Research Article

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Landscape crop composition effects on cotton yield, *Lygus hesperus* densities and pesticide use

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Abstract

BACKGROUND: Landscape crop composition surrounding agricultural fields is known to affect the density of crop pests, but quantifying these effects, as well as measuring how they translate to changes in yield, is difficult. Using a large dataset consisting of 1498 records of commercial cotton production in California between 1997 and 2008, we explored the relationship between landscape composition and cotton yield, the density of *Lygus hesperus* (a key cotton pest) at field-level and within-field spatial scales and pesticide use.

RESULTS: We found that the crop composition immediately adjacent to a cotton field was associated with substantial differences in cotton yield, *L. hesperus* density and pesticide use. Furthermore, crops that tended to be associated with increased *L. hesperus* density also tended to be associated with increased pesticide use and decreased cotton yield.

CONCLUSION: Our results suggest a possible mechanism by which landscape composition can affect cotton yield: by increasing the density of pests which in turn damage cotton plants. Our quantification of how surrounding crops affect pest densities, and in turn yield, in cotton fields has significant impacts for cotton farmers, who can use this information to help optimize crop selection and ranch layout.

Keywords: applied pest management; landscape composition; pest control; cotton; *Lygus hesperus*; pesticide use; agricultural informatics

1 INTRODUCTION

An increasing world population, along with urbanization which is shrinking agricultural land area, is generating pressure to increase crop yields on existing farms.[1] In order to increase crop yields, farmers need quantitative information about how the decisions they make affect yield. This information can enable farmers to make optimal crop management decisions that maximize crop productivity and reduce the need for costly, environmentally damaging inputs such as pesticides and fertilizers.

One of the decisions farmers make that can substantially affect crop performance is the determination of ranch layout, i.e. which crops to grow in which fields during the same growing season. Ranch layout can affect crop performance in various ways. Firstly, as certain crops may act as sources and sinks of certain crop pests, the identities of crops grown near an agricultural field can affect the pest densities in that field, and these pests may in turn affect yield.[2] For example, some crops may act as pest sources if they attract and support the build-up of localized populations of particular pests. These localized pest populations may then attack crops in nearby fields, potentially inflicting yield loss or necessitating insecticide applications. Alternatively, some crops may act as pest sinks when they attract and retain individuals of a particular pest species that preferentially attacks that crop, thereby diverting those pests from nearby crops and potentially preventing yield loss.[3] Whether or not a nearby patch serves as a source or a sink of herbivores depends on the relative birth, death, immigration and emigration rates in each of the habitats.[4] Secondly, landscape composition surrounding agricultural fields has been shown to affect the density of natural enemies (which attack crop pests) in those fields; these effects may translate to differences in pest suppression and, in turn, crop damage.[2,5–7]

Despite the large body of evidence that landscape composition can affect populations of both crop pests and natural enemies, there is virtually no documentation of how these effects correlate with, or cause, changes in crop yield.[2] The economic and environmental costs associated with pesticide applications incentivize profit-maximizing farmers only to treat pest populations that are likely to affect yield. This makes quantification of the yield effects associated with landscape effects on pest populations extremely important for providing actionable insights to farmers. In addition, while some studies have documented correlations between landscape composition and insecticide use at the level of a county,[8]

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there has been very little research demonstrating relationships between landscape composition and insecticide use at the level of a field. Furthermore, the relationships between landscape composition and pesticide use in California cotton fields are not known. These existing gaps in the literature are motivations for this study.

Currently, many farmers make important crop management decisions, such as ranch layout, with incomplete information. Farmers often do not have access to data-driven scientific evidence about which management practices maximize yield, so they are left to base important decisions on personal experience and intuition. The goal of our project is to give farmers the tools to make better-informed decisions that are based on robust, data-driven evidence. Here, we focus on the decision of ranch layout, specifically seeking to quantify the association between neighboring crops and the pest densities and yield in cotton fields.

To do this, we compiled a dataset consisting of 1498 records of commercial cotton production across California from 1997 to 2008. This 'ecoinformatics'[9] approach allowed us to capitalize on a rich, existing, but underutilized data source – the data that farmers and crop consultants collect about their agricultural operations. Farmers and crop consultants often collect meticulous records about their crops, including data on pest densities and yield. While these data are used to guide short-term crop management decisions, the power of these data is greatly magnified when aggregating data from many farms, as this affords the statistical power to pick out subtle trends and to quantify important relationships in the data.[9]

Our approach of collecting data from actual commercial farms, instead of conducting our own field experiments, is particularly attractive for addressing questions about factors that operate at broad spatial scales, such as landscape composition. Studying the effects of adjacent crops on a field's pest densities and yield using only small plots could lead to misleading results, as many key agricultural pests disperse across wide geographies.[10] In particular, *Lygus hesperus*, a key pest of cotton[11–14] and the focus of our study, is known to travel across agricultural landscapes at scales of at least 1 km.[15] Spatial movement of agricultural pests makes questions of landscape composition difficult to study experimentally owing to the vast land areas that would need to be under experimental manipulation.

The role of surrounding crops in the severity of *L. hesperus* pressure in cotton has been recognized for decades.[16,17] Numerous previous studies have demonstrated relationships between landscape composition surrounding cotton fields and the *L. hesperus* densities in those fields.[18–22] Despite this rich body of research, these landscape effects on *L. hesperus* densities in cotton fields have not been connected to corresponding effects on yield and farmer pesticide use.

A quantitative understanding of the effects of landscape composition on pest densities and yield could be of practical use to farmers in several ways. Firstly, for a farmer who has not yet decided which crops to grow, knowledge of the effects of landscape composition allows a farmer to make a more informed decision about which crops to grow, so as to reduce the likelihood of adverse effects of neighboring crops. Assuming a farmer has committed to growing certain crops, this information could still be used optimally to arrange these crops across fields. In both cases, other factors, such as crop rotation, soil types and the economic value of different crops, would also likely be taken into consideration when deciding which crops to grow in which fields. Finally, even if ranch layout has already been determined, knowing what neighboring crops are associated with higher likelihood of pest problems may help farmers and crop consultants to focus pest detection efforts on fields at higher risk of pest infestations.

To explore the relationship between landscape composition and crop performance, we analyzed our data using statistical models. In this study, we specifically focused on one component of landscape composition: the crop fields immediately adjacent to a focal crop field. Firstly, we explored the association between landscape composition (at the scale of immediately adjacent crops) and cotton yield. Secondly, we explored the association between landscape composition and the early-season density of *L. hesperus*, a key pest of cotton. We then compared the estimated effects of landscape composition on pest density with the estimated effects of landscape composition on yield, to explore the possibility that the effects on pest density may explain the effects on yield. Using a smaller dataset, we explored the relationship between adjacent crops and the density of *L. hesperus* in immediately adjacent portions of the field, with the goal of providing increased confidence in the relationship between adjacent crops and *L. hesperus* density. Finally, we explored the relationship between landscape composition and pesticide use in cotton fields, seeking to connect effects on *L. hesperus* density with changes in farmer behavior.

2 MATERIALS AND METHODS

2.1 Dataset

We built our dataset by aggregating historical crop records from 1498 commercial cotton crops in California's San Joaquin Valley; these observations were collected from 566 unique fields and span cotton plantings from 1997 to 2008. The dataset integrates records collected by both farmers and professional crop consultants hired to monitor field conditions and recommend crop management strategies. The following variables were used in our analyses:

1. *Surrounding crops.* For 1088 of the 1498 crops, our dataset contained the identity of the crop grown in each of the eight fields immediately adjoining the focal field (to the north, northeast, east, southeast, south, southwest, west and northwest). Seventeen unique crops were grown in adjacent fields (any crops with fewer than 30 observations were excluded from the analysis): alfalfa, almonds, barley, corn, cotton, garbanzo beans, garlic, grapes, lettuce, melons, onions, pistachios, potatoes, safflower, sugar beets, tomatoes and wheat.
2. *Cotton yield.* Cotton lint yield was measured, once per crop, in bales acre^{-1} (converted to kg ha^{-1} for our analyses) and recorded for 1240 of the 1498 records.
3. *Field-level* Lygus hesperus *densities.* Crop consultants measured *L. hesperus* densities approximately weekly, primarily during June and July. The consultants' sampling procedure consisted of 50 swings of a sweep net across the top of the plant canopy. As not all consultants sampled on the same days or at exactly the same intervals for all fields, we transformed successive samples into mean *L. hesperus* density estimates (insects sweep^{-1}) by calculating the area under the linear curve of *L. hesperus* density versus time and dividing by the number of days in the sampling interval. These data were collected at the field level, i.e. the consultants recorded a single pest density for each field on each day the field was sampled. June *L. hesperus* density was recorded for 1497 of the 1498 total crop records in the database.
4. *Within-field* Lygus hesperus *densities.* For 914 of the 1498 crops, our database contained additional information about within-field densities of *L. hesperus*. These records come from

434 unique fields between 2005 and 2008. The within-field *L. hesperus* samples were obtained in the same manner as the field-level *L. hesperus* density samples, but the quadrant of the field in which the sample was taken, i.e. the edge of the field closest to the sample location, was also recorded (north, east, south or west).
5. *Pesticide applications*. The dates, product names and insect targets of all pesticide applications were recorded.
6. *Crop rotation*. The identity of the crop grown in the same field during the previous growing season was recorded for 1273 of the 1498 records in the dataset.
7. *Cotton species*. Our database contained records of two different cotton species: *Gossypium barbadense* L. (upland cotton) and *Gossypium hirsutum* L. (Acala cotton). The cotton species was known for 1452 of the 1498 records. Within each species, several different cotton varieties were planted, but this factor was not considered in the analysis because we did not reliably have this information for every field.
8. *Field ID*. Each field was assigned a unique ID so that we could identify repeated observations of the same field in different years.
9. *Ranch ID*. Fields near each other were clustered into ranches by the farmers who own the fields.
10. *Year*. The year in which the crop was grown was recorded for each unique field–year combination.
11. *Field location*. The latitude and longitude approximating the center of each field was obtained using ranch maps provided by the farmers and crop consultants who provided data for this project.

2.2 Models

2.2.1 *Model 1: Association between landscape composition and yield*

Firstly, we quantified the association between which crops were grown immediately adjacent to a focal field and the yield of the cotton crop in that field. To do so, we employed a generalized additive mixed model.[23,24] A generalized additive model was an attractive modeling approach, as it provides a straightforward way explicitly to model a spatial trend in the dependent variable.[25] The dependent variable in this model was the field's yield. The main independent variables of interest were the number of fields, out of the eight adjacent fields, that were planted with each of the 17 crops. Additionally, we included several other independent variables in the model to control for other factors that could plausibly explain some variability in yield:

1. *Spatial trend in yield*. It is reasonable to expect fields close to one another in space to be more similar to each other than those far away. For example, nearby fields likely experience more similar climatic conditions and more similar soil types than do fields further from each other. Nearby fields may also experience more similar pressure from pests and diseases, the distribution of which across the landscape may not be constant. As weather and pest pressure are two factors believed to affect cotton yield, spatial trends in these factors may lead to spatial trends in cotton yield. Failing to model this trend could taint inferences about other variables in the model, as the assumption of independence between fields would be violated. To help model the spatial trend in yield across the fields in our dataset, we included a smoothed interaction term between longitude and latitude in the model. This is a common approach used for modeling data with spatial trends.[25] To verify that this approach had adequately accounted for the spatial trend in our data, we performed Moran's *I*-test for spatial autocorrelation with the residuals of the model.
2. *Crop rotation*. Previous research has suggested that crop rotation is associated with changes in cotton yield.[26] To control for this potential yield driver, we included a categorical independent variable in the model specifying the identity of the crop grown in the same field the previous year.
3. *Cotton species*. Records in our database consisted of two different cotton species; as these species are known to differ in yield,[26] we included cotton species as a categorical independent variable.
4. *Ranch*. To control for yield variability between ranches, the ranch ID was included in the model as a random effect.
5. *Field*. To control for field-specific variability in yield, the field ID was included in the model as a random effect.
6. *Year*. To control for any year-to-year variability in yield, the crop year (from 1998 to 2008) was included in the model as a random effect.

Each unique field–year combination was treated as a unique replicate, i.e. if the database contained data from the same field from two or more years, then the data from each year was treated as a separate observation. We used the 'gamm4' function in the 'gamm4' R package, v.0.2-3, for fitting the generalized additive mixed model.

2.2.2 *Model 2: Association between landscape composition and field-level* L. hesperus *density*

Next, we quantified the association between which crops were grown immediately adjacent to a focal field and the density of *L. hesperus* in that field. We again employed a generalized additive mixed model, with the exact same structure as model 1, but we replaced yield with *L. hesperus* density as the dependent variable. Specifically, we used the average *L. hesperus* density during the entire month of June as the dependent variable, as previous studies have suggested that cotton is particularly susceptible to yield loss from *L. hesperus* herbivory early in the growing season.[27]

2.2.3 *Model 3: Relationship between* L. hesperus *effects and yield effects*

In the first model, we estimated, for each of the 17 crops, a parameter describing the expected change in yield associated with each additional adjacent field that contained that crop. In the second model, we estimated the expected change in June *L. hesperus* density associated with each additional adjacent field containing each crop. Next, to better understand and quantify any potential relationship between the neighboring crops' association with changes in yield and their association with changes in *L. hesperus* density, we performed a Bayesian linear regression[28] of the estimated effects of each crop on yield versus the estimated effects of each crop on *L. hesperus* density.

Additionally, to account for uncertainty in the estimated effects of the crops on both yield and *L. hesperus* density, we drew samples of the crop-specific parameter estimates from each of the first two models and repeatedly performed the linear regression using each sample. Specifically, we drew 10 000 samples of the 17 crop-specific yield effect parameters from model 1 using the estimated covariance matrix and assuming a multivariate normal distribution. We repeated this sampling from model 2 for the pest parameters. For each of these 10 000 samples, we performed a

Bayesian linear regression of the yield effects versus the *L. hesperus* effects. We obtained 10 000 posterior samples from each of the 10 000 regressions and discarded the first 5000 as burn-in. Non-informative N(0,100) priors were used for the intercept and slope, along with a non-informative inv-gamma(0.001, 0.001) prior for the variance. Models were fitted using the Stan probabilistic programming language[29] accessed using the RStan package v.2.5.0.[30]

2.2.4 *Model 4: Association between landscape composition and within-field* L. hesperus *density*

We fitted a similar model to model 2 using the records with additional data on the within-field densities of *L. hesperus*. In this model, each unique field–quadrant–year combination was included as a unique replicate. The response variable was June density of *L. hesperus*. The main predictor variable of interest was the identity of the crop grown in the field immediately adjacent to the quadrant in which the pest density was measured; this categorical variable was included as a fixed effect (cotton was taken to be the baseline crop, so indicator variables for all other crops were included). As in models 1 and 2, we also included fixed effects for the crop grown the previous year and the cotton type, random effects for field, ranch and year and a smoothed latitude–longitude interaction term. To control for the fact that multiple samples from different locations in the same field in the same year may not be independent, we also included a random effect for the field–year combination.

2.2.5 *Model 5: Relationship between field-level and within-field* L. hesperus *effects*

In the second model, we estimated, for each of the 17 crops, a parameter describing the expected change in June field-level *L. hesperus* density associated with each additional field, of the eight fields surrounding the focal field, that contained that crop. In the fourth model, we estimated the changes (relative to cotton) in June within-field *L. hesperus* density expected when each of the other 16 crops is planted immediately adjacent to the quadrant of the field in which the *L. hesperus* density was measured.

To quantify any potential relationship between the neighboring crops' association with field-level and within-field *L. hesperus* density, we performed a Bayesian linear regression of the estimated effects of each crop on field-level *L. hesperus* density versus the estimated effects of each crop on within-field *L. hesperus* density. Similarly to model 3, we used the parameter estimates and estimated covariance matrix to draw samples of the crop-specific parameter estimates from each model and repeatedly performed the linear regression using each sample. Cotton was excluded because it was used as the baseline crop in model 4, where the identity of the immediately neighboring crop was a categorical variable (as opposed to a continuous variable for each crop ranging from 1 to 8, as in model 2); hence, no cotton-specific parameter was estimated in model 4.

Specifically, we drew 10 000 samples of the other 16 crop-specific field-level pest effect parameters from model 2 using the estimated covariance matrix and assuming a multivariate normal distribution. We repeated this sampling from model 4 for the within-field pest effect parameters. For each of these 10 000 samples, we performed a Bayesian linear regression of the field-level versus within-field *L. hesperus* parameters. We obtained 10 000 posterior samples from each of the 10 000 regressions and discarded the first 5000 as burn-in. Non-informative N(0,100) priors were used for the intercept and slope, along with a non-informative inv-gamma(0.001, 0.001) prior for the variance.

2.2.6 *Model 6: Association between landscape composition and pesticide applications*

We also quantified the association between which crops were grown near a focal cotton field and the number of pesticide applications targeting *L. hesperus* that were applied to that field. We again employed a generalized additive mixed model, identical in structure to model 1, but with the dependent variable being the number of pesticide applications, during the entire growing season, for which farmers nominated *L. hesperus* as one of the targets.

2.2.7 *Model 7: Relationship between* L. hesperus *effects and pesticide application effects*

Finally, to better understand and quantify any potential relationship between the neighboring crops' association with field-level *L. hesperus* density and their association with the number of pesticide applications targeting *L. hesperus*, we performed a Bayesian linear regression, exactly like model 3, of the estimated effects of each crop on the number of pesticide applications targeting *L. hesperus* versus the estimated effects of each crop on field-level June *L. hesperus* density.

3 RESULTS

3.1 Model 1: Association between landscape composition and yield

The estimated effects of each crop on cotton yield (specifically, the estimated change in cotton yield associated with each additional field of the eight adjacent fields planted to that crop) are displayed in Fig. 1A. Three crops – grapes (-96.7 ± 95.5 kg ha^{-1}), safflower (-55.1 ± 51.4 kg ha^{-1}) and potatoes (-40.8 ± 38.2 kg ha^{-1}) – had 95% confidence intervals that were entirely negative, suggesting that these crops, when planted adjacent to a cotton field, were associated with decreased cotton yield. We performed Moran's *I*-test for spatial autocorrelation with the model's residuals; we found no evidence of spatial autocorrelation ($I = 0.003$, $P = 0.98$).

3.2 Model 2: Association between landscape composition and field-level *L. hesperus* density

The estimated effects of each crop on field-level *L. hesperus* density (specifically, the estimated change in June *L. hesperus* density associated with each additional field of the eight adjacent fields planted to that crop), are displayed in Fig. 1B. Six crops – grapes (0.38 ± 0.24 insects sweep^{-1}), safflower (0.50 ± 0.13 insects sweep^{-1}), pistachios (0.13 ± 0.12 insects sweep^{-1}), onions (0.11 ± 0.10 insects sweep^{-1}), tomatoes (0.08 ± 0.05 insects sweep^{-1}) and almonds (0.12 0.10 insects sweep^{-1}) – had 95% confidence intervals that were entirely positive, suggesting that these crops, when planted adjacent to a cotton field, were associated with increased *L. hesperus* density. One crop – cotton (-0.06 ± 0.02 insects sweep^{-1}) – had a 95% confidence interval that was entirely negative, suggesting that cotton, when planted adjacent to a cotton field, was associated with decreased *L. hesperus* density in the focal cotton field. We performed Moran's *I*-test for spatial autocorrelation with the model's residuals; we found little evidence of spatial autocorrelation ($I = 0.021$, $P = 0.11$).

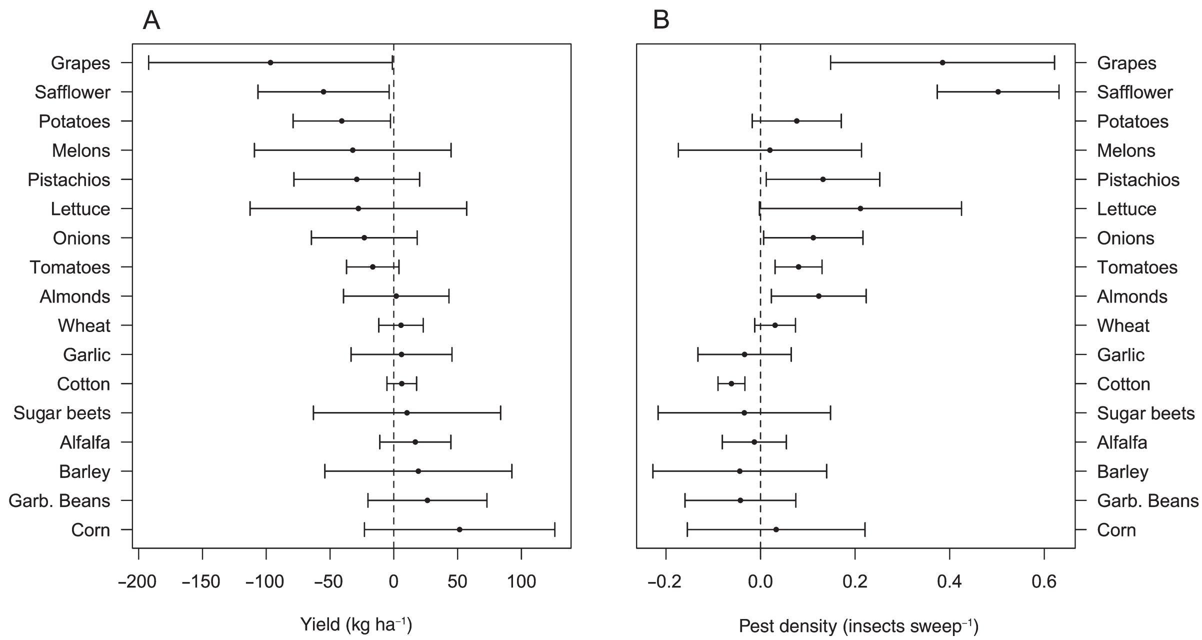

Figure 1. The estimated changes in cotton yield from model 1 (A) and June *L. hesperus* density from model 2 (B) associated with each additional field of the eight adjacent fields planted to different crops. 95% confidence intervals are also displayed.

3.3 Model 3: Relationship between *L. hesperus* effects and yield effects

Crops associated with increased *L. hesperus* density tended also to be associated with decreased cotton yield, and crops associated with decreased *L. hesperus* density tended also to be associated with increased cotton yield. For 14 of the 17 crops, the direction of the estimated effect of that crop on *L. hesperus* density and the direction of the estimated effect of that crop on yield were opposite.

The fit of the Bayesian linear regression of the estimated effects of each crop on yield versus the estimated effects of each crop on *L. hesperus* density is displayed in Fig. 2. The estimated slope of that regression was -175.5 (kg ha^{-1})/(insects sweep^{-1}), with a 95% highest posterior density interval of (-306.7, 3.4). The posterior probability of a negative slope in the model regressing estimated yield effects against estimated pest effects was 97.42%.

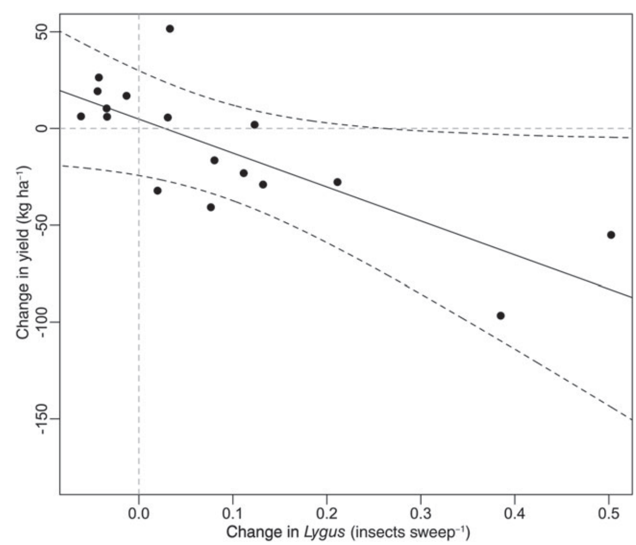

Figure 2. The estimated changes in cotton yield from model 1 versus the estimated changes in June *L. hesperus* density from model 2 for each of the 17 crops, along with the fitted linear regression of the former against the latter and the 95% highest posterior density interval bounds of the fit (dashed lines).

3.4 Model 4: Association between landscape composition and within-field *L. hesperus* density

The estimated effects of each crop on within-field *L. hesperus* density (specifically, the estimated change in June *L. hesperus* density in the quadrant of the field immediately adjacent to each of these crops, compared with the case when another cotton field – the baseline in the model – is immediately adjacent) are displayed in Fig. 3. Six crops – lettuce (2.28 ± 0.83 insects sweep^{-1}), potatoes (0.56 ± 0.27 insects sweep^{-1}), almonds (0.55 0.47 insects sweep^{-1}), sugar beets (0.51 ± 0.45 insects sweep^{-1}), afalfa (0.29 ± 0.21 insects sweep^{-1}) and tomatoes (0.18 ± 0.17 insects sweep^{-1}) – had 95% confidence intervals that were entirely positive, suggesting that these crops, when planted adjacent to a cotton field, were associated with increased *L. hesperus* density in the portion of the cotton field nearest the adjoining field. We performed Moran's *I*-test for spatial autocorrelation with the model's residuals; we found weak evidence of spatial autocorrelation ($I = 0.002$, $P = 0.59$).

3.5 Model 5: Relationship between field-level and within-field *L. hesperus* effects

Crops associated with increased within-field *L. hesperus* density in the immediately adjacent part of cotton fields tended also to be associated with increased field-level *L. hesperus* density when planted as any one of the eight crops adjacent to a cotton field. For 12 of the 16 crops, the directions of the estimated effects of that crop on within-field and field-level *L. hesperus* density were the same.

The fit of the Bayesian linear regression of the estimated field-level versus within-field *L. hesperus* effects is displayed in Fig. 4. The estimated slope of that regression was 0.10 [(insects

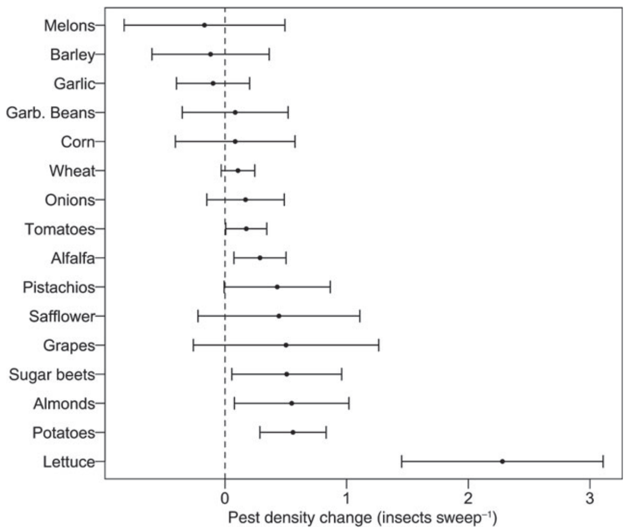

Figure 3. Estimated changes (and 95% confidence intervals) in June *L. hesperus* density in field quadrants when various crops are planted in the field immediately adjacent to that quadrant. All values are relative to the situation in which cotton is grown in the adjacent field.

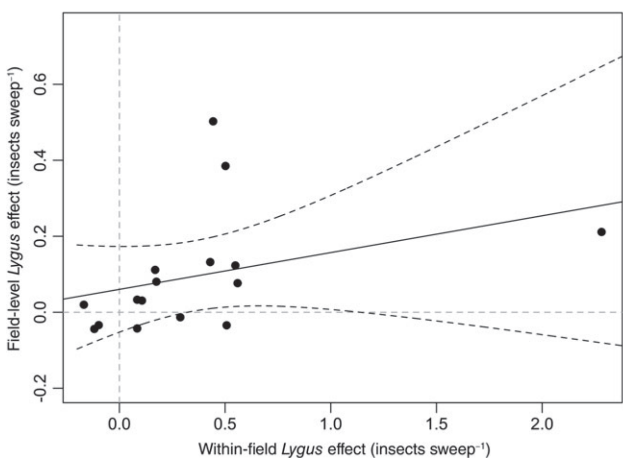

Figure 4. The estimated change in field-level June *L. hesperus* density from model 2 versus the estimated changes in within-field June *L. hesperus* density from model 4, along with the fitted linear regression of the former against the latter and the 95% highest posterior density interval bounds of the fit (dashed lines).

sweep^{-1} for each additional field, of the eight adjacent fields, planted to that crop)/(insects sweep^{-1} when that crop is immediately adjacent)], with a 95% highest posterior density interval of (−0.08, 0.29). The posterior probability of a positive slope (i.e. a positive association between field-level and within-field *L. hesperus* effects) was 86.24%.

3.6 Model 6: Association between landscape composition and pesticide applications

The estimated effects of each crop on the number of pesticide applications targeting *L. hesperus* (specifically, the estimated change in season-long pesticide applications targeting *L. hesperus* associated with each additional field of the eight adjacent fields planted to that crop) are displayed in Fig. 5A. Three crops had 95% confidence intervals that were entirely positive, suggesting that these crops were associated with an increased number of pesticide applications targeting *L. hesperus*: safflower (0.97 ± 0.21 applications), grapes (0.62 ± 0.39 applications) and onions (0.30 ± 0.17 applications). One crop, cotton, was associated with fewer *L. hesperus* applications when planted adjacent to a cotton field (-0.06 ± 0.04 applications).

3.7 Model 7: Relationship between *L. hesperus* effects and pesticide application effects

Crops associated with increased field-level *L. hesperus* density tended also to be associated with an increase in the number of pesticide applications targeting *L. hesperus*. For 14 of the 17 crops, the directions of the estimated effects of that crop on field-level *L. hesperus* density and the number of pesticide applications targeting *L. hesperus* were the same.

The fit of the Bayesian linear regression of the estimated pesticide use effects versus the estimated *L. hesperus* effects is displayed in Fig. 5B. The estimated slope of that regression was 1.46 (applications)/(insects sweep^{-1}), with a 95% highest posterior density interval of (0.57, 2.38). The posterior probability of a positive slope (i.e. a positive association between *L. hesperus* effects and pesticide application effects) was 99.87%.

4 DISCUSSION

Using a large observational dataset containing historical records of commercial cotton production in California, we explored and quantified the relationships between crop landscape composition and *Lygus hesperus* density, cotton yield and farmer pesticide use. Various crops, when grown immediately adjacent to cotton, were associated with changes in *L. hesperus* density, cotton yield and the number of pesticide applications targeting *L. hesperus*.

Furthermore, crops that tended to be associated with increased *L. hesperus* density tended also to be associated with decreased yield – there was a 97.42% posterior probability of a negative relationship between each crop's estimated effect on *L. hesperus* and its estimated effect on yield. This result suggests a possible mechanism by which crop landscape composition can affect cotton yield: certain crops may increase the density of *L. hesperus* in nearby fields, and those pests may in turn reduce yield through herbivory on the cotton crop. The mechanism by which nearby crops increase *L. hesperus* densities in cotton fields may vary depending on the crop. For example, safflower, which was associated with both higher *L. hesperus* and lower yield when grown near to a cotton field, is known to be a favorable host for *L. hesperus*.[20] Therefore, it may attract large *L. hesperus* populations, which may spill over into adjacent cotton fields. Furthermore, safflower dries down and is harvested in early summer, at which time it ceases to be a suitable host for *L. hesperus*. *L. hesperus* populations may then move away from the safflower field and attack adjacent cotton fields.[20] Our results are consistent with other studies that have shown increased *L. hesperus* densities in cotton fields when safflower is planted nearby.[19,22] Increased *L. hesperus* density associated with nearby grapes and onion fields has also been suggested by a previous study,[22] and the decrease in *L. hesperus* density associated with nearby cotton fields is consistent with the findings of several other studies.[19,22]

We found strong evidence that crops associated with increased *L. hesperus* density were also associated with increased numbers of pesticide applications targeting *L. hesperus*: there was a 99.87% posterior probability of a relationship in this direction. In particular, for three crops for which we found strong evidence (i.e. entirely

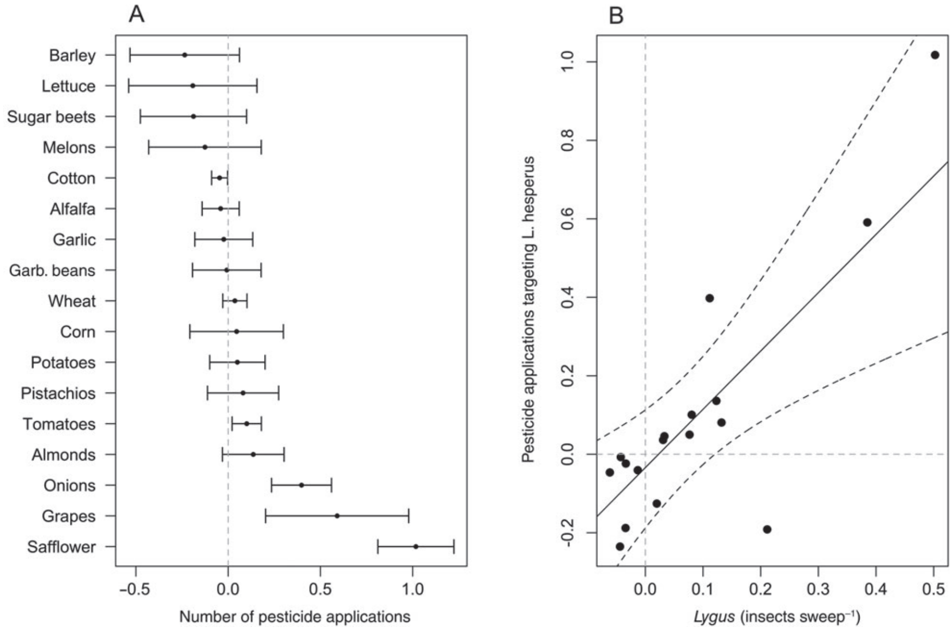

Figure 5. (A) The estimated change in the number of pesticide applications during the growing season targeting *L. hesperus* associated with each additional field of the eight adjacent fields planted to different crops (model 6); 95% confidence intervals are also displayed. (B) The estimated changes in the number of pesticide applications targeting *L. hesperus* from model 6 versus the estimated changes in June *L. hesperus* density from model 2 for each of the 17 crops, along with the fitted linear regression of the former against the latter and the 95% highest posterior density interval bounds of the fit (dashed lines).

positive 95% confidence intervals) of increased *L. hesperus density* – safflower, grapes and onions – we also found strong evidence of increased numbers of pesticide applications targeting *L. hesperus*. The strong trend for crops associated with increased *L. hesperus* density also to be associated with increased numbers of pesticide applications targeting *L. hesperus* suggests that the changes in *L. hesperus* density were of great enough magnitude to warrant detectable changes in farmer behavior. This highlights the importance of considering landscape composition in decisions about ranch layout and crop placement, as pesticide applications can be both costly to the farmer and damaging to the environment.[31]

Using the results of model 1, we compared (a) the estimated effects of various crops on yield when grown adjacent to a cotton field during the same growing season with (b) the estimated effects of the same crops on yield when grown in the same field during the previous growing season. Using the results from model 2, we repeated this comparison for estimated effects on June *L. hesperus* density. In both cases, we found no significant association between the same-season landscape effects and the across-season crop rotation effects. These results suggest that the mechanisms by which same-season landscape composition and crop rotational histories affect cotton yield and *L. hesperus* density may differ.

While it is widely appreciated that landscape composition surrounding agricultural fields can affect the density of crop pests in those fields, our study extends this knowledge by (a) quantifying these effects on pest density, (b) quantifying the association between landscape composition and yield, (c) revealing an association between landscape effects on yield and effects on pest density that provides a plausible mechanism for the observed yield changes and (d) demonstrating that landscape effects on pest density were associated with changes in farmer pesticide application behavior. Twelve of 16 crops were associated with within-field and field-level changes in *L. hesperus* density that were in the same direction, and there was an 86.24% posterior probability of a positive association between within-field and field-level *L. hesperus* effects. These parallel effects provide increased confidence that pest movement may be driving yield changes associated with landscape composition surrounding cotton fields. The validity of landscape effects on *L. hesperus* density is further corroborated by the increase in pesticide applications targeting *L. hesperus* that was observed in cotton fields near to crops that were also associated with increased *L. hesperus* pressure, because the increased pesticide use is likely a response to increased density of *L. hesperus*. However, further research is needed to confirm that this hypothesized mechanism is actually responsible for the yield changes that we observed to be associated with neighboring crops. In addition, future reseach is needed to study how landscape composition at wider spatial scales influences pest density, yield and pesticide use; in this study, owing to data availability, we focused only on immediately adjacent crops.

The changes in yield associated with neighboring crops are likely of economic significance to cotton growers. For example, yield decreases of 96.7 and 55.1 kg ha^{-1} were associated with each additional adjacent grape and safflower field respectively. Compared with the average cotton yield in our dataset of 1737.3 kg ha^{-1}, this translates into yield differences of 5.6 and 3.2% respectively. The economic significance of these changes depends on various factors, including growers' production costs and commodity prices. However, these changes in yield are likely to be economically significant, especially for growers working with very small profit margins.

Any research methodology has inherent strengths and weaknesses which affect the type of questions for which the method is best suited. A main drawback of our approach of analyzing a historical, observational dataset is that it makes formal causal inference very challenging. This stems from the fact that our analyses rely on observational data, where, unlike in a controlled experiment, it is not possible definitively to prove that there was not another, unmeasured factor that actually caused the change in the variable of interest. Some factors, such as soil conditions and the amount of irrigation used on each field, could also affect cotton crop performance but were not a part of this dataset and therefore not included in our analyses. Despite this drawback, a major benefit of our approach is that it allowed us to use a large dataset to explore a question that would be very difficult to study experimentally. Experimentally manipulating landscape composition is extremely difficult, as it requires a researcher to have a large geographic area under experimental control. While small test plots may be more tractable, they reduce the realism of the experiment, as large spatial scales are needed to capture the spatial dynamics of highly mobile pests.

Optimizing the layout of crops across a landscape is one way in which farmers can reduce crop damage from insect pests and, in turn, increase yield and reduce pesticide use. Such optimizations may play an important part in our agricultural future, as the need to increase yield and the desire to reduce pesticide use become increasingly urgent. Here, we have shown how large datasets from commercial agriculture can be aggregated and applied to quantify the effects of landscape composition on pest densities and yield – information that is critical in order to made data-driven decisions about optimal crop layout.

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