Historical collections data reveals neonicotinoid and pyrethroid pesticide use is linked to the shrinking of native bee ranges across the United States

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Keywords: native bees, neonicotinoids, pyrethroids, climate change, occupancy models

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Abstract

Native bees have been well documented to be in decline, the reasons include climate change, pesticide use, and disease spillover. One candidate explanation in the United States widespread use of neonicotinoid and pyrethroid pesticides. Laboratory and field studies have shown that neonicotinoids affects survival, behavior, colony production, and immune responses in honey bees and native bees. However, it is unclear whether these documented negative impacts translate into large declines across native bee communities. Demonstrating this is difficult because the change of neonicotinoids has coincided with climate change, and because monitoring many species of bees at a country wide scale is challenging. By aggregating the largest data-set on bee occurrences that comprises museum records, ecological surveys, and community science data, and explicitly modelling climate change, agricultural use, and neonictoid and pyrethroid application, we ~~are able to~~ show for the first time that neonicotinoids and pyrethroids are a major cause of bee declines across the United States and contributed to range loss of up to xxx% of the species in certain agricultural regions. These results suggest that there is a trade-off between pesticide use and preserving pollinators.

Keywords: native bees, neonicotinoids, pyrethroids, climate change, occupancy models

Introduction

The decline in native pollinators has been a trend observed in the past few decades across many areas of the world [1–6]. Reports from Europe and North America highlight that multiple species of bees are declining [3, 7]. Pollinator declines has consequences for pollination services. Insect pollination (from both native and managed bees) is needed in approximately 75% of crop species worldwide, and 88% of flowering plant species [1, 2]. Further, the majority of crop pollination is produced by native pollinators worldwide, and native pollinators can enhance yields regardless of managed bee abundances [8–10]. Overall, this suggests that the decline of native pollinators can have strong effects on pollination services, even when honey bees and managed bees are used.

Pollinator declines are thought to be multi-causal, where multiple threats are affecting these species simultaneously. Climate change [6], land-use change and habitat loss [11], disease and pathogens [12, 13], dietary stress, and pesticide use [11], have been linked or hypothesized to be linked to these declines. A major factor hypothesized to affect both managed and native bee populations are the common and widespread use of pesticides. Bees are often exposed to cocktails of pesticides throughout their life [14]. Neonicotinoids and pyrethroids are two types of insecticides that are strongly implicated in bee declines. Neonicotinoids are a class of neuro-active insecticides, similar to nicotine, that target the central nervous system [15]. Neonicotinoids are either sprayed or applied as seed treatments, and are found throughout plant tissues such as pollen and nectar. Pyrethroids are a second class of insecticides, similar to pyrethrins, that target the closure of voltage-grated sodium channels in axonal membranes [16]. The usage of these compounds is widespread across the United States, and particularly the usage of neonicotinoids specifically rapidly increased since the mid-1990s when it was introduced (Fig. 1, Supp. Fig. S1, S2).

Both neonicotinoids and pyrethroids are highly toxic to bees (measured by their lethality of honey bees in laboratory assays), and there is growing laboratory and field evidence that these are harmful to managed and native bees. Low doses of neonicotinoids have been found to reduce colony growth and reproductive success on honey bees (*Apis Mellifera*) [17], reduced growth rate and production of queens for bumble bees (*Bombus terrestris*) [18, 19], reduced nesting success in solitary bees [19] in field conditions. Under realistic field conditions, negative effects on reproduction and population dynamics have been observed for bumble bees and solitary bees (*Bombus terrestris*, *Osmia bicornis*, *Osmia lignaria*) [20, 21]. Pyrethroids have also been documented to affect honey bees, particularly due to the synergistic effects of fungicides [22]. Together these results demonstrate clean docummented effects of neonitocinoids and pyrethroids at laboratory and local scales. However, the effect of pesticides on native pollinators is difficult to assess at a large taxonomic and spatial scales. A critical piece remaining is understanding whether these documented negative impacts translate into large declines across communities of hundreds of native bees.

Using the largest database of bee records, aggregated from museum records, surveys, and community science records [23], we reconstructed the effect of neonicotinoid and pyrethroid application on native bee ranges, while accounting for climate change and agricultural cover during the same period. We used multi-species occupancy models to determine the effect of combined neonicotinoid used (controlling for lethality using LD50 for honey bees (Supp. Table S1)), maximum temperature, precipitation, and agricultural cover. We reconstructed visit history for each year using other species observed within the same genus, and estimated occupancy for three year periods. This analysis included occurrence records for $1,106$ bee species across the following families: Andrenidae had 222 species, Apidae had 296 species, Colletidae 70 species, Halctidae 225 species, Megachilidae 284 species, and Melittidae 9 species.

Results

Overall we found that the increasing of neonicotinoids or pyrethroids use across regions decreased occupancy across three regions consistently across hundreds of species (Basin and Range, Northern great plane, and South East Fig. 2). Furthermore, when dividing species on whether they nest above or below-ground, we found that below-ground nesting species had significantly lower occupancy in the South East and the Northern Great plains (Fig. 3). These results point to negative effects across hundreds of species as these mean effects represent the mean for all species. In fact, the South East includes 456 species (402 below-ground and 54 above-ground nesting), the Northern Great plains includes 327 species (287 below, and 40 above-ground nesting), and the Basin and Range includes 707 species (584 below, and 123 above-ground nesting). Previous studies that estimate mean environmental effects using multi-species occupancy models, like those found here, commonly find great variation in species responses, such that mean effects cancel out [5, 6].

Because species responses can vary within a region, we estimated the percent area lost expected due to neonicotinoid use alone compared to the counterfactual of no neonicotinoid use. We estimated area lost because occupancy (interpretable as the proportion of counties occupied) does not take into account that the area differs between counties in different regions, therefore area takes into account occupying many small counties or few large ones.

Discussion

Overall we found significant and negative effects of pesticide use after controlling for agricultural cover and climate change across hundreds of bee species since the mid-1990s. While we cannot dis-entangle the effects of neonicotinoids, or pyrethroids alone (because they are highly correlated), we show that regions and counties with high pesticide application do result in lower occupancy of hundreds of native bees. We also highlight that this study was only possible due to the transparent release of pesticide use data by the USGS and the large mobilization and bee occurrences. Extension of this approach to Canada or Mexico requires the need for both transparent spatially explicit pesticide data, and the curation of new inventories, particulalry in poorly covered areas.

Methods

Data Sources

Bee records

We acquired records of North American occurrence records comprising six bee families (Andrenidae, Apidae, Colletidae, Halictidae, Megachilidae, and Melittidae) from GBIF and SCAN. These records were cleaned to ~~(i)~~ ensure taxonomic names were correct~~, (ii)~~ erroneous records were removed following [23]. Records from *Apis Mellifera* were removed and the data was restricted the contiguous US. The total number of occurrence records obtained form Chesshire *et al.* [23] was 1,923,814 occurrence records for 3,158 bee species from 1700 to 2021. From these 1,923,814 occurrence records, many were multiple observations of the same species in the same date, in the same location and occupancy analyses only require the presence, not the abundance of a species in a locale. The number of unique species x date x location was 634,597. Because our emphasis was on post 1990s pesticide application, we filtered any observation before 1994 and after 2016. This resulted in 207,954 observations for 2,183 bee species. Further, we removed any species that had less than 10 unique observations (unique dates and locations). This filter further reduced the number of species to 1,183 and 204,346 observations. Finally, we also removed species that were present in less than 3 years or 3 counties, resulting in 1,107 bee species with a total of 199,462 unique records. We also removed *Agapostemon angelicus* because females cannot be differentiated from *A. texanus*.

These 1,106 bee species were distributed such that Andrenidae had 222 species, Apidae had 296 species, Colletidae 70 species, Halctidae 225 species, Megachilidae 284 species, and Melittidae 9 species.

Species Ranges

For each species we constructed plausible species ranges by drawing a convex hull around all observations and finding the counties that fell within the convex hull. This resulted in the plausible set of sites where the occupancy of each species could be modelled.

While this may include counties where a species cannot be found, this greatly reduces the bias of including all possible sites for every species [5, 24]. This is particularly problematic for models that do not have spatial predictors in occupancy (such as model 1).

Site level environmental predictors

Agriculture:

Land cover data was obtained from the National Land Cover Database (NLCD), which provides national wide data on land cover at a $30m$ resolution for every 2-3 years from 2001 to 2016. The NLDC provides data for 16 land use categories. Of relevance to us is the category of ”Cultivated crops” (hereafter agriculture), which contains areas used for the production of annual crops (such as corn, soybeans, vegetables, etc.), perennial woody crops (such as orchards and vineyards), and land actively tilled [25, 26]. For each county, we calculate the proportion of the county covered in agriculture. While this database does not cover every year in our study, we interpolate the data within years. We note that agricultural percent cover varied little between 1995 and 2015.

Pesticide use:

Pesticide use data was obtained from USGS Pesticide National Synthesis Project, which provides national data on pesticide use for each county for every year from 1992 to 2021. The pesticide use data is provided as Kg of active ingredient used in each county for 448 types of active ingredients [27, 28]. From these active ingredients, we selected the data available for neonicotinoids and pyrethroids. Specifically the active ingredients we included in our analyses were the following neonicotinoids: Acetamiprid, Clothianidin, Dinotefuran, Imidacloprid, Thiamethoxam, and Thiacloprid; and the following pyrethroids: Cyfluthrin, Cypermethrin, Permethrin, Tefluthrin, Tralomethrin, Fenvalerate, Deltamethrin, Cyhalothrin-Gamma, Resmethrin, and Fluvalinate-Tau. Because pesticides vary in their lethality, in order to combine all of these pesticides we weighed each one by their LD50 on honeybees. The data for the LD50 was acquired from the EPA ECOTOX Database [29]. We downloaded all records for all pesticides for *Apis Mellifera*, which is the species most commonly tested, that have an endppoint of LD50. For all results, the mean response was standardized to be in units of ng/bee, and any study that could not be standardized to this unit was removed. For each compound and only dermal exposure, we calculated the mean LD50 (Supp. Table S1). For each county, year, and compound, we divided the Kg of active ingredient applied by the mean LD50 for honey bees. For the counties, year and compound combinations that did not have data, we set a zero use. To calculate the total pesticide use we summed the Kg of pesticides used per year per county across compounds (controlling for lethality). To ensure the data was more normally distributed we logged these values and then scaled it by subtracting by the mean and dividing by the standard deviation to ensure predictors were comparable. Since the use of pyrethroids and neonicotinoids is highly correlated (correlation per year varies between 0.30 when neonicotinoids were rarely applied in 1996 to 0.94 in 2008), we tested either neonicotinoids, or pyrethroids, or the addition of both in the model, but we could not tested as separate covariates.

Temperature and precipitation:

We obtained climatic variables (both temperature and precipitation) from the CHELSA high resolution climate data [30, 31]. Through the CHELSA time series we were able to obtain monthly precipitation and maximum temperature at 30 arc sec resolution. To calculate the yearly maximum temperature for every county, we extracted the maximum temperatures in July and August and averaged the values for within county, and of these we selected the maximum value per year. To calculate total precipitation, we extracted the precipitation for every month of the year, and averaged it within each county and across every year. Both temperatures and precipitations were scaled across all counties and years.

Data Processing

Because the pesticide use data is reported at the level of county (see below), we calculate every other environmental predictor at the level of county and report each county as a ”site”. Further, we subdivide all counties into six agricultural regions based on USDA Farm Resource regions. The USDA Farm Resource Regions are: Basin and Range, Central, Northern Great Plains, Fruitful Rim, Heartland, Prairie Gateway, Northern Crescent, Mississippi Portal, Eastern Uplands, and Sourhtern Seaboard. Because some of these regions were too small to model, we combined some of these regions into: Central (combines Heartland, and Prairie Gateway regions) and South East (combines Southern Seaboard, Eastern Uplands, and Mississippi Portal) (Supp Fig. S3).

We estimate occupancy every three year period, where each year was considered as a visit. In order to infer the visitation process, we infer species absences only when other species within the same genus were observed in a given year, in a given county that falls within the range of each species. This assumes that search effort, collection, identification, and digitization of a species is comparable to species within the same genus. While this may not be the case individually across all 1000s species, it allows for genera to be under-identified or under-digitized compared to other genera.

Occupancy models

We developed a multi-species occupancy model for bee occurrence records in the contigous United States that estimates the effect of neonicotinoids on species occupancy while accounting for changes in maximum temperature, annual precipitation, and the percent of agricultural cover during the same time period. We build on work done by [5**?** , 6], that tested the validity of the methods of applying occupancy models to large-scale presence-only data sets.

Specifically we use the following model:

$$
\begin{aligned}
\mathrm{logit}(\psi[i,j,k]) = &\psi_0 + \\
&\psi_{\text{species}}[i] + \\
&\psi_{\text{area}} \times \text{area}[j] + \\
&\psi_{\text{temp}}[i] \times \text{temp}[j,k] + \\
&\psi_{\text{temp2}}[i] \times \text{temp}[j,k]^2 + \\
&\psi_{\text{precip}}[i] \times \text{precip}[j,k] + \\
&\psi_{\text{pesticide}}[i] \times \text{pesticide}[j,k] \\
&\psi_{\text{agri}}[i] \times \text{agri}[j,k]
\end{aligned}
\tag{1}
$$

Here, ψ_0 denotes mean occupancy, $\psi_{\text{species}}[i]$ denotes a species specific random intercept, ψ_{area} denotes a fixed effect of area on occupancy, to account for the fact that some counties are larger than others. $\psi_{\text{temp}}[i]$, $\psi_{\text{precip}}[i]$, $\psi_{\text{pesticide}}[i]$, and $\psi_{\text{agri}}[i]$ denote species-specific linear effects of temperature, precipitation, pesticide use, and percent of agricultural cover, respectively and ψ_{temp2}, denotes a species-specific quadratic effect of temperature.

We assume that species-specific slopes and intercepts are normally distributed about some mean. Specifically,

$$
\begin{aligned}
\psi_{\text{species}}[i] &\sim \mathcal{N}(0, \sigma_{\psi\text{species}}) \\
\psi_{\text{temp}}[i] &\sim \mathcal{N}(\mu_{\psi\text{temp}}, \sigma_{\psi\text{temp}}) \\
\psi_{\text{temp2}}[i] &\sim \mathcal{N}(\mu_{\psi\text{temp2}}, \sigma_{\psi\text{temp2}}) \\
\psi_{\text{precip}}[i] &\sim \mathcal{N}(\mu_{\psi\text{precip}}, \sigma_{\psi\text{precip}}) \\
\psi_{\text{pesticide}}[i] &\sim \mathcal{N}(\mu_{\psi\text{pesticide}}, \sigma_{\psi\text{pesticide}}) \\
\psi_{\text{agri}}[i] &\sim \mathcal{N}(\mu_{\psi\text{agri}}, \sigma_{\psi\text{agri}}),
\end{aligned}
\tag{2}
$$

where $\mu_{\psi\text{temp}}$, $\mu_{\psi\text{temp2}}$, $\mu_{\psi\text{precip}}$, $\mu_{\psi\text{pesticide}}$, and $\mu_{\psi\text{agri}}$ denote the mean effect of each corresponding predictor, across species, and σ terms denote the variances about these means. We note that because we expect species temperature optima to be a negative quadratic, we truncate $\mu_{\psi\text{temp2}}$ to be negative.

In both of the above models, we model detection probability as

$$
\begin{aligned}
\text{logit}(p[i,j,k]) = & p_0 + \\
& p_{\text{era}} \times k + \\
& p_{\text{species}}[i] + \\
& p_{\text{site.era}}[j,k]
\end{aligned}
\tag{3}
$$

where p_0 denotes the mean detection probability, p_{era} denotes a slope of detection through time, p_{species} denotes a species specific random intercept of detection, and $p_{\text{site}}[j,k]$

denotes a site-specific random effect that is era-specific. This latter term allows detection to vary relatively independently across sites and between eras. Specifically, we assume

$$
\begin{aligned}
p_{\text{species}}[i] &\sim \mathcal{N}(0, \sigma_{p\text{species}}) \\
p_{\text{site.era}}[j,k] &\sim \mathcal{N}(\mu_{p\text{site.era}}, \sigma_{p\text{site.era}}).
\end{aligned}
\tag{4}
$$

We fit six models, one where the pesticides was neonicotinoids alone, a second where the pesticide was pyrethroids alone, and a third where pesticide was the addition of neonicotinoids and pyrethroids. The second set of models included the same set of pesticides but we evaluated the effect on below and above ground nesting bees separately, where each group had a separate mean $\mu_{\psi\text{pesticide}}$, but they share the same variance $\sigma_{\psi\text{pesticide}}$.

We fit models in JAGS [32] and assess model convergence both by visually inspecting chains and checking The Gelman-Rubin statistic (we ensured that Rhat was < 1.1 for all parameters). We use flat~~, uninformative~~ priors for all parameters and ran models for $100,000$ iterations, discarding the first 1000 iterations and thinning by 100 across 3 chains. For all analysis we used R V4.0.4 [33]. For spatial manipulations we used the packages `sp` [34]; for data manipulation and visualization we used `tidyverse` [35] and `data.table` [36]; for running models, we used `rjags` [37], `R2jags` [38], and `runjags` [39].

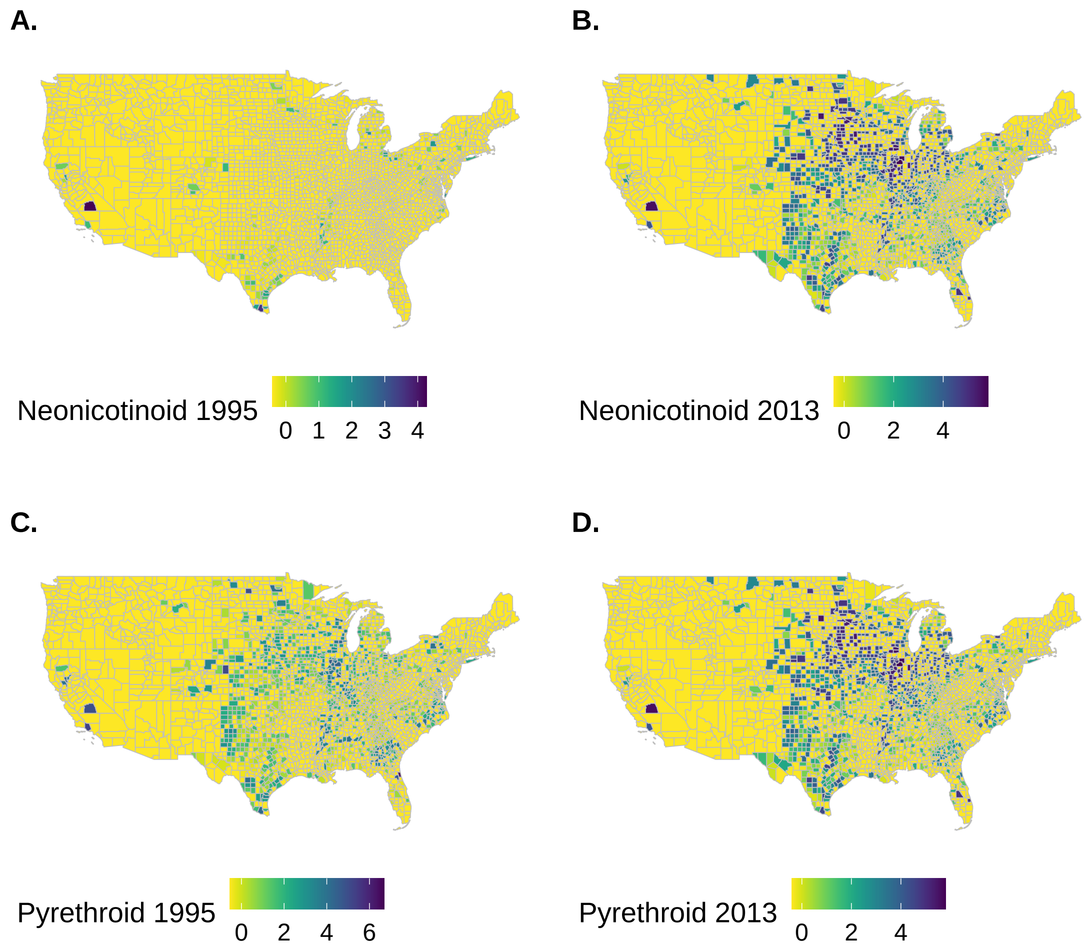

Figure 1: Pesticide use across the United States is prevalent. While neonicotinoid use increased rapidly since 1995, pyrethroid use was already established in many agricultural regions of the United States. However, the use pattern between Pyrethroids and Neonicotinoids is very similar at the county level.

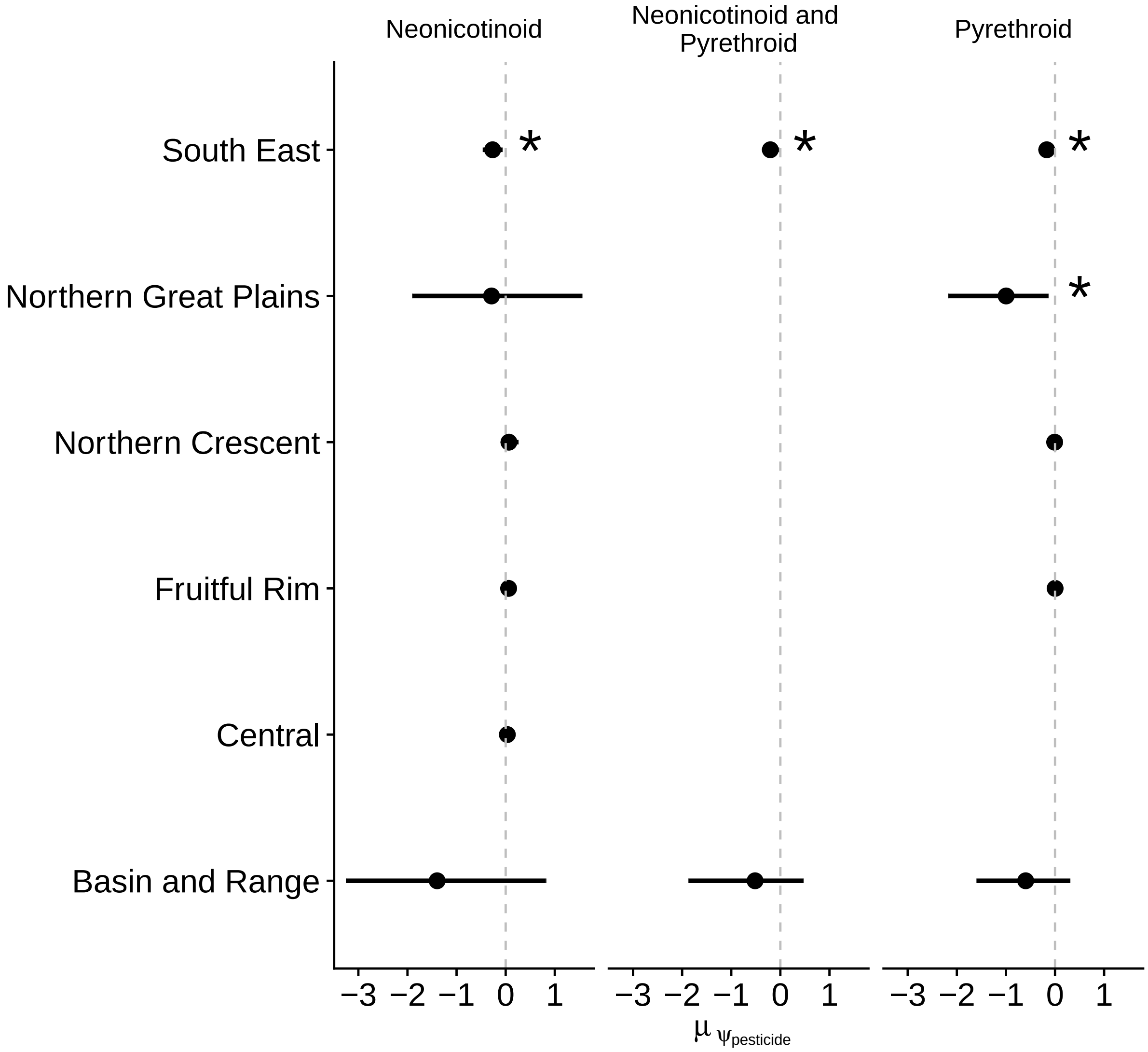

Figure 2: The mean slope effect of pesticide use across all species $\mu_{\psi\text{pesticide}}$. We found negative effects of pesticides in the Basin and Range, Northern Great Plains, and South East regions. Stars denote significant effects.

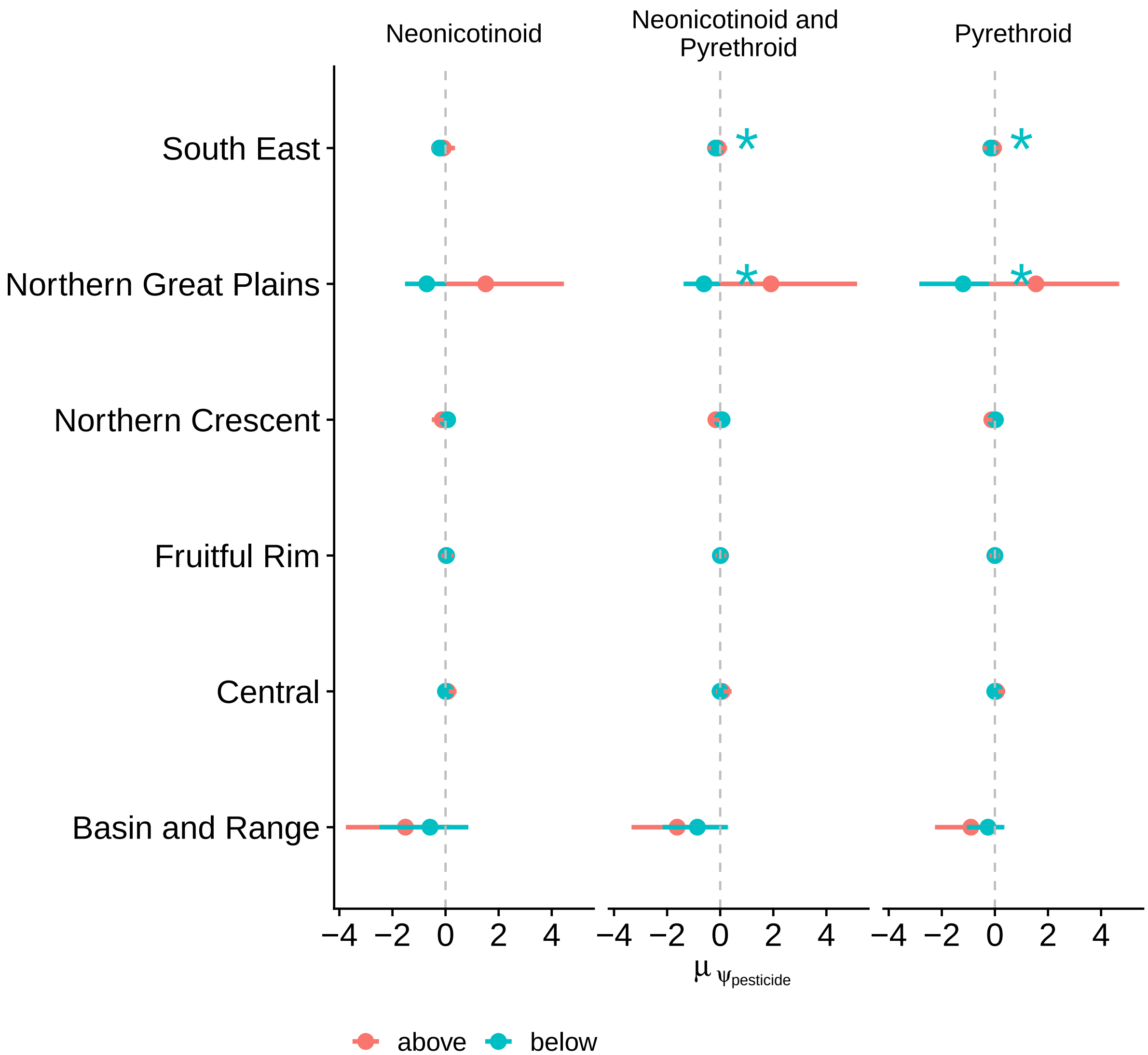

Figure 3: The mean slope effect of pesticide use across all species $\mu_{\psi\text{pesticide}}$, divided on whether species are above-ground or below-ground nesting. We found negative effects of pesticides in the Basin and Range, Northern Great Plains, and South East regions. Stars denote significant effects.

Figure 4: Percent of area lost due to neonicotinoid use for every species compared to no neonicotinoid use.

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Supplementary Information

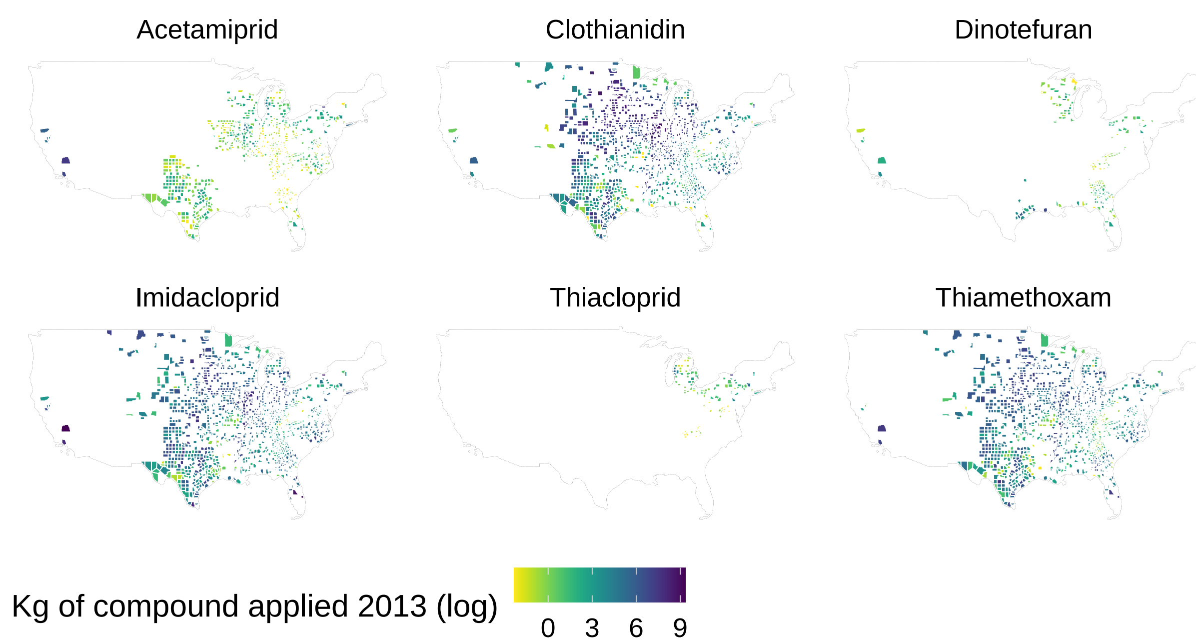

Figure S1: Individiual neonicotinoids application (log of Kg) at the county level.

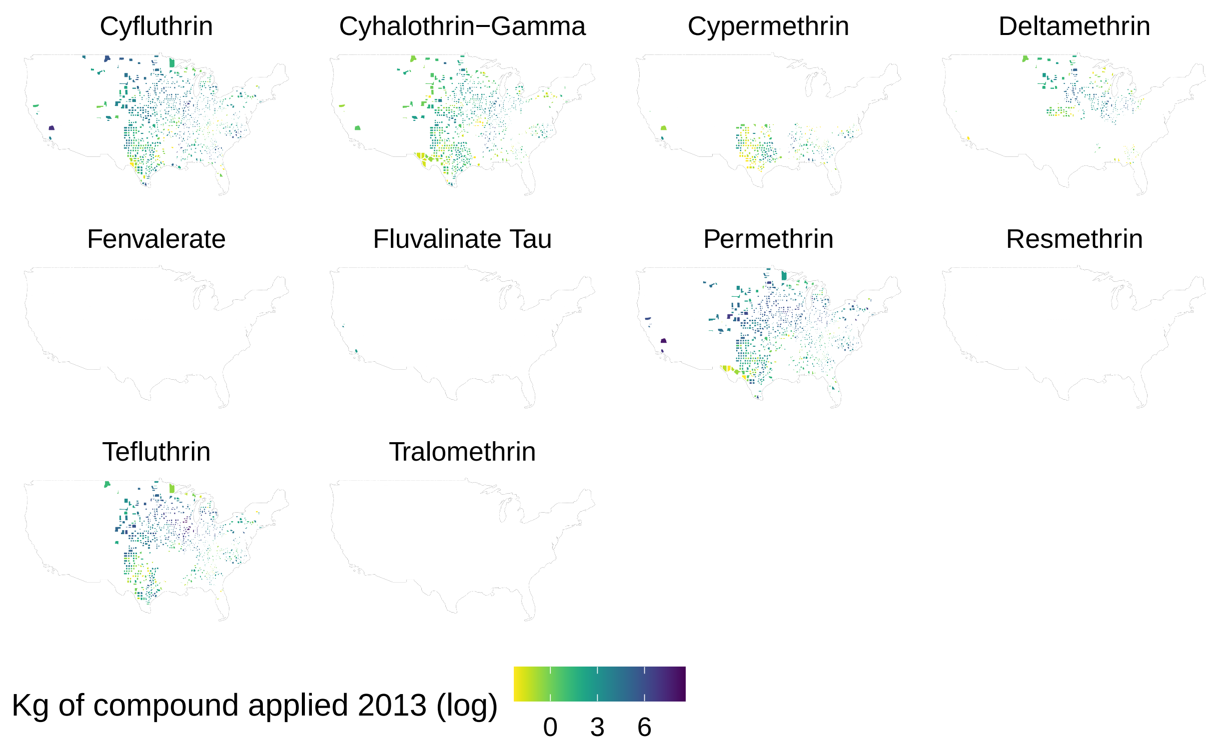

Figure S2: Individiual pyrethroid application (log of Kg) at the county level.

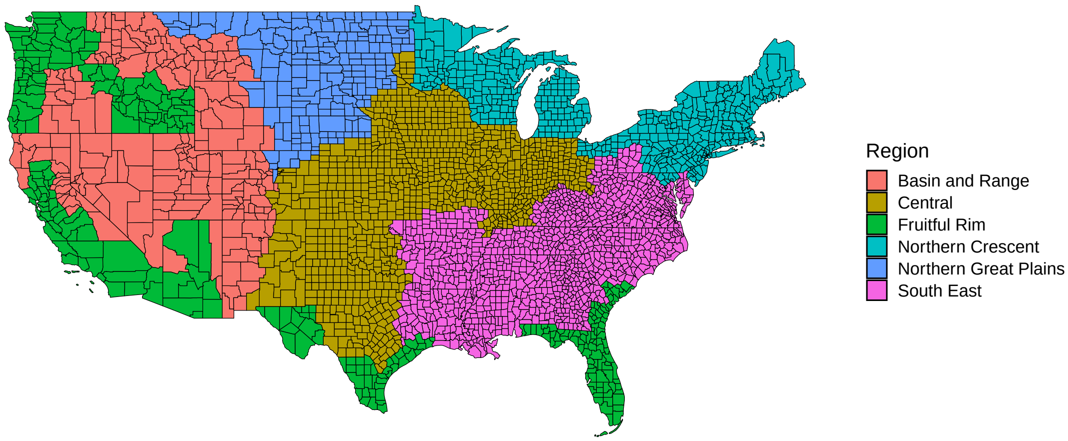

Figure S3: The contiguous United States was divided into four regions: West, Center, North East and South East. These regions were divided based on EPA Ecoregions.

Compound	Mean LD50 (ng/bee)
Neonicotiniods	
Imidacloprid	59.62
Thiamethoxam	93.21
Acetamiprid	8382.50
Clothianidin	35.47
Thiacloprid	56330.00
Dinotefuran	34.72
Pyrethroids	
Cyfluthrin	36.35
Cypermethrin	158.70
Permethrin	53.00
Tefluthrin	170.00
Tralomethrin	90.50
Fenvalerate	6.30
Deltamethrin	16158.79
Cyhalothrin-Gamma	18.05
Resmethrin	49.75
Fluvalinate Tau	12433.33

Table S1: Mean LD50 (dose where half of the individuals die) for all pesticides evaluated. The lower the LD50 the higher the toxicity of the compounds.