, a reduction in risk was indicated since 1994, and for lacewings since the mid-2000 s based on the data available for this taxon (Fig. 1). For honeybees and bumble bees, only a limited change was indicated, while for earthworms and especially solitary bees, risk tended to increase over time (Fig. 1). There is a degree of concordance between the outcomes of our spatial and temporal analysis and experimental evidence on the pesticide groups and classes most likely to cause harm to our focal species. For bees, risk in the early years was linked to several insecticide classes including organophosphates, pyrethroids, organochlorines and neonicotinoids. However, in later years, bee risk was dominated by neonicotinoids, especially for solitary bees. There is a large evidence base demonstrating the negative impact of neonicotinoid insecticides on bees (Goulson et al., 2018), and compared to honeybees, other bee species are known to have high sensitivity (reviewed in Arena & Sgolastra 2014). Although neonicotinoid use declined by 2016 as the effect of the moratorium for use on mass flowering crops came into force, restrictions on use of two neonicotinoids, acetamiprid and thiacloprid, did not occur until after 2013 and some other neonicotinoids were authorised for use on winter wheat and sugar beet beyond 2016. Hence, some risks due to this insecticide class remained in later years, contributing to risk for sensitive species.

Pesticides, including insecticides and herbicides, are known to have negative effects on the distribution and abundance of non-target arthropods (Sánchez-Bayo, 2021). Trend patterns in the data suggest that risks from different classes of pesticides differed across these two beneficial arthropods. Insecticides from the organophosphate class had the largest contribution to risk in parasitic wasps, and herbicides (particularly chlortoluron) the largest contribution to risk in lacewings. In addition to indications of direct toxic effects of herbicides (e.g., glyphosate arrests development and impairs cocoon formation to lacewings; Defarge et al., 2023), declines in predatory arthropods have been noted in locations where herbicides are used. From such observations in the field, it can be difficult to attribute such community effects to either herbicide exposure directly, or to the removal of plants resulting in a reduction of habitat resources, such as overwintering and oviposition sites (Sánchez-Bayo, 2021). The results here do, however, suggest that direct herbicide effects could play a role, especially given the apparent potency of chlortoluron to lacewings.

The are, however, some reasons to be cautious about the interpretation of the lacewing data. The data for this taxon are based on a cumulative assessment for only 63 of the 179 actives for which PNECs are available, of which 11 were insecticides. Given the limited substance coverage for lacewings the potential exists to underestimate the impact of those unstudied pesticides on lacewings. The International Organization for Biological Control (IOBC) developed a testing method for natural enemies using standardised species and methods, where pesticide toxicity data are classified according to a tiered system consisting of set levels of mortality (Sterk et al., . 1999). Concerns have been raised that this testing approach underestimates effects because the set levels of mortality used (harmless, 29 % mortality; slightly harmful, 79 % mortality) would lead to severe detrimental effects on parasitoid populations in nature (Stark & Banks 2024). Also, concerns have been raised that this testing method could underestimate the toxicity of systemic insecticides like neonicotinoids, because it does not take into account the time-cumulative toxicity of this class of pesticides, which may also be poorly taken up by contact due to their low lipophilicity (Sánchez-Bayo & Tennekes, 2020). There is a need for a concerted research effort to fill data gaps and refine methodological approaches to improve our ability to conduct robust environmental risk assessments for non-target insects useful for biological control, such as parasitic wasps and lacewings.

4.2. Wider relevance

Policy makers, regulatory agencies and farmers are all usually aware of the hazards of pesticides and the need to understand the risks their use poses to species. The approach we have adopted here, using usage data, early tier exposure approaches and available ecotoxicity values, provides these stakeholders with a further approach to understand how pesticide properties, practitioner choices and crop distributions all act to affect risk to different non-target organisms in time and space. Our spatial and temporal visualisation of data can provide information on how regulatory decisions change risk, where pressure is greatest and which taxa have, are, or will be affected. For example, the UK government, under the Sustainable Farming Incentive (SFI) for England, provides financial incentives under IPM4 for “No use of insecticide on arable crops and permanent crops”. Modelling of patterns of risk over time can help understand the extent to which these policies change farming practices and so change risk. Of the 179 pesticides included in this study, on the University of Hertfordshire Pesticide Property Database (Lewis et al., 2016), 102 have an ‘approved’ status under EC Regulation 1107/2009 (Supplementary file 2). Our approach could therefore also encourage reassessment of certain chemicals with highest risks identified and alternative management options such as switching to use of pesticides among substance groups shown to have lower impacts on the different organism groups.

Pesticide usage information currently represents the most tractable approach for estimating risk, as these data are often readily available for a larger number of pesticides. This approach is, however, not without its limitations, as the data may be incomplete and provide only an indication of true exposure compared to the use of comprehensive chemical exposure monitoring data. Despite these caveats, the approach implemented here could, however, be used for similar analysis in other areas where similar or better-quality usage data is available. Input data on usage was taken from the Pesticide Usage Survey for England using data available for years from 1994 to 2016. These data are provided by farmers for annual reporting of pesticide use in agriculture. Models are required to scale-up these data to national, spatially explicit estimates of application rates. Although there are some issues with this process (for details see Jarvis et al., 2020, Mancini et al., 2020), use of this type of input data offers some flexibility, and in principle the modelling approach could be used wherever national level pesticide use information exists e.g., Scotland, and in European Union member states required to collect such data under Regulation (EC) No. 1185/2009 (Mancini et al., 2020).

4.3. Conclusion

Pesticide use represents a significant threat to terrestrial (and aquatic) biodiversity. Hence, understanding risks can aid in studies of the impacts of different environmental drivers on wildlife populations. Given the concerns over the potential for pesticide effects on wildlife (Wan et al., 2025), there is a need for reliable datasets predicting mixture toxicity in space and time. Our analyses provides such a data layer.

CRediT authorship contribution statement

Melanie Gibbs: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Francesca Mancini:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Claire Carvell:** Writing – review & editing, Resources, Methodology, Funding acquisition. **Gary Powney:** Writing – review & editing, Methodology. **Colin A. Harrower:** Writing – review & editing, Data curation. **Grace Skinner:** Writing – review & editing, Data curation. **Ellie Dearlove:** Writing – review & editing, Data curation. **Alexander Robinson:** Writing – review & editing, Data curation. **Carolin L. Schultz:** Writing – review & editing, Methodology, Data curation. **Susan Jarvis:** Writing – review & editing, Methodology, Data curation. **Richard Pywell:** Writing – review & editing, Resources, Methodology, Formal analysis, Conceptualization. **Ben A. Woodcock:** Writing – review & editing, Resources, Funding acquisition. **David Spurgeon:** Writing – original draft, Resources, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Claire Carvell reports financial support was provided by UK Research and Innovation Natural Environment Research Council. Richard Pywell reports financial support was provided by UK Research and Innovation Natural Environment Research Council. Ben Woodcock reports financial support was provided by UK Research and Innovation Natural Environment Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2025.109856.

Data availability

To allow for further exploratory analysis (e.g., studies to link patterns of biodiversity change to pesticide use), we have made the underlying and interpreted datasets for which we have ownership (i.e. not the underlying PUS data which is only available under a costly commercial licence) freely available in the NERC EDS Environmental Information Data Centre: DOI: 10.5285/9406c9e9-7b41-4f15-84be-dbbf98fe372e.

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