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Abstract

During 2007, counties across the Midwestern US with relatively high levels of landscape simplification (i.e., widespread replacement of seminatural habitats with cultivated crops) had relatively high crop-pest abundances which, in turn, were associated with relatively high insecticide application. These results suggested a positive relationship between landscape simplification and insecticide use, mediated by landscape effects on crop pests or their natural enemies. A follow-up study, in the same region but using different statistical methods, explored the relationship between landscape simplification and insecticide use between 1987 and 2007, and concluded that the relationship varied substantially in sign and strength across years. Here, we explore this relationship from 1997 through 2012, using a single dataset and two different analytical approaches. We demonstrate that, when using ordinary least squares (OLS) regression, the relationship between landscape simplification and insecticide use is, indeed, quite variable over time. However, the residuals from OLS models show strong spatial autocorrelation, indicating spatial structure in the data not accounted for by explanatory variables, and violating a standard assumption of OLS. When modeled using spatial regression techniques, relationships between landscape simplification and insecticide use were consistently positive between 1997 and 2012, and model fits were dramatically improved. We argue that spatial regression methods are more appropriate for these data, and conclude that there remains compelling correlative support for a link between landscape simplification and insecticide use in the Midwestern US. We discuss the limitations of inference from this and related studies, and suggest improved data collection campaigns for better understanding links between landscape structure, crop-pest pressure, and pest-management practices.

1. Introduction

Each year, farm fields across the US receive more than 30 000 metric tonnes of insecticide active ingredients (Grube *et al* 2011), bringing direct economic benefits to farmers. Insecticide application commonly increases the yields and aesthetic quality of crops, returning roughly $4 for every $1 invested (Metcalf 1994). Unfortunately, insecticide application also has substantial indirect costs to farmers, their communities, and to society, more broadly (Pimentel *et al* 1992). These costs come from the negative effects of insecticides on human health (Weichenthal *et al* 2010), vertebrate wildlife (Mineau and Whiteside 2006, Gibbs *et al* 2009), and beneficial insects (Theiling and Croft 1988).

Insecticide is not uniformly applied to farmland across the US, however (Mineau and Whiteside 2006). Across counties in the Midwestern US, the percentage of cropland treated with insecticide ranges from nearly 0% to more than 60% (Meehan *et al* 2011). This spatial variation is driven by a complex hierarchy of factors, some cultural and some agricultural, that likely vary in importance across space (Meehan *et al* 2011) and over time (Larsen 2013). For example, spatial variation in insecticide use could arise from spatial variation in the social and environmental perspectives (Reimer *et al* 2013) and the risk tolerances (Pannell 1991) of farmers. Spatial variation could also be attributed to crop geography, where some regions apply relatively more insecticides because the market prices of certain crops, such as fruits and vegetables, are especially sensitive to pest damage (Babcock *et al* 1992). All else being equal, spatial variation in insecticide use is likely to arise from spatial variation in pest pressure on a crop (Stern 1973, Pedigo *et al* 1986).

Spatial variation in pest pressure on a crop could occur for several reasons. For example, climate and soil nutrients (e.g., potassium) vary across space, with implications for the natural defenses of plants (Gershenzon 1984), as well as the population dynamics of both crop pests (Huberty and Denno 2004, Myers and Gratton 2006) and their natural enemies (Thomson *et al* 2010). Also, the characteristics of agricultural landscapes vary considerably across space. That is, landscapes vary in the amount of cropland and semi-natural habitat they contain, with implications for colonization and reproduction of crop pests (Margosian *et al* 2009) and their natural enemies (Risch *et al* 1983, Bianchi *et al* 2006, Chaplin-Kramer *et al* 2011).

In a recent study, Meehan *et al* (2011) demonstrated links between landscape structure, pest pressure, and insecticide use across the Midwestern US. Specifically, the study compared county-level variation in landscape simplification, defined as the proportion of a county occupied by harvested cropland, (from the 2007 Cropland Data Layer, CDL; USDA NASS 2007b), pest-aphid abundance (during 2007, from a regional aphid trapping network; USDA CSREES 2010), and insecticide use, defined as the proportion of harvested cropland in a county treated with insecticides (from the 2007 Census of Agriculture, COA; USDA NASS 2007a). Meehan *et al* (2011) found that counties with relatively high levels of landscape simplification had relatively high pest abundances. In turn, counties with relatively high pest abundances had relatively high insecticide use. In sum, even after accounting for several other potential drivers (e.g., crop geography, farmer income, equipment availability, and the prevalence of transgenic corn), there appeared to be a positive association between landscape simplification and insecticide use, mediated by landscape effects on crop pests or their natural enemies. These findings were noteworthy because they provided support, albeit correlative, for putative causal relationships between landscape characteristics, pest pressure, and agronomic outcomes at an unprecedented geographic scale.

In a subsequent study, Larsen (2013) analyzed COA data from 1987 through 2007, and found that the relationship between landscape simplification and insecticide use in the Midwest was quite variable when evaluated over longer time spans. In that study, the relationship varied from negative, to non-existent, to positive, depending on the year. The paper discussed several factors, some mechanistic and some methodological, that could explain variation in the relationship between landscape simplification and insecticide use. Mechanistic factors explored included annual weather patterns, which were not related to variation in the relationship, and changes in federal insecticide regulations, which required additional data from future agricultural censuses for a robust evaluation (Larsen 2013). Methodological factors explored included whether landscape simplification was estimated from COA data or CDL data, and how stringent the site selection criteria were, neither of which seemed related to variation in the relationship between landscape simplification and insecticide use (Larsen 2013).

One potentially important methodological difference between Meehan *et al* (2011) and Larsen (2013) was the treatment of spatial structure in the data. Meehan *et al* analyzed data using simultaneous autoregressive error models (SAR) (Anselin and Bera 1998, Bivand *et al* 2008) to account for spatial structure in the data not accounted for by landscape simplification or other explanatory variables in their model. A SAR error model is a form of spatial regression, where spatial structure in data not explained by independent variables is modeled using a spatial correlation coefficient, often termed lambda ($-1 \leqslant \lambda \leqslant 1$), and a spatial weights matrix that specifies the relationship between neighboring study areas (Anselin and Bera 1998, Dormann *et al* 2007, Bivand *et al* 2008). In contrast, Larsen used ordinary least squares (OLS) regression to estimate the effects of landscape simplification and the other explanatory variables. In this case, the spatial structure in the data was not modeled, resulting in spatially autocorrelated residuals. Cluster-robust standard errors (CRSE) (Wooldridge 2003) were used to correct for the effect of spatially autocorrelated residuals on hypothesis tests. However, several simulation studies have shown that parameter estimates from OLS regressions can be unreliable when there is strong spatial autocorrelation in model residuals, whereas SAR models, and other spatial regression approaches that explicitly model unexplained spatial structure, are more likely to yield parameter estimates that are closer to actual values (Florax and Folmer 1992, Franzese and Hays 2007, Kissling and Carl 2008, Beale *et al* 2010, Saas and Gosselin 2014).

In 2014, new data on insecticide use from the 2012 COA became available. We took this opportunity to reevaluate the relationship between landscape simplification and insecticide use in the Midwest. The specific goals of this study were to (1) add the new 2012 COA data to other readily available COA data from 1997, 2002, and 2007; (2) use the National Land Cover

Dataset (NLCD) (Jin *et al* 2013) from 1992, 2001, 2006, and 2011 as a consistent means to estimate landscape simplification back to 1997 via remote sensing; and (3) compare two distinctly different statistical approaches, SAR and OLS, for evaluating the relationship between landscape simplification and insecticide use. In sum, the overall objective of the study was to assess the consistency of the relationship given new data and different methodological approaches.

2. Methods

We downloaded COA data from the years 1997, 2002, 2007, and 2012 from the Quick Stats online database maintained by the National Agricultural Statistics Service (NASS) of the US Department of Agriculture (USDA) (http://quickstats.nass.usda.gov/). We did not include COA data from other years in the analysis because these data were not available in this database. COA variables of interest included areal proportions of harvested cropland within a county that were (1) treated with insecticide at least once during the growing season, (1) planted in corn for grain production, (3) planted in soybean and small grains, and (4) planted in orchards and vegetable crops, as well as (5) the net income of producers per harvested acre, per county, per year. Net incomes were left as reported; values were not adjusted for inflation (Meehan *et al* 2011). We note that the general conclusions of this study do not change, even when net income is removed entirely from all models. For a small number of county-by-year combinations, there was a single soybean or small grain farmer (1%) or fruit or vegetable producer (10%) recorded by the COA. In these cases, the COA sets the acreage for these crops as unknown, to protect grower anonymity. When this occurred, we input the average crop acreages for a county from the remaining COA years. Net income was not available for any county in 1997 via the Quick Stats database, so we substituted 2002 income data into the 1997 analysis to avoid having to drop 1997 from the analysis, altogether. Again, we note that our general conclusions about landscape simplification were not dependent upon net income. In total, we included 575 counties in our analysis that (1) comprised greater than 3% cultivated cropland and (2) had actual or imputed COA values for all model variables for all four census years.

Landscape simplification estimates for each of the 575 counties came from the 1992, 2001, 2006, and 2011 NLCD (http://www.mrlc.gov/). The NLCD is a land cover dataset, derived from satellite remote sensing, formatted as a raster for use in geographic information systems, with a spatial resolution of 30 m and a spatial extent covering the conterminous US. Landscape simplification was represented as the areal proportion of a county occupied by cultivated crops. In the 2001, 2006, and 2011 NLCD, cultivated crops comprises a distinct land use class that includes all annual crops and perennial fruit crops. For the 1992 NLCD, we created an aggregate cultivated crops category by combining orchard, row crop, and small grain categories. The proportion of a county occupied by cultivated crops is strongly correlated with several other landscape simplification metrics that represent removal of seminatural habitat, and increasing cropfield size and connectivity (Meehan *et al* 2011). 1997 COA data were compared with the average of NLCD landcover proportions from 1992 and 2001. 2002, 2007, and 2012 COA data were compared with NLCD landcover proportions from 2001, 2006, and 2011, respectively.

We used SAR models (Anselin and Bera 1998, Bivand *et al* 2008) to model the proportion of cropland treated with insecticides. Lagrange multiplier tests (Anselin and Bera 1998, Bivand *et al* 2008) and model AIC values (table S1) both suggested that a spatial-error model was clearly preferred over a spatial-lag or a mixed lag-and-error model, other forms of simultaneous autoregressive models commonly used by econometricians (Anselin 1988). The dependent variable in SAR models was the proportion of harvested cropland in a county that was treated with insecticide. The five independent variables included (1) the proportion of a county in cultivated land, the proportions of harvested cropland in (2) corn, (3) soybeans and small grains, or (4) orchards and vegetables, and (5) the net income of farmers per acre of harvested cropland. The spatial weights matrix was a row-standardized matrix derived from a k-nearest neighbor analysis, where neighborhoods included the 24 nearest neighbors of a focal county. This number of neighbors approximately included first and second-order neighbors of focal counties. On average, the centroids of neighboring counties were 82 km (SD = 35 km) away from focal counties. We also derived weight matrices using a constant-distance approach, where neighborhoods included counties with centroids within 100 km of a focal county; the spatial scale of neighborhoods were similar in both cases, and yielded qualitatively similar results. The spatial scale of our neighborhoods was similar to the agricultural statistics districts (ASDs) used to produce CRSE in Larsen (2013). Multicollinearity across independent model variables was assessed via matrix condition numbers, which ranged from 2 to 14, far less than the value of 30 that indicates strong multicollinearity. SAR models were fit via maximum likelihood using the *spdep* package (Bivand 2013) for R statistical computing software (R Core Team 2014). In this implementation, an estimate for λ is determined through optimization, and other parameter estimates are computed subsequently using generalized least squares (GLS) (Bivand 2013). We evaluated spatial autocorrelation in SAR model residuals using Moran's I (Bivand 2013).

We compared SAR model results with those from OLS regressions and cluster-robust techniques, where

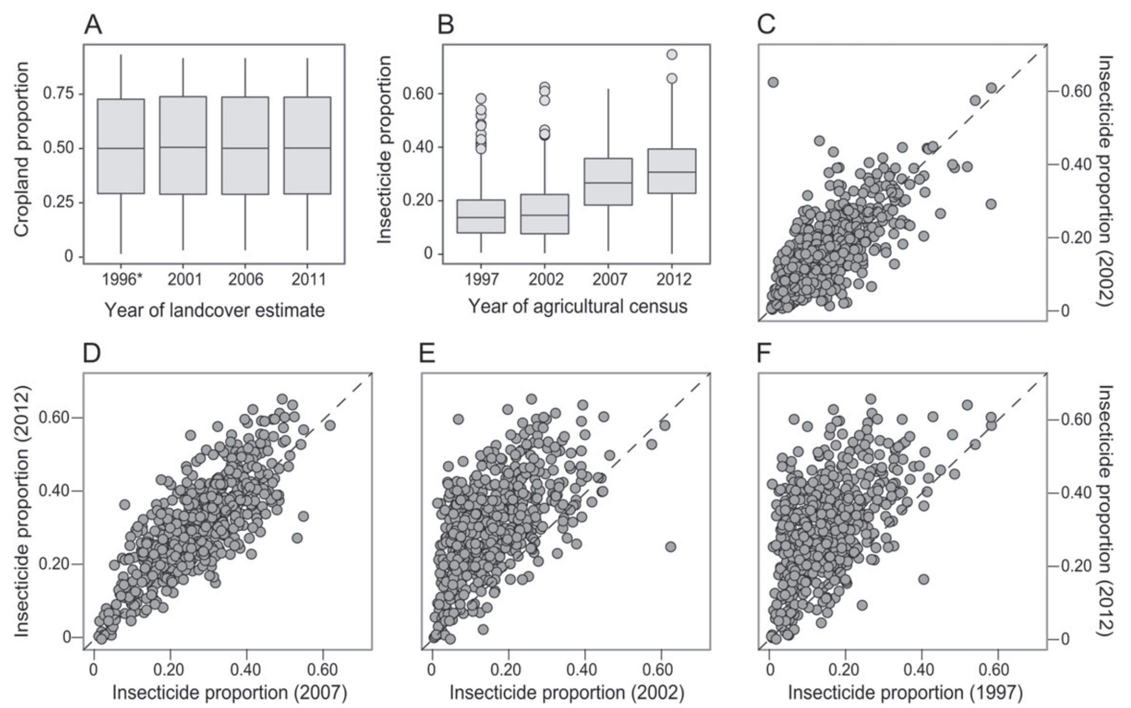

Figure 1. Univariate and bivariate distributions of the proportion of a county in cropland (cropland proportion) and the proportion of cropland treated with insecticide (insecticide proportion) for 575 counties in the Midwestern US between 1997 and 2012. The asterisk in (A) highlights that cropland proportion estimates for 1996 were averages from 1992 and 2001. Dashed lines in (C) through (F) have intercept = 0 and slope = 1. Only four notable bivariate distributions are shown, for brevity.

clusters were the same ASDs used in Larsen (2013). CRSEs were computed using the *sandwich* (Zeileis 2004) and *lmtest* (Zeileis and Hothorn 2002) packages for R statistical computing software. We evaluated spatial autocorrelation in OLS model residuals using Moran's *I* (Bivand 2013). We visualized the spatial scale of autocorrelation in OLS residuals in two ways: by mapping them using the *sp* package (Pebesma and Bivand 2005) and by producing spline correlograms using the *ncf* package (Bjornstad 2013) for R statistical computing software.

SAR modeling is a spatial regression technique that relies on assumptions about neighborhood structure. In specifying neighborhoods, an analyst must consider different forms of connectivity, numbers of neighbors, spatial extents of neighborhoods, and ways in which neighboring observations are weighted, all of which have an impact on analysis results (Stakhovych and Bijmolt 2009). In the interest of being thorough, in addition to SAR modeling, we also took a more data-driven approach (Beguería and Pueyo 2009), and modeled relationships between landscape simplification, insecticide use, and other variables of interest using a second form of GLS. Here we used residuals from OLS regressions to produce empirical estimates for parameters of exponential variogram models. Variogram models were subsequently used in GLS models to characterize the spatial autocorrelation not accounted for by the independent variables (Dormann *et al* 2007). GLS models were computed using the *nlme* package (Pinheiro *et al* 2014) for R statistical computing software (R Core Team 2014). We evaluated spatial autocorrelation in SAR model residuals using Moran's *I* (Bivand 2013).

3. Results

When estimated using the NLCD, the degree of landscape simplification has remained fairly consistent over the past 15 years in the 575 Midwestern counties included in this analysis (figure 1(A)). The average proportion of a county in harvested cropland hovered around 0.50 between 1997 and 2012. The temporal consistency of this proportion is similar to what others have reported for this region (Larsen 2013, Plourde *et al* 2013). Although increased production of corn and soybean has been linked with cropland expansion across the US (Lark *et al* 2015), most new production of these crops in these counties came at the expense of other crops (Wallander *et al* 2011, Plourde *et al* 2013). Although landscape simplification in the region has remained fairly consistent over time, it has varied greatly across space. The average minimum proportion of a county in cropland in this study was approximately 0.03 between 1997 and 2012, while the average maximum was approximately 0.92.

The proportion of harvested cropland in a county treated with insecticides varied markedly over both time and space (figure 1(B)). These patterns were evident in the analysis by Larsen (2013), and were reinforced with the addition of 2012 COA data. Over time,

Table 1. Estimates (1 standard error) for all parameters in the SAR error model, and for the proportion of a county in harvested cropland and residual[a] Moran's *I* for ordinary least squares (OLS) and generalized least squares (GLS) models[b].

	Parameter estimate per year			
Parameter	1997	2002	2007	2012
SAR				
Proportion county in cropland	0.04 (0.02)	0.06 (0.02)	0.10 (0.02)	0.10 (0.02)
Proportion cropland in corn	0.35 (0.04)	0.29 (0.04)	0.36 (0.04)	0.31 (0.05)
Proportion cropland in soy and small grains	−0.07 (0.03)	−0.07 (0.03)	0.07 (0.03)	0.15 (0.04)
Proportion cropland in orchards and vegetables	0.90 (0.06)	0.92 (0.06)	0.87 (0.06)	0.76 (0.07)
Net income per harvested acre	0.000 11 (0.000 02)	0.000 03 (0.000 02)	0.000 09 (0.000 01)	0.000 15 (0.000 02)
Model intercept	0.02 (0.03)	0.06 (0.03)	0.004 (0.02)	0.03 (0.03)
Lambda	0.90 (0.03)	0.90 (0.03)	0.85 (0.05)	0.88 (0.04)
Moran's *I* for model residual	0.03 (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)
OLS				
Proportion county in cropland	−0.05 (0.04)	−0.01 (0.04)	0.11 (0.03)	0.08 (0.04)
Moran's *I* for model residual	0.37 (0.01)	0.40 (0.01)	0.20 (0.01)	0.32 (0.01)
GLS				
Proportion county in cropland	0.08 (0.02)	0.06 (0.02)	0.08 (0.02)	0.09 (0.03)
Moran's *I* for model residual	−0.01 (0.01)	−0.02 (0.01)	−0.01 (0.01)	0.01 (0.01)

[a] Model residuals were calculated as predictions minus observed values, where predictions accounted for spatial correlations for SAR and GLS models.

[b] Additional details for all models can be found in table S1.

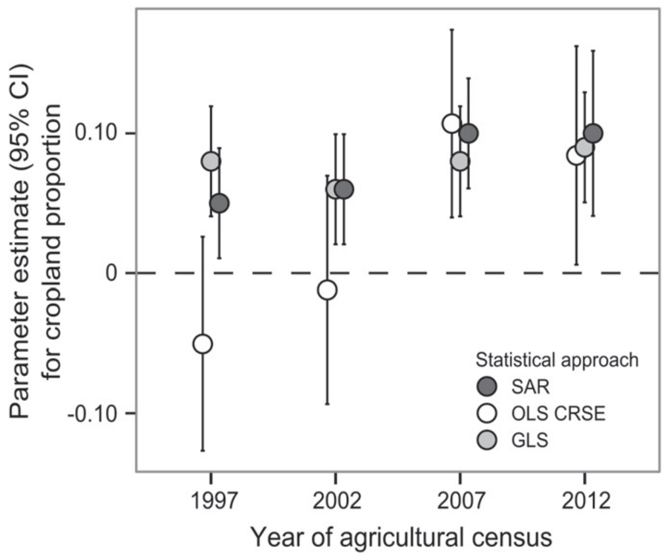

Figure 2. Coefficients (and 95% confidence intervals) for the proportion of a county in cropland terms from simultaneous autoregressive error (SAR) models, ordinary least squares (OLS) regressions using cluster-robust standard errors (CRSE), and geostatistical generalized least squares (GLS) models of the proportion of cropland treated with insecticide in 575 counties in the Midwestern US between 1997 and 2012.

the average proportion of harvested cropland treated with insecticide doubled, increasing from 0.15 to 0.31 between 1997 and 2012, with the largest jump occurring between 2002 and 2007. Across space, the minimum proportion of harvested cropland treated with insecticides over the four census periods was 0.01 or less, whereas the maximum proportion ranged from 0.58 in 1997 to 0.75 in 2012. Regarding the spatio-temporal congruence of insecticide use, the proportion of harvested cropland treated within a county over time was positively related between years. Those associations were particularly strong between 1997 and 2002 (figure 1(C)) and between 2007 and 2012 (figure 1(D)). When those associations were not as strong (figures 1(E) and (F)), it was largely due to increases in insecticide use in many counties.

The extensive spatial variation in both landscape simplification and insecticide application allowed us to explore their relationships using space-for-time substitutions, a common approach in large-scale ecological studies (Pickett 1989, Fukami and Wardle 2005). We found that general conclusions about the consistency of these relationships depended strongly on the statistical approach chosen (table 1, figure 2, table S1). Using SAR error models, we found that landscape simplification was positively related to insecticide use during each year of the study (table 1, figure 2, table S1, figure S1). The spatial autocorrelation coefficient, lambda, was an important component of the SAR error models in all years ($0.85 < \lambda < 0.90$, tables 1, S1). Moran's I tests showed little remaining spatial autocorrelation in the pure residuals of SAR error models ($0.01 < I < 0.03$, tables 1, S1).

In contrast, computing OLS regressions and CRSEs using the same dataset, the relationship between landscape simplification and insecticide use varied considerably, from negative to positive over the four censuses (table 1, figure 2, table S1). Spatial structure in the data was not explicitly modeled in OLS regressions, and Moran's I tests showed strong spatial autocorrelation in OLS residuals during each of the four censuses ($0.20 < I < 0.40$, tables 1, S1, figure S2).

SAR models always fit the data better than the OLS models (table S1). For example, AIC values of SAR models (−1595 to −1324, depending on year) were between 130 and 285 AIC units lower than those from OLS regressions (−1415 to −1107). Generally, the model with the lowest AIC value is considered the most likely model in a model set (Burnham *et al* 2011). The degree to which other models are competitors depends on the differences between their AIC values and that of the most likely model (often represented as ΔAIC). Models with ΔAIC values greater than 6–8 are usually considered unlikely (Burnham *et al* 2011). Thus, ΔAIC values of 130–285 suggested a strong advantage of SAR models over OLS regressions for these data.

Table 1, figure 2, and table S1 show that the GLS approach, with its empirical characterization of residual autocorrelation, yielded results that were qualitatively similar to those of the SAR error approach. The AIC values of GLS models (−1507 to −1227, depending on year) were intermediate between those of SAR and OLS models (table S1). Moran's I tests showed little remaining spatial autocorrelation in the pure residuals of GLS models ($-0.01 < I < 0.01$, tables 1, S1). The similarity between SAR error and GLS parameter estimates suggests that the SAR results did not derive from unreasonable assumptions about the nature of neighborhoods.

4. Discussion

Applied ecologists have been studying the effects of landscape characteristics on crop pests and their natural enemies for decades, with a goal of discovering ways to maximize agricultural production while minimizing insecticide use, and thus increasing the long-term sustainability of agriculture (Risch *et al* 1983, Landis *et al* 2000, Tscharntke *et al* 2005). At this point, links between landscape structure and natural enemy community characteristics are fairly clear: natural enemies tend to be relatively less abundant and less taxonomically diverse (Bianchi *et al* 2006, Chaplin-Kramer *et al* 2011) and less effective at removing crop pests (Werling *et al* 2011, Meehan *et al* 2012) in relatively simple landscapes dominated by annual crops. Links between landscape structure, overall pest pressure, and pest-control measures are not as clear, however (Bianchi *et al* 2006, Chaplin-Kramer *et al* 2011). The study by Meehan *et al* (2011) offered evidence for links between landscape simplification, pest pressure, and pest-control effort over an unprecedented geographic extent. But a follow up study by Larsen (2013) suggested that the positive association between landscape simplification and insecticide use found in 2007 by Meehan *et al* (2011) was unusual, and that the relationship varied in direction, from negative to positive, depending on the year.

The results of the present study suggest that a positive association between landscape simplification and insecticide use may be more prevalent than recently reported. We suggest that much of the variability in the relationship reported by Larsen (2013) is related to not considering spatial structure in the data, which manifested as strong spatial autocorrelation in OLS regression residuals. A connection between residual autocorrelation and unreliable parameter estimates has been reported in several disciplines, including economics (Basu and Thibodeau 1998, Rey and Montouri 1999), political science (Franzese and Hays 2007, Robinson and Noriega 2010), sociology (Baller *et al* 2001, Voss *et al* 2006), epidemiology (Lorant *et al* 2001, Havard *et al* 2009), and ecology (Kuhn 2007, Le Rest *et al* 2013). The issue has motivated a number of simulation studies, which demonstrate the advantages of spatial regression methods over OLS for producing reliable parameter estimates and valid hypothesis tests when data have spatial structure not captured by other model variables (Florax and Folmer 1992, Anselin and Bera 1998, Franzese and Hays 2007, Kissling and Carl 2008, Beale *et al* 2010, Saas and Gosselin 2014). These simulation studies describe a variety of possible causes behind the association between strong residual autocorrelation and poor OLS performance, ranging from the omission of important spatially-structured independent variables (Franzese and Hays 2007) to parameter shifts due to the lower precision of OLS estimates (Beale *et al* 2010, Saas and Gosselin 2014).

Of the various types of spatial regression techniques (Dormann *et al* 2007, Beale *et al* 2010), we initially employed SAR error models to explore relationships between landscape simplification and insecticide use. This approach, commonly used by econometricians (Anselin 1988, Arbia 2006, LeSage and Pace 2009), has been shown in simulation studies to perform well when there is strong spatial autocorrelation in OLS residuals (Kissling and Carl 2008, Beale *et al* 2010). An important step in building SAR models is specifying the nature of neighborhood effects, and conclusions can be sensitive to these assumptions (Stakhovych and Bijmolt 2009). These assumptions, however, can be informed by exploratory data analysis. For example, the spatial extent of neighborhoods in the present study were informed by maps and spatial correlograms of residuals from OLS regression (figure S2). GLS modeling used empirical variograms of OLS residuals to estimate parameters for parametric spatial correlation functions (Dormann *et al* 2007, Beguería and Pueyo 2009). We explored GLS as an alternative method to estimate the association between landscape simplification and insecticide use, and found that results were very similar to those from SAR models (table 1, figure 2, table S1), yet still quite different from those of OLS models. (Note that additional geographically weighted regression (figure S3) and Bayesian spatiotemporal modeling (figure S4) results are reported in supplemental materials.) Ultimately, residual maps, correlograms, and empirical variograms all demonstrated that simple OLS models were missing important spatial information, either in the form of substantive spatial processes or spatially-structured independent variables. Meehan *et al* (2011) and Larsen (2013) both explored additional variables, related to the availability of insecticide application equipment, the prevalence of transgenic corn, weather patterns, and government insecticide regulations. It is also possible that spatial structure in the data is related to the local movements and dispersal of crop pests or their natural enemies. Unfortunately, the cause of spatially structured residuals is still not clear. In the meantime, we suggest that spatial regression techniques be used to account for this unidentified spatial structure when estimating the effects of other independent variables, such as landscape simplification, on insecticide use.

There were other differences, besides the statistical approach, between the present analysis and that of Larsen (2013). First, Larsen's study included COA data from 1987 and 1992. We did not include data before 1997 because these data were not available via the Quick Stats database, and because remotely-sensed land cover data for the region is not readily available before 1992. Had we included 1992 and 1987 data in our analysis, we might have found no relationships, or possibly significant negative relationships (Larsen 2013), between landscape simplification and insecticide use. However, even in the case where significant negative relationships were found in 1987 and 1992, it would still be reasonable to conclude that the relationship between landscape simplification and insecticide use tends to be positive. Second, in the present study, we used remotely-sensed NLCD data to estimate landscape simplification, whereas most estimates in Larsen (2013) were derived from the COA (i.e., the total area of a given county was divided by the COA estimate for harvested cropland in that county for a given year). We do not suspect that this difference was responsible for our differing conclusions, as Larsen (2013) showed that results based on remotely-sensed and census-based land cover data were very similar. In fact, analyses using remotely-sensed data were slightly more conservative with regards to identifying statistically significant associations between landscape simplification and insecticide use (Larsen 2013).

Thus far, we have focused mostly on the direction of the relationship between insecticide use and landscape simplification. Regarding other explanatory variables, the association between insecticide use and fruit and vegetable production was strongly positive, regardless of which statistical methods were used (table S1), and the ranges of coefficients from this study overlapped those in Meehan *et al* (2011) and Larsen (2013). The strong association with fruit and vegetable production reflects the fact that a large share of fruit and vegetable crops are routinely treated with insecticides (USDA NASS 2010), partly to preserve aesthetic value (Babcock *et al* 1992). The association between insecticide use and corn production was also positive, regardless of modeling approach (table S1), and the ranges of coefficients from this study overlapped those in Meehan *et al* (2011) and Larsen (2013). In contrast, the association between insecticide use and soybean and small-grain production varied between modeling approaches (table S1). In this study, and that of Larsen (2013), the association was not statistically significant in the context of OLS regression. Using spatial regression, however, the association went from significantly negative to significantly positive between 1997 and 2012. It is possible that the increasingly positive association between insecticide use and soybean and small grain production reflects the recent widespread adoption of neonicotinoid-treated seed in soybean (Douglas and Tooker 2015). The association between insecticide use and farmer income tended to be positive regardless of modeling approach. However, the association was more often significantly positive when using spatial regression than when using OLS regression. Regarding the association between insecticide use and the proportion of a county in cropland, model coefficients for 2007, from both SAR and GLS models (tables 1, S1), were similar to that in Meehan *et al* (2011). Also, the cropland proportion coefficients from OLS (tables 1, S1) were similar to those from Larsen (2013). When taken together these results suggest that, when comparing this study, Meehan *et al* (2011), and Larsen (2013), the use of spatial regression versus OLS was the most important methodological difference affecting general conclusions about associations between insecticide use and other variables.

One similarity between this study and that of Meehan *et al* (2011) was the finding that the magnitude of the landscape simplification effect was relatively small.

As an illustration, imagine two counties, both with the same proportions for each crop type, and the same farmer net incomes per unit area. However, imagine that these counties differed in the degree to which they were dominated by harvested cropland, with the first county comprised of 75% harvested cropland, and the second comprised of 25% harvested cropland. Given average 2012 values for the other input variables, and 2012 parameter estimates from the SAR error model in table 1, the proportion of harvested cropland treated with insecticide would be approximately 0.35 for the first county and 0.30 for the second county. This is a relatively small difference in insecticide use with a relatively large difference in landscape simplification. There are numerous possible explanations for a low sensitivity of insecticide application to landscape simplification. For instance, it might be that landscape structure is important for natural enemies of pests (Bianchi *et al* 2006, Chaplin-Kramer *et al* 2011, Werling *et al* 2011), but that many pest populations are not particularly sensitive to natural enemy activity. In fact, some pests benefit from non-crop habitat, where they might find alternative hosts or overwintering habitat (Bahlai *et al* 2010). However, this explanation is not entirely consistent with results from Meehan *et al* (2011), who found that both insecticide use and pest aphid abundance increased in relatively simplified landscapes. Another possible explanation for a low sensitivity of insecticide application to landscape simplification is that many farmers do not base insecticide application decisions on pest pressure (e.g., Reisig *et al* 2012). Indeed, a central goal of integrated pest management programs is to encourage farmers to move away from prophylactic or calendar-based insecticide applications, to monitor pest populations more closely, and to base insecticide use decisions on estimates of pest pressure and economic crop damage (Ehler 2006). For now, it seems reasonable to conclude that there has been a consistent, positive, but relatively weak association between landscape simplification and insecticide use across the Midwestern US between 1997 and 2012.

Clear interpretation of associations between landscape characteristics and pest-management practices will require better information on the mechanisms linking landscape structure, pest and beneficial insect abundance, and crop losses. One strength of Meehan *et al* (2011), over the present study and that of Larsen (2013), was the inclusion of pest abundance data. This additional data gave more weight to the interpretation that the positive association between landscape simplification and insecticide use was mediated by landscape effects on crop pests or their natural enemies. Liere *et al* (2014) recently explored this causal chain in detailed field experiments, showing that variability in landscape composition can cascade to affect the abundance of predatory insects, their effectiveness at controlling insect pests on crops, and ultimately have an impact on crop yield. Unfortunately, when working at larger spatial and temporal scales, data on crop pest pressure, or other biologically important variables, is very difficult to find (but see Parsa *et al* 2012, Meisner and Rosenheim 2014). Without information on these intermediate links, we need to temper our inference about the mechanisms driving landscape simplification and insecticide use relationships. Indeed, defining clear links between landscape characteristics, crop pest abundance, and pest control measures will require a new generation of concerted research efforts. An idealized effort would include (1) widespread, standardized collection of georeferenced data on pest pressure, pest predation, and insecticide application that is crop, pest, and insecticide specific and (2) further discussion of best practices for analyzing these data.

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