Title: Spillover effects of organic agriculture on pesticide use on nearby fields

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Abstract: The environmental impacts of organic agriculture are only partially understood and whether such practices have spillover effects on pests or pest control activity on nearby fields remains unknown. Using about 14,000 field observations per year from 2013-2019 in Kern County, CA, we estimate that organic crop producers benefit from surrounding organic fields, decreasing overall pesticide use and pesticides targeting insect pests. Conventional fields, in 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.

One-Sentence Summary: Surrounding organic cropland reduces pesticide use on organic fields, while increasing pesticide use on conventional fields.

Main Text

Increasing yields while reducing the environmental footprint of crop production is a major challenge of the 21st century. Organic agriculture is one potential solution that is 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 California Air Resource Board's (CARB) Scoping Plan for Achieving Carbon Neutrality (*4*) portend a further and more dramatic increase in organic production (*5*). Yet, the benefits and drawbacks of organic agriculture remain a topic of active research. While 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 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*). Since 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 whether and how pests and their predators spillover to affect pest control on other fields and farms in the landscape.

The vast majority of the most persistent and human health or 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, though not mutually exclusive, the reduced reliance on chemical pest control in organic agriculture could result in organic fields having higher levels of pests that spillover to other fields (*25*). Bianchi et al. (*25*) illustrate theoretically that these two counteracting effects of organic agriculture can lead to a lose-lose as pesticide use on conventional agriculture reduces natural enemy control, which release pests to increase on organic fields and become a source of pest propagules for conventional fields. Yet, Bianchi et al. (*25*) also show that if organic fields are spatially clustered, natural enemies of pests persist and pest spillovers are reduced. This mechanism suggests 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 (e.g. *26*). In the economics literature, scholars (e.g. *27*) show that landowners reduce their pest eradications efforts in response to reduced pest eradication efforts of their neighbors. This "race to the bottom" is caused by the pest spillovers that reduce the ability of the farmer to control the pests on her land and therefore discourages control efforts in response to increased pest spillovers. 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 ecologic 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, for example, natural enemy spillover, 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, for example, pest spillover, 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.

Here, we seek to understand how surrounding organic crop production influences pesticide use on organic and conventional fields. We address the following questions: 1) How does surrounding organic agriculture impact pesticide use on other fields? 2) Is this effect different for conventional and organic focal fields? 3) Which type of pesticides is most influenced by organic agriculture and is this similar for organic and conventional fields? We focus on Kern County, CA, which is one the United States' leading crop producing and pesticide employing counties, with over $7.4B in annual agricultural production and over 13 million kg of annual 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 7,300 organic and 91,0000 conventional field-year observations representing about 14,000 permitted fields each year between 2013-2019. 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 unique to farmer, year, region and crop type. Based on our results, we then ask (4) how does net pesticide use change as a function of the amount of organic agriculture in the landscape? and (5) do 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 3y of organic-approved pesticide use (see Data). We report about 7.5% of permitted fields and about 5.5% of permitted area, accounting for multi-cropped fields, are organic in 2019 with organic cropland distributed across much of the agricultural region in Kern County, CA, though often clustered (Fig. 1). While 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 if surrounding organic cropland leads to an increase or decrease in pesticide use rates (kg ha^{-1}) on organic and conventional focal fields, where surrounding is defined as a circular area of 2.5km radius (1963ha) around the focal field, following prior literature (*16*, *32*). All models also include covariates for the amount of total cropland ("cropland extent"), adjusted permitted field size (ha), 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 93km^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 a different approach 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.

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 ha^{-1} of active ingredients ("AI") (Fig. 2, Fig. S1, 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 surrounding organic agriculture leads to a small, but significant increase in pesticide use rates on conventional focal fields, reflecting the pooled model. We observe 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. In contrast, the same 10% increase in surrounding organic cropland leads to a 3% decrease in total pesticide use on organic focal fields (Fig. 2, Table S2).

Pesticides encompass 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 insecticide only and insecticide/fungicide dual action chemicals (e.g. sulfur), fungicides only, and herbicides only. Of the taxa-specific categories, 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. Here we see that the "all pesticide" result is primarily reflecting chemicals targeting insect pests or both insect pests and molds (Fig. 2, Table S2-S3). We see that a 10% increase in surrounding organic cropland leads to a 0.3% increase in insecticide use rates (kg ha^{-1}) for conventional focal fields, while leading to a decrease of 2% for organic focal fields. In contrast, we see little effect of surrounding organic cropland on herbicide or fungicide use rates on organic fields (Fig. 2, Table S3).

Organic cropland could influence pest and natural enemy abundance at the local or landscape scale, or some combination. To flexibly model the effect of surrounding organic cropland over space, we analyzed the amount of organic cropland in each of five concentric annuli of 500m width from the focal field out to the 2.5km boundary. Here, 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 2500m. The largest magnitude of the effect is in the first annuli, defined as a circular buffer of 0-500m 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 (500-1000m buffer) and beyond, though remains significant or marginally significant (Fig. 3; Table S4). We see a similar response for insecticides, mostly driven by dual action insecticide/fungicide chemicals (Fig. 3; Table S4, Fig. S2).

We conducted several robustness tests related to calculations of surrounding organic cropland (Table S5-S6, Fig. S3), model specification (Fig. S4-S8, Table S7-S9), and alternative measures of pesticide use (pesticide products, area treated, net applied toxicity (Parker et al.(*37*)); Table S10-S11). We also evaluate whether organic fields and their neighboring fields have similar pesticide dynamics to conventional fields before becoming organic in an event study (Fig. S9-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 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 a nonlinear relationship between the share of organic agriculture in the landscape and total insecticide use. In landscapes with high levels of organic agriculture, pesticide use decreases regardless. However, at low levels of organic cropland dispersed across the landscape, the increased pesticide use due to spillovers (possibly of pests) from organic fields onto conventional fields overwhelm the decreased pesticide use due to the direct effects of organic agriculture plus the spillovers onto organic fields (Fig. 4). This increase in overall pesticide use in response to increases in organic agriculture at low levels of organic agriculture is completely mitigated by a spatial concentration (clustering) of organic agriculture. This spatial concentration reduces pesticide-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 pesticide use at the landscape level compared to 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 California's Air Resource Board's (CARB) target (20%) are above that threshold at which overall pesticide use declines. The simulation results suggest 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 and the Pesticide National Synthesis Project (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 area treated with insecticides and herbicides from the bi-decadal USDA Census of Agriculture from 1997-2017 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, 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 level of organic agriculture and then decline at higher levels, and that this impact is more pronounced for insecticides than for herbicides (Fig. 5,Table S12-S14). We visualize this nonlinear relationship in Figure S11.

Discussion

Crop pests respond to both local and landscape characteristics. While 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.

While 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*). Here we find 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. Were Kern to increase organic production to 20% of cropland, as suggested by California's Air Resource Board, that would represent over a 260% increase using 5.5% as the baseline. Such a change, depending on the spatial distribution, would have a notable impact on pesticide, and particularly, insecticide use. Our simulation suggests that in aggregate, such an increase in organic production would reduce insecticide use by about 10%, if clustered, or only about half that if dispersed. Given over 7M kg of insecticide active ingredients were applied in Kern in 2019, the difference between clustered and dispersed represents over 350,000 thousand kg y^{-1} of insecticide active ingredients per year.

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 spillover to impact 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*). In 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 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, while 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 mainly immediately adjacent fields or other crops in multi-crop 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 multi-cropped fields. However, there remains a benefit of surrounding organic agriculture at distances between 1-2.5 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. Yet, 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 the majority of variation in pesticide use. Here 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 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 the majority of agricultural regions in the US or globally. Pesticide use is, unfortunately, 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*). Yet, our national-scale robustness test suggests the overall relationships observed in Kern persist elsewhere, despite differences in crop composition and climate.

Methods and Materials

Data

Pesticides data: We obtained field-by-day pesticide use reports for Kern County for 2013-2019 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 1) we are primarily interested in how organic agriculture impacts different pest taxa, proxied by pest control type, 2) toxicity is specific to the environmental end point of interest (e.g. fish, mammals, birds), and 3) 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 Table S10-S11 for additional robustness tests.

Fields data: We downloaded the Kern County agricultural fields shapefiles for 2013-2019 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 (kg ha^{-1}). 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. While 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 (<30d) 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 2013-2019 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 3,410 of 4,881 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. Since field polygons change when crops are rotated or across years, we rasterized the field polygons at 30m and overlaid the annual rasters to determine if 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 towards zero (attenuation bias).

Surrounding characteristics: We define "surrounding" as a circular area of 2.5km 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 2.5km radius was chosen based on the landscape buffers used in previous research on natural enemies and pests (*16*, *32*), though we extend out to 5km 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, 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 impact pesticide use rates. 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; ~93km^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 while 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 since "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 pre-multiply pesticide use (kg ha^{-1}) by 100 to reduce distortions for small values (*35*). A version of our model with region and year dummy variables is specified as,

$$IHS(y_{irt}) = \gamma_r + \delta_t + \alpha IHS\left(Surround_{Org_{irt}}\right) + IHS(X_{irt})'\beta + Org_{irt} + \varepsilon_{irt} \qquad (1)$$

where IHS(y_{irt}) denotes IHS transformed pesticide use (kg ha^{-1}) 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 (proportion) 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 γ_r and δ_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 equation (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 (Figure 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,

$$IHS(y_{irt}) = \begin{bmatrix} \mu \; + \alpha_o \, ShareOrganic + \; \alpha_{oo} \;\; ShareOrganic \times IHS(SurroundOrganic) \\ +\alpha_{oc} \, (1 - ShareOrganic) \times IHS(SurroundOrganic) \end{bmatrix} \mu^{-1} \times 100 \tag{3}$$

for a vector of hypothetical organic agriculture shares ($ShareOrganic$) and taking the direct impact of organic agriculture on insecticide use (α_o) as well as well as the spillovers of organic agriculture on organic (α_{oo}) and conventional (α_{oc}) agriculture into account. We predict this equation 2,000 times using random draws from the join distribution of regression coefficients following the approach of (*51*). Each line in Figure 4 represents an individual prediction. The other components of the simulation are the current mean level of pesticide use on conventional fields (μ) 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 μ 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. For 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 Figure S12. While this approach is simpler, it also assumes independent parameter distributions since α_o, α_{oo}, and α_{oc} come from the three different regressions (All, Org, Conv respectively). However, the simulation results remain unchanged.

Nationwide extension

To test the external validity of our results, we repeat our analysis at the national level. Since 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 on 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 (kg) 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.

Econometeric 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,

$$IHS(Pest_{it}) = \alpha_1\, IHS(OrganicLand_{it}) + \alpha_2 IHS(OrganicLand_{it})^2 + IHS(X_{it})'\beta\ + \gamma_i + \delta_t + \varepsilon_{it} \quad (4)$$

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 Table S12 -S14.

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Supplementary Materials

Supplementary Methods

Figs. S1 to S13

Tables S1 to S14

References (55-58)

Figure Legends & Tables

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

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 (kg ha^{-1}) 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 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 SI (Table S2-S3).

Fig. 3. The effects of organic cropland at different distances from organic focal fields for total pesticide active ingredients (kg ha^{-1}; closed circle), all insecticide use (open circle), and two subcategories of insecticides. The y-axis is pesticide elasticity, or the percent change in total 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 500m 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% confidence interval using standard errors clustered on farmer ID. Tables with the coefficient and standard error estimates, number of observations, and other covariates are in the SI (Table S4).

Fig. 4: Simulation of the impact of organic agriculture on total insecticide use based on 2,000 random draws from the joint normal parameter distribution of specification T,Y,C,F-Int reported in Figure S1. The outcomes are expressed in inverse hyperbolic sine (IHS) transformed insecticide use relative to the 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 grey line shows the 2019 level of organic agricultural area in Kern County. The dotted black line shows the CARB target for organic agriculture.

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.

	Conventional	Organic
Field Size (Ha)	31.74 (33.78)	18.99 (14.82)
Cropland Extent (Ha)	1748.37 (601.8)	1977.50 (818.7)
Surrounding Organic (Ha)	71.88 (223.1)	837.09 (608.2)
Same Owner (Ha)	434.47 (443.7)	720.84 (594.9)
Same Crop (Ha)	444.38 (407.4)	166.09 (246.4)
Crop Diversity	0.70 (0.183)	0.85 (0.107)
All Pesticide AI (Kg ha^{-1})	26.65 (82.73)	8.61 (26.34)
All Insecticide AI (Kg ha^{-1})	18.43 (68.43)	7.29 (24.27)
N	91,155	7,352

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 (ha) 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 multi-cropping (see Data, Supplementary Methods).