Pesticide Drift in Iowa:

Can GIS and Regression Analysis Help Identify the Environmental Determinants of Drift?

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Introduction

As modern agriculture continues expanding, with industrial-scale monocrop operations dominating the agricultural acreage in the United States, farmers' are increasing their reliance on pesticide application to reduce yield losses. Sometimes, though, these pesticides move away from the target crop, causing negative impacts to plants, wildlife, and/or humans. This airborne movement of pesticides is called pesticide drift, and it is causing significant economic, environmental, and human health problems.

It is impossible to come up with a solution to the problem if we do not first understand the problem, and understanding this particular problem is a major challenge because very little empirical data exists for cases of pesticide drift. Since drift is only known if it is reported and reports contain sensitive identifying information like addresses and health information, it is difficult to come across datasets large enough to conduct spatial or statistical analysis. This project was able to solve the first major problem – a lack of data – through a successful Freedom of Information Act Request (FOIA). The FOIA data was then used to investigate basic spatial patterns and potential environmental correlates of pesticide drift in Iowa, contributing a small piece of a information to the pesticide drift puzzle.

Literature Review

Besides protecting crops against diseases, weeds, and pests, pesticides can be used to improve food safety, minimize energy inputs, and keep agricultural prices low for consumers (Cooper and Dobson, 2007; Damalas, 2009). The benefits of pesticide use in the agricultural sector are apparent, especially from an economic standpoint. But from both an environmental and human health perspective, the costs of pesticide use are outstanding.

It has been suggested that pesticides used for agricultural production have contributed to the massive decline in amphibians, important indicator species, in California over the past few decades (Lips, 1998; Boone & Semlitsch, 2001). Researchers have shown correlations between certain pesticides and other environmental problems, too, like water pollution, air pollution, and declines in soil health (Stoate et al., 2001; reamer & Prokopy, 2009; Power, 2010).

Perhaps more pressing are the impacts that pesticides can have on humans. Many studies have shown that exposure to pesticides can cause acute human health impacts, like skin irritation, eye irritation, and nausea (Lee et al., 2011; Sarwar, 2015; Damalas and Eleftherohorinos, 2011). Others have shown that exposure to certain pesticides can be linked to more serious, long-term human health problems, like cancer and hormone disruption (Baldi et al., 2010; Karabelas et al. 2009; Van Maele-Fabry et al., 2010). By uncovering the spatial patterns and potential correlates of pesticide drift in Iowa, we can contribute useful information that could help mitigate these environmental and human health problems.

Addressing the Problem – Data & Methods

To address the problem, which is simply a gap in the basic understanding of pesticide drift cases in Iowa, I developed two research questions and three hypothesis. One research question focuses on the spatial distribution of pesticide drift cases, while the other focuses on potential explanatory factors. The two research questions and their associated hypotheses are as follows:

1. What does pesticide drift in Iowa look like - are reports of pesticide drift in Iowa clustered?

    H1: A local Moran's I will show statistically significant hot and cold spots

2. Do different weather conditions and human variables have any relationship with how far pesticides drift?

    H2: Weather-related attributes like temperature, wind speed, and relative humidity will be statistically significant correlates of pesticide drift distance

    H3: Human-related attributes, like application type and whether or not the applicator was commercially licensed, will be a statistically significant correlate of pesticide drift distance

The data used to answer the research questions is from the Iowa Pesticide Bureau, at the Iowa Department of Agriculture. The data were obtained through a FOIA request filed by the Great Plains Center for Agricultural Health at the University of Iowa College of Public Health. The data were received as 470 handwritten paper reports, one sheet for each reported case of pesticide drift from 2010-2015, and was manually put into an Excel Workbook by graduate students at the University of Iowa College of Public Health. The data include report numbers, date and time of drift, weather conditions the day of the drift, exact location of the drift, target crop, distance between target crop and impacted plants/animals/humans (drift distance), type of application (aerial vs. ground), pesticide class found at drift site (insecticide, herbicide, fungicide), concentration of chemicals, and other fields.

The other data used to answer the research questions and test the hypotheses is a shapefile of Iowa counties from the Iowa Department of Natural Resources. The shapefile was last modified on March 20, 2018 and is publicly available on the Iowa Geodata website. The county shapefile was used both for cartographic purposes and as the area unit for aggregating drift reports.

Before importing the drift data into ArcMap, all fields were re-named to be compatible with ArcMap, individual records were cleaned extensively to remove special characters and irrelevant notes, and the street addresses were assigned latitude and longitude values through the Texas A&M geocoder (about 420 cases) and manual geocoding (about 40 cases). The data were then imported into ArcMap, along with the Iowa counties shapefile.

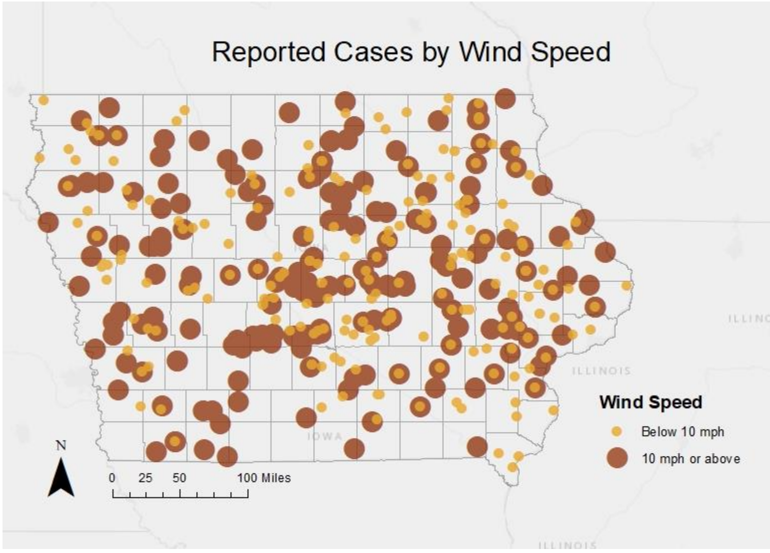

Figure 1 shows reported cases of drift, using proportional symbols to represent high windspeeds and low wind speeds.

The first step in exploring the spatial distribution of pesticide drift cases in Iowa is simply projecting the data and exploring the spatial extent. I visualized the data in a handful of different ways, including a proportional symbol map to show cases by wind speed and a cartographic symbols map to show drift cases by application type. The two maps are shown in Figure 1 and Figure 2, respectively.

The method used to test H1 was a Anselin Local Moran's I, or cluster and outlier analysis, on the count of pesticide drift reports per county. For this, the spatial conceptualization used was contiguity, edges and corners. To test H2 and H3, a

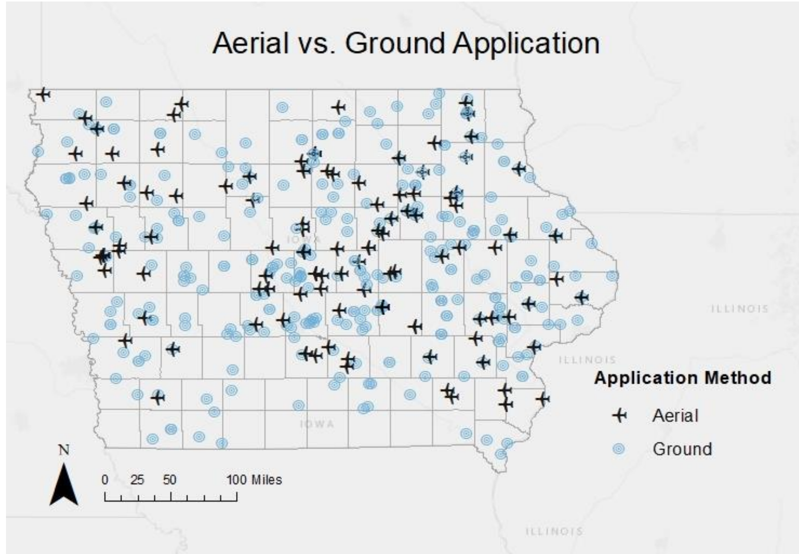

Figure 2 shows confirmed cases of pesticide drift by application type.

regression analysis was performed in GeoDa using drift distance as the dependent variable and various weather and human-related independent variables. The independent variables used were temperature, relative humidity, wind speed, application type (aerial vs. ground), person applying the pesticides (commercial applicator vs. other) and target crop. The dependent variable, pesticide drift distance, and the independent weather-related variables were all tested for spatial autocorrelation to determine if a regression analysis that accounts for spatial autocorrelation was necessary. Figure 3, below, shows the results of the Global Moran's I test for spatial autocorrelation. All tests used Euclidean distance and row standardization. Since the results showed spatial autocorrelation, a regression analysis that accounts for spatial autocorrelation was used so any resulting statistical significance of explanatory variables would not be inflated.

VARIABLE	MI INDEX	Z-SCORE	P-VALUE
Drift distance (dependent)	0.839	22.365	0.000**
Relative Humidity (independent)	0.2218	5.674	0.000**
Temperature (independent)	0.1238	3.217	0.001**
Wind Speed (independent)	0.103	2.662	0.008**

Figure 3 shows that the environmental variables considered are spatially autocorrelated.

Results & Discussion

The results of the Anselin Local Moran's I/cluster and outlier analysis are shown in Figure 4. There is a large high-high cluster in central Iowa, a large low-low cluster that includes nearly every county along Iowa's southern border with Missouri, and a small low-low cluster in northern Iowa. There are also two high-low clusters and three low-high clusters.

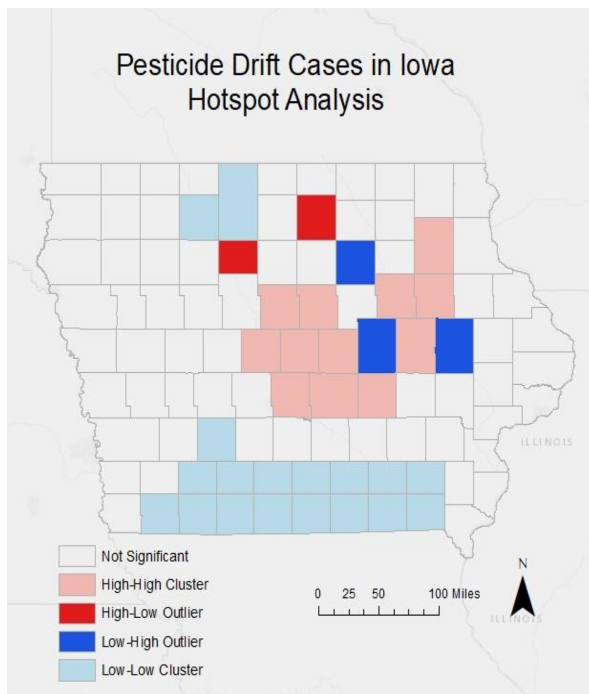

Figure 4, Anselin's Local Moran's I Analysis Results

This is an interesting result. Pesticide drift is often associated with agriculturally-dominated areas. While Iowa as a whole is dominated by agricultural land, Polk County, which is included in the large high-high cluster, is a relatively urban county. Maybe this is because there are more people around Polk County to potentially experience drift, or maybe it is because most of the education and outreach around pesticide drift in Iowa is done by the Iowa State University Extension and Outreach Office, which is located is located in central Iowa, just north of Polk County.

It is also interesting that nearly the entire southern part of Iowa makes up a low-low cluster. This could be the result of how sparsely populated those counties are, or maybe it has to do with a lack of education and outreach around pesticide drift, relative to other counties in Iowa. These are all ideas that could be investigated in future research.

As mentioned in the previous section, the regression analysis was done in GeoDa. Since the global Moran's I results showed that the weather-related independent variables and the dependent variable, drift distance, were spatially autocorrelated, I created a weights file and ran an ordinary least squares (OLS) regression correcting for spatial autocorrelation. The OLS showed an acceptable multicollinearity condition level, at 13.15, and indicated that I should implement a spatial lag model. The results for the spatial lag regression model are shown in Figure 5, below.

Variable	Coefficient	Standard Error	Z-value	Probability
Temperature	-1.56	0.98	-1.59	0.11205
Relative Humidity	0.14	0.80	0.20	0.85733
Wind Speed	12.30	3.41	3.61	0.00031**
Aerial Application$^{0/1}$	273	46.91	5.82	0.00000**
Commercial Applicator$^{0/1}$	-30.58	33.11	-0.92	0.35569
Corn as Target Crop$^{0/1}$	25.27	31.30	0.81	0.41948

*Figure 5 **indicates statistical significance; $^{0/1}$ indicates a binary independent variable; R^2= 0.227*

Temperature, relative humidity, application type, applicator type, and target crop were not statistically significant correlates of drift distance. Wind speed and application type, however, did yield statistically significant results. The regression results suggest that wind speed is positively correlated with drift distance, with a p-value < 0.001, meaning that higher wind speeds lead to further drift distances. This is a known phenomenon, and while no laws exist in the United States restricting pesticide application based on wind speed, companies that sell pesticides advise against application when wind speeds exceed 10 miles per hour. This wind speed advisory can be found on the labels of most major pesticides, including Monsanto's Roundup (glyphosate and dicamba) and Dow's Surpass (acetochlor) labels.

The R^2 of .227 shows that the model is not an exceptional fit for the data, but it does show that the independent variables tested contribute somewhat in explaining drift distance, the dependent variable. For a problem as complex as pesticide drift distance, where things as specific as the age of the pesticide spraying device, human decisions, land cover, and droplet size all contribute, an R^2 of .227 is not horrible. There are some useful results, but plenty of room for improvement.

Conclusion

While the economic benefits of pesticide use in modern agriculture are apparent, so too are the negative environmental and human health impacts. These negative impacts are particularly problematic when pesticides drift away from target crops, affecting unsuspecting humans, animals, and plants. In order to develop an effective solution to the problem, we need to first get a basic understanding of the problem itself. This project used five years' worth of pesticide drift reports, GIS methods, and statistical analysis to address some of the gaps in our current understanding of pesticide drift in Iowa. The GIS results showed that reports of drift are clustered in the central part of the state, and the regression analysis showed that wind speed and aerial application of pesticides are statistically significant, positive correlates of pesticide drift distance.

There are a lot of questions remaining, most of which cannot be answered without major improvements in data collection and publication. Since the human and environmental costs of drift are so severe, an emphasis should be put on making pesticide drift data available and funding research on the topic.

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