Agricultural landscape simplification does not consistently drive insecticide use

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The increase in agricultural production over the past 40 y has greatly altered land-use patterns, often resulting in simplified landscapes composed of large swaths of monocultures separated by small fragments of natural lands. These simplified landscapes may be more susceptible to insect pest pressure because of the loss of natural enemies and the increased size and connectivity of crop resources, and a recent analysis from a single year (2007) suggests this increased susceptibility results in increased insecticide use. I broaden the temporal analysis of this connection between landscape simplification and insecticide use by examining cross-sectional and panel data models from multiple decades (US Department of Agriculture Census of Agriculture years 2007, 2002, 1997, 1992, 1987) for seven Midwestern states composed of over 560 counties. I find that although the proportion of county in cropland—my metric for landscape simplification—was positively correlated with insecticide use in 2007, this relationship is absent or reversed in prior census years and when all years are analyzed together. This broader temporal perspective suggests that landscape simplification has inconsistent effects on insecticide use and that multiyear studies will be key to unlocking the true drivers of variation in insecticide application.

pesticides | ecosystem services | land-use policy | longitudinal data

Agricultural production has grown to meet the demands of an increasingly large and wealthy human population. The development of high-yield crop varieties combined with the widespread use of irrigation, synthetic fertilizers, pesticides, and land-use changes that marked the "Green Revolution" have enabled an enormous increase in crop production per area (1–3). As a result of these technologies, cereal production has doubled (1). This increased production is credited with reducing poverty and improving nutrition intake for millions of people worldwide (1, 4).

However, this increase in production also has costs. There are concerns that the loss of natural enemies and biodiversity caused by the increased size and connectivity of agricultural land, the trend toward monocultures, and the conversion of natural habitat—termed "landscape simplification"—makes farms more susceptible to pest outbreaks (5–8). With increased risk of pest outbreaks comes enhanced pesticide use. Although other aspects of intensive farming also have negative externalities, such as synthetic fertilizers and eutrophication, pesticides have received some of the most widespread scrutiny and their reduction (or at least efficient use) has become a priority for policy makers, as evidenced by integrated pest management (9). The emphasis on pesticide use stems from serious human health concerns related to pesticide exposure in farm workers (3, 10, 11), pesticide residues in food and water sources (9, 12), and bioaccumulation of pesticides in higher trophic levels (13).

Despite popular ecological thinking that the connection between landscape simplification and pesticide use is clear, both theoretical and empirical studies have found ambiguous results. Agroecological theory holds that landscapes composed of a high proportion of cropland are more susceptible to pest outbreaks because of their habitat homogeneity and reduced natural enemy populations. Therefore, more simplified landscapes would experience more pest problems and consequently use more pesticides. Conversely, economic theory of pesticide use suggests that the application of pesticides by a neighboring farm may have positive externalities for surrounding farms as a result of pesticide drift or pest suppression (9). Additionally, as the amount of land in cropland increases, opportunities for invasion or refuge from pesticide applications may be reduced, thus leading to a negative effect of landscape simplification on pesticide use. Three recent reviews of empirical, landscape-scale ecological studies evaluating the effect of landscape complexity on insect pests reported similarly equivocal results, with some studies finding reduced pest pressure, pest abundance, or pest diversity, whereas others find no relationship or the opposite relationships (6, 14, 15).

The variability in the literature may reflect the inadequacy of current study designs to disentangle the net effect of landscape simplification on pesticide use. Confounding variables, such as crop type, or endogenously determined variables, such as farm size or income, could give misleading results if not properly controlled for. Alternatively, studies that are small scale or over short time periods may miss important underlying drivers of pest abundance.

Many ecological processes governing agricultural pest abundance occur over a large spatial scale. Pests disperse large distances, both naturally and aided by the movement of people and goods. Agricultural pests are thus likely governed in large part by metapopulation processes (i.e., immigration and extinction) (16). Within an agricultural landscape pests may go locally extinct from crop patches because of pesticide use or because of stochasticity influencing small populations, only to be recolonized from a persistent metapopulation existing in the surrounding agricultural matrix or from a new invasion into the system. Natural enemies too may require resources outside of individual

Significance

Increases in agricultural production have greatly altered land-use patterns, often resulting in simplified landscapes composed of large monocultures separated by fragments of natural lands. It is thought that these simplified landscapes enable agricultural insect pests to thrive due to an absence of predators and abundant food, necessitating greater insecticide use. Despite the logic of this theory, empirical support is lacking. Using a multiyear analysis it becomes clear that the presence and direction of the relationship between landscape simplification and insecticide use varies greatly between years. In some years more simplified landscapes have increased pest pressure, whereas in other years there is no relationship or it is reversed. Understanding the nature of this variability is critical for land use policy.

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crop fields for alternative prey and shelter for overwintering or from disturbances, such as pesticide application or harvest (17). Furthermore, the periodic disturbance of crop fields may disrupt predator–prey dynamics by reducing natural enemies directly (17) or by temporarily reducing pest populations to the level below which predators can be supported. As a result of pest and natural enemy dispersal and immigration, the effect of local processes on regional abundances may be small, despite large effects on within-field abundances. Thus, small-scale studies that fail to account for the landscape-scale dynamics of agricultural pests and their natural enemies could result in spurious associations of what promotes or limits pest abundance. For these reasons, landscape-scale studies provide the best insight into the effect of habitat simplification on pests (15).

Beyond metapopulation dynamics and trophic interactions, invasion and spread of insect pests and natural enemies are partly stochastic processes influenced by yearly environmental conditions and by the timing of insect pest (9) and natural enemy arrival (18). Thus, temporal scale may be equally as important as spatial scale to disentangle the effects of landscape simplification on pest abundance. For example, a heat wave at the right time of the growing season may result in widespread pest mortality and high crop yields, whereas a heat wave at a different time of the season may stress crops, making them more susceptible to pest outbreak but having little effect on the pests themselves. This variability over time could appear like ambivalent results of landscape simplification when it is instead the result of the interaction between insect pests and weather.

If we are to mitigate the effects of pesticide use on both human health and ecological systems, it is necessary to understand the underlying abiotic or biotic factors resulting in differences in pesticide use. Here I take advantage of longitudinal data from the US Department of Agriculture (USDA) Census of Agriculture to revisit whether landscape simplification is a consistent driver of insecticide use. I perform cross-sectional analyses for five USDA census years (2007, 2002, 1997, 1992, 1987) in seven Midwestern US states (Illinois, Indiana, Iowa, Michigan, Minnesota, Ohio, and Wisconsin) at the county level. I follow this with a panel data analysis using a fixed-effects model, which identifies the effect of landscape simplification on insecticide use using year-to-year variation within counties. I specifically focus on insecticides in these states to compare this multiyear analysis with a recent single-year study by Meehan et al. (7). I check the robustness of these results by comparing data from the USDA Census of Agriculture (19) to the National Agricultural Statistics Service Cropland Data Layer (20), and check different selection criteria for included counties. I compare these results to that of Meehan et al. (7), who used the same data sources and model specifications for 2007 only, and find that incorporating multiple years of data as I do here provides insights impossible to glean from a single data year.

Results

Descriptive Analyses. Time trends for each covariate for each state were plotted to ensure that no unexpectedly large changes in land use were present in the data. Within each state, proportion of the county in cropland, proportion of cropland in corn, soybeans and small grains, and fruit and vegetable orchards, and net income per harvested hectare (in 2007 dollars) remained similar over the study period, 1987–2007 (Figs. 1 and 2). The proportion of the cropland treated with insecticides averaged 0.191 across all states and time periods, with the lowest average of 0.147 occurring in 1997 and the highest average of 0.259 occurring in 2007 (Fig. 2).

Econometric Analyses. The coefficient of interest was the metric for landscape simplification (i.e., proportion of county in cropland), and thus these results focus on that coefficient. For all

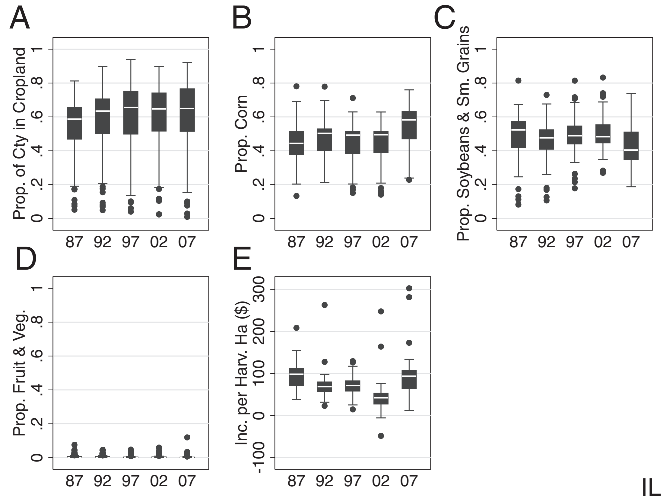

Fig. 1. (*A*–*E*) Time trends for covariates for Illinois. County is abbreviated "Cty" and "Prop. (crop type)" indicates proportion of cropland in (crop type). Covariates remained similar over the period from 1987 to 2007 indicating that the counties were comparable over this time frame. Other states displayed a similar pattern over time.

models, proportion of cropland in corn, soybeans and small grains, and fruit and vegetable orchards are included as covariates. Their coefficients and SEs are reported in Tables 1 and 2, and Tables S1–S3.

Using the most recent census year available (2007), I tested the effect of data source, model specification, and the potential for endogeneity of income. I first compared these results to that of Meehan et al. (7) who, using the same model specification, found a significant positive effect of landscape simplification on insecticide use using data for 2007 from the Census of Agriculture and the NASS CDL. Because the NASS CDL data are only available for the census year 2007 and more recent years, I compared these results with similar data from the USDA Census of Agriculture to understand if differences in results could be attributable to differences in data sources. Regardless of data source or of the selection (exclusion) criteria of counties in the analysis (*Methods*), I found a significant positive coefficient on proportion of county in cropland in 2007. The NASS data and selection criteria used by Meehan et al. (7) provided the most conservative estimate, whereas the census definition yielded the most liberal estimate of the effect of landscape simplification on insecticide use (Table 1).

To check whether the potential endogeneity of income was having an effect on the estimates, I reran the above regressions removing income per harvested hectare from the regression equations. In all specifications, the coefficients were similar, with or without income included in the regression (Table S1), indicating that income was not biasing the regression coefficients.

For the census years before 2007, all data were derived from the Census of Agriculture. For all model specifications, I found the effect of landscape simplification to vary widely among census years (Fig. 3, Table 2, Fig. S1, and Table S2). In 2002 and 1997, the coefficients on proportion of the county in cropland were generally negative and always nonsignificant, whereas in 1992 the estimates were negative and significant. Depending on the model specification, 1987 was either negative and significant or negative but not significant. Table 2 shows the results from the model that included all counties and Table S3 shows the results for all other selection criteria.

To determine whether either of the major crops was driving the variation in the results, I reran the above regressions for counties

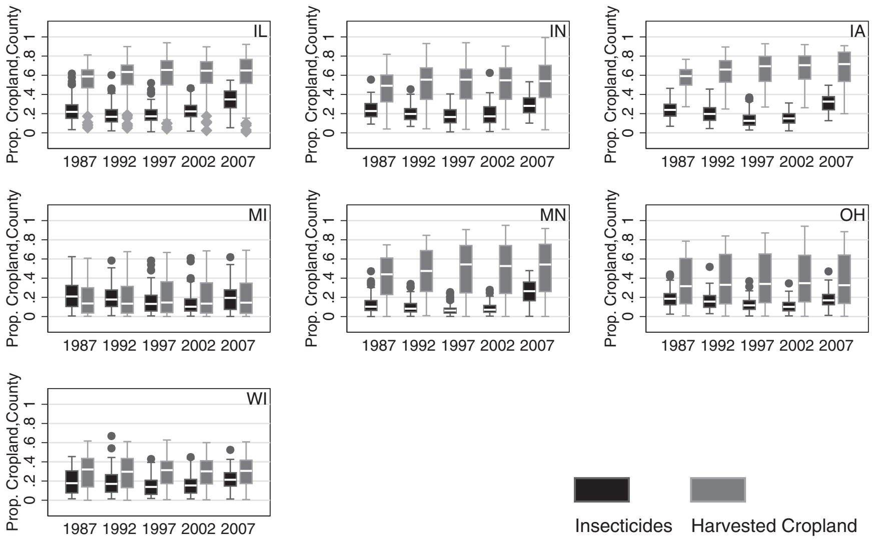

Fig. 2. Time trends in dependent variable, proportion of cropland treated with insecticides, and the landscape-simplification metric, proportion of the county in cropland, for all states and all years. Proportion of cropland treated with insecticides and proportion of the county in cropland are roughly similar within each state across all time periods, although all states had at least a small increase in proportion of treated area in 2007.

with more than half of cropland in corn, more than half of cropland in soybeans, and more than one-fifth of cropland in each corn and soybeans. Neither the counties with a high percentage of corn, soybeans, nor the combination consistently reflected the results from the full model, indicating that the variation observed was not simply reflecting variation driven by one crop type.

For the fixed-effects models, I tested models with just county, just year, or both county and year fixed effects. The fixed-effects model exploits the year-to-year (census-to-census) variation in land-use at the county level to estimate how landscape simplification affects insecticide use, after controlling for year effects that are shared by all counties (*Methods* and *SI Text*). Both year and county fixed effects were found to be statistically important. An *F*-test assuming homoskedastic SEs (for computational feasibility) rejected the null hypothesis that year fixed effects were equal to zero [$F_{(4,3028)} = 97.223$, $P < 0.0001$] and that county effects were equal to zero [$F_{(619,2418)} = 5.035$, $P < 0.0001$], indicating that unobserved heterogeneity in both year and county was present. Controlling for year effects proved very influential. Without year effects, the coefficient on proportion of county in cropland was negative and significant for all but one model specification (Table 2 and Table S3). However, after controlling for year effects, I found no significant relationship between proportion of county in cropland and proportion of cropland treated with insecticides (Table 2 and Table S3).

Table 1. Landscape simplification has a positive effect on insecticide use in 2007, regardless of data source or selection criteria

Model components	1	2	3
Proportion of county in cropland	0.0975**	0.1362**	0.1297**
	(0.0343)	(0.0293)	(0.0296)
Income per harvested hectare	0.0001	0.0002**	0.0001*
	(0.0001)	(0.0000)	(0.0000)
Proportion corn	0.4957**	0.4008**	0.4100**
	(0.0962)	(0.0697)	(0.0671)
Proportion soybeans and small grains	0.0508	−0.0029	−0.0000
	(0.0386)	(0.0356)	(0.0367)
Proportion fruit and vegetable	0.9549**	0.8928**	0.8546**
	(0.0790)	(0.0545)	(0.0631)
Constant	−0.0450	−0.0134	−0.0095
	(0.0335)	(0.0147)	(0.0139)
Observations	562	596	603
R^2	0.59	0.65	0.65
SE clusters	ASD	ASD	ASD
No. clusters	62	63	63
NASS cropland	X		
Census cropland		X	X
NASS selection	X		
Census selection		X	

In column 1 cropland was defined based on the NASS CDL (see text). In columns 2 and 3 cropland was defined as total harvested acres based on the Census of Agriculture. All three specifications used cluster robust SEs, clustering on the ASD within each state. In columns 1 and 2 counties were excluded if the respective definition of proportion of county in cropland < 0.01. In column 3 no counties were excluded. For each covariate, the regression coefficient is the top number in the cell with the standard errors below in parentheses. X indicates the data source and selection criteria. *P < 0.05, **P < 0.01.

Discussion

Annual expenditure on insecticides is over 4 billion dollars in the United States (21), which equates to the use of almost 100 million pounds of active ingredients (21). Given the many health and environmental consequences related to insecticide exposure, it is critical to understand what farm, landscape, or environmental characteristics drive the insect pests that motivate insecticide use. It has long been thought that landscape simplification is one of these characteristics. Reviews of empirical evidence for this theory have been largely inconclusive (6, 14, 15), although a recent statistical analysis of the Midwestern United States in 2007 found a strong, positive relationship between landscape simplification and insecticide use (7).

Here I analyzed data from five USDA Census of Agriculture years using cross-sectional and fixed-effects models. The cross-sectional results show that landscape simplification does not consistently drive higher insecticide use. Although the coefficient on proportion of county in cropland, my metric for landscape simplification, is positive and significant in the 2007 analyses, that relationship is absent or reversed in prior census years. Furthermore, adjacent census years, such as 2002–2007 and 1992–1997, show large changes in the magnitude and changes in significance of the landscape-simplification coefficient.

Table 2. Cross-sectional analysis of census years 2007–1987 and fixed-effects analysis

Model components	2007	2002	1997	1992	1987	A	B	C
Proportion of county in cropland	0.1297**	0.0044	−0.0249	−0.0810*	−0.0865*	−0.0080	−0.1379**	−0.0133
	(0.0296)	(0.0438)	(0.0391)	(0.0394)	(0.0391)	(0.0164)	(0.0409)	(0.0397)
Income per harvested hectare	0.0001*	0.0000	0.0001	0.0001*	0.0002*	0.0001*	0.0001	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Proportion corn	0.4100**	0.3256**	0.3412**	0.3897**	0.5873**	0.4269**	0.6936**	0.4830**
	(0.0671)	(0.0544)	(0.0617)	(0.0744)	(0.0695)	(0.0298)	(0.0479)	(0.0575)
Proportion soybeans and small grains	−0.0000	−0.0073	−0.0324	−0.0694	0.0094	−0.0391*	−0.3525**	−0.3875**
	(0.0367)	(0.0362)	(0.0386)	(0.0482)	(0.0446)	(0.0184)	(0.0468)	(0.0502)
Proportion fruit and vegetables	0.8546**	0.7998**	0.8568**	0.7018**	0.8202**	0.7914**	0.4733**	0.3305**
	(0.0631)	(0.0895)	(0.0618)	(0.0752)	(0.0566)	(0.0452)	(0.0962)	(0.0973)
Constant	−0.0095	0.0226	0.0214	0.0585*	−0.0209	0.0181	0.0904*	0.1638**
	(0.0139)	(0.0159)	(0.0138)	(0.0241)	(0.0199)	(0.0100)	(0.0374)	(0.0415)
Observations	603	604	612	613	606	3,038	3,038	3,038
R^2	0.65	0.29	0.36	0.38	0.56	0.48	0.75	0.79
SE clusters	ASD	ASD	ASD	ASD	ASD	County	County	County
No. clusters	63	62	63	63	63	620	620	620
Year effects						Y	N	Y
County effects						N	Y	Y

Cropland was defined using the census metric, total harvested acres. All counties were included in each analysis. Column A includes year fixed effects, column B includes county fixed effects, and column C includes both, as indicated by the Y (included) and N (not included). The number of counties varies year-to-year because counties missing data on insecticide use or cropland in a given year were dropped. For each covariate, the regression coefficient is the top number in the cell with the standard errors below in parentheses. *$P < 0.05$, **$P < 0.01$.

It is evident that the drivers of insecticide use may not be easily or reliably identified using single time-period studies. Using a fixed-effects model to remove unobserved characteristics, I find a nonsignificant relationship between landscape simplification and proportion of county in cropland. Counterintuitively, these results suggest that as cropland increases, the proportion of cropland sprayed with insecticides is unaffected.

The existence of a null relationship between landscape simplification and insecticide use is not unlike the results of Hutchison et al. (22), who reported large reductions in the European corn borer in non-*Bacillus thuringiensis* corn as a positive externality from *B. thuringiensis* corn plantings. Although pesticides may have negative effects on public health, biodiversity, and ecosystem services, the application of pesticides by a nearby farm may reduce pest incidence on surrounding farms because of pesticide drift or pest suppression (9).

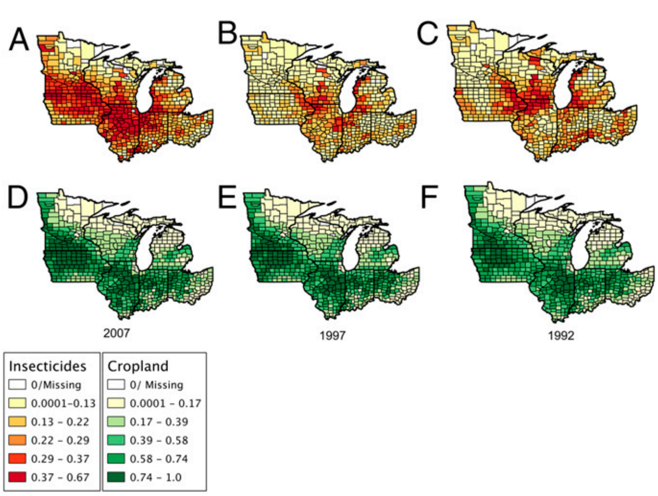

Fig. 3. Map of proportion of cropland treated with insecticides (*A*–*C*) and proportion of the county in cropland (*D*–*F*) for 2007, 1997, and 1992 (see Fig. S3 for 2002 and 1987). The within- and between-county proportion of cropland treated with insecticides varies greatly between years. A positive correlation between cropland and insecticides is visually evident in 2007 and is absent in 1997 and reversed in 1992. The legend is based on 2007 quintiles with the range of the first and last quintile extended to incorporate the lowest (highest) values of the other years.

Additionally, as the amount of land in cropland increases, opportunities for invasion from natural or untreated areas may be reduced. As a result of landscape simplification, natural lands have been isolated to farm boundaries, fallow lands, or wood lots (6). Numerous ecological studies have found that these fragmented natural or less intensively managed areas can act as a source for natural enemies (e.g., ref. 23) and pest species (15) that recolonize species poor crop fields (5). If the cost of pest invasion is greater than the benefits of natural enemy pest suppression stemming from noncropland, these habitats can have a net negative impact on the farmer in terms of pest control.

The above mechanisms may explain why a null relationship is observed in the fixed-effects model; however, they do not account for the importance of year. What could explain the wild variation in the landscape simplification coefficient in the cross-sectional analyses and why year fixed effects are so important? There are a number of drivers that could be behind the year-to-year variability, and deciphering which mechanism is at play is critical because different policy measures are needed to address different types of drivers.

For example, a stochastic driver such as weather could be the culprit. Insect development is strongly influenced by weather conditions, such as temperature and precipitation, and thus yearly differences in these or other environmental conditions could have an important effect on insecticide demand and the relationship between landscape simplification and insecticide use. Preliminary analysis indicates that the effect of weather on this relationship is complex. [Preliminary analysis using growing season precipitation and degree days based on the National Climatic Data Center Global Historical Climatology Network-Daily file does not explain the variation in the cross-sectional relationship between landscape simplification and insecticide use.] This finding may be because the timing of pest arrival relative to the growing season may determine the likelihood of pest outbreaks and the benefits of applying insecticides (9). Furthermore, temperature and precipitation affect the survival and development of different pests (and their enemies) differently, and thus which pests and enemies are present may determine the effect of weather on the relationship between landscape simplification and insecticide use. Refined data on pest outbreaks or type and timing of insecticide use are currently not available for the study area examined. However, the development of such data or further empirical study focusing on abiotic conditions would greatly increase our understanding of the link between weather events and insect outbreaks, and thus increase our ability to forecast variation in insecticide use both now and under future climate change.

It is also conceivable that the change in the relationship between landscape simplification and insecticide use between 2007 and all previous years reflects a systematic and predictable trend in insecticide use. For example, in 1996 there was a major change in the regulation of pesticides in the form of the Food Quality Protection Act (FQPA). FQPA prompted the reevaluation of all (and restriction of many) registered pesticides, and promoted the use of more selective, less persistent "reduced-risk" pesticides via a fast-track registration process (24).

FQPA could affect the relationship between landscape simplification and insecticide use because insecticides that are effective against a multitude of insect pests and persist in the environment for longer periods of time may have provided higher positive externalities to surrounding crop fields, thus necessitating less insecticide use in landscapes dominated by agricultural fields. The implementation of FQPA and the resulting use restrictions took 10 y, and phasing out of certain chemicals is still in progress (24). Because changes in available insecticides were occurring between 1996 and 2007, it is difficult to statistically evaluate the effect of FQPA on the results reported here. Future Census' of Agriculture (i.e., 2012, 2017) or more refined insecticide data that include information on the active ingredient in use could elucidate how policy changes are interacting with the relationship between landscape simplification and insecticide use.

Agriculture has vast impacts on the Earth's environment and these impacts are only expected to grow as demand increases in the coming decades (25). The challenge, as Balmford et al. (26) discuss, is how to meet the increasing demand with the least effect on native biodiversity and the ecosystem services intact ecosystems provide. There are various advantages and disadvantages to whether increased demand should be met by increased intensity of farming on current agricultural land (land-sparing) or by increased land conversion to agriculture to be farmed with more biologically harmonious farming methods (land-sharing) (26–29). In the Midwestern United States, it appears that land-sparing at the county level (i.e., more simplified landscapes) does not lead to consistent increases in the proportion of cropland treated with insecticides. However, without understanding what is behind the year-to-year variation in the relationship between landscape simplification and insecticide use, it is impossible to predict how land-sharing or land-sparing as a policy initiative would affect insecticide use in the future. As suggested by this study and recent empirical reviews (14, 15), the presence and direction of the relationship between landscape simplification and insecticide use can be positive, negative, or null. If this variation is driven by variation in yearly weather, whether simplified landscapes cause more or less insecticide use could flip flop unpredictably. If the variation is driven by extreme weather or weather characteristics that will be altered with climate change, perhaps there will be some directionality. If the relationship between landscape simplification and insecticide use is an indirect consequence of management policies, perhaps 2007 is a glimpse of the future. The data available are currently inadequate to decipher the underlying mechanisms. However, given the different policy implications of a stochastic driver, such as weather, versus a predictable driver, such as regulatory change, developing the necessary data sources to tease apart the underlying causes is imperative.

Perhaps most importantly, this study emphasizes the need for longer-term research agendas, especially when investigating a politically, economically, and ecologically important question, such as insecticide or pesticide use. Analyses of single census years provide wildly varying estimates of the effect of landscape simplification on insecticide use. It is evident that the relationship between landscape simplification and insecticide use is spatially and temporally context-dependent, and that there are a number of ways that context could be determined. Although it remains unclear what underlying mechanisms are providing the context, it is abundantly clear that the relationship between landscape simplification and insecticide use observed in 2007 does not hold for previous census years. It is time to move beyond simply asking whether landscape simplification drives insecticide use and instead focus on what factors may explain the variability in this relationship over time and space.

Methods

NASS Data. To first replicate Meehan et al. (7), I obtained remotely sensed land cover data from the NASS 2007 CDL for the counties in the following states: Illinois, Indiana, Iowa, Michigan, Minnesota, Ohio, and Wisconsin. Like Meehan et al. (7), cropland was defined as the sum of all land in field crops (minus nonalfalfa hay), vegetable, fruit, and nut crops, and proportion of the county in cropland was defined as cropland divided by the total area in the county based on the NASS data (NASS specifications only). Fifty-six counties with a proportion of cropland <0.01 were removed, as were five counties that were missing data on the area treated with insecticides for the census year 2007, leaving 562 counties.

Census of Agriculture Data. Data on the total land in county, total harvested cropland, income, area treated with insecticides, area of corn (grain and silage), soybeans, small grains (barley, oats, wheat), vegetables, and fruit and nut orchards were obtained for the 1987, 1992, 1997, 2002, and 2007 Census' of Agriculture. Income was adjusted for inflation and reported in 2007 dollars. To extend the analysis beyond 2007, I needed to define "cropland" based on a census metric rather than on the NASS CDL, which did not exist for the Midwest for years before 2007. I redefined "cropland" as total harvested acres, and proportion of county in cropland as total harvested acres divided by total land in the county (from the census data). Using this definition, only 12 counties were excluded in 2007 for proportion of cropland <0.01. Proportions of cropland treated with insecticide and proportion of cropland in a given crop type were calculated as insecticide (crop) area divided by total harvested cropland. Observations were dropped if they were missing data (or if data were withheld to avoid identifying individual farms) on the dependent variable (insecticide use) or the covariate of interest (harvested cropland). For the other covariates, I set withheld values to zero to avoid dropping a large number of counties (over 100 in 1987), which were missing one of the covariates (dropping all observation with missing data or with zero values for any covariate did not affect the patterns observed).

I used the NASS Agricultural Pesticide Use Database (30) to check that proportion of the cropland treated with insecticide reflected the amount (pounds of active ingredients) of insecticides applied at the state level (*SI Text* and Fig. S2).

Statistical Approach. To analyze whether landscape simplification drives insecticide use, I use both cross-sectional analyses for each of the five census years and fixed-effects models on all five census years. Please see the *SI Text* for additional information on these techniques. For both analyses the outcome variable was proportion of cropland treated with insecticide and the coefficient of interest was proportion of the county in cropland. Because insecticide use varies by crop type, I included covariates for proportion of the cropland in corn, proportion of the cropland in soybeans and small grains, and proportion of the cropland in fruit and vegetable orchards following Meehan et al. (7). I also included a covariate for 2007 adjusted income to control for the possibility that higher income farms would use more insecticides (see *SI Text* for additional model details).

Cluster-robust standard errors (SEs) are used to account for spatial autocorrelation in the above models. The USDA defines Agricultural Statistics Districts (ASD) within each state to reflect similarities in "geography, climate, and cropping practices" (31). There are roughly nine ASDs in each state (e.g., northwest, north central, northeast) composed of several counties. I chose to cluster on the ASD for the cross-sectional models allowing for covariance between counties in an ASD. [I checked for additional spatial correlation outside of ASDs using Conley SEs (32, 33), allowing for arbitrary correlation for counties within 100 km and 150 km of a given county centroid. Patterns of significance were largely the same.] For the fixed-effects models there is an observation in each county for each year, and thus I take advantage of the repeated observations per county and cluster at the county level (34). I chose cluster-robust SEs rather than heteroskedasticity-robust or spatial autoregressive errors to allow for arbitrary covariance between counties within an ASD or within counties over time (35, 36). The choice of SEs does not change the estimate of the coefficient but does change the range of the 95% confidence interval and thus whether or not the coefficient is considered statistically significant. All analyses were completed in Stata 12SE. I used Quantum GIS 1.8.0 to make Fig. 3, Fig. S3, and to obtain county centroid coordinates.

Model Robustness Checks. I checked the robustness of the cross-sectional results for different selection criteria and different definitions of cropland. For 2007, I first followed Meehan et al. (7) and removed all counties that had less than 1% cropland based on the NASS CDL data. I repeated the analysis, again for 2007, using the census definition of cropland and removed counties whose census percent cropland was less than 1%. I repeated the analysis a final time not excluding any counties. Additionally, for 2007 I ran analyses with the NASS CDL definition of proportion of county in cropland and the census definition of proportion of county in cropland to see how the difference in definition influenced the magnitude of the coefficient. For years before 2007 the census definition of proportion of county in cropland was the only metric available and, thus, was the covariate included for 1987–2002 cross-sectional analyses and all fixed-effects models. For selection in the cross-sectional years before 2007 I tried: (*i*) removing all counties that were not included by the Meehan et al. (7) selection criteria in 2007; (*ii*) removing counties that were not included by the census selection criteria; and (*iii*) not removing any counties. For the fixed-effects models I additionally tried only including counties that had data in all years (i.e., a balanced panel).

Finally, I addressed the possibility that these estimates suffer from endogeneity bias stemming from the income covariate. In other words, if income drives insecticide use but the converse is also true, that insecticide use drives income, then the estimates of the slope coefficient on income and all of the other covariates correlated with income will be biased (37). To evaluate this potential endogeneity problem, I reran the 2007 models excluding income. If endogeneity of income is biasing the estimates of the coefficients, I expected the coefficients on the other covariates to change when income is removed.

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