Pesticide application rates and their toxicological impacts: why do they vary so widely across the U.S.?

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Abstract

Pesticide usage in the U.S. has more than doubled since 1960, raising concerns on its human and ecological health implications. The literature indicates that pesticide application rates for the same crop vary widely across geographies, while the magnitude of variation and its underlying drivers are poorly understood. Here, we present a new dataset on farm-level pesticide application for maize in the U.S. Using the dataset, we derived four human and ecological health impact metrics, (1) environmental impact quotient, (2) acute hazard quotient, (3) chronic hazard quotient, and (4) freshwater ecotoxicity, and analyzed their relationships with various climatic and biophysical factors including precipitation, growing degree days (GDD), soil conductivity, and irrigation practices. Our results show that the potential human and ecological health impact of pesticide use per unit maize harvested vary by 5–7 orders of magnitude across the 891 maize-producing counties in the U.S. All four best-fitted models are statistically significant, explaining 21% to 28% of the variations in the impact intensities across counties. Among the climatic and biophysical factors examined, GDD was the most significant variable for all four metrics. This suggests that climate change may adversely affect human and ecological health impact intensities of pesticide use for maize, which may increase 22%–471% by 2100 under the 2 °C warming scenario. Besides, electrical conductivity and the percentage of cropland irrigated were significant for multiple impacts. The large remaining variability unexplained by our analysis suggests that behavioral and management factors, which were not captured in our model, play a crucial role in pesticide use, calling for the interventions targeting them.

1. Introduction

The use of pesticides is recognized as one of the main human and ecological health concerns [1–3]. Nearly 2.7 million metric tons of pesticides are used globally, of which U.S. alone accounts for 0.5 million metric tons [4]. In the U.S., pesticide use in terms of the total mass applied has been more than doubled since 1960 [5]. Exposure to pesticides has been linked to human health impacts, such as adverse birth outcomes, neurotoxicity, and risk for certain cancers [2, 3], as well as ecological health impacts, such as biodiversity loss [1, 6–8]. Toxic impact intensities of chemicals are materialized in a local context, where location-specific parameters such as climatic conditions, geospatial factors, and population play important roles in determining the magnitude of the impact [9–12]. Among others, the amount of pesticide use by mass is known to vary widely across locations and farms. Using fine-resolution pesticide use data available in California, Larsen et al, for example, showed that spatial heterogeneity of pesticides use and associated birth defect outcomes are both high [3].

Although crop-specific pesticide use data are sampled at farm-level to represent farm-level usages in the U.S., they are weighted and aggregated at state-level when made available to the public—with a notable exception for California, where more detailed
data are publicly available [13]. Existing nation-wide studies, therefore, evaluated the spatial heterogeneity of pesticide use and associated toxic impact intensities at state-level. Yang et al., for example, evaluated the spatial disparity of toxicity impacts of producing the same amount of crops in the U.S. and found that the human cancer and non-cancer health impacts and freshwater ecotoxicity from herbicide vary over one order of magnitude across states [14]. Larsen A.E. (2013) analyzed the relationship between landscape simplification and insecticide use by mass in the Midwestern U.S. and found that the insecticide use vary by over two orders of magnitude at county-level [15]. Several other studies on the spatial heterogeneity of pesticide use and its impacts in the U.S. either quantified toxicity impacts at state-level [16, 17] or conducted county-level analysis by only using the total amount of pesticide use by mass without considering the differences in pesticides’ fate, transport, exposure, or toxicity [18, 19].

In this study, we compiled a new dataset on human and ecological health impact intensities of pesticide use for maize based on farm-level pesticide use data. This new dataset allowed us to analyze the spatial heterogeneity of pesticide use, associated human and ecological health impact intensities, and their biophysical predictors at an unprecedented resolution. Due to confidentiality concerns, the farm-level data were aggregated into county-level under the guidance from the National Agricultural Statistics Service (NASS). We calculated the human and ecological health impact intensities of pesticide use at the NASS site using multiple metrics at county-level resolution and examined their spatial patterns and the biophysical predictors of their variabilities.

The objectives of our study are, first, to understand the variabilities of human and ecological health impact intensities of pesticides use for maize in the U.S. using active ingredient-specific impact metrics, and, second, to identify the biophysical and climatic drivers behind the variabilities.

2. Materials and methods

We estimated the potential human and ecological health impacts of pesticides per tonne of maize for all surveyed farms (n = 1977) and aggregated them per county. We analyzed the spatial patterns of human and ecological health impact intensities across counties and identified significant predictors that explain the variability using multiple regression analysis.

2.1. Human and ecological health impact intensities calculation

In this study, active ingredient-specific pesticide use data from individual farms were aggregated into human and ecological health impact intensities using four metrics: environmental impact quotient (EQI) [20], acute hazard quotient (Acute HQ) [21], chronic hazard quotient (Chronic HQ) [21], and freshwater ecotoxicity (Ecotox) [22]. They are elaborated here: (1) EIQ value for each active ingredient is calculated by a formula that considers both the potential environmental and human health impacts of pesticides [23]. (2) Acute HQ is represented by acute rat oral median lethal dose (LD50) in mg kg−1, while (3) Chronic HQ is represented by 24-month rat oral No Observed Adverse Effect Level (NOAEL) in mg kg−1 d−1. (4) Ecotox value for each active ingredient is represented by freshwater ecotoxicity characterization factor (CF) in the unit of PAF-m3-day/kg-emitted, which is the potentially affected fraction of species in the freshwater per day by per kg of a chemical emitted. Ecotox CF considers each chemical’s fate, exposure and effect on freshwater species [22]. To estimate the fate of pesticides, we adopted the approach by Berthoud et al., using a chemical’s vapor pressure to estimate its fraction emitted to air [24]. Furthermore, we assumed 0.5% of the chemical emitted to water, while the remaining emitted to soil [14]. It should also be noted that Hazard Quotation (HQ) approaches focus solely on the relative hazard of chemicals and do not consider fate, transport, and exposure.

The approaches to calculate these four toxic impact intensities of pesticide use are shown in equations 1–4, where N is the total number of active ingredients (ai) applied to one tonne of maize in a year, Amount is the total weight of each active ingredient applied in kg, and j is the environmental compartment of air, water, and soil.

\[
\text{EIQ Impact} = \sum_{ai}^{N} \text{Amount}_{ai} \times \text{EIQ}_{ai} \quad (1)
\]

\[
\text{Acute HQ Impact} = \sum_{ai}^{N} \frac{\text{Amount}_{ai}}{\text{LD}_{50ai}} \quad (2)
\]

\[
\text{Chronic HQ Impact} = \sum_{ai}^{N} \frac{\text{Amount}_{ai}}{\text{NOAEL}_{ai}} \quad (3)
\]

\[
\text{Ecotox Impact} = \sum_{j}^{N} \sum_{ai}^{N} \text{Amount}_{ai} \times \text{emission} \% \times \text{CF}_{ai} \quad (4)
\]

Across all surveyed farms, a total of 94 types of active ingredients were used as pesticides in 2010 for maize production, the majority of which were herbicides (66.0%), followed by insecticides (23.4%), fungicides (7.5%), and others (3.1%). Toxicity values were not available for a few active ingredients: six active ingredients for EIQ values, one for rat oral LD50, three for rat NOAEL, and 15 for freshwater ecotoxicity (table S1). To fill in the data gap, we used appropriate median toxicity values of the available active
ingredients applied to maize production [25]. The pesticide human and ecological health impact intensities were first computed at farm-level, and then averaged at county-level.

2.2. Identifying the predictors for spatial patterns
Pesticide use varies widely due to the various underlying factors including, but not limited to, climate, soil properties, irrigation level, farmer’s income and percent of land in crop [18, 26–29]. A multiple regression model can analyze the relationship between these factors and human and ecological health impact intensities of pesticide use.

Two major climate variables that influence maize growth and pesticide use are temperature and precipitation [26, 30–34]. Maize is particularly sensitive to high temperatures during growing season, with temperatures above 29 °C being harmful to maize yield [31, 35–39]. Further, increasing temperature decreases pesticide effectiveness due to increased volatilization and degradation rates of certain pesticides, therefore resulting in increased application of pesticides [40–43]. Warm temperature could also accelerate insect population growth as well as weed growth, which may further raise the application rate of pesticides and decrease crop yields [44–47]. Growing degree days (GDD) is used to reflect the effect of temperatures on maize yield [26, 48]. The values of GDD were computed following equation 5 [49], where $N$ is the total number of days during the maize growing season, and $T_{\text{base}}$ was set to 9 °C [49]. The growing season is from 1st May to 30th September for maize [39]. GDD is in the unit of °C day.

$$\text{GDD} = \sum_{i=1}^{N} \text{GDD}_i = \sum_{i=1}^{N} \frac{T_{\text{min}} + T_{\text{max}}}{2} - T_{\text{base}} \quad (5)$$

The total precipitation (in mm) and the average soil moisture (in mm) during the growing season are our metrics for precipitation and soil moisture, respectively. Maize can be produced under precipitation levels ranging from 200 mm to 2000 mm, within which precipitation has been generally found to be positively correlated with yield [50, 51]. In addition, shifting rainfall patterns, which result in precipitation extremes (i.e. excess rainfall or drought), can affect maize yield and pesticide use. Excess rainfall can result in a reduced yield partly due to delayed fieldwork, decreased fertilizer response, soil erosion, root anoxia, prevalence of leaf fungal pathogens, and spread of foliar diseases [50, 52, 53]. Increased precipitation also favors hydromorphic weeds and plant pathogens, which may lead to additional weed pressure and herbicides costs [30, 41, 54]. On the opposite side of the rainfall spectrum, drought can be a main constraint to maize production, particularly in rain-fed regions [55, 56]. Summer droughts can affect weed management and lessen the effectiveness of pesticides because of the low levels of soil moisture [57, 58]. Water irrigation level is another important factor, as it can be applied to reduce the adverse effect of extreme heat and low precipitation [26].

Several other soil parameters, including percent of silt, percent of clay, percent of organic matter, electrical conductivity (EC) (in mS m$^{-1}$), and pH, may also play a role in maize yield [28, 29, 59, 60]. Furthermore, farm-related income at county-level and the percent of land in maize may also influence pesticide use. Farm-related income can affect farmers’ educational level and farm efficiency [27]. The percent of county land in maize can be considered as an indicator of land simplification, which was shown to be positively correlated with insecticide use in the Midwestern U.S. [18]. Finally, we included state dummy variables ($\gamma_s$) to control for state-specific unobserved factors that are shared by all counties within a state such as pest management policy.

In this study, we evaluated the relationship between the four impact intensities and 12 variables that include climatic, technological, geological, and economic states: GDD, precipitation, Palmer Drought Severity Index (PDSI), percent of irrigation (the percentage of cropland irrigated), farm-related income, percent of land in maize per county, and soil properties (soil moisture, percent of silt, percent of clay, percent of organic matter, EC, and pH) (equation 6). Due to missing observations on farm-level income and maize percentage of total land, 747 out of 891 maize-growing counties were left to build the regression models. Variance inflation factor (VIF) values were computed in R to check multi-collinearity between independent variables. All of the covariates were acceptable, with VIF values ranging from 1.5 to 8.3, and 10 was used as a threshold [61]. Spatial autocorrelation was checked using Moran’s I test and $p$-values were all greater than 0.1, indicating no spatial autocorrelation in the models [62]. We employed the log-transformation of those four impact intensities in our regression models to decrease the data variability and make them conform more closely to the normal distribution.

We estimate the following model for county, $i$, in state, $s$,

$$\ln(\text{toxicity impact})_{is} = \beta_0 + \gamma_s + \beta_1 \cdot \text{GDD} + \beta_2 \cdot \text{Precipitation} + \beta_3 \cdot \text{PDSI} + \beta_4 \cdot \text{Soil Moisture} + \beta_5 \cdot \text{Percent of Silt} + \beta_6 \cdot \text{Percent of Clay} + \beta_7 \cdot \text{Organic Matter Content} + \beta_8 \cdot \text{Electrical Conductivity} + \beta_9 \cdot \text{pH} + \beta_{10} \cdot \text{Percent of Irrigation} + \beta_{11} \cdot \text{Farmer Income} + \beta_{12} \cdot \text{Percent of Land in Corn} + \epsilon_{is} \quad (6)$$
2.3. Data

EIQ values for each chemical were obtained from Eshenaur et al. [23], as updated in 2012. Rat oral LD$_{50}$ and NOAEL were compiled from Kniss’s study [21] and ChemIDPlus [63] was searched to fill in the data gap. Ecotox CFs were downloaded from USEtox 2.0 [64]. Data on maize production and pesticide use for year 2010 came from the Agricultural Resource Management Survey (ARMS), sponsored by the U.S. Department of Agriculture Economic Research Service and NASS [65]. For surveyed farms, the amount of each active ingredient use was computed per tonne of maize produced. In total, this includes data for 1977 farms, across 891 counties and 19 states. The number of surveyed farms differs among counties to reflect U.S. farm distribution. Some counties may have more than three surveyed farms, while others may only have one or two surveyed farms.

The climate data of daily minimum and maximum air temperature and daily precipitation came from the GRIDMET dataset, and the monthly soil moisture and PDSI came from TERRACLIMATE, both of which were developed in the Climatology Lab at the University of Idaho [66, 67]. The data for 2010 during the growing season were gathered and averaged at county-level based on area through the ‘climatER’ package in R [68]. The county-level irrigation data came from the Census of Agriculture by the USDA NASS [69]. We used irrigation data in 2012 as a proxy for 2010 since that is the closest year available. The raw soil data were from USDA STATSGO2 database [70] and averaged at county-level by area in ArcGIS [71]. Farm-related income and maize planted acres were downloaded from USDA NASS Quick Stats from the 2010 survey [13]. The percent of land in maize was calculated by dividing each county’s maize planted acres by its land area in county and then multiplying by 100.

3. Results

3.1. Disparity in pesticide use and its potential human and ecological impacts

Pesticide use among farms was highly variable according to the types of active ingredients as well as applied amounts. Figure 1 shows the top 20 pesticides used by the largest number of farms among the surveyed farms. Among them are 18 herbicides, one insecticide (tefluthrin), and one fungicide (pyraclostrobin). Glyphosate isopropylamine salt is the most frequently applied pesticide by farms (71.3%), followed by atrazine (29.1%), s-metolachlor (19.8%), and acetochlor (19.6%). Even for farms using the same pesticide, the amount applied per tonne of harvest varies 2–4 orders of magnitude.

The potential human and ecological health impacts of pesticides are also highly variable (figure S1 (available online at https://stacks.iop.org/ERL/15/124049/mmedia)), with EIQ values range from 9.4 to 88 (1.0–2.0 on a log scale), freshwater ecotoxicity CF values range from 6.4 to 250 000 (0.8–6.4 on a log scale) in PAF-m$^3$-day/kg-emitted, rat oral median lethal dose (LD$_{50}$) values range from 1.3 to 8800 (0.1–3.9 on a log scale) in mg kg$^{-1}$, and rat oral NOAEL values range from 0.06 to 20 000 (−1.2–4.3 on a log scale) in mg kg$^{-1}$ d$^{-1}$. EIQ values for each active ingredient were used to calculate EIQ impact intensities, rat oral LD$_{50}$ values were used to calculate Acute HQ impact intensities, rat oral NOAEL values were used to calculate Chronic HQ impact intensities, and freshwater ecotoxicity CF values were used to calculate Ecotox impact intensities. For LD$_{50}$ and NOAEL values, the lower the values, the more toxic the chemicals are [21].

3.2. Spatial disparity in the impact intensities of pesticide use

Coefficient of variation (CV) values were used to evaluate the variations of human and ecological health impact intensities among farms within a county. CV values were computed for 479 counties that has more than one farm by dividing the standard deviation by the county mean [72]. A CV value less than 1 is considered low-variance, and a CV value greater than 1 is considered as high-variance [72]. The average CV across those counties is 0.76 for EIQ impact, 0.98 for Ecotox impact, 0.87 for Acute HQ impact, and 1.21 for Chronic HQ impact. Therefore, the overall variance of the human and ecological health impacts of the farms within a county is not high, except for Chronic HQ impact which is slightly larger than 1. However, the variations within a state are higher with the average CVs for all impacts being greater than 1 (1.42 for EIQ impact, 2.96 for Ecotox impact, 1.99 for Acute HQ impact, and 2.24 for Chronic HQ impact).

Figure 2 shows the overall variations of human and ecological health impact intensities of maize production at county-level for (a) EIQ impact, (b) Ecotox impact, (c) Acute HQ impact, and (d) Chronic HQ impact. The four human and ecological health metrics used exhibited high level of correlation but not without meaningful differences among them. Across all 891 counties, a broad range was found in all four impact intensities: seven orders of magnitude for Chronic HQ impact, six orders of magnitude for Acute HQ impact, and five orders of magnitude for EIQ impact and Ecotox impact. To produce one tonne of maize, EIQ impact intensities vary from 7.5 × 10$^{-4}$ to 55 across the U.S. counties, Ecotox impact intensities vary from 4.8 × 10$^{-2}$ to 3.1 × 10$^4$ in unit of PAF-m$^3$-day, Acute HQ impact intensities vary from 6.8 × 10$^{-6}$ to 2.6 × 10$^3$, and Chronic HQ impact intensities vary from 9.3 × 10$^{-7}$ to 3.1 (figure 2).

Figure 3 shows the distribution of county-level EIQ impact intensities for each of the 19 states and for all states combined. As shown in figure 3, the
Figure 1. The top 20 pesticides used by the largest number of farms and the range of use amounts per unit of maize produced among farms across the United States in 2010. The percentages of farms represented by the data are shown in the parenthesis on the vertical axis.

Figure 2. Average human and ecological health impact intensities of maize production at the county-level for (a) EIQ impact, (b) Ecotox impact, (c) Acute HQ impact, and (d) Chronic HQ impact. Quantile classification method is implemented.

distribution of county-level impact intensities generally resembles the shape of a flat-bottomed lab flask characterized by a wide base and an elongated bottleneck toward the top. In other words, the intensities of human and ecological health impacts remain relatively low in most counties, while a few counties exhibit extremely high values. While the counties at the top bottleneck of the distribution are few,
Figure 3. The distribution of EIQ impact intensities at county-level for each state and all states. The orange line indicates the mean value among counties in a certain state. The shapes of these violin plots indicate the density of data points, the wider the shape, the more data points locating there.

due to the sheer intensities that are often several orders of magnitude higher than the average, those counties may dominate the overall potential human and ecological health impacts of pesticide use for maize in each state.

It is also notable that some states exhibit higher intra-state variability in impact intensity values (see e.g. Iowa and Illinois). The highest county-level EIQ impact intensities are found in counties in North Carolina, Kansas and Pennsylvania, and the lowest EIQ impact intensities are found in counties in Illinois, Indiana, and North Dakota (figure 3). Similar high-variance can be found for Ecotox impact, Acute HQ impact and Chronic HQ impact (see figures S2–S4). While the states where the counties with highest and lowest impact intensities are located vary across the impact metrics tested (figures S2–S4), North Carolina is often among the states with highest county-level impact intensity and North Dakota is often the one with the lowest.

3.3. Predictors of inter-county variability
We applied linear regression to relate the four human and ecological health impact intensities of pesticide use (EIQ, Ecotox, Acute HQ, Chronic HQ) to GDD, precipitation, PDSI, percent of irrigation, farm-related income, percent of land in maize per county, and soil properties (soil moisture, percent of silt, percent of clay, percent of organic matter, EC, and pH). State was used as a dummy variable to control for state-specific variations. The best-fit model results after model selection based on Akaike information criterion (AIC) values are shown in table 1 and the full model results are shown in table S2. All four best-fitted models are statistically significant, and they explain 21% to 28% of the variation in human and ecological health impact intensities across counties in the U.S.

Table 1 shows that all four human and ecological health impact intensities of pesticide use are negatively related to EC and pH values. Those
correlations are quite strong at the 0.05 significance level, except for EC in Acute HQ ($p < 0.1$) and pH in Chronic HQ ($p > 0.1$). The negative correlations are partly due to the positive correlations between yield and EC, and yield and soil pH [73, 74]. Regions with a higher EC indicate a higher clay content, a higher organic matter content, and a higher yield potential [75]. The negative effect of pH may be due to low soil pH levels reducing nutrients availability to crops and increasing the solubility of toxic metals, resulting in a low crop yield [76].

Precipitation and PDSI are not statistically significant ($p > 0.1$). The percent of irrigation is statistically positive correlated with the potential human and ecological health impacts of Ecotox ($p < 0.001$) and Chronic HQ ($p < 0.01$), and soil moisture is statistically positive correlated with Ecotox impact ($p < 0.05$). PDSI can range from −10 (extreme drought) to 10 (extreme wet) [77], however, PDSI values in our dataset only vary from −2.7 to 7.4 (figure S5). This indicates that no severe drought event happened in the maize producing counties in 2010. A high percent of irrigation is mostly in counties in Colorado, Nebraska, Kansas, Texas, and Georgia (figure S6), and the high precipitation is more concentrated in counties in Wisconsin, Iowa, Missouri, and North Carolina (figure S7). Irrigation is usually applied to counterbalance the adverse effects of high heat and low precipitation. The positive effect of irrigation may be caused by counties with sufficient precipitation and a relatively high irrigation rate, as the resulting excessive soil water would favor hydromorphic weeds and increase herbicide use [30, 41]. The percent of county land in maize has a significantly moderate positive correlation with Chronic HQ impact ($p < 0.05$). After accounting for several covariates, there are significant and positive relationships between all four human and ecological health impact intensities of pesticide use and GDD. This indicates that counties with higher GDD values during the growing season tend to have higher impact intensities in all four impacts.

Table 1. Best-fit model results from regression of toxic impact intensities maize production from 747 counties in 19 states of the U.S. The dependent variables of those four toxic impact intensities are log-transformed. In each cell, the regression coefficient is the top value.

| Coefficient | Log EQI | Log Ecotox | Log Acute HQ | Log Chronic HQ |
|-------------|---------|------------|--------------|----------------|
| Intercept   | −0.5690 | −0.9914    | −11.2194***  | −9.3228***     |
|             | (1.1688)| (1.7046)   | (1.3495)     | (2.7893)       |
| GDD         | 0.0014*** | 0.0024*** | 0.0014***    | 0.0038***      |
|             | (0.0003)| (0.0004)   | (0.0003)     | (0.0007)       |
| Soil Moisture | —      | 0.0019*   | —            | —              |
|             |         | (0.0008)  |              |                |
| Percent of Silt | —      | —         | —            | 0.0226*        |
|             |         |           |              | (0.0119)       |
| Percent of Organic Matter | —      | —         | —            | 0.0288        |
|             |         |           |              | (0.0203)       |
| Electrical Conductivity | −0.1792** | −0.3583** | −0.1578.     | −0.4415**      |
|             | (0.0684)| (0.1109)  | (0.0806)     | (0.1619)       |
| pH          | −0.2973* | −0.3672*  | −0.3119*     | −0.6318        |
|             | (0.1268)| (0.1859)  | (0.1453)     | (0.3017)       |
| Percent of Irrigation | —      | 0.01588*** | 0.0062.      | 0.0201**      |
|             |         | (0.0040)  | (0.0032)     | (0.0065)       |
| Farmer-related Income | —      | —         | 0.0322        | —              |
|             |         |           | (0.0227)     |                |
| Percent of Land in Corn | −0.7191| —         | —            | 2.7598*        |
|             | (0.4689)|           |              | (1.0971)       |
| N = 747     | N = 747 | i = 747   | N = 747      |
| R2 = 0.28  | R2 = 0.28 | R2 = 0.27 | R2 = 0.21   |

4. Discussion and conclusion

In this paper, we quantified the human and ecological health impact intensities of maize production in the U.S. at county-level, using four metrics including EIQ impact, freshwater ecotoxicity (Ecotox impact), Acute HQ impact, and Chronic HQ impact. Acute HQ impact intensities vary by six orders of magnitude, and EIQ impact intensities and Ecotox impact intensities vary by five orders of magnitude. North Carolina and Pennsylvania have relatively high impact intensities for all impact categories, while Nebraska and Minnesota have relatively low impact intensities for Ecotox, EIQ, and Acute HQ. However, across 891 maize producing counties, Chronic HQ impact has the largest variability, and the maximum value is seven orders of magnitude larger than the minimum value.

The underlying biophysical and climatic drivers of the variabilities in human and ecological health impact intensities of pesticide use for maize were
analyzed using a multiple regression model. Consistently significant and positive correlations are found between all four impact intensities of pesticide use and GDD, with no significant effects of precipitation and PDSI. The positive effect of GDD is partly because of the accelerating growth of weeds and pest populations due to the warm temperature and increasing CO2 concentration [47], and partly because of a lower yield under the extreme warm temperature [48]. Maize is sensitive to high temperatures and temperatures above 29 °C are harmful to maize yield [48]. Moreover, high temperature can not only decrease pesticide effectiveness by increasing volatilization and degradations rates of pesticides [40–43], but also accelerate insect and weed growth rates [44–47].

The significant influence of GDD on the variability of the potential human and ecological health impacts of pesticides suggests that climate change may affect toxicity impacts of pesticide use for maize. Under the 2 °C warming scenario, Butler et al showed that GDDs in the U.S. are expected to increase by 285–335 °C·day [26]. In that case, EIQ impact intensity, Ecotox impact intensity, Acute HQ impact intensity, and Chronic HQ impact intensity are expected to increase by 26%–95%, 53%–202%, 22%–102% and 104%–471%, respectively, under the 2 °C warming scenario.

Although our study developed statistically significant models with more detailed data, there is still 70% to 80% of the variation in the impact values that could not be explained by the variables included in our models. The unexplained variation may be caused by various factors including human and managerial factors. For example, agricultural extension and technology service staffs, pesticide formulators, and retailers play an important role in farmers’ decision on the choice of pesticide and the quantity of use [78, 79]. Retailers may influence some pesticide overuse, and farmers who choose to consult advisors may use lesser amount or less toxic pesticides. In particular, the literature indicated that the influence of pesticide retailers was associated with pesticide overuse [79]. Other behavioral factors in pesticide use include farmers’ knowledge level, awareness of pesticide use and its associated potential environmental and health impacts, and the willingness to pay for safer pesticides [78–80]. Previous studies found that training retailers, educating farmers, and the use of agricultural extension programs may reduce the use of pesticides and associated toxic impacts [78, 79]. Furthermore, Tang et al, observed that farmers who perceive climate risk tend to increase the quantity of pesticide use, indicating that farmers’ perceptions of climate risk alone may exacerbate the impacts of pesticides [81].

Future research can further improve our study in a number of fronts. First, our models were built upon county-level aggregated data for both dependent variables of the potential human and ecological health impacts and explanatory variables. However, pesticide use can be very locality-specific and depends on the needs at farm-level, and this aggregation step may have reduced or removed some distinct effects of locality-specific variables such as soil types and organic matter content. Second, despite the fact that we used state as a dummy variable to control for the state-level pest management or conservation programs in agricultural systems, those programs rely primarily on voluntary action by farmers who can make their own decisions on the adoption of those practices [82, 83], and this may have an impact on farmer pesticide use at the county-level. Third, toxicity data were unavailable for some of the active ingredients included in our analysis, and therefore we used an imputation approach based on median values. This can be further improved by using other more advanced approaches, including structural similarity methods such as the Chemical Life Cycle Collaborative (CLiCC) tool [84]. Finally, we acknowledge that the metrics such as LD50 used in these calculations, though widely practiced and accepted in the literature, address only part of the entire toxicological landscape, and that other indicators, toxicological and epidemiological, would further enrich the evaluation.

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Data availability

The data that support the findings of this study are available upon reasonable request from the authors. Due to confidentiality requirements, the farm-level data collected in the Census of Agricultural by the National Agricultural Statistics Service (NASS) analyzed in the current study are not publicly available. It can be obtained via application from USDA’s NASS using form ADM-042.

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