RESEARCH ARTICLE SUMMARY

ORGANIC AGRICULTURE

# Spillover effects of organic agriculture on pesticide use on nearby fields

Ashley E. Larsen*, Frederik Noack, L. Claire Powers

**INTRODUCTION:** Reducing the environmental footprint of agriculture while maintaining or improving yields is a major challenge of the coming decades. Organic agriculture is often suggested as a means to improve agricultural sustainability through more natural production methods, particularly in regards to pesticides and pest control. However, the environmental impacts of organic production practices are only partially understood and it remains unknown whether such production practices have spillover impacts, beneficial or not, for surrounding producers.

**RATIONALE:** Organic crop production includes a suite of on-farm practices that differ from conventional management techniques. These practices include using different pest management approaches, which may result in the spillover of agricultural pests and/or their natural enemies to nearby agricultural fields resulting in higher or lower pest damage and pesticide use. Here we seek to identify the direct and spillover effects of surrounding organic cropland on pesticide use on both organic and conventional crop fields. To do so, we used field-level pesticide use and crop data for ~14,000 fields over seven years in Kern County, California, alongside US-wide data on organic agriculture and pesticide use.

**RESULTS:** We find that the presence of surrounding organic cropland generally leads to a decrease in pesticide use on organic fields, which appears mostly driven by a reduction in insecticides. By contrast, surrounding organic agriculture leads to a small but significant increase in pesticide use on conventional fields. Based on these results, we simulate how changing the proportion of organic cropland changes net insecticide use. While net insecticide use decreases at high levels of organic cropland, at commonly observed levels net insecticide use increases due to the positive (insecticide increasing) effects of surrounding organic cropland on conventional fields. This effect can be entirely mitigated by clustering organic cropland. A coarser, national-scale analysis further evidences the inverted U-shape relationship between organic cropland area and net insecticide use.

**CONCLUSION:** These results suggest that efforts to increase organic cropland could lead to a decrease in pesticide use, but that is more likely at higher levels of organic cropland in the landscape. At low levels of organic cropland, the opposite is expected. Spatially clustering organic fields and spatially separating organic and conventional fields could reduce the environmental footprint of both organic and conventional croplands. ■

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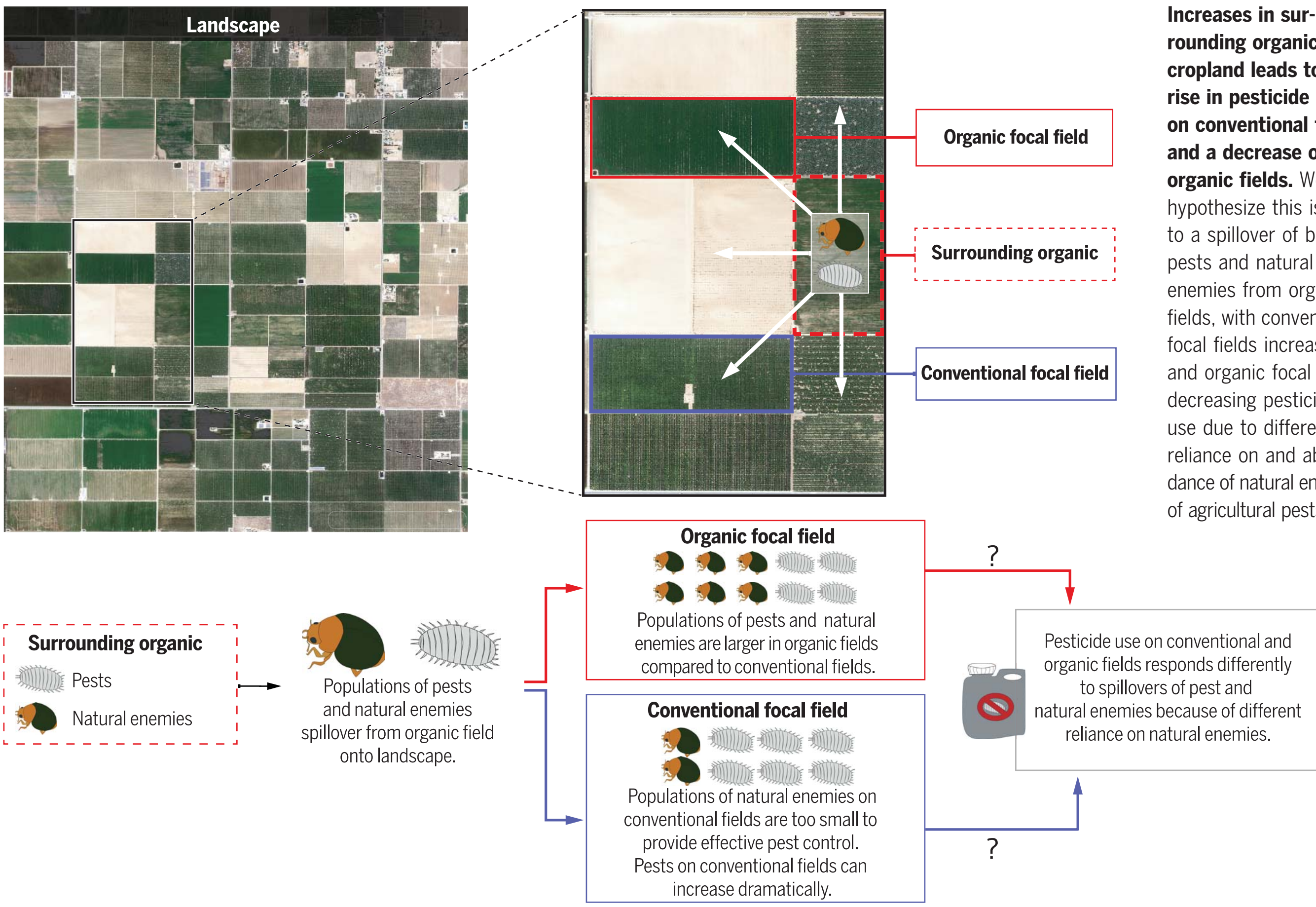


**Increases in surrounding organic cropland leads to a rise in pesticide use on conventional fields and a decrease on organic fields.** We hypothesize this is due to a spillover of both pests and natural enemies from organic fields, with conventional focal fields increasing and organic focal fields decreasing pesticide use due to different reliance on and abundance of natural enemies of agricultural pests.

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# Spillover effects of organic agriculture on pesticide use on nearby fields

Ashley E. Larsen[1]*, Frederik Noack[2], L. Claire Powers[3]

**The environmental impacts of organic agriculture are only partially understood and whether such practices have spillover effects on pests or pest control activity in nearby fields remains unknown. Using about 14,000 field observations per year from 2013 to 2019 in Kern County, California, we postulate that organic crop producers benefit from surrounding organic fields decreasing overall pesticide use and, specifically, pesticides targeting insect pests. Conventional fields, by contrast, tend to increase pesticide use as the area of surrounding organic production increases. Our simulation suggests that spatially clustering organic cropland can entirely mitigate spillover effects that lead to an increase in net pesticide use.**

Increasing yields while reducing the environmental footprint of crop production is a major challenge of the 21st century. Organic agriculture is one potential solution widely recognized by consumers and policy makers. Although organic production covers less than 2% of global agricultural lands, it has grown from 15 million ha in 2000 to over 73 million ha today (*1*–*3*). Continental policy initiatives, such as the European Union's Farm to Fork strategy, as well as regional targets such as the California Air Resource Board (CARB) scoping plan for achieving carbon neutrality (*4*) portend a further and more substantial increase in organic production (*5*). However, the benefits and drawbacks of organic agriculture remain a topic of active research. Although organic production generally improves environmental conditions such as soil and water quality (*1*, *6*–*8*), these improvements often come with a substantial yield tradeoff (*9*, *10*), which makes the overall environmental impact of organic production ambiguous or at least context-dependent (*11*). The focus of comparison thus far has been at the field level. However, field-level changes in management also determine the composition and configuration of agricultural landscapes, which in turn influence the persistence, richness, and abundance of many taxa (*12*–*14*) including both beneficial and pest organisms (*15*–*17*) and associated pesticide use (*18*, *19*). Because on-farm decisions may influence pests and natural enemies of pests beyond the farm gate, the net environmental impacts of organic crop production necessarily include if and how pests and their predators spill over to affect pest control on other fields and farms in the landscape.

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The vast majority of the most persistent and environmentally concerning pesticides such as organophosphates and organochlorines are banned in organic agriculture, as are many widely used herbicides and genetically modified seeds (*20*). As such, organic fields, even if they do use pesticides (*21*), may host a different suite of species in different relative abundances than conventionally managed fields (*22*, *23*). For example, organic agriculture may harbor more beneficial organisms such as natural enemies that control pests (e.g., birds, spiders, parasitoids, predatory beetles; hereafter natural enemies) (*24*) due to a reduction in persistent and broad-spectrum pesticide use (*25*). Alternatively, although not mutually exclusive, the reduced reliance on chemical pest control in organic agriculture could result in organic fields having higher levels of pests that spill over to other fields (*25*). Bianchi *et al.* (*25*) illustrate theoretically that these two counteracting effects of organic agriculture can lead to a lose-lose situation as pesticide use on conventional agriculture reduces natural enemy control on organic fields, leading to increased pest spillover onto conventional fields. However, Bianchi *et al.* (*25*) also show that if organic fields are spatially clustered, natural enemies of pests persist and pest spillover is reduced. This mechanism suggests that conventional and organic fields may have opposite responses to increasing organic agriculture in their surroundings, and such a mechanism, driven by the interaction of pesticides, pests, and natural enemies, may induce producers to cluster organic fields in space.

Ecology, however, is not the only mechanism (*26*). In the economics literature, scholars show that landowners reduce their pest eradication efforts in response to reduced pest eradication efforts by their neighbors (*27*). This race to the bottom is caused by pest spillover that reduces the ability of the farmer to control the pests on their land and therefore discourages control efforts in response to increased pest spillover. In other words, if pest propagules are constantly spilling over from the landscape, the focal farmer may spray pesticides to kill their pests but the high level of pest immigration reduces the benefits of doing so. In addition to economic and ecological feedbacks, farmers may simply learn from their neighbors and reduce their pesticide use in response to the reduction of pesticide use on neighboring farms (*28*, *29*). These economic and behavioral mechanisms suggest that both conventional and organic fields may decrease pesticide use in response to increasing organic agriculture. We evaluate the different predictions generated by these ecological, economic, and behavioral theories.

If growers receive a net pest control benefit from surrounding organic fields via natural enemy spillover, for example, the benefit of organic production in reducing environmental pollution has thus far been understated. On the other hand, if growers experience a net pest control cost from surrounding organic fields in response to pest spillover, for example, the benefits of organic production for the environment are diminished. Lastly, if organic fields in the landscape have differential impacts based on whether the receiving field is organic or conventional, then important policy opportunities arise related to targets for organic agriculture and for incentivizing spatial coordination of organic production within and between farms.

We seek to understand how surrounding organic crop production influences pesticide use on organic and conventional fields. We address the following questions: (i) How does surrounding organic agriculture affect pesticide use on other fields? (ii) Is this effect different for conventional versus organic focal fields? (iii) Which type of pesticide is most influenced by organic agriculture and does this differ between organic and conventional fields? We focus on Kern County, CA, one of the leading crop-producing and pesticide-employing counties in the US, with over \$7.4B in annual agricultural production and over 13 million kg of pesticide active ingredients application in 2018, reflecting the production of many high-value crops such as almonds, grapes, lettuce, and carrots (*30*, *31*). We analyze field-level crop and pesticide use data for about 7300 organic and 91,000 conventional field-year observations representing about 14,000 permitted fields each year between 2013 and 2019. We rely on a series of panel data models that leverage the spatial and temporal variation of agricultural composition to estimate the effect of surrounding organic cropland, after controlling for other local and landscape factors and heterogeneity in pest control behavior specific to year, region, crop type, and farmer. Based on our results, we then simulate how net pesticide use changes as a function of the amount of organic agriculture in the landscape and evaluate whether the general trends observed in Kern County hold at the national scale.

## Results

### *Empirical analysis in Kern County, CA*

We identified certified organic crop fields based on both state registration and 3 years of organic-approved pesticide use. We report that about 7.5% of permitted fields and about 5.5% of permitted area in 2019—accounting for multicropped fields—were organic, with organic cropland distributed across much of the agricultural region in Kern County, CA, though these areas were often clustered (Fig. 1). Although both organic and conventional fields had substantial surrounding cropland, organic cropland generally had a much larger fraction of surrounding organic cropland and a greater amount of surrounding cropland owned by the same farmer. Organic fields were generally smaller in size and in regions of greater crop heterogeneity (Table 1).

In our first analysis, we sought to identify whether surrounding organic cropland leads to an increase or decrease in pesticide use rates (kg per ha) on organic and conventional focal fields, where "surrounding" is defined as a circular area with a 2.5 km radius (1963 ha) around the focal field, following prior literature (16, 32). All models also include covariates for the amount of total cropland (cropland extent), field size (hectares), and percent of surrounding cropland managed by the focal farmer (share own). Organic fields and pesticide use are not randomly distributed and may be co-determined by location and time-specific characteristics such as soil quality or policies, weather, and demand shocks. Similarly, knowledge spillovers or economies of scale—e.g., through shared infrastructure or supply chains—can create distinct clusters of similar agricultural practices within the landscape (28, 29, 33, 34). We therefore control for region and year heterogeneity with region, defined as the public land survey (PLS) Township, which is roughly 93 km$^2$, and year dummy variables, or fixed effects in causal inference terminology (table S1). Thus, the coefficients in our baseline specification are identified using only deviations in pesticide use rates and amount of organic agriculture from the local average, after removing temporal fluctuation shared by all observations in the study region. Additionally, organic farmers may have different approaches to agriculture or plant different crops with different pesticide use patterns. We therefore also control for crop type and farmer, again using a series of dummy variables.

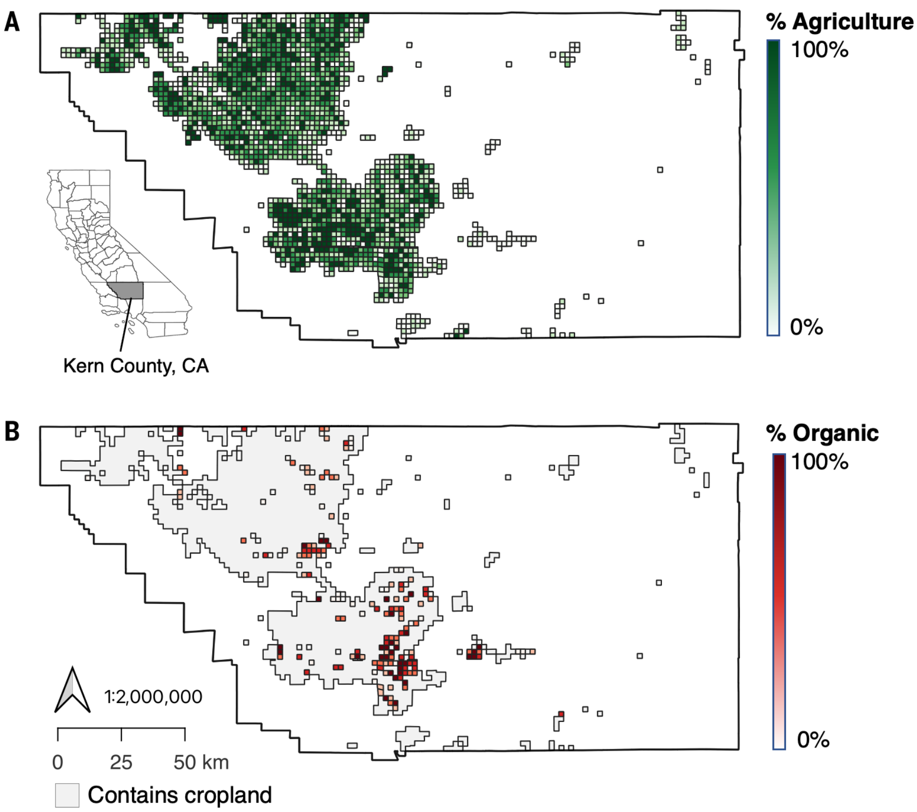


**Fig. 1. Percent of Kern County Public Land Survey (PLS) sections occupied by cropland and organic cropland in 2019.** PLS sections (~2.6 km$^2$ regions) containing any cropland (**A**) or organic cropland (**B**) are indicated by black outlines. PLS sections containing cropland but no organic cropland are indicated by gray shading in (B). In both panels, darker colors indicate a higher percentage.

Across specifications, we inverse hyperbolic sine (IHS)–transform dependent and independent variables [see statistical approach (35)] and include standard errors clustered at the farmer level to account for the correlation between farmer and organic treatment (36). We focus on the results of our most stringent model specification, which includes year, region, crop type, and farmer dummy variables. Pooling all fields, we find that the amount of surrounding organic cropland results in a small but significant positive effect on total pesticide use rates, defined as kg per ha of active ingredients (AI) (Fig. 2, fig. S1, and table S2). Here and throughout, significance is based on a two-tailed $t$ test. Running analyses separately for organic and conventional fields, which allows organic and conventional focal fields to have different responses to all covariates, we see that surrounding organic agriculture leads to a small but significant increase in pesticide use rates on conventional focal fields, reflecting the pooled model. We observe that a 10% increase in surrounding organic cropland area leads to a 0.3% increase in total pesticide use on conventional focal fields in our most stringent model. Throughout this study, we interpret the coefficients of IHS-transformed variables as elasticities that approximate percentage changes similar to coefficients of log transformed variables. By contrast, the same 10% increase in surrounding organic cropland leads to a 3% decrease in total pesticide use on organic focal fields (Fig. 2 and table S2).

The term "pesticides" encompasses a broad range of pest control products that target very different pest taxa that may respond differently to surrounding organic cropland. We thus split total pesticides into target taxa–specific categories: insecticides (further divided into insecticides only and insecticide/fungicide dual action chemicals, such as sulfur), fungicides only, and herbicides only. Of the taxa-specific categories, we focus on insecticides throughout as it is the most common type of pesticide applied in this region (Table 1), and also because insect pests are mobile and thought to be responsive to landscape characteristics. We see that the all-pesticide result primarily reflects chemicals targeting exclusively insect pests or both insect pests and molds (Fig. 2 and tables S2 and S3). We see that a 10% increase in surrounding organic cropland leads to a 0.3% increase in insecticide use rates (kg per ha) for conventional focal fields, and a decrease of 2% for organic focal fields. By contrast, we see little effect of surrounding organic cropland on herbicide or fungicide use rates on organic fields (Fig. 2 and table S3).

Organic cropland could influence pest and natural enemy abundance at either the local scale, the landscape scale, or some combination of the two. To flexibly model the effect of surrounding organic cropland over space, we

**Table 1. Summary statistics (mean, standard deviation in parentheses) for conventional and organic fields.** Cropland Extent, Surrounding Organic, Same Crop, and Same Owner are measured as area (hectares) within a 2.5-km buffer (1963 ha area) around the focal field centroid. These variables can exceed 1963 ha due to crop rotations. Permitted field size, pesticide use rates, and landscape characteristics are adjusted for multicropping (see Methods, Supplementary Methods).

| | Conventional | Organic |
|---|---|---|
| Field Size (ha) | 31.74 | 18.99 |
| | (33.78) | (14.82) |
| Cropland Extent (ha) | 1748.37 | 1977.50 |
| | (601.8) | (818.7) |
| Surrounding Organic (ha) | 71.88 | 837.09 |
| | (223.1) | (608.2) |
| Same Owner (ha) | 434.47 | 720.84 |
| | (443.7) | (594.9) |
| Same Crop (ha) | 444.38 | 166.09 |
| | (407.4) | (246.4) |
| Crop Diversity | 0.70 | 0.85 |
| | (0.183) | (0.107) |
| All Pesticide AI (kg per ha) | 26.65 | 8.61 |
| | (82.73) | (26.34) |
| All Insecticide AI (kg per ha) | 18.43 | 7.29 |
| | (68.43) | (24.27) |
| *N* | 91,155 | 7352 |

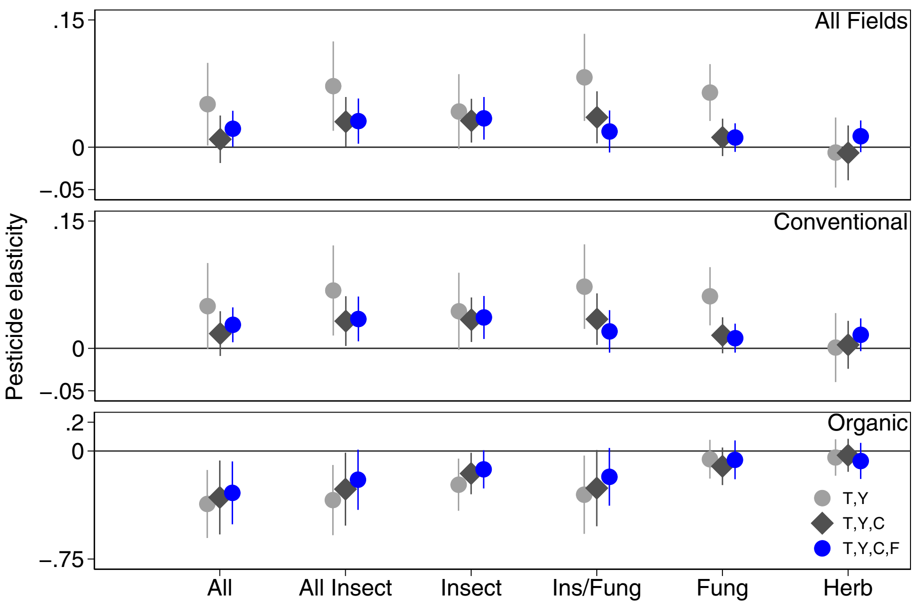


**Fig. 2. Effects of surrounding organic cropland on aggregate and separate types of pesticide use on conventional (Conventional) and organic (Organic) focal fields for models with a combination of PLS Township (T), Year (Y), Crop (C), and Farmer (F) dummy variables.** The *y*-axis, which differs for organic versus conventional and all, is pesticide elasticity, or the percent change in a given type of pesticide use (kilograms per hectare) for a 1% change in the area of surrounding organic cropland. The *x*-axis indicates different pesticide types: all pesticide active ingredients (All); all pesticides that target insect pests (All Insect); pesticides that only target insect pests (Insect); pesticides with dual action for insect pests and molds (Ins/Fung); pesticides that only target molds (Fung); and pesticides that only target weeds (Herb). The horizontal line indicates zero. The most stringent and therefore preferred model is indicated in blue. The symbol indicates the slope coefficient and the bars indicate the 95% confidence interval (CI) using standard errors clustered at the farmer ID to account for autocorrelation of the errors of fields within the same farm. Tables with the coefficient and standard error estimates, number of observations, and other covariates are in the SM (tables S2 and S3).

analyzed the amount of organic cropland in each of five concentric annuli with 500-m width from the focal field out to the 2.5-km boundary. Rather than including one covariate for surrounding organic cropland, as previously, we now have five. This enables organic cropland to have a different relationship at different distances from the focal field. We focus exclusively on organic focal fields because few conventional fields have organic agriculture in the immediate surroundings. Again, using the panel data model with region, year, crop, and farmer dummy variables and including covariates for focal field size, cropland extent, and share own, we see a large local effect of organic agriculture on organic fields, but also a smaller landscape effect extending out to 2500 m. The largest magnitude of the effect is in the first annuli, defined as a circular buffer of 0 to 500 m from the centroid of the focal field. For organic focal fields, a 10% increase in organic cropland area in the first annuli leads to about a ~2% decrease in total pesticide use rate. The magnitude of the relationship is reduced substantially in the second annuli (500- to 1000-m buffer) and beyond, though it remains significant or marginally significant (Fig. 3 and table S4). We see a similar response for insecticides, mostly driven by dual action insecticide/fungicide chemicals (Fig. 3, table S4, and fig. S2).

We conducted several robustness tests related to calculations of surrounding organic cropland (tables S5 and S6, and fig. S3), model specification (figs. S4 to S8 and tables S7 to S9), and alternative measures of pesticide use (pesticide products, area treated, net applied toxicity) [Parker *et al.* (*37*)] (tables S10 and S11). We also evaluated whether organic and neighboring fields have similar pesticide dynamics to conventional fields before becoming organic using an event study (figs. S9 and S10; Supplementary Methods). Our panel data coefficient estimates were generally robust to different definitions of organic, model specifications, and measures of pesticide use. The event study shows that all fields have similar patterns of pesticide use prior to the adoption of organic practices, when fields that will become organic start to diverge from the general pattern of pesticide use on conventional fields. Further, our event study finding that conventional focal fields increase pesticide use in response to reduced pesticide use on surrounding organic fields only after surrounding fields become organic strengthens the interpretation of our estimated effect as causal.

### *Simulation analysis*

Building on our empirical model, we simulated the effect of organic agriculture on insecticide use (see simulation methods). We find that the mixed effect of spillovers from organic agriculture onto neighboring agricultural fields creates

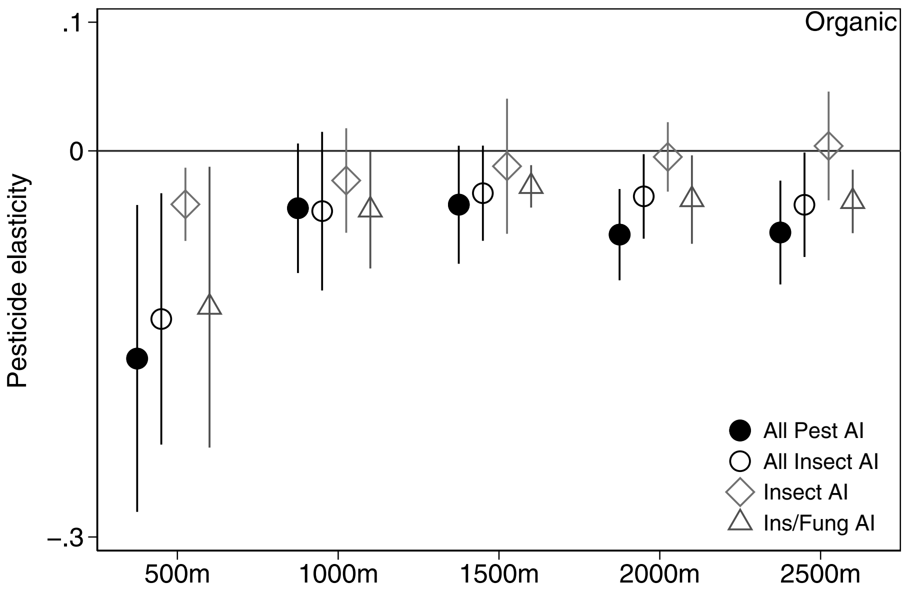


**Fig. 3. The effects of organic cropland at different distances from organic focal fields for total pesticide and insecticide active ingredients.** Closed circles indicate all pesticide use (kilograms per hectare), open circles indicate all insecticide use, and two subcategories of insecticides are also included. The *y*-axis is pesticide elasticity, or the percent change in pesticide use rate for a 1% change in the area of surrounding organic cropland. The *x*-axis indicates the coefficient for the impact of organic cropland in different annuli of 500 m width from the focal field. All models include region (PLS Township), year, crop, and farmer dummy variables. The symbol indicates the slope coefficient and the bars indicate the 95% CI using standard errors clustered on farmer ID. Tables with the coefficient and standard error estimates, number of observations, and other covariates are in the SM (table S4).

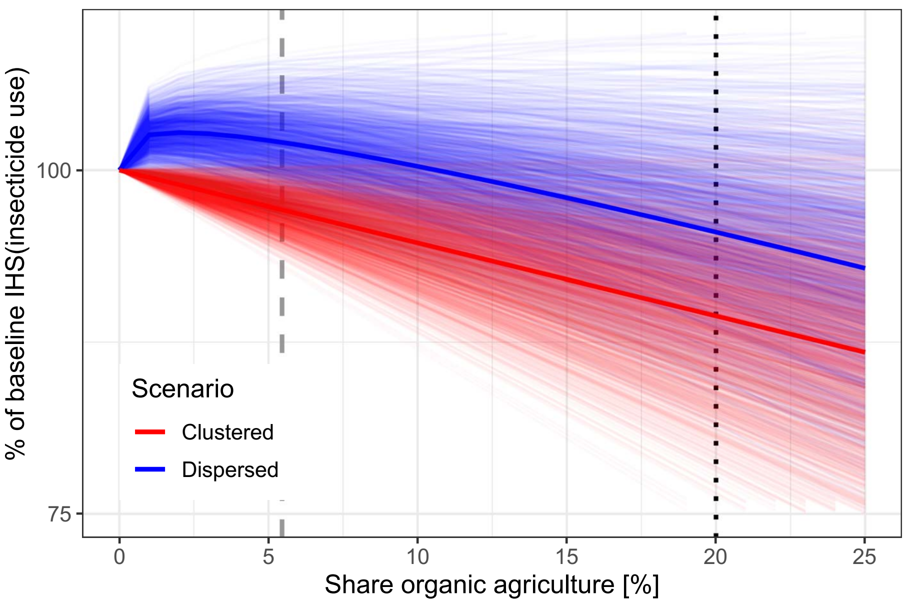


**Fig. 4. Simulation of the impact of organic agriculture on total insecticide use based on 2000 random draws from the joint normal parameter distribution of specification T,Y,C,F-Int reported in fig. S1.** The outcomes are expressed in IHS-transformed insecticide use relative to "baseline" insecticide use of 100% conventional agriculture. The thick lines are the mean simulated outcomes. The blue lines (Dispersed) assume an equal spatial distribution of organic agriculture and includes the spillovers of organic agriculture on neighboring fields. The initial increase in total insecticide use is caused by the positive spillovers of organic agriculture on conventional fields that overcompensates the reduction of insecticides on the focal and neighboring organic fields. The red lines (Clustered) assume spatially concentrated organic agriculture such that there are only spillovers of organic fields on organic fields. The dashed gray line shows the 2019 level of organic agricultural area in Kern County. The dotted black line shows the CARB target for organic agriculture. To back transform to approximate the level of pesticides, use sinh(IHS(prediction) * IHS(mean insecticide use on conventional fields with no surrounding organic agriculture)/100) (*54*).

a nonlinear relationship between the share of organic agriculture in the landscape and total insecticide use. In landscapes with high levels of organic agriculture, insecticide use decreases regardless. However, at low levels of organic cropland dispersed across the landscape, the increased insecticide use due to spillovers (possibly of pests) from organic fields onto conventional fields overwhelm the decreased insecticide use due to the direct effects of organic agriculture plus the spillovers onto organic fields (Fig. 4). This increase in overall insecticide use in response to increases in organic agriculture at low levels of the latter is completely mitigated if organic fields are spatially concentrated (clustered). This spatial concentration reduces insecticide-increasing spillovers on conventional fields. The current area of organic cropland in Kern County is ~5.5% of total cropland, below the level at which organic agriculture reduces insecticide use at the landscape level compared with no organic agriculture, were the organic fields in Kern County dispersed (Fig. 1). The European Union's Farm to Fork target for organic agriculture (25%) and the CARB target (20%) are above that threshold at which overall insecticide use declines. The simulation results suggest that the benefits of organic agriculture, with respect to spillovers, materialize at higher levels of conversion to organic agriculture, or if organic agriculture is spatially concentrated, to increase the negative (pesticide-decreasing) spillovers of organic agriculture on pesticide use on neighboring organic fields.

### *National model*

We evaluated the external validity of our results and simulation using national-scale data from the Census of Agriculture (see Nationwide Extension). Although we cannot distinguish pesticide use on conventional and organic fields at the national scale, we can test whether pesticide use increases initially and then declines in response to an increasing area under organic agriculture, as predicted by our simulation results. To do so, we first calculate organic land at the county-year level using information on the number of organic farms and average farm size. We use data on areas treated with insecticides and herbicides from the bi-decadal USDA Census of Agriculture from 1997 to 2017 as outcome variables. We then estimate how insecticide (or herbicide) use changes as a function of both the linear and the square of organic agricultural area, while controlling for other covariates and including county and year dummy variables. As previously stated, we IHS-transform both our outcome and predictor variables. The estimated coefficients are positive for the linear term and negative for the squared term, suggesting an initial increase of pesticide use and a subsequent decline of pesticide use with increasing levels of organic agriculture. The national results therefore reinforce our finding from Kern County, where pesticides increase at low levels of organic agriculture and then decline at higher levels, and that this impact is more pronounced for insecticides than for herbicides (Fig. 5 and tables S12 to S14). We visualize this nonlinear relationship in fig. S11. In a robustness test, we use data from the USGS Pesticide National Synthesis Project. The results are qualitatively similar.

## Discussion

Crop pests respond to both local and landscape characteristics. Although much research has focused on how local and landscape features such as field size, the extent of cropland or the abundance of (semi) natural habitat influences pest burdens (*16*), natural enemy abundance (*15*, *16*), and insecticide use (*38*), there have been comparatively few studies that investigate whether organic fields function as a source of pests, a source of natural enemies, both, or neither.

Although organic-approved pesticides are not necessarily less toxic to environmental endpoints such as fish (*39*), theory suggests that differences in pest management on analogous organic and conventional fields may change the way pests and natural enemies accumulate both at local and landscape scales (*25*). We find that surrounding organic agriculture drives a small but significant increase in pesticide use on conventional fields while leading to a larger and also significant or marginally significant decrease in pesticide use on organic fields. Our simulation predicts the net change in IHS-transformed insecticides at different amounts of organic cropland for scenarios with dispersed and clustered organic fields. Transforming the IHS predictions back to approximate the levels of insecticide use, we see changing from a baseline of 0% to 5% organic cropland results in an increase in insecticide use to 109% of the baseline, if organic fields are dispersed. At 20% organic cropland, insecticide use decreases to 83% of baseline use. If organic fields are clustered, however, the same changes would result in 90% and 64% of baseline insecticide use for 5% and 20% organic cropland, respectively. Given that over 7 M kg of insecticide active ingredients were applied in Kern in 2019, the difference between clustered and dispersed organic agriculture therefore represents sizable differences in the amount of insecticides that would be applied annually.

The contrasting sign of the relationship for organic and conventional focal fields suggests that organic fields harbor higher levels of both insect pests and natural enemies, as suggested by prior meta analyses (*22*), that spill over to affect other fields. Conventional focal fields may realize more of the negative effects, either due to lower treatment thresholds or due to reduced persistence of natural enemies in conventional fields, as predicted by theory (*25*). By contrast, organic fields may realize a benefit of surrounding organic cropland because a landscape of reduced synthetic pesticides may enable more effective control by natural enemies (*22*, *23*, *25*).

In line with conceptual understanding and empirical agroecological research, we find that surrounding organic cropland primarily influences insect pest control. Decades of research suggest that insect pests and natural enemies are influenced by local and landscape composition and configuration (*15*, *40*). Further, insecticides are the most widely used types of pesticide in California's high-value agriculture (*30*) and herbicides are rarely used for organic fields in this system. Thus, although local and landscape features, including surrounding organic fields, could influence weeds and herbicide use in other systems and our national-scale robustness test suggests it may, it is not wholly surprising that little effect is observed here.

Focusing on organic fields, we find that the influence of surrounding organic fields is greatest for fields within 0.5 km of the focal field, which are primarily immediately adjacent fields or other crops in multicrop fields. This large local benefit of clustering may help explain why organic fields tend to be part of larger farms (*21*) and are much more commonly multicropped fields. However, there remains a benefit of surrounding organic agriculture at distances between 1 to 2.5 km from an organic field for some pesticides, suggesting there is also a landscape-level effect of organic agriculture on net pests and pest control. As farmers and policy makers consider how to increase organic production, leveraging the pest control benefits of clustered organic production may generate more viable organic and conventional agriculture with less environmental pollution stemming from pesticide use. This benefit of clustering, our simulation suggests, remains sizeable even if organic agriculture reaches 25% of cropland. Thus, it may be valuable to incentivize local clustering of organic fields to reduce pesticide use on both organic and conventional farms, regardless of organic targets.

We have suggested that the mechanism underlying our results is the influence of primarily insect pests and/or natural enemy populations spilling over from organic fields. However, we lack data on pest abundance or damage and thus are using pesticide amounts as an imperfect proxy. There are, of course, many aspects that drive farmer pesticide use decisions beyond pests themselves. Characteristics such as crop value (*41*), pest susceptibility (*42*), and farmer risk preferences (*43*–*45*) explain most of the variation in pesticide use. Our goal was to isolate the spillover effect, if any, of surrounding organic cropland on different types of pesticide use on other fields rather than to explain the greatest variation in pesticide use. As such, we sought to remove these influences through a series of dummy variables in a least-squares dummy variable approach. We are suggesting that the variation in pesticide use that remains after removing region, year, farmer, and crop characteristics is reflective of pest pressure. Field studies that measure pest and/or natural enemy abundance in and near organic fields would be extremely useful to evaluate the plausibility of our suggested mechanism. There are additional caveats to our work. For one, we lack information on many other aspects of production such as yields and profits and thus are unable to evaluate potential tradeoffs between different policy goals. Additionally, Kern County is just one county and grows a larger diversity of high value crops than most of the agricultural regions in the US or globally. Pesticide use data is not available at the field-level outside of California which makes both isolating organic fields and elucidating the effect of surrounding organic fields on pesticide use extremely difficult. We expect the magnitude of effects will depend on the mobility and pesticide response of the pest/natural enemy community (*25*), which is likely to be crop-specific and any given crop may or may not reflect the average effect observed here (*38*, *41*, *46*). However, our national-scale robustness test suggests that the overall relationships observed in Kern persist elsewhere despite differences in crop composition and climate.

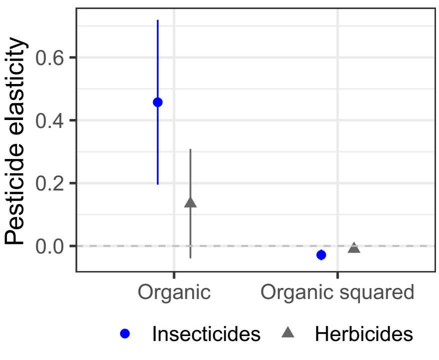


**Fig. 5. National-scale analysis illustrating the nonlinear relationship between the amount of organic cropland and pesticide use.** The *y*-axis is pesticide elasticity, or the percent change in total pesticide use rate for a 1% change in the area of organic cropland. The *x*-axis indicates the coefficient for the level term (organic) and the squared term (organic squared) and the symbols indicate insecticides (blue circle) and herbicides (gray triangle), as well as the 95% CI with standard errors clustered at the county and year level. All models include county and year dummy variables.

## Methods and Materials

### Data

#### Pesticides data

We obtained field-by-day pesticide use reports for Kern County for 2013 to 2019 from the California Department of Pesticide Regulation. The pesticide use report data include information on permit (farmer), site, pesticide active ingredients used, amount used, and date applied, among other information. These data are from state-mandated pesticide use reports submitted to the County Agricultural Commissioner following pesticide use on production agriculture. Using the California Department of Pesticide Regulation (CDPR) Product Database, we then classified pesticides as insecticides (insecticides, insect growth regulators, miticides, repellents), herbicides, or fungicides. We split total pesticides into target-taxa specific categories: insecticides, further divided into insecticide only and insecticide/fungicide dual action chemicals (e.g., sulfur), fungicides only, and herbicides only. We focus on insecticides throughout because it is the most common type of pesticide applied in this region (Table 1) and because insect pests are thought to be responsive to landscape characteristics. There are additional, less commonly used types of pesticides such as rodenticides that are incorporated into the all pesticide category, but not investigated separately. We rely on target taxa rather than toxicity because (i) we are primarily interested in how organic agriculture impacts different pest taxa, proxied by pest control type, (ii) toxicity is specific to the environmental end point of interest (e.g., fish, mammals, birds), and (iii) toxicity information for all products in use in California is not readily available for any, let alone most, environmental endpoints and is particularly sparse for organic-approved products (*21*). See Supplementary Methods and tables S10 and S11 for additional robustness tests.

#### Fields data

We downloaded the Kern County agricultural fields shapefiles for 2013 to 2019 from the County Agriculture and Measurement Standards website (kernag.com). These data include information on farmer, site, date active, and commodity, among other information. A field is a unique farmer-site-crop-year combination and thus field IDs change when crops are rotated. Linking the field and pesticide use reports, we summed pesticide use over the duration of the crop's growing season and divided it by area permitted to create pesticide use rates (kilograms per hectare). Field polygons that did not have pesticide use records for a given type of pesticides were given a zero for that pesticide use rate.

Multi-crop fields are those with multiple crop types grown simultaneously. Although each crop on a multi-crop field is given a unique ID, which associates with the pesticide use data, the area for each crop is not delineated separately. We determined the number of crops by calculating the number of observations that had the same location, farmer ID and date active. For fields that are multi-cropped, we divided permitted area by the number of crops to more accurately calculate pesticide use rates, as well as surrounding agricultural extent and surrounding organic agriculture (Supplementary Methods).

To avoid counting any potential permit modifications as separate fields, we maintained one observation with the same geometry, commodity, year and permit if the commodity was a perennial or if it was an annual crop with an implausibly short growing season (< 30 days) taking the maximum area and duration of cultivation for calculating spatial overlap variables and taking the sum of pesticide use and the maximum of other covariates for focal fields. We further ran robustness tests removing all overlapping fields of the same commodity (Supplementary Methods).

#### Organic designation

We built on methods for identifying organic fields described in Larsen *et al.* 2021 (*21*). In brief, we obtained a list of organic crop producers by permit-site, Assessor's Parcel Number (APN) and/or Public Land Survey (PLS) Section for 2013 to 2019 through a public records request to the California Department of Food and Agriculture (CDFA). We first matched on permit-site ID and year, if provided, as that directly links to a specific polygon. For the majority that did not include permit-site ID we intersected field polygons from Kern County and within the APN and/or PLS Section to determine which APN or PLS Section contained organic producers. This resulted in 3410 of 4881 unique records matching a field, PLS Section or APN and corresponded to over 12,000 crop fields. However, not all fields in an APN or PLS Section are organic. As such, we further defined organic fields as locations within an APN or PLS Section containing organic producers and that only use organic approved pesticides for 3 consecutive years. Organic-approved pesticides were based on checking the individual pesticide labels and/or the Organic Materials Review Institute Product List and Washington State Department of Agriculture Organic Input Material List. Because field polygons change when crops are rotated or across years, we rasterized the field polygons at 30 m and overlaid the annual rasters to determine whether a given polygon had only organic-approved pesticide use for the current and prior two years. We tested models with a less stringent definition including locations that only use organic approved pesticides for the current year within an APN or PLS Section containing organic producers (fig. S3). There is no perfect means to identify organic fields and it is likely we measure organic fields with some error. Measurement error in the amount of surrounding organic agriculture and other landscape covariates (i.e., the independent variables) would bias our coefficient results toward zero (attenuation bias).

#### Surrounding characteristics

We define surrounding as a circular area of 2.5 km radius from the centroid of the focal field and measure organic area (ha), total cropland area (ha) and share of the 1963-ha buffer cropped by the focal farmer (minus the focal field area), correcting for multi-cropped fields (*19*). A 2.5-km radius was chosen based on the landscape buffers used in previous research on natural enemies and pests (*16*, *32*), though we extend out to 5 km as a robustness test (Supplementary Methods; fig. S2). We measure surrounding as the centroid of the focal field to centroid of other fields, rather than a buffer around the perimeter focal field edge to avoid the nonlinear changes in buffer area with size of the focal field (Supplementary Methods). We further limit surrounding to include fields that were active during the growing season of the focal field. In some years (2018 and 2019), date inactive was missing in a large fraction of observations. Based on the monthly distribution of end dates in other years, we determined the missing end dates were the end of the year.

### Statistical approach

The goal of our analysis is to understand how surrounding organic fields affect pesticide use. In the ideal scenario, we could randomly assign surrounding fields to be organic or conventional and measure the impact on pest control on focal fields. As that is infeasible, we leverage a panel (or longitudinal) data approach to remove heterogeneity unique to farmers, local regions (defined by Public Land Survey Township; ~93 km$^2$), years, and/or crops using a combination of dummy variables in a least-squares dummy variable approach (also referred to as a within estimator or fixed effects in causal inference). These dummy variables remove characteristics that may be correlated with both the amount of surrounding organic agriculture and the level of pest control, as such unobserved variables would bias our coefficient estimate on the effect of surrounding organic fields. For example, time-invariant variables such as soil quality could be correlated with both the amount of organic agriculture and the amount of pesticides applied whereas general trends could be correlated with both pesticide use and the share of organic agriculture. Failing to account for such variables would induce a correlation between our covariate of interest (surrounding organic agriculture) and our errors thereby biasing our coefficient estimate (47–49). Ideally, we would also test models with field dummy variables, but because field is not a constant unit, but rather changes over time with crop rotations or planting decisions, this is not feasible.

As some fields use zero pesticides in a growing season, we inverse hyperbolic sine transform our data to accommodate both nonlinear relationships and zero pesticide use (35). We premultiply pesticide use (kilograms per hectare) by 100 to reduce distortions for small values (35). A version of our model with region and year dummy variables is specified as,

$$IHS(y_{irt}) = \gamma_r + \delta_t + \alpha IHS(Surround\_Org_{irt}) + IHS(X_{irt})^{'}\beta + Org_{irt} + \varepsilon_{irt} \tag{1}$$

where IHS($y_{irt}$) denotes IHS-transformed pesticide use (kilograms per hectare) of farmer $f$ on field $i$ growing in region $r$ and year $t$. Our covariate of interest is the amount of surrounding organic ha, denoted *Surround_Org*, with surrounding cropland extent (ha), focal field size, and share (fraction) of surrounding area cultivated by the focal farmer denoted by the vector $X$. As with log-log elasticities, IHS-IHS transformation can be interpreted as the percentage change in pesticide use for a 1% change in a covariate. The parameters $\gamma_r$ and $\delta_t$ denote region and year dummy variables that absorb region-specific characteristics (e.g., soil quality) and year shocks that affect all fields in Kern County (e.g., weather). Other specifications included dummy variables to absorb characteristics shared by fields growing the same crops (pest susceptibility, value) and those grown by the same farmer (e.g., farmer risk preferences).

The above specification yields a single slope estimate for the effect of surrounding organic area on pesticide use, with an indicator variable, *Org*, allowing for only a different intercept for organic and conventional fields. To test the hypothesis that focal fields may have differential responses to surrounding organic area and other covariates based on their management (organic, conventional), we reran our analysis individually for organic and conventional focal fields by dropping the *Org* covariate and subsetting the data for organic and conventional fields, respectively. This allows for a unique intercept and a unique slope for the effect of surrounding organic area (and all other covariates) on organic versus conventional focal fields. We also reran our analysis on different types of pesticides (insecticides all, insecticides only, insect/fungicides, herbicides only, fungicides only), to evaluate whether the relationship between surrounding organic and pesticide use was dependent on the target taxa. Lastly, in an alternative approach, rather than run separate regressions for organic and conventional fields, we include an interaction term between *Org* and *Surround_Org*, which captures the differential effect of surrounding organic agriculture on pesticide use on organic fields. We interact *Org* with all covariates for similar reasons. We include the level terms (*Org, Surround_Org,* covariates). We de-mean *Surround_Org* to allow for a more convenient interpretation of the dummy variable (50). We use this approach for our simulation because it provides a joint parameter distribution, but continue with separate regressions in our main results such that the dummy variables or fixed effects capture the heterogeneity unique to conventional and organic farmers, regions and crops.

### Simulation

To predict total pesticide use under different hypothetical levels of organic agriculture we proceeded in four steps. First, we estimated a version of Eq. (1) with an interaction terms between surrounding organic and the dummy variable for whether a field was organic, as described above. In addition, we interact the organic dummy variable with all other variables, to allow for heterogeneous response of organic agriculture to changes in field size, the extent of agriculture, etc. The coefficients on surrounding organic were qualitatively unchanged from T,Y,C,F model run separately (fig. S1, T,Y,C,F versus T,Y,C,F-Int), but in addition we get a coefficient for the direct impact of organic agriculture on insecticide use. Second, we randomly draw the parameters from the joint distribution of the estimates. Third, we then predict the change in insecticide use from a level of zero organic farming for all levels of organic agriculture between zero to 25% based on the random parameter draw. Specifically, we predict,

$$IHS(y_{irt}) = \begin{bmatrix} \mu + \alpha_o\ ShareOrganic + \alpha_{oo} ShareOrganic \times IHS(SurroundOrganic) \\ + \alpha_{oc}(1 - ShareOrganic) \times IHS(SurroundOrganic) \times 100 \end{bmatrix} \mu^{-1} \tag{2}$$

for a vector of hypothetical organic agriculture shares (*ShareOrganic*) and taking the direct impact of organic agriculture on insecticide use ($\alpha_o$) as well as the spillovers of organic agriculture on organic ($\alpha_{oo}$) and conventional ($\alpha_{oc}$) agriculture into account. We predict this equation 2000 times using random draws from the joint distribution of regression coefficients following the approach of (51). Each line in Fig. 4 represents an individual prediction. The other components of the simulation are the current mean level of insecticide use on conventional fields ($\mu$) (Table 1) as well as the area of surrounding organic agriculture (*SurroundOrganic*), defined as the share of organic agriculture multiplied by the mean area of current agricultural land in the buffer. The specific value of $\mu$ is less important because the outcomes are normalized to percent. We focus on two scenarios regarding the spatial distribution of organic agriculture. The first scenario assumes an equal spatial distribution of organic agriculture. Here, we assume that the share of organic fields in surrounding area equals the overall share of organic agriculture or in the second scenario ("Clustered") we assume that organic and conventional fields are spatially concentrated such that all fields in the buffer of the focal fields are either organic, if the focal field is organic, or conventional, if the focal field is conventional. For all simulations, we assume that all other covariates remain unchanged. We present a similar approach, but with parameter estimates and standard deviation from table S3 for Insect All in fig. S12. Although this approach is simpler, it also assumes independent parameter distributions Because $\alpha_o$, $\alpha_{oo}$, and $\alpha_{oc}$ come from the three different regressions (All, Org, Conv, respectively). However, the simulation results remain unchanged. In both approaches, the simulation predicts the net change in IHS-transformed insecticides. The level of insecticides can be approximated from the IHS result using sinh(IHS(prediction) * IHS(insecticide use on conventional fields with no surrounding organic agriculture)/100) (Fig. 4) (54). This back transformation is just an approximation for several reasons. Most importantly, the simulated outcome is a weighted mean of IHS-transformed insecticide use on conventional and organic fields. Because $\sinh(a_1 IHS(y_1) + a_2 IHS(y_2)) \neq a_1 \sinh(IHS(y_1)) + a_2 \sinh(IHS(y_2))$, the approximation differs from the true value. Thus, figure 4 accurately illustrates the IHS-transformed outcomes, but it should not be used to calculate insecticide reductions in absolute levels beyond a rough approximation.

### Nationwide extension

To test the external validity of our results, we repeat our analysis at the national level. Because we lack field-level data at the national scale, we focus on the aggregate pattern and test whether they match the predicted, hump-shaped pattern of aggregate pesticide use in response to organic agriculture from our Kern County simulation. For this approach, we combine data from the USGS Pesticide National Synthesis Project with data from the USDA Census of Agriculture.

#### Organic agriculture

The USDA Census of Agriculture provides data on the number of operations with certified organic sales, the number of operations with cropland and the total acreage of cropland at the county level for 2007, 2012, and 2017. To compute the county-level land under organic agriculture, we use the number of operations with certified organic sales multiplied by the average farm size (cropland/number of operations with cropland), both at county-level. We include county and year dummy variables in our empirical estimation to account for the possibility that we systematically over or underestimate the area of organic agriculture due to e.g., differences in farm sizes of conventional and organic operations.

### Pesticides

We use pesticide use data from the USDA Census of Agriculture and the USGS Pesticide National Synthesis Project. The USDA Census of Agriculture collects data on the area treated with chemicals to control weeds, insects, nematodes, and fungi for 1997, 2002, 2007, 2012, and 2017. As a second measure, we use data from the USGS that combines farm surveys of pesticide use with estimates of harvested crop acres to produce county-level data on various pesticides for every year between 1992 and 2017. We select the two most-used herbicides and the two most-used insecticides from Fernandez-Cornejo *et al.* (*52*) for our analysis. We measure pesticide use based on the kilograms of active ingredients.

### Cropland

More than 78% of pesticides in the US are used on four crops: corn, soybeans, potatoes and cotton (*52*). We therefore control for cropland and these four crops in all regression specifications as they may be correlated with the expansion of organic agriculture. Further, hay receives little pesticides, and we control for the area under hay production as well.

### Econometric analysis

The results from the simulation of aggregate insecticide use in Kern County suggest that insecticide use increases initially with organic agriculture due to the increased use of insecticides on conventional fields in response to organic agriculture. This effect is outweighed by the reduced use of insecticides on organic lands at higher levels of organic agriculture. Here, we test whether pesticide uses increase initially and then decline in response to an increasing area under organic agriculture. We therefore estimate,

$$IHS(Pest_{it}) = \alpha_1 IHS(OrganicLand_{it})$$
$$\alpha_2 IHS(OrganicLand_{it})^2 + IHS(X_{it})^{'}\beta + \gamma_i + \delta_t + \varepsilon_{it} \quad (3)$$

where $Pest_{it}$ is the area treated with insecticides and herbicides in county $i$ and in year $t$, $OrganicLand_{it}$ the area under organic agriculture, and $X$ is a vector of covariates including total cropland and the area under corn, soybeans, potatoes, cotton, and hay. The last three terms are county dummies (fixed effects), year dummies, and the error term. In a robustness test, we use the quantity of active ingredients of the two most widely used herbicides and insecticides as the outcome variable. In addition, we estimate a specification in which we drop the squared term of organic land to test whether pesticide use is monotonically declining with organic agriculture, as predicted by our second simulation scenario. We report the Akaike information criterion and the Bayesian information criterion for all specifications.

We transform all variables using inverse hyperbolic sine transformation. We cluster standard errors using two-way clustering at the county and year level. We report our results in tables S12 to S14.

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### SUPPLEMENTARY MATERIALS

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Supplementary Methods
Figs. S1 to S13
Tables S1 to S14
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MDAR Reproducibility Checklist

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