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The effect of agricultural land retirement on pesticide use

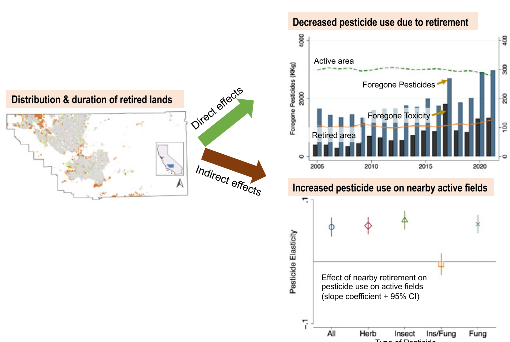
Ashley E. Larsen [a,*], Amy Quandt [b], Iris Foxfoot [a], Nicol Parker [a], Daniel Sousa [b]

[a] Bren School of Environmental Science & Management, UC Santa Barbara, United States of America
[b] Department of Geography, San Diego State University, United States of America

HIGHLIGHTS

- Land retirement was evaluated for its influence on pesticide use.
- We find ~100 kha/y are idle, with 1.3-3 M kg of pesticide use foregone.
- Retired lands increase pesticide use on nearby active fields.
- Trend in pesticide use is reversed at high levels of revegetation cover.

GRAPHICAL ABSTRACT



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ABSTRACT

Agricultural land retirement generates risks and opportunities for ecological communities and ecosystem services. Of particular interest is the influence of retired cropland on agricultural pests and pesticides, as these uncultivated lands may directly shift the distribution of pesticide use and may serve as a source of pests and/or natural enemies for remaining active croplands. Few studies have investigated how agricultural pesticide use is impacted by land retirement. Here we couple field-level crop and pesticide data from over 200,000 field-year observations and 15 years of production in Kern County, CA, USA to investigate: 1) how much pesticide use and applied toxicity are avoided annually due to the direct effects of retirement, 2) whether surrounding retirement drives pesticide use on active cropland and what types of pesticides are most influenced, and 3) whether the effect of surrounding retirement on pesticide use is dependent on the age or revegetation cover on retired parcels. Our results suggest about 100 kha are idle in any given year, which equates to about 1.3-3 M kg of pesticide active ingredients foregone. We also find retired lands lead to a small increase in total pesticide use on nearby active lands even after controlling for a combination of crop-, farmer-, region- and year-specific heterogeneity. More specifically, the results suggest a 10 % increase in retired lands nearby results in about a 0.6 % increase in pesticides, with the effect sizes increasing as a function of the duration of continuous fallowing, but decreasing or even reversing sign at high levels of revegetation cover. Our results suggest increasingly prevalent agricultural land retirement can shift the distribution of pesticides based on what crops are retired and what active crops remain nearby.

1. Introduction

Globally, croplands, people who depend on them, and ecosystems and landscapes where they are located, are under increasing stress from environmental and economic pressures (Hanak et al., 2017; Rosenzweig et al., 2014). As a result, retired agricultural lands - areas that were once used as cropland, but are no longer in production (Baxter and Calvert, 2017) – are increasingly common in many agricultural landscapes. How agricultural land retirement influences surrounding farmers and the environment is thus an area of increasing interest (Brewer et al., 2022; Crawford et al., 2022; Lortie et al., 2018).

* Corresponding author.
E-mail address: alarsen@ucsb.edu (A.E. Larsen).

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Agricultural retirement is estimated to cover 430–580 Mha globally (Campbell et al., 2008). While agriculture in proximity to urban areas is often converted to development (Brain et al., 2023), retired agriculture in rural areas may return to semi-natural land cover or oscillate in and out of agricultural production with varying economic and/or environmental conditions. Though once predominantly found in low-value, rain-fed agriculture, retired lands are likely to become more common in high-value croplands. Increasingly long and severe droughts are reducing surface water supplies and driving increased reliance on limited groundwater resources (Langridge and Van Schmidt, 2020), which, in turn, is leading to policy initiatives seeking to reduce environmental harms associated with overdrafts (Hanak et al., 2019; Roberts et al., 2021; Thomas, 2019).

Land retirement in intensive, high-value cropping systems has myriad risks and opportunities for ecological and environmental health (Bourque et al., 2019; Bryant et al., 2020; Lortie et al., 2018; Quandt et al., n.d.). For example, many high-value crops use a considerable amount of agricultural pesticides (Rosenheim et al., 2020). While an important tool for enabling high and stable crop yields (Waterfield and Zilberman, 2012), pesticides are also associated with numerous potential environmental harms, ranging from species declines to adverse human health outcomes (Gill et al., 2012; Köhler and Triebskorn, 2013; Larsen et al., 2017; Li et al., 2020). Foregone application on otherwise high pesticide-use nut, fruit and vegetable crops may therefore have important implications for the spatial and temporal distribution of environmental pollution.

Retired agricultural land may also indirectly impact agricultural pests and pesticide use through its effects on surrounding, active agriculture. Retired agricultural lands, whether temporary or permanent, could provide non-crop habitat and shelter from disturbance that enables overwintering and reinvasion of both beneficial and pest species (de Paz et al., 2022; Martin et al., 2019). Spillovers of beneficial organisms such as birds, spiders, and other natural enemies of crop pests from retired fields could result in more viable production and reduced pesticide application on fields surrounding retired land (Estrada-Carmona et al., 2022; Landis, 2017; Thomine et al., 2022; Tscharntke et al., 2016). However, spillover of insect pests and seed rains of weeds could instead increase pesticide use on remaining parcels (Tscharntke et al., 2016), with potential knock-on consequences for natural systems.

Here we leverage a unique time series of crop and pesticide use data that covers over 15y of production to understand the direct and indirect effects of land retirement on pesticides in high-value croplands. We address the following questions: 1) how much formerly active cropland is idle in any given year and how much pesticide use is foregone on these uncultivated lands? 2) does retired land influence pesticide use on nearby cultivated fields, and if so, does the effect differ for different types of pesticides? 3) does the duration of, or revegetation cover on, retired lands matter with respect to pesticide use by nearby growers? We focus on Kern County, CA, which is located in the southern San Joaquin Valley and is one of the US's highest crop-producing counties by value. Kern produces around $8B of gross agricultural production (Kern County Department of Agriculture and Measurement Standards, n.d.) and uses 13 Mkg of agricultural pesticide use annually (*Summary of Pesticide Use Report Data 2018*, 2019). Major crops in Kern County include nut (almond and pistachios) and fruit trees, vineyards, and vegetable crops (tomatoes, carrots, etc.). Kern County is also acutely dependent on water availability and likely to experience substantial land use change as a result of climate-driven water scarcity and associated policy (Bryant et al., 2020; Hanak et al., 2019).

2. Methods

2.1. Identifying and characterizing retired lands

Vector files representing crop field boundaries from 1997 to 2021 were downloaded from the Kern County Agricultural Commissioner's Office (http://www.kernag.com/gis/gis-data.asp). These geospatial data include information such as farmer (“permit”), area in production, and crop type (“commodity”, “commodity code”), from which we derived crop family. Using the set of permitted fields between 1997 and 2021, we identified fields that changed from production to lack of production or vice versa (see SI methods). Retirement was defined as either a parcel permitted as “uncultivated agriculture” with no other crop produced on that physical location during the year, or as a parcel that did not receive a permit in the focal year, but was cultivated at some point in the time series. Throughout “focal year” is the year of analysis or t in Eq. (2).

Since “fields” are not fixed in space, but rather are defined as a farmer-site-crop-year combination and can aggregate or split based on farmer planting decisions, tracking land retirement and age of retirement is challenging. To do so, we further refined the permitted field polygons to identify unique field fragments that were not divided during the time series (See SI methods). We dropped field fragments less than ~0.4 ha (1 ac) to reduce minor changes in field dimensions that likely reflect changes in data recording rather than different planting decisions, leaving about 67,000 unique field fragments and eliminating 3237 permitted fields. For fragments that were retired, we calculated area, duration of continuous retirement relative to the focal year, and recorded the last crop produced. We calculated (1) the amount of foregone pesticide use based on last crop produced, fragment area, and focal year, (2) vegetation statistics on each retired fragment in each year, and (3) the amount of retired land of different age and revegetation levels to understand how nearby retirement impacts pesticide use on active fields (see below).

We use the longest time series available (1997–2021) to make as comprehensive an estimate of surrounding retirement and retirement age as possible, but use 2005–2021 for our analysis of foregone pesticide use and the effects of nearby retirement since <100 % of fields and pesticide use were recorded in early years. Undoubtedly fields were also retired permanently prior to 1997, which we would not observe in our time series. Thus, our estimate of foregone pesticide use due to direct retirement is an underestimate.

2.2. Pesticide use data

California mandates the collection of pesticide use data on production agriculture, which includes information such as date of application, product number, and amount of product used, among other data. The field-level, daily pesticide use data were sourced from the California Department of Pesticide Regulation (CDPR) Pesticide Use Reports when available (pre-2021) and the Kern County Agricultural Commissioner's Office for 2021. Both data sources are based on the same data collection and produce nearly identical results (Fig. S1). Pesticide data were merged with the pesticide product table, provided in the annual download from the CDPR, in the corresponding year. For 2021, we merge the County Agricultural Commissioner's data with the 2020 product table. Fields in the vector data that had no corresponding entry in the pesticide use data were assumed to receive zero pesticides in that year.

2.3. Pesticide applied toxicity

To quantify applied toxicity, we prioritized ecotoxicological observations available through the Pesticide Properties Database (PPDB). The database derives ecotoxicological endpoints from European and United States regulatory agencies where able, and where peer-reviewed literature, ecotoxicity prediction tools, and other resources are consulted, verified datasets receive the highest priority. Toxicity information in the PPDB was not available for all active ingredients and species investigated; however, the data reflect available information for the applied pesticides through the United States and European regulatory agencies. For the present investigation, we consider acute endpoints where half of the sample population will experience mortality (LD50/LC50) for honeybees (contact), birds (oral), mammals (oral), and earthworms (soil concentration).

Applied toxicity refers to the mass of pesticide applied to an area with the potential to do harm. Leveraging the high resolution pesticide application rate data from the pesticide use reports and following the methods of

Parker et al. (Parker et al., n.d.), applied toxicity of the j^th county or watershed is calculable for the i^th pesticide and k^th taxon of interest as:

$$TI_{i,j} = \Sigma \frac{M_{i,k}}{T_{i,k,}} \tag{1}$$

where TI is the Toxicity Index, M is the mass of applied pesticide (by active ingredient), and T is the adverse health-effect concentration of concern for the species or taxonomic groups of interest. For the present investigation, we consider applied toxicity to terrestrial organisms summarized by Kern County. Though applied toxicity does not consider exposure, which is required for risk assessment, it enhances our understanding of where hazards exist (US EPA Office of Pollution Prevention and Toxics, 2022) without the high degree of uncertainty of fate and transport models over large extents (Dubus et al., 2003; Srivastava et al., 2007; Zheng and Keller, 2006).

2.4. Foregone pesticide use and toxicity

From daily, field-level pesticide use data, we calculated mean annual pesticide use (kg ha^{-1} of active ingredients) by crop-year. We calculated foregone pesticide use based on the crop-year specific pesticide use rates using kg ha^{-1} average for the crop last produced on the retired fragment. In other words, if a field fragment produced pistachios in 2010, and was then retired, we calculated crop-specific foregone pesticide use in 2015 as the pistachio-specific 2015 average kg ha^{-1} multiplied by the area of the retired field fragment. Similarly, we calculated applied toxicity based on the crop-year specific pesticide use—calculating the average, applied toxicity for a given crop-year, multiplied by ha of each type of now-retired crop and summed over all now-retired crops to create an annual total. For fields with intra-annual rotations in the year prior to retirement, we used the last crop rotated to define the crop last produced on the retired fragment. Kern County was intensively cultivated for decades prior to the beginning of our dataset. Unfortunately, we cannot capture the land use history on each plot. We evaluate a version of the foregone pesticide use analysis multiplying pesticide use by 1.5× on fields last growing annual crops to evaluate the potential influence of within year crop rotations on our estimate of foregone pesticide use (Fig. S2).

2.5. Revegetation

Data coverage and cloud screening: Revegetation of retired lands was evaluated using multispectral satellite imagery. All available Landsat 5, 7, and 8 images from WRS-2 Path 42, Rows 35 and 36 were downloaded as Collection 2, Level 2 surface reflectance from the USGS EarthExplorer web portal (https://earthexplorer.usgs.gov/). Due to the favorable geometry of the WRS-2 grid in this area, the entire Central Valley portion of the study area is captured by data from a single orbital path. Images with any perceptible cloud cover over the study area were removed, resulting in retention of data from 156 of the 526 acquisition dates. Image tiles from the two rows were mosaicked into a single tile and spatially subset to match the study area. A small number of agricultural areas in the eastern portion of Kern County (Sierra foothills and Mojave Desert) were present in the County vector files but not imaged by Path 42 data and were thus excluded from this analysis.

Estimation of Vegetative Cover: Photosynthetic vegetative cover on retired lands was then quantified using spectral mixture analysis (SMA) of Landsat imagery. Briefly, SMA assumes linear optical mixing within each pixel's field of view and uses a simple linear model to estimate the areal abundance of constituent spectrally distinct endmember (EM) materials (Adams et al., 1986; Gillespie et al., 1990; Smith et al., 1990). Multispectral reflectance of Earth's ice-free land surface can be well-modeled by three such EM materials: soil and non-photosynthetic vegetation Substrates, illuminated photosynthetic Vegetation, and Dark targets like shadow and water (S, V, and D) (Small, 2004). Unlike some spectral indices, SMA V fraction are linearly scalable across over 4 orders of magnitude (Sousa and Small, 2017). We point the interested reader to (Sousa and Small, 2023) for further information on the relationship between SMA V fraction and several common spectral indices. Here we use intercalibrated endmembers derived from a diverse compilation of global targets to empirically account for changes in spectral responses between Landsat 5/7 TM/ETM+ and Landsat 8 OLI (Sousa and Small, 2017), also comparing to locally-derived image EMs. We compute the first three statistical moments (mean, standard deviation, skewness) of the V fraction time series for each year, then compute the spatial mean of the pixels within each uncultivated parcel. A 60 m inner buffer was first applied to each field polygon to minimize the impact of edge effects and geolocation uncertainty. The result is a quantitative, physically-based annualized estimate of the aggregate photosynthetic vegetative cover on each retired parcel.

2.6. Statistical approach

Nearby retirement: To understand how retired lands impact nearby active lands, we calculated the area of retired lands within a 2.5 km buffer of each active field. A 2-3 km buffer is commonly used as the landscape of influence for insect pests and natural enemies (Karp et al., 2018; Landis, 2017). While any duration of retirement may provide habitat for some species, the value of the refugia likely increase with the duration of retirement and the level of revegetation. As such, we calculated the area of retired lands of different retirement duration (1, 2–4, 5–8, 8+ years) and of different revegetation quartiles within the buffer. Since we were interested in the effect of surrounding retirement on actively cultivated fields, we dropped focal fields labeled as "uncultivated agriculture" (N = 14,326 of >227,000 total observations from 2005 to 2021), as well as others for whom we could not decipher a crop family (e.g. nursery plants; N = 1267).

Statistical methods: In the ideal scenario, we could randomly assign the area of retired lands nearby active fields and measure the impact on pesticide use. In the absence of the experimental ideal, we use a within-estimator approach ("fixed effects" in causal inference terminology; Wooldridge, 2002; Larsen et al., 2019). If "fields" did not change year-to-year, such an approach could compare a field in one year to itself in another year with different amounts of surrounding land retirement. Since fields change over time, and we only observe pesticide use at the whole field level (rather than field fragments), we instead include a series of dummy variables for year, region (93 km^2 Public Land Survey Township), farmer, and crop type. Dummy variables function to de-mean pesticide use, retirement, and other covariates by, for example, region; thus, largely time-invariant heterogeneity such as soil quality, which may be correlated with both the amount of retirement and the amount of pesticide use, is removed. Dummy variables for farmer, crop type, and year may capture farmer-specific risk preferences, crop-specific pest susceptibility or value, and year shocks such as weather that affect all fields in the county, respectively. A version of our model can be written as,

$$IHS(y_{irt}) = \gamma_r + \delta_t + \alpha IHS(RetiredHa_{irt}) + IHS(\mathbf{X_{irt}})^{'}\boldsymbol{\beta} + \varepsilon_{irt} \tag{2}$$

where our covariate of interest is the amount of retired land ("*RetiredHa"*) near field *i*, in region, *r*, and year, *t*, which, like other covariates and the outcome variable, is inverse hyperbolic sine (IHS) transformed to accommodate zero values and non-linear relationships. y_{irt} denotes pesticide use (kg ha^{-1}). The vector $\boldsymbol{X}$ denotes covariates for size of the focal field and the amount of permitted cropland, defined as total permitted area minus area of annual uncultivated agriculture, in the buffer that overlaps with the growing season of the focal field. γ_r and δ_t denote region and year dummy variables; other specifications included farmers and crop type, as well. IHS transformed variables can be interpreted as % change-% change, similar to log-log specifications (Bellemare and Wichman, 2020). Pesticide use variables were pre-multiplied by 100 to reduce distortions for small values (Bellemare and Wichman, 2020), though doing so does not influence the interpretation. Thus, α can be interpreted as the percent change in pesticide use for every 1 % change in nearby retired lands, and the vector β can similarly be interpreted, but for changes in focal field size and surrounding cropland extent. Lastly, ε_{irt} represents the stochastic error term, which is clustered at the farmer (permit number) level to account for autocorrelation of fields within the same farm.

Eq. (2) results in one slope coefficient estimating the effect of a change in retired lands nearby on pesticide use. To evaluate the effect of duration of retirement (or revegetation state), we replace the single covariate for retired land with a series of variables representing the area in different age classes (or revegetation quartiles). This allows us to flexibly model the relationship between retirement duration (revegetation level) and pesticide use. Additionally, since retired lands may affect different pest taxa differently, we rerun our analysis predicting how different metrics of retirement influence pesticides functioning only as insecticides, only as herbicides, only as fungicides, and those that have dual action as fungicides/insecticides, which captures widely used sulfur pesticides. We similarly evaluate pesticide-applied toxicity to different taxa to understand if there are differences in the types and toxicity of foregone pesticide use as a function of retired lands.

All statistical analyses were completed in Stata 16 MP, using the reghdfe package (Correia, 2019). Creating the time series of field fragments was completed in R and mapshaper, while calculating proximity between field fragments was completed in arcpy. For the remote sensing analysis, mosaicking and spatial subsetting were completed using GDAL (Rouault et al., 2022). SMA was implemented using Python 3.8.8 and the publicly available scripts described by (Sousa et al., 2022). Visual cloud screening and statistical computation were performed in ENVI 5.6.1.

3. Results

Land retired for one or more years during our time series existed throughout the county, but was concentrated in the northwest (Fig. 1), though some occurred near urban areas (Fig. S3). The most common crops to be retired, based on the last cultivated crop type, were cotton, wheat, and carrots.

Overall, the area of land permitted at least once in our times series and retired was fairly similar year to year, at around 100 kha, which corresponded to foregone pesticide use of 1.3-3 M kg, based on crop-year-specific pesticide use rates (Fig. 2). The relative stability of the amount of retired lands is reflected in the Kern County Annual Crop Reports, which reports less than a 10 % change in the total harvested area between 2005 and 2021 (http://www.kernag.com/caap/crop-reports/crop-reports.asp).

Foregone pesticide-use rates and applied toxicity generally trended together, with both tending to increase over time (Fig. 2). Pesticide-applied toxicity to bees is responsible for the overwhelming majority of foregone applied toxicity over time (Fig. S4).

For active fields during our time series, there were ~ 150 ha, on average, within the nearby buffer of radius 2.5 km (~1950 ha total) occupied by retired cropland. In general, most of the retired cropland near active fields was fairly old, with ~52 ha being retired for <5 years, and the rest retired for over 5y (Table 1). The average active field used about ~26 kg ha^{-1} of pesticide active ingredients.

We began analyzing the effect of nearby retirement on pesticide use by specifying a series of increasingly stringent models that included a combination of region (PLS Township), year, crop, and farmer dummy variables. Overall, we find increasing retired lands nearby leads to an increase in pesticide use rates. Including crop dummies, with or without farmer, resulted in a coefficient estimate roughly a third of the size of the model specified with just region and year (Fig. S5), indicating crop was correlated with IHS transformed measures of retired land area nearby. We continue with the most stringent model that includes region, year, crop and farmer dummy variables.

For total pesticide use, we report a 10 % increase in the amount of retired lands nearby leads to about a 0.56 % increase in total pesticide use rates (kg ha^{-1}). Breaking it down by the target taxa, we find slightly larger effects for herbicides, insecticides and fungicides (0.58–0.61 %; Fig. 3).

Retired lands could differentially affect surrounding fields based on the duration of retirement or the level of revegetation, as both may be expected to affect habitat quality and occupancy for beneficial and pest species. Across all types of pesticides, except dual action insect/fungicides, we find the coefficient on retirement increases with duration of continuous retirement. For most types of pesticides besides insecticides, we only observe a significant ($p < 0.05$) coefficient after 8y of continuous retirement (Fig. 4, Table S2), suggesting retired lands become burdensome for insect pest control early, and are increasingly burdensome for all pest control, besides dual action insecticide/fungicide AI, with the duration of retirement. In contrast to duration of retirement, area of nearby retired land in the lowest quartile of vegetation cover led to an increase in pesticide use, while land in the highest quartile had a null or significant, negative effect, depending on processing approach (Figs. S6, S7).

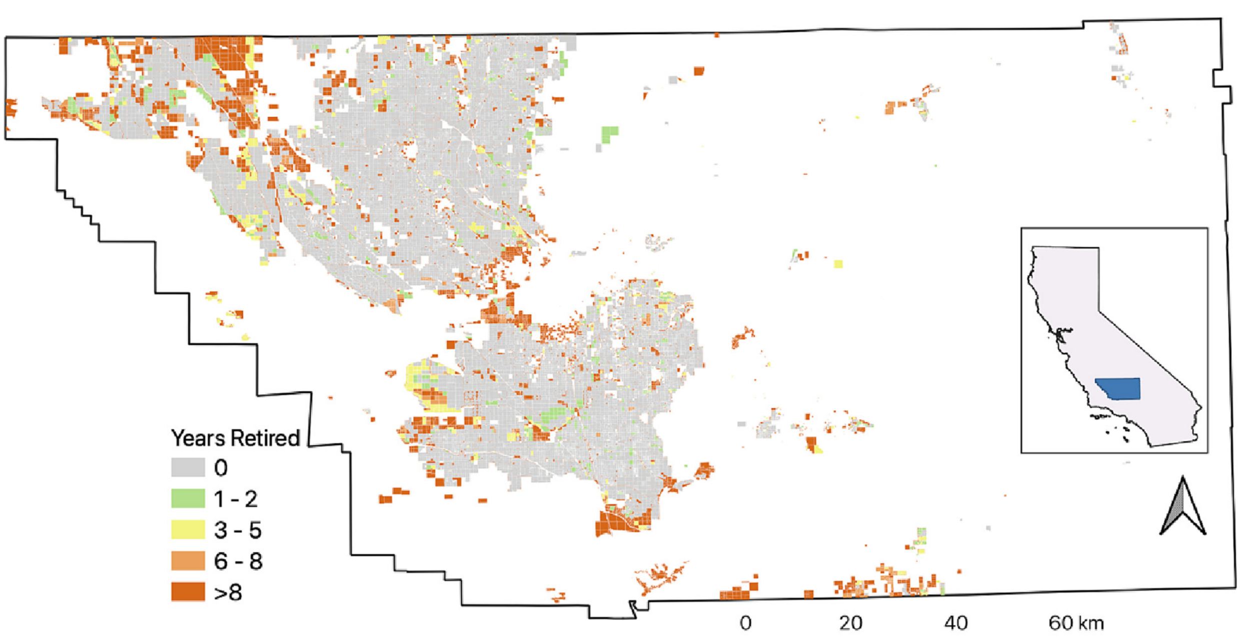

Fig. 1. Distribution of agriculture (gray) and retired agriculture categorized by duration of continuous preceding retirement (colors) for Kern County (blue inlay) in 2020. We estimate there were ~ 289,000 ha of land cultivated at least once in 2020 (gray), and 116,000 ha of retired land of different ages (see legend).

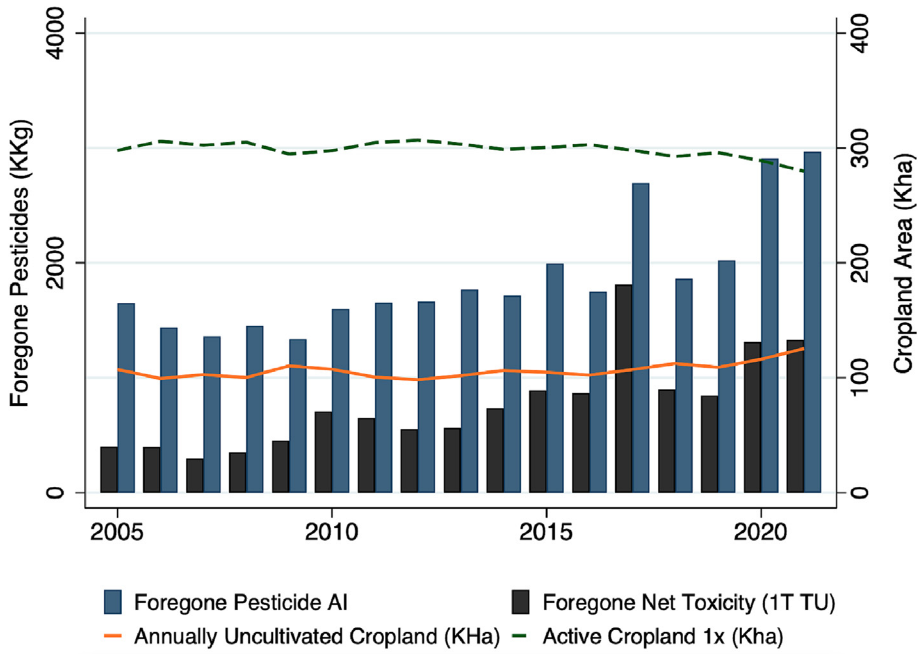

Fig. 2. Time trends in key variables. Annual fallowed lands (kHa; orange line) and cropland cultivated at least once during the year (kHa; green dash) are fairly stable over time, while foregone pesticide active ingredients (kKg; black bars) and foregone applied toxicity to investigated taxa (toxicity index of 1 T; navy bars), calculated using crop-year specific pesticide use rates, trend together and are more variable over time.

Crops differ in their pest communities and thus may be expected to respond differently to nearby retired lands. We rerun our analysis for the six most commonly grown crops, representing over half of both total cropped area and pesticide use, between 2005 and 2021 including region, year, and farmer dummy variables. In doing so, we allow for a crop-specific slope, as well as intercept, for the effect of retirement on pesticide use. Here we see that there is considerable heterogeneity by crop type. For several high-value, high-pesticide-use crops such as almonds and grapes, nearby retirement led to a much larger increase in pesticide use than the all-crop average (Fig. 5). For others, including pistachios and carrots, there is little effect. However, as might be expected, the effects differ depending on the type of pesticide used. Many commonly grown crops increase insecticide-only use rates in response to nearby retirement, while the effects on insecticide/fungicides are more muted and on fungicides are more variable by crop type (Fig. 5, Fig. S8-S9).

4. Discussion

Agricultural land retirement reverberates across numerous social, ecological and environmental axes. Here we sought to understand how land retirement affects agricultural pesticide use through both foregone application and landscape effects on remaining active fields. We report three main findings: 1) Retired agricultural land, or land cultivated at least once between 1997 and 2021 but uncultivated for at least one full year, accounts for about 100kha in any given year and represents about 1.3-3 M kg of foregone pesticide active ingredients. We do not observe strong time trends in retired lands, though the amount of retired lands, foregone pesticides,

Table 1
Summary statistics for pesticide use and the amount of surrounding retired land surrounding active fields 2005–2021. Pesticide "AI" represents the average pesticide use rates (kg ha^{-1} active ingredients). The various retired variables represent the average area (ha) of retired lands of different retirement durations (1y, 2-4y, 5-8y, >8y) and all combined (all) in the 2.5 km radius buffer (~1963 ha) around active fields.

Variable	Mean (SD)
Pesticide AI (kg ha^{-1})	25.61 (72.85)
Retired Ag All (Ha)	150.41 (187.7)
Retired 1y (Ha)	21.90 (49.16)
Retired 2-4y (Ha)	30.44 (63.34)
Retired 5-8y (Ha)	28.19 (58.26)
Retired 8y + (Ha)	69.86 (108.5)
N	211,820

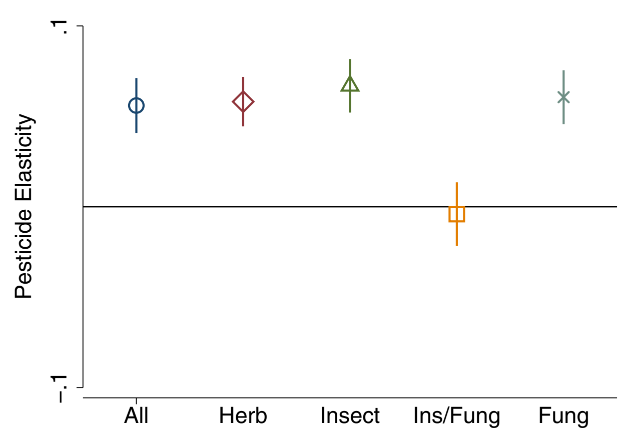

Fig. 3. Coefficient estimates for the effect of nearby retired lands on total pesticide use rate and pesticide use rate by target taxa on active fields. Coefficients are indicated by symbols and the 95 % CI is indicated by the bars. Coefficients can be interpreted as percent change-percent change (elasticity). "All" indicates total pesticide use (kg ha^{-1}), "Herb" indicates kg of pesticides targeting only weeds, "Insect" indicates kg of pesticides functioning only as insecticide, miticide, insect growth regulator or repellents, "Fung" indicates kg of pesticides targeting only fungi and molds, and "Ins/Fung" indicates dual action pesticides targeting both insect and fungi pests. For all types of pesticides, except dual action insect/fungicides, nearby retired lands lead to a significant increase in use rates. All models include covariates for the amount of cropland nearby and focal field size, dummy variables for region, year, crop and farmer, and standard errors clustered at the farmer (permit number) level. See Table S1 for coefficient estimates and number of observations.

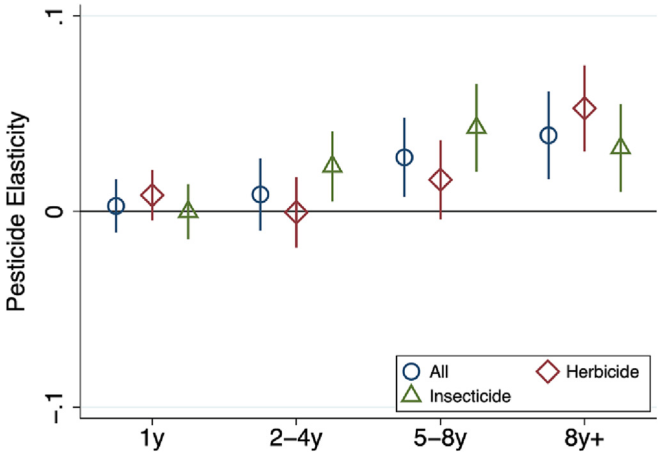

Fig. 4. Coefficient estimates for the effect of nearby retired lands on total pesticide ("All"), herbicide, and insecticide use rates by duration of continuous retirement. Coefficients are indicated by symbols and the 95 % CI is indicated by the bars. Coefficients can be interpreted as percent change-percent change (elasticity). Herbicides are defined here as pesticides targeting only weeds, insecticides as pesticides functioning only as insecticide, miticide, insect growth regulator or repellents. All models include covariates for the amount of active cropland nearby and focal field size, dummy variables for region, year, crop and farmer, and standard errors clustered at the farmer level. For simplicity, we focus the results on all pesticides, herbicides and insecticides because there are ecological predictions regarding landscape-level effects. See Table S2 for coefficient estimates and number of observations for these models and insect/fungicide and fungicide pesticides.

and associated foregone applied toxicity appear to be increasing. 2) Nearby retired lands lead to an increase in several types of pesticides on active fields, and this relationship increases with the duration of retirement; 3) the effects of nearby retirement are heterogeneous by crop type, with some high spray crops such as almonds and grapes associated with a much larger increase in pesticides in response to nearby retirement than the all-crop average.

Agricultural lands are retired for myriad reasons. Though often assumed to be the lowest-value crops, we observe several medium to high-value crops like cotton and pistachios are commonly retired. Though still not a random draw of crop composition, the retirement of high-value, high-spray crops results in a substantial amount of foregone pesticide use on the order of about 1.3-3 M kg of active ingredients, depending on the year. Still, the spatial distribution of retirement, and thus, foregone, field-applied pesticides, is clustered indicating any environmental health benefits associated with a reduction in pesticide applications and associated toxicity to different taxa will be as well. Notably, we observe pesticide use during production and thus do not account for any additional foregone pesticide use applied in the supply chain.

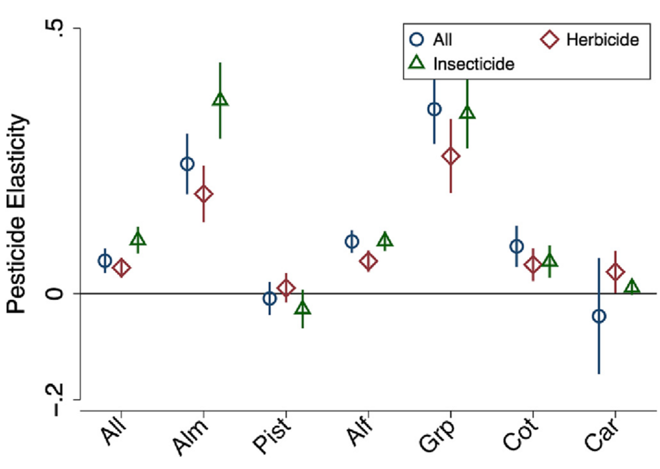

Fig. 5. Coefficient estimates for the effect of nearby retired lands on total pesticides (blue circle), herbicides (red diamond) and insecticide (green triangle) use rates by crop type. "All" indicates all crops combined, "Alm" indicates almond, "Pist" pistachios, "Alf" alfalfa, "Grp" grape, "Cot" cotton, "Car" carrot. Coefficients are indicated by symbols and the 95 % CI is indicated by the bars. Coefficients can be interpreted as percent change-percent change (elasticity). All models include covariates for the amount of cropland nearby and focal field size, dummy variables for region, year and farmer, and standard errors clustered at the farmer level. See Table S3-S5 for coefficient estimates and number of observations.

Many of the retired lands near active croplands have been retired for several years. Biodiversity and ecosystem service benefits tend to accrue with the duration of retirement (Crawford et al., 2022; Isbell et al., 2019), though even ephemeral retirement may improve landscape connectivity (McComb et al., 2022). Interestingly, we observed an increase in both herbicide and insecticide on active fields with nearby retired lands, and an increase in the magnitude of the coefficient with the duration of time retired. This suggests that both insect and weed pest spillover from retired lands, and likely that the level of weed and insect pest pressure increases with the amount of time since cultivation. This contrasts, to some degree, with agroecological principles that suggest uncultivated (semi) natural lands like field margins may reduce insect pest pressure due to spillover of natural enemies (Haan et al., 2020; Tscharntke et al., 2016). While this may still occur, particularly on fields with higher vegetation cover, it appears insect pest pressure increases, on average, with increasing nearby retired lands. Agriculture in Kern County is intensive and diverse. With respect to the former, the soil may be so far disturbed from natural nutrient and water cycles that the vegetation that recovers passively is invasive and weedy (Lortie et al., 2018). With respect to the latter, highly diverse cropland may reduce the relative habitat benefits of uncultivated land covers since heterogeneous crop cycles may already provide substantial habitat heterogeneity (Estrada-Carmona et al., 2022; Sirami et al., 2019). Lastly, we find the effect of retirement on both insect and weed pest control increases with the duration of retirement, though decreases with vegetation cover. These contrasting trends suggest that management of retired parcels may determine pest buildup and spillover. We cannot differentiate between native and invasive plant cover nor remnant crop plants over the time series, which likely impacts pest control through different, conflicting pathways. Field studies measuring vegetation composition following retirement would be valuable to elucidate the mechanisms behind our results.

Importantly, though perhaps unsurprisingly, we report substantial crop-specific heterogeneity in the effect of surrounding retirement on pesticide use. Different crops have different suites of pests and natural enemies that may respond differently to retired lands depending on, for example, dispersal ability, diet breadth, pest diversity, and other life history characteristics (Rosenheim et al., 2020). Across all pesticide types, we find grapes have a consistently large and positive response to surrounding retirement. For example, while a 10 % increase in nearby retirement leads to around a 0.6 % increase in most pesticide use rates (kg ha^{-1}AI) on average, the same increase in retirement leads to over a fivefold greater increase for grapes. Grapes were also the crop responsible for the highest applied toxicity over the analysis period (33 %), driven primarily by imidacloprid, and almost all toxicity was to honeybees. More generally, foregone applied toxicity to honeybees dwarfed other endpoints, reflecting the high toxicity of modern pesticides to honeybees noted elsewhere (DiBartolomeis et al., 2019; Douglas et al., 2020). As such, land retirement in Kern County could substantially change local pressures on pollinators, depending on the crop idled and the crops nearby. The crop-specific response to nearby retired lands implies certain growers and near-field areas are likely to be better or worse off, with respect to pest control and health risks, as retirement becomes more frequent with future groundwater limitations. Growers and extension agents may thus consider switching crops depending on the spatial evolution of land retirement nearby. Additionally, as with grapes, the majority of toxicity is driven by a few, highly toxic insecticides. Thus, employing existing, lower-toxicity alternatives could also mitigate some environmental concerns stemming from retirement-driven pesticide increases.

There are several important caveats to our study. First, Kern County is just one county. Though we might expect similar results in other parts of the Central Valley, and other high-value and water-limited growing regions, temperate or tropical agricultural systems are likely to have different relationships. Second, the unique field and pesticide data are user reported. The PUR data are extensively checked for outliers (California Department of Pesticide Regulation, 2002), and our statistical approach such as farmer dummy variables should reduce the error associated with individual farmer reporting behavior in our landscape analysis. Nevertheless, our results depend on accurate crop reporting and valid permits. Additionally, we do not have complete land use histories and fail to capture all potential crops grown on a given parcel, and thus we underestimate foregone pesticides, particularly on annual croplands. Lastly, we lack data on farm management. While some farmers may leave retired fields untended, others may till or otherwise manage them. Our remote sensing analysis aims to uncover the relationship between revegetation and pesticides, but more detailed information on the type of revegetation (and pest pressure) from field-based studies would undoubtedly improve our mechanistic understanding. Such data would also improve our understanding of the potential value associated with different management of retired parcels.

In summary, retired agricultural lands are an increasing land cover with underexplored implications for surrounding human and natural communities. Our results suggest agricultural land retirement has direct environmental benefits in the form of reduced pesticide use, yet leads to an increase in pesticide use on surrounding active fields. Given the ongoing (Pancorbo et al., 2023) and expected increase in retired land under groundwater policies in California (Hanak et al., 2019) and other water-limited systems, understanding the spatial distribution of environmental benefits and costs to retired lands is crucial for improving the environmental and economic sustainability of these agricultural systems.

CRediT authorship contribution statement

AEL, DS, AQ conceived of the study. IF, DS, NP, AEL collected and analyzed data. AEL led writing of the manuscript. All authors contributed revisions.

Data availability

Data to replicate the main analysis are available on Dryad (DOI: 10.25349/D9Q02T).

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.165224.

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