The Impact of Climate Change on Chemical Inputs:

Evidence of Pesticide Usage from China

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Abstract

Pesticides have been applied widely to prevent, mitigate, or destroy pests and diseases to improve crop yield and quality. However, under climate change, including the change in the spatiotemporal distribution of temperature and precipitation, pest pressure and optimal pesticide application rates are likely to vary, thereby pesticide use is expected to be affected. In this study, we systemically assess the impact of climate change on pesticide use by examining regional variations and the effects of extreme weather using a novel panel from China during 1998-2016. Meanwhile, this study pioneers in using the chain rule to decompose the aggregate of influence of climate change into three components, namely, effects of planted area, intensity, and structure. The results show that pesticide usage trends to first increase and then to decrease as the temperature rising and daily precipitation increasing. Moreover, the impact of climate change on pesticide use varies across regions. The northeast regions of China is more sensitive to climate change in pesticide use than the other regions. Considering strict land constraints, this study furthermore shows that intensive effects dominate the impact of climate change on pesticide use. Intensive effect dominates 93 percent of the temperature impact and dominates 145 percent of the precipitation impact.

Keywords: Climate change; Pesticide usage; Decompose; Maximum entropy

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1 Introduction

To increase food security, agriculture has become increasingly dependent on pesticide with these chemicals emitting into atmosphere, pedosphere and hydrosphere. Regular inflow and high persistence can lead to high pesticide concentrations in environmental compartments over time and affect non-target species, hence they have adverse impacts on the environment and human health. For example, grain production has doubled over the last 40 years as a consequence of changes in plant protection and other agricultural technology, including a 15–20-fold increase in pesticide use worldwide. The use of pesticides causes adverse externalities on human health and environment. For example, for every 100 agricultural workers, between one and three suffer acute pesticide poisoning, leading to many thousands of fatalities; developing countries experience 99% of the deaths while using 25% of the world's production of pesticides (Chakraborty and Newton 2011). However, these impacts might be sensitive to climate change because pest pressure and optimal pesticide application rates vary with weather and climate conditions (Koleva and Schneider 2009; Noyes et al. 2009; Olesen and Bindi 2002). Given the general acceptance of major climate change effects, it is obvious that an effect on pesticide use can also be expected.

It is ecologically difficult to completely seize the links between climate and pesticide usage given the high degree of complexity of the relationship. The impacts of climage change on pesticide use include several pathways. First, climate change can reduce concentrations of pesticides due to a combination of increased volatilization and accelerated degradation, both strongly affected by a high moisture content, elevated temperatures and direct exposure to sunlight (Delcour, Spanoghe, and Uyttendaele 2015; Noyes et al. 2009). Typically, global warming is acknowledged to accelerate the degradation of chemical components due to accelerated microbial and chemical reaction rates and may reduce concentrations of pesticides in the environment (Bloomfield et al. 2006; Delcour et al. 2015). In general, timing and intensity of rainfall influence pesticide persistence and efficiency (Rosenzweig et al. 2001). Pesticide uptake and transport in plants, are affected by precipitation and will be limited in case of decreased transpiration under dry circumstances. Typically, elevated soil moisture contents and increased precipitation, also enhance pesticide degradation (Noyes et al. 2009).

Second, altered climate conditions can create a thriving environment for insect and pathogen attacks. Higher temperatures and wetter conditions may allow faster development times for weeds, pests and diseases, and probably allow for additional generations within a year (Bale et al. 2002; Bloomfield et al. 2006; Goel, McConnell, and Torrents 2005; Rosenzweig et al. 2001). Moreover, warmer winters reduce winterkill, and consequently, increase insect populations in subsequent growing seasons. Wet conditions bring on severe insect and plant pathogen infestations. Excessive soil moisture may drown soil-residing insects (Rosenzweig et al. 2001). Drought changes the physiology of host species, leading to changes in the insects that feed on them, and can reduce populations of friendly insects (such as predators or parasitoids), spiders and birds, influencing the impact of pest infestations.

Third, climate change seems likely to change the growth rate of crops that would indirectly change the pesticide usage. Higher temperatures and increased CO_2 concentrations, associated with a substantial change in photosynthetic activity, promote plant growth and expansion. A high growth rate can cause a dilution of the absorbed pesticide concentration in plants, decreasing the pesticide residue (Delcour et al. 2015; Patterson et al. 1999). A lengthening of the active growing season potentially allows for increased farming. This possibility might result in increased pesticide use. Pesticide uptake and transport in plants, are affected by precipitation and will be limited in case of decreased transpiration under dry circumstances.

Fourth, there are indications that climate change causes phenology and geographic distribution changes in a wide range of ecosystems. Research figures out that infestations often coincide with modifications in climate conditions (Jackson et al. 2011; Rosenzweig et al. 2001). This is not illogical as temperature affects not only the availability of host plants and refuges, but also improves dispersal, migration and population characteristics such as reproduction and growth rates (Delcour et al. 2015). For instance, warmer winters will exceed the threshold for diapause at the southern edge of the range and distributions will shift north, thus many of specifies will expand their geographical ranges to higher latitude and altitudes(Bale et al. 2002). It is probable that the geographical ranges of these species will expand northwards in a warmer climate.

Once farmers' adaption behavior was considered, the impact of climate change on pesticide use will become more complicated. For example, because of the reduced pesticide tolerance of crops under stress, the use of another range of new pesticides will possibly be needed. On the other hand, a shift in the use of certain classes of current pesticide products is the most probable evolution (Delcour et al. 2015). Moreover, changes in crop management techniques, particularly reducing the intensification of cropping, increase of crop rotations and reduction in monocultures, could decrease the activity of pests.

There have been few studies investigating the relationships between pesticides and climate change (Bloomfield et al. 2006). Chen and Mccarl (2001) used state level pesticide usage data and examined the effect of climate variations on the average and variability of U.S. per area pesticide costs across the U.S. as a proxy for investigating the consequence for pest populations. They found that the increases of rainfall and temperature increase the pesticide usage. The impacts of temperature and rainfall on the cost variability vary across crops. Overall, crop damage by pests and weeds is a consequence of complex ecological dynamics between two or more organisms, and therefore, is difficult to estimate and predict.

This paper contributes to the investigation of the relationship between pesticide usage and climate change using a novel panel of 2,657 counties in China from 1998 to 2016. Given the high degree of complexity of the link between climate and pesticide usage, empirical analysis will bring more insights that can help policymakers measure the comprehensive costs of climate change. We systemically assess the impact of climate change on pesticide usage by examining regional and seasonal variations. This study pioneers in using the chain rule to decompose the aggregate of influence of climate change into three components, namely, effects of planted area, intensity, and structure. Moreover, this study contributes in providing a maximum entropy approach to recover crop specific pesticide usage at county level to dissolve the challenge of data limitation.

The results show that pesticide use is associated with temperature, precipitation, and extreme weather. We found that there is a non-linear relationship between the growing season temperature and pesticide usage. In this case, pesticide usage trends to first increase and then to decrease as the temperature rising. Furthermore, it is found that the marginal effect evaluated 19.5℃ (the sample average) is -1.16% on pesticide total usage for growing season temperature. In terms of precipitation, there is also an inverted U-shaped relation between pesticide usage and growing season precipitation. And the marginal effect evaluated 3.27 mm (the sample average) is -1.89%. Under extreme weather, the higher temperature or more precipitation, the less on pesticide use. Moreover, the impact of climate change on pesticide use varies across regions. The northeast region of China is more sensitive to climate change in pesticide use than the other regions. Considering strict land constraints, this study furthermore shows that temperature and precipitation have a significant impact on pesticide intensity, crop planting structure and total planting area. Among them, intensive effects dominate the impact of climate change on pesticide use. By measuring marginal effect at the sample average level, it is found that intensive effect dominates 93 percent of the temperature impact and dominates 145 percent of the precipitation impact.

The rest of the study is organized as follows. Section 2 introduces the background of pesticide usage in China. Section 3 outlines the theoretical framework of analysis and empirical estimation strategy. Section 4 introduces data sources and the maximum entropy program to recover pesticide intensity in each county. Section 5 describes our results on the impacts of climate change on aggregate pesticide usage, decomposition results and pesticide use regulation discussions. Section 6 provides the concluding remarks.

2 Pesticide usage in China

China has experienced the rapid increase of pesticide use in last decades. The total amount of pesticides used per year grew from 0.76 million tons in 1990 to 1.5 million tons in 2018 (see Figure 1). The intensity of pesticide use increased from 5 kg per ha in 1990 to 9 kg per ha in 2018, which is 3.1 times of the average value in worldwide (FAO 2020). Typically, the average utilization rate of pesticides is 35%, 30% lower than utilization rates in developed countries (Jin and Zhou 2018).

[Insert Figure 1 around here]

Due to the severe non-point polltuion driven by pesticide overuse, China's ministry of agricultural in 2015 realeasd Zero Growth of Pesticide Use plan (ZGPU) by 2020. It requires to achieve annual growth rates of chemical fertilizer use of less than 1% from 2015 to 2019, and strive to realize zero growth of chemical fertilizer use for principal crops by 2020 (Jin and Zhou 2018). The practical objective of the ZGPU plan is to keep the use of pesticides per unit of land area below the average level in the years 2016 to 2019, and strive to achieve zero growth in the total use of pesticides by 2020. As the strict regulation from 2015, the total use of pesiticide has been in the track of reduction in Figure 1. Consider the fact that total planted area keeps increasing in the last decade and there is a minor change for the crop strucure, the recent reduction of pesticide use is driven by the efficiency improvement of pesticide-intensive crops such as fruits and vegetable accounting for 14% of planted area. For example, apple production and vegetables have reduced pesitcide consumption by one fourth and one fifth from 2012 to 2018, respectively. However, the less pesticide-intensive crop such as grain accounting for 70% of planted area has reached a stable platform since 2012.

On the other hand, it is expected that China's food consumption will continuously increase along with economic growth. Based on recent projection, household income will be increased by around 5% annually by 2027 (Lannes et al. 2018), and total poulation will increase to 1.45 billion by 2030 (UN 2013). Hence, these trends drive sustained growth of per capita food consumption in the near future (Ye et al. 2013). As pesticide is extremely important for mitigate the vulnerability of food production, strict pesticide use regulation is adding potential volatility to China's domestic food supply.

3 Methodology

3.1 Total impact of climate change on pesticide use

Unlike standard factors of production such as land, labor, and capital, pesticide does not increase potential output. It only increases the share of potential output that producers realized. Hence, under the background of climate change we modified the classical damage control conceptual framework proposed by Lichtenberg and Zilberman (1986) and define the relationship between production pesticide use and output as

$$Q = F(X, G(P); W) \qquad (1)$$

where Q denotes output, the production funciton F is assumed to possess the concave propertity, and X is a direct production input vector such as labor, fertilizer, etc. $G(P)$ is the proportion of the destructive capacity of the damaging agent eliminated by the application of a level of control agent P, such as pesticide. Function G is monotonically increasing with respect to P, which means that G converges to 1 when infinite amout of P application. W denotes climate variables that can affect both crop growh and the damage control efficiency.

Then the demand of pesticide can be expressed as

$$P = f(Q, X, W). \qquad (2)$$

It turns out that the effects of climate change on aggregate pesticide demand vary over different climate factors, and sequentially become an empirical question.

In the empirical estimation, the key variables used in Equation (2) are elaborately incorporated to a reduced form (see Equation (3)). To identify the effect of climate change on the pesticide use, county level panel in China from 1998-2012 are used to estimate the empirical model as follows.

$$\mathrm{Ln}P_{rt} = \beta_0 + \beta_1 W_{rt} + T_t + D_r + u_{rt}, \qquad (3)$$

where P_{rt} denotes the total pesticide use in county r in year t. W_{rt} is a set of climatic factors. W_{rt} denotes climate variables that can affect both crop growh and the damage control efficiency. Even if damage due to pests, weeds, etc., were absent, farm production would still be affected by the variability of rainfall, temperature, length of the growing season, and other factors beyond the producer's control (Saha, et al., 1997). For example, precipiation may stimulate the growth of crop. However, moisture levels also have a significant impact on the pest control effectiveness of certain pesticide (Saha, et al., 1997), and stimuate the growth of weeds. Hence, variable W_{rt} captures the interactions of beween crop growth and the damage control. Meanwhile, W_{rt} denote climate conditions that also affect damage control inputs. For example, warm winter improves pest overwintering, dispersal, migration and population characteristics (Delcour, et al., 2015), but it seems not affect crop development in the growing season.

A time-invariant county fixed effect D_r is used to control for heterogeneity, such as soil quality, land topgraphy, and different agricultural production practices including rotation or tillage. On the other hand, there is a consistent advancement related to pesticide use such as new pesticide varieties and the adoption of genetically modified crop. Hence, we also control time trend T_t to remove the unobserved factors common to all regions in a given year, such as the introduction of a new crop variety, adoption of new production technologies, legislation, pest resistance, or other temporal shocks. We use u_{rt} is an error term. $\boldsymbol{\beta}$ is the parameter vector to be estimated.

3.2 Decompose the impact of climate change on pesticide use

To investigate details about the impacts of climate change on pesticide use, total pesticide use can be decomposed as follows

$$P = \sum_i P_i = \sum_i \frac{P_i}{L_i}\frac{L_i}{L} L = \sum_i PI_i \cdot SI_i \cdot L \tag{4}$$

where P is the total pesticide use in one specific region, P_i is the pesticide use for crop i, L is the total land used for crop production, L_i denotes cultivated land area for crop i, PI_i refers to crop i's pesticide intensity, and SI_i is the share of crop i according to planting area.

Since pesticide use is affected by climate, we could use chain rule to take a derivation of P with respect to W to have

$$\frac{\partial P}{\partial W} = \underbrace{\sum_i \frac{\partial PI_i}{\partial W} \cdot SI_i \cdot L}_{\text{Intensive effect}} + \underbrace{\sum_i \frac{\partial SI_i}{\partial W} \cdot PI_i \cdot L}_{\text{Structural effect}} + \underbrace{\sum_i \frac{\partial L}{\partial W} \cdot PI_i \cdot SI_i}_{\text{Extensive effect}} \tag{5}$$

Therefore, we could apply the following estimations to identify the effects of climate change on intensity, structure, and planted area.

$$\begin{cases} \text{Ln}PI_{i,rt} = \alpha_{10} + \alpha_{11} W_{rt} + T_t + D_r + \varepsilon_{rt} & (6) \\ SI_{i,rt} = \alpha_{20} + \alpha_{21} W_{rt} + T_t + D_r + e_{rt} & (7) \\ \text{Ln}L_{rt} = \alpha_{30} + \alpha_{31} W_{rt} + T_t + D_r + v_{rt} & (8) \end{cases}$$

where $PI_{i,rt}$ and $SI_{i,rt}$ denote pesticide intensity and planted area based share of crop i of county r in year t, respectively. Typically, we did not take logarithm for $SI_{i,rt}$ as it is proportion. In practice, we divide all crops into six categories, which represents $i \in (\text{grain, potato, cotton and linen, sugar crop, oil} - \text{bearing crop, and vegetable and fruits})$. L_{rt} is the total planted area of county r in year t. $SI_{i,rt}$ denotes cropping structure for crop i in county r in year t. $[\varepsilon_{rt}\ e_{rt}\ u_{rt}]$ is a vector of error term in the above regressions. $\boldsymbol{\alpha}$ is the parameter vector to be estimated, and we drop the subscript i for all crops in order to simplify notations. Given the mean value of pesticide intensity PI_i, crop share SI_i, and planted area L, vector $[\alpha_{11}\ \alpha_{21}\ \alpha_{31}]$ can be used for the estimations of $\frac{\partial PI_i}{\partial W}$, $\frac{\partial SI_i}{\partial W}$, and $\frac{\partial L}{\partial W}$, respectively. Then, these parameters are used to decompose the climate change effect on intensity effect, structure effect and planted area effect as introduced above.

Given the potential spatial and serial correlation in the error term, we estimate the model by clustering standard errors at both the county level and the city-by-year level, following the two-way clustering strategy discussed in Cameron, Gelbach and Miller (2011).

4 Data

4.1 Data sources

The climate data are obtained from the China Meteorological Data Sharing Service System, which provides the daily average temperatures as well as precipitation recorded in 825 weather stations in China from 1998 to 2016. As the distribution of weather stations is not exactly consistent with county territory, that is, there is more than one station in a few counties while no station in some other ones. Hence, the spatial interpolation method based on the observed climatic information is used to generate weather data for each county. First, the inverse distance weighted (IDW) method was used to interpolate the climate data from 825 weather stations across China to a spatial field with a grid spacing of 500 meter (Yi et al. 2016). Then, the values of each grid located in a county were averaged to represent the mean status of that county. Based on the data from 825 meteorological stations across the country, interpolation methods were used to derive the climate indicators for each county, including daily average temperature, daily minimum temperature, daily maximum temperature, and average daily rainfall. The climate variables required for this study are calculated from these indicators. Besides, this study uses the quadratic growing season average temperature and precipitation as an alternative specification of climate variables. Specifically, the growing season is determined by the five-day moving average method, which is defined as the period when the average daily temperature is stable over 8℃.

Agricultral production data including county-level total pesticide use, planted area, and crop structure are collected from the database of the Institute of Agricultural Information at the Chinese Academy of Agricultural Sciences (CAAS). It covers 2657 counties from 30 provinces/municipalities in the mainland of China from 1998 to 2016. Summary statistics for these data are shown in Table 1.

[Insert Table 1 around here]

4.2 Recover county level pesticide use

During the estimation for crop-specific pesticide usage with respect to climate change in Equaiton (5), we face a challenge to have county-level pesticide usage for each crop. The only available crop specific pesticide use data is at provincal level. In addition, CAAS only reports aggregate pesticide use over all crops in each county. Hence, we develop a maximum entropy program to recover pesticise usage for every crop in each county.

Let A_{gi} be the observed planted area of crop i in county g, and T_{gi} be the pesticide usage for crop i in county g. We could represent pesticide usage intensity by $F_{gi} = \frac{T_{gi}}{A_{gi}}$, which is to be estimated. After consult with agronomists, we set F_i^- and F_i^+ as pesticide usage intensity lower and upper bound, respectively, i.e., $F_i^- \leq F_{gi} \leq F_i^+$. Observed total pesticide usage in county g is $T_g = \sum_{i=1}^{I} T_{gi}$, and total pesticide usage in each province is $T = \sum_{g=1}^{G} T_g$ if G is the number of counties in a province. In addition, observed provincial pesticide use for crop i is $F_i = \sum_{g=1}^{G} \frac{F_{gi} A_{gi}}{\sum_{i=1}^{I} A_{gi}}$.

We define $p_{gi} = \frac{T_{gi}}{T}$ as the share of pesticide useage for crop i in county g. Apparently, we could treat these shares as probabilities and then apply the maximum entropy principle. Then, the maximum entropy problem is set by

$$\max_{p_{gi}} - \sum_{i=1}^{I} \sum_{g=1}^{G} p_{gi} \ln p_{gi}$$

Subject to

$$\begin{cases} \sum_{i=1}^{I} \sum_{g=1}^{G} p_{gi} = 1 \\ \sum_{i=1}^{I} p_{gi} = \frac{T_g}{T}, & \forall\, g = 1, \dots, G \\ \sum_{g=1}^{G} \frac{p_{gi}\, T}{\sum_{i=1}^{I} A_{gi}} = F_i, & \forall\, i = 1, \dots, I \\ \frac{F_i^- A_{gi}}{T} \leq p_{gi} \leq \frac{F_i^+ A_{gi}}{T}, & \forall\, i = 1, \dots, I,\ \ g = 1, \dots, G \end{cases}$$

After p_{gi} is solved, we can recover crop specific county level total pesticide useage T_{gi} and intensity F_{gi}. It is found that the differenes between yearly observed aggregate pesticide usage and the ones recoved by the maximum entropy program over counties are all less than 5%, which is shown in Table A1 in Appendix.

5 Results

By taking Hausman test, the random effect model is rejected at 1% statistial level. Hence, the following estimaitons are based fixed effect model.

5.1 Total impact of climate change on pesticide useage

Table 2 reports the baseline results for the aggregate impact of climate change on pesticide use. The first column presents the results based on OLS.The second to the fourth column reports the results of fixed effect model,including two-way fixed effects model，one-way clustering fixed effects model and two-way clustering fixed effects model.The four models derive similar estimates. Column (4) reports that pesticide usage trends to first increase and then to decrease as the temperature rising and daily precipitation increasing.Using the estimated coefficients of the first and second terms, it is found that the use of pesticides peaks when the growing season average temperature and precipitation reach 18.2 ℃ and 1.4 mm. Given the fact that China has been experienced with 0.59℃ and 0.69 mm increase for growing season average temperature and precipitation in the last two decades respectively, climate change has driven the reduce of pesticide usage by 1.1%.

[Insert Table 2 around here]

5.2 Robustness checks for different starting temperature

Given that different starting temperatures may lead to different length of growing periods, accordingly, starting temperatures other than 8 ℃ in order to determine the growth period are also included to test the sensitivity of pesticide usage to different growing season in this study. Overall, the consideration of different starting temperatures does not change our previous findings in Section 5.1, as shown in Table 3.

5.3 Heterogeneity analysis by regions

We further investigates heterogeneous impacts of climate change on pesticide usage by regions. The impacts of growing season temperature and precipitation over regions shows significant differences in Table 4 Pesticides in North， Northeast,East , Central and South China increase first and then decline as the growing season average temperature rises,while it does not have impacts in Southwest and Northwest China as they are the coldest region in growing season of China. However, due to differences in the temperature of different regions, pesticides in North and Northeast China are in the rising stage, while East , Central and South China are in the falling stage.Furthermore, 1 °C increase Northeast and North China will lead pesticide useage to increase by about 6%, while 1 °C increase East , Central and South China will lead pesticide useage to reduce by about 6%,3%and 4%.

The impact of more precipitation shows more significant heterogeneity. For example, pesticides in Southwest China decrease first and then increase as growing season average daily precipitation increasing, which is inconsistent with the benchmark model. Through calculations and statistics, it is found that growing season average daily precipitation in Southwest China is 3.65mm, which falls to the left of the inflection point. This indicates that with the increase in precipitation, the use of pesticides in Southwest China has decreased, which is consistent with the results of the basic model.In additional, the differences of marginal impacts of precipitation on pesticide useage among regions are straightforward. 1 mm more daily growing season precipitation in Northeast China is more than 10 times of the one in North China.

5.4 Nonlinear impacts

This study first examins the nonlinear impacts of increasing temperature on pesticide usage by constructing multiple temperature bins. Figure 2 (a) and Figure 2(b) displays point estimates and the 95% confidence bands of coefficient estimate of temperature bins, which are obtained based on Equation (3). Given a chosen temperature interval for every 2 °C in Figure 2(a), and 3 °C in Figure 2(b), a typical temperature bin counts the number of days within the growing season with temperature exposures falling into the bin,and we omitted the lower than 0 °C case for reference.The selection of temperature cutoffs follows convention in the literature such as Schlenker and Roberts (2009), Chen and Yang (2019), and Cui (2020). Overall, we find temperature has a non-linear relationship with the use of pesticides , which reminds that pesticides first increase and then decrease as the temperature rising. Moreover, we found a turning point around 28°C, which is robust over different temperature intervals, showing that heat drives less pesticide usage than the one with relatively low temperature exposure.Along with that, Figure 2(a) and Figure2(b) shows estimations using an eighth-order polynomial function, which provide similar trends and thresholds.

[Insert Figure 2 around here]

Similarly, we constructed a series of precipitation bins to examine the impact of rainfall change on pesticide usage. As precipitation pattern changes result in the movement and distribution of chemicals (Rosenzweig et al. 2001; Schiedek et al. 2007), we found the change of pesticide usage due to the variation of rainfall intensity in Figure 2(c) and Figure 2(d). When growing season daily precipitation is more than 15 mm, farmers would rapidly redue pesticide usage to avoid ineffective losses.

5.5 Decomposing impact of climate change on pesticide useage

Decomposing the aggregate pesticide usage properly will deepen the understanding of the impact of climate change. Tables A4-A6 in Appendix report the three effects of climate change based on Equation (5). First, increased growing season temperature will stimulate intensive pesticide use for potato and cotton crop, but it reduces the pesticide intensity for oil, vegetable and fruit. In the meantime, growing season precipitation increases pesticide intensity for sugar crop, and oil-bearing crop, but it reduces the pesticide intensity for cotton, vegetable and fruit. Second, we observed warm growing season temperature leads to more sown areas for grain, but less sown areas for cotton. It seems that grain crop is the only one that will be more produced if hotter is expected. The reason is straightforward as it is more suitable for mechanized production to replace labor in hotter weather than other crops. Meanwhile, we observed more growing season precipitation lead to more sown areas for oil-bearing crop, and vegetable and fruit, but less sown areas for cotton, grain and sugar crop. A good explanation for this is that wetter weather is not suitable for the growth of cotton, due to causing more pests, but suitable for the growth of other crops such as vegetables and fruits. Third, the increases of growing season precipitation stimulate the total planted area. Typically, 1 mm increase of growing season daily precipitation drives 2.6% increase of the planting area.

We further investigate crop specific impacts of temperature and precipitation for each of the three different effects. Technically, we implemented the mean values of pesticide intensity, crop structure, and planted area from 1998 to 2016 in Equation (5) to measure crop-specific impacts of temperature and precipitation on the use of pesticide. The results are shown in Table 5 and 6. First, vegetable and fruit are the main drive in intensive, structural and extensive effects for the impacts of temperature and precipitation. It is valuable to mention that the overall impact of precipitation and temperature on pesticide intensity is negative. In addition, more precipitation leads to less grain production which helps reduce pesticide usage through structural effect.

Given the above estimation, we continue to report the share for the three effects within the total impact of climate change on pesticide usage in Figure 3. Detailed information is shown in Table A5 in Appendix due to limited space. To ensure our decomposition to be acceptable, we compared the aggregation over the three effects based on Equation (5) with the direct impact based on Equation (3) in the last column of Table A5. The minor differences show that our decomposition is credible. It is found that intensive effects dominate the impact of climate change on pesticide use. Intensive effect dominates 93 percent of the temperature impact, while structural and extensive effect share the rest impact. Besides, intensive effect dominates 145 percent of the precipitation impact, although intensive effect could largely reduce pesticide usage with respect to more precipitation.

[Insert Figure 3 around here]

5.6 Forecast of pesticide use change under climate change

Predicting the extent of the pesticide use variation responding to climate change is helpful for policy makers to fully consider pesticide regulations. Again, we combine the estimates in Section 5.1 and the future climate data to project the change of pesticide usage driven by climate change. Projections of future climate factors were collected from WorldClim-Global Climate Data, which generates climate predictions according to the constantly updated global climate models for the following time periods: 2021-2040, 2041-2060, 2061-2080, and 2081-2100. In the lead up to the IPCC AR6, the energy modelling community has developed a new set of emissions scenarios driven by different socioeconomic assumptions. On the one hand, comparing with the four representative greenhouse gas (GHG) concentration pathways (RCPs), we used the updated new versions SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5, respectively[1]. On the other hand, this article chooses climate data derived from the global climate models BCC-CSM2-MR, which represent a projection for future global temperature and precipitation changes. Considering different projections for future SSPs and future global temperature and precipitation, we eventually chose the field to four scenarios for four time period. Given the vast heterogeneity across regions in China, we further conduct analysis by different regions.

[Insert Figure 4 around here]

This article calculates the projected changes in growing season average

[1] Introduction is available at https://www.carbonbrief.org/cmip6-the-next-generation-of-climate-models-explained

temperature across regions,which are the differences between the future growing season average temperature and the growing season average temperature during the sample period (1998–2016). Figure 4 shows the variations of pesticide use in different regions due to future temperature change for the four time period.In general, we find that future global warming will significantly lower China's pesticide usage. Specifically, in the panel of Figure 6 (2021~2040), under the BCC-CSM2-MR model, pesticide in the shortern term is projected to reduce by 0.6~2.6% under SSP1-2.6 and by 0.8–2.7% under SSP5-8.5. During the medium term (2041~2060), corresponding declines in pesricide are slightly larger, by 0.8~3.1% under SSP1-2.6 and by 1.8–3.5% under SSP5-8.5.In the rest panel of Figure 4 , the declines in pesticide in the long term are projected to be considerably greater than those in the shortern and medium term.By 2081~2100, China's pesticide is projected to decrease by 3.7~5.1%.

Similarly, Figure 5 presents the effects of future precipition change on pesticide. All findings from predictions in Figure 4 are in line with Figure 5. The most remarkable difference between Figure 5 and Fugure 4 is that the projected reductions in pesticide for temperature are nearly twice as large as the decline in pesticide due to precipitation, as shown by the different scale of values on the vertical axis.

[Insert Figure 5 around here]

6 Conclusions

By introducing a maximum entropy program to recover crop-specific pesticide usage information at county levels, this study assesses the impacts of climate change in China. Our investigation confirms the findings of climate change affecting pesticide usage, as reported in existing literature.

We demonstrate that both elevated temperature and precipitation reduce total pesticide usage under the background of China's agricultural production. Overall, pesticide usage trends to first increase and then to decrease as the temperature rising and daily precipitation increasing.Typically,the temperature and precipitation impact is more significant for Northeast China. Especially, our results uncovered three different components and corresponding shares of the impacts of climate change on total pesticide usage including intensive effect, structural effect and extensive effect. More importantly, we provide an assessment scenario under climate change.

Due to data limitations, this study has following deficiencies. First, we cannot identify the impacts of climate change on the three types of pesticide including insecticide, fungicide, and herbicide. That will be more informative for accurate regulations and scientific research funding guidance if further studies can identfy those individual impacts. Second, farm household's practical responses to climate change will help us understand how much various adaptation strategies can change pesticide usage such as changing rotation and using traditional anti-reversible varieties.

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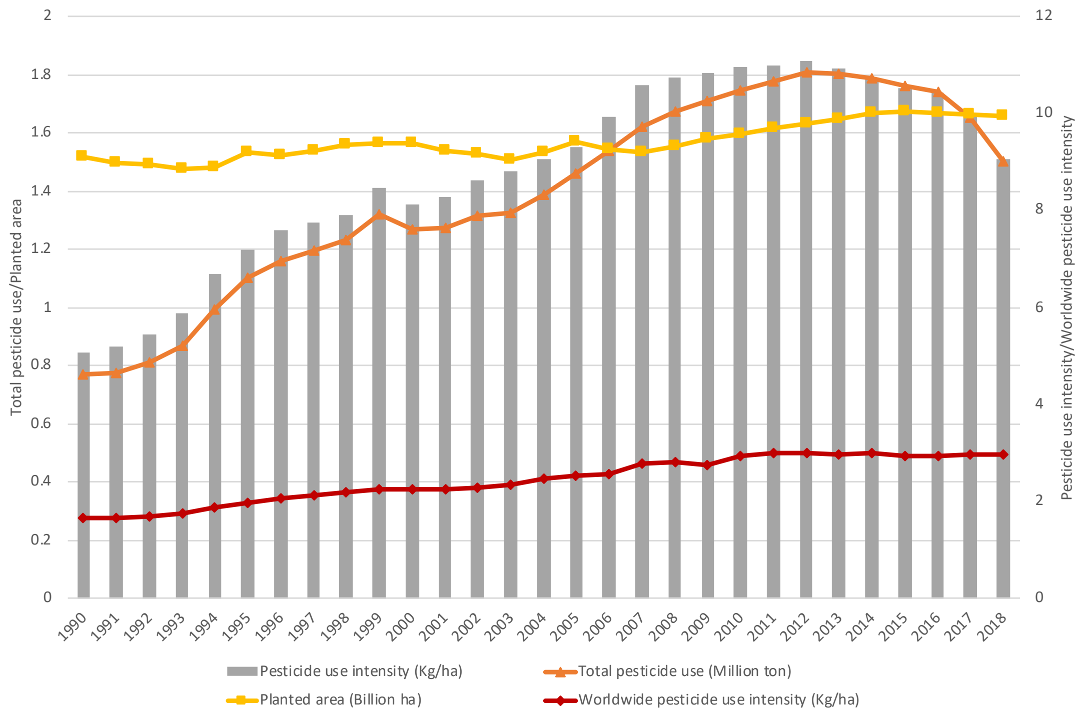
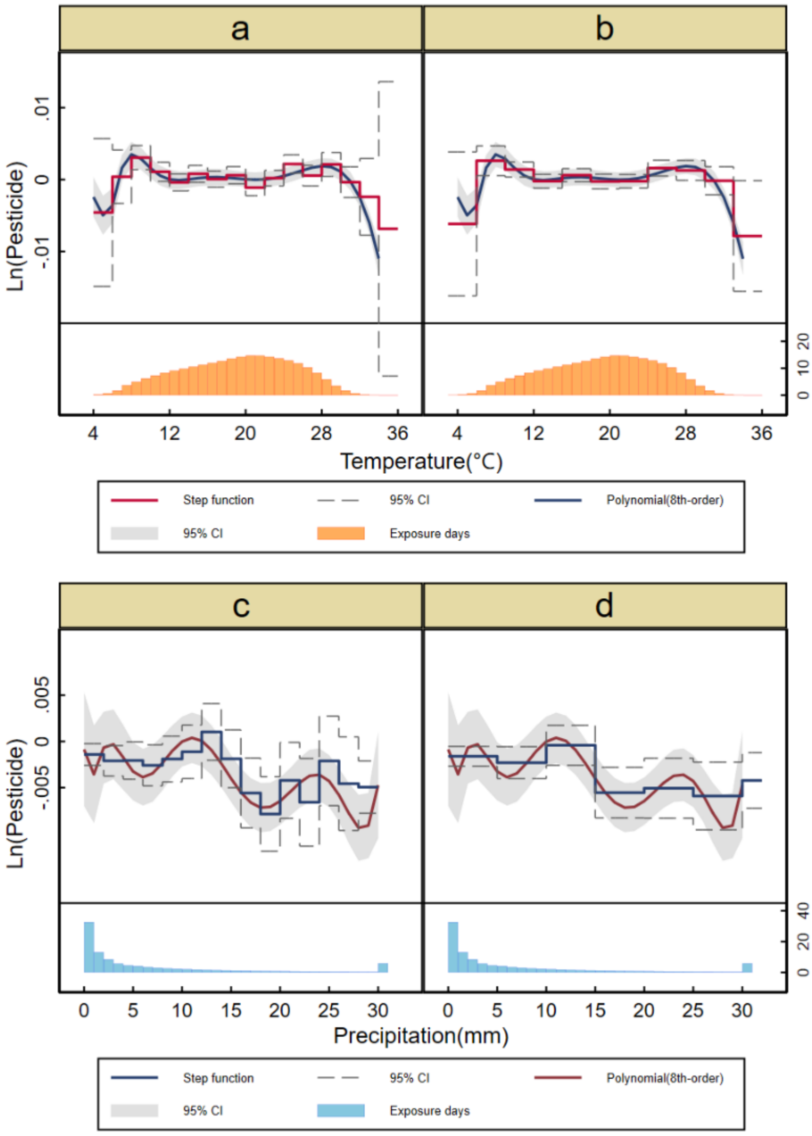


Data sources: China's National Bureau of Statistics.

Figure 1 Pesticide usage in China



Notes: This figure displays changes in logarithm of pesticide usage if a county is exposed for one day to 2℃ (Panel a.), 3℃ (Panel b.), 2mm (Panel c.), and 5mm (Panel d.) temperature intervals (solid line) where we sum temperatures exposure days fall within each interval. The 95% confidence bands are added by dash lines. The smooth lines fit coefficient estimates of each temperature range using an eighth-order polynomial function. Histograms at the bottom show the distribution of mean of temperature bin and precipitation bin in the data, respectively.

Figure 2 Nonlinear impacts of temperature on pesticide usage

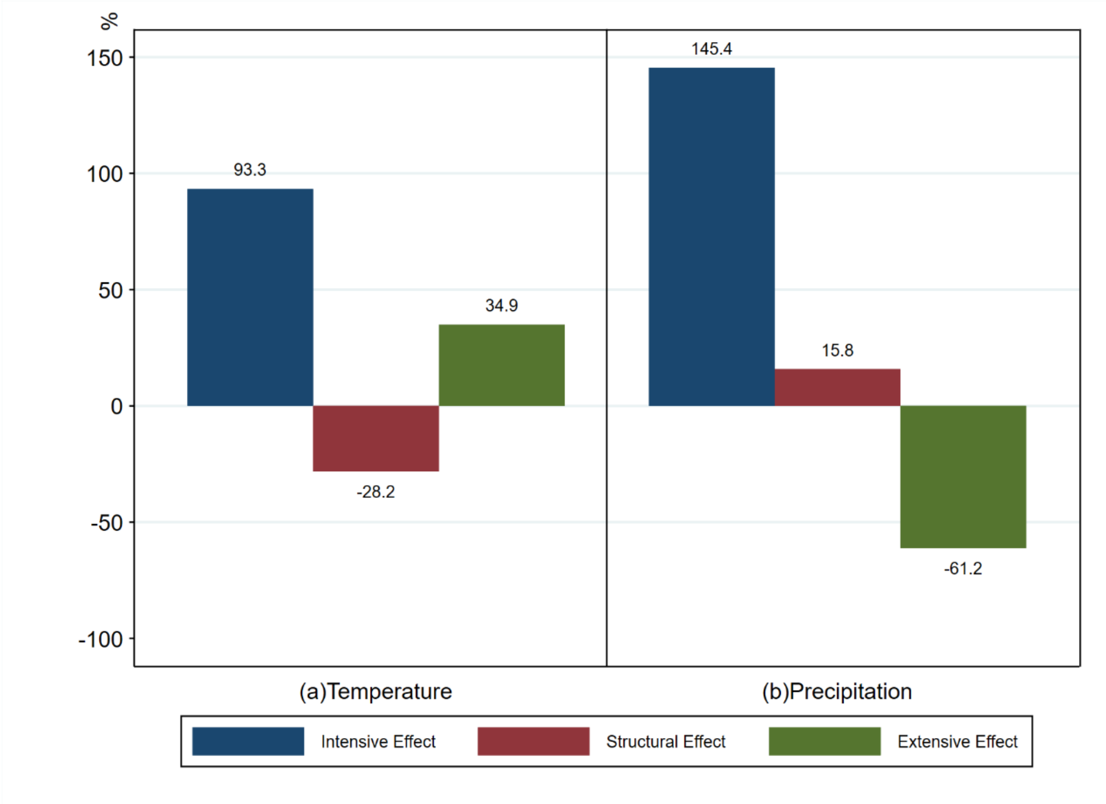
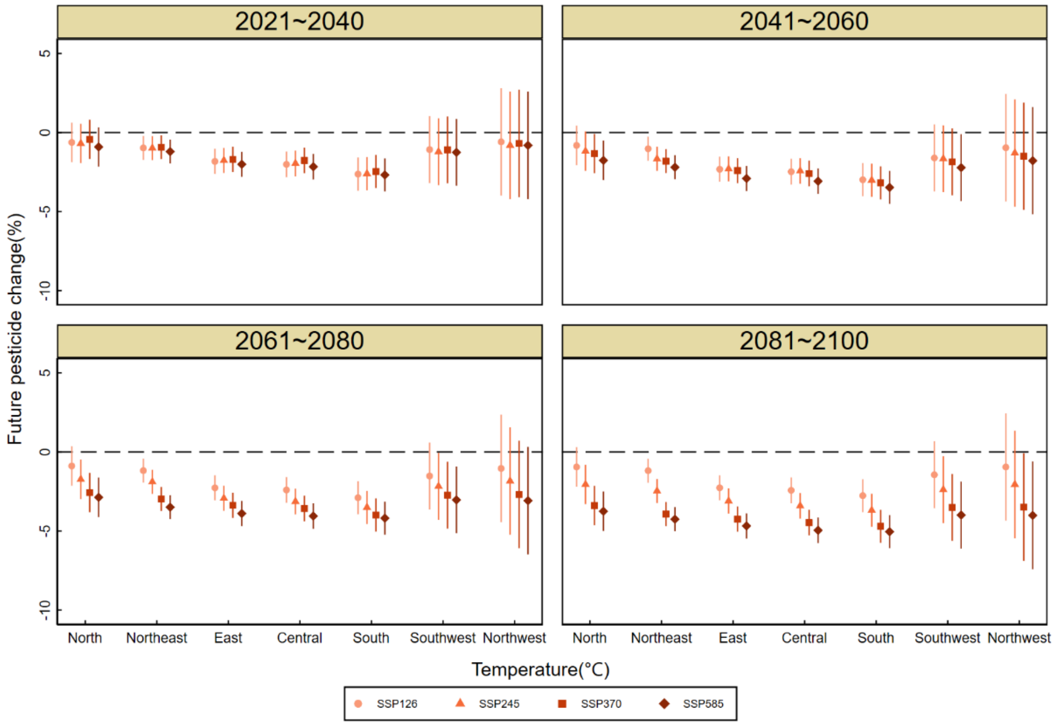
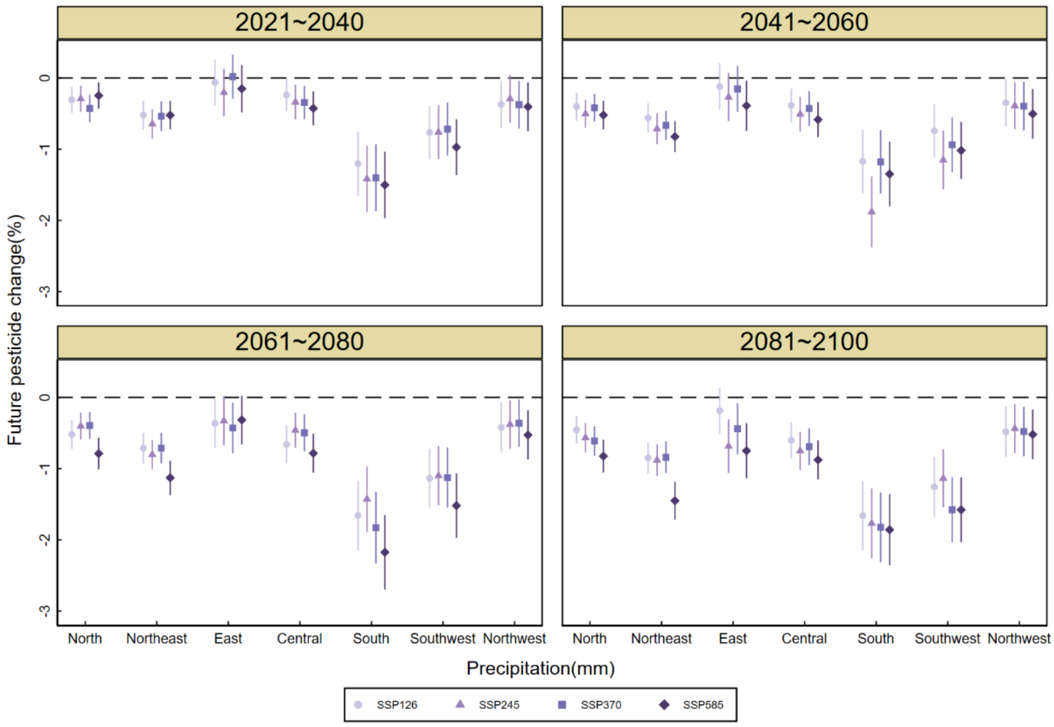


Figure 3 Decompose the impact of climate change on pesticide usage



Notes: Graph (2021~2040) displays predicted percentage changes in pesticide usage over regions due to future temperatures changes under four emissions scenarios of the BCC-CSM2-MR climate model by 2021-2040. Graph (2041~2060), Graph (2061~2080) and Graph (2081~2100) display the corresponding changes in the long term. A star indicates the point estimates in pesticide usage changes based on the most plausible changes in temperature, and whiskers represent ranges in pesticide usage changes based on lower and upper bounds in temperature change. The color represents the different SSPs scenarios impact of temperature impacts.

Figure 4 Predicted impacts of future temperature on pesticide over regions



Notes: Graph (2021~2040) displays predicted percentage changes in pesticide usage over regions due to future precipitation changes under four emissions scenarios of the BCC-CSM2-MR climate model by 2021-2040. Graph (2041~2060), Graph (2061~2080) and Graph (2081~2100) display the corresponding changes in the long term. A star indicates the point estimates in pesticide usage changes based on the most plausible changes in precipitation, and whiskers represent ranges in pesticide usage changes based on lower and upper bounds in precipitation change. The color represents the different SSPs scenarios impact of precipitation impacts.

Figure 5 Predicted impacts of future precipitation on pesticide over regions

Table 1 Summary statistics

Variable	Mean	S.D.	Minimum	Maximum
Economic factors				
Total pesticide usage (kg)	574941.66	603271.33	1.80	5558524.00
Total planted area (Thousand ha)	53.83	46.48	0	619.92
Grain pesticide intensity (kg/ha)	6.50	6.00	0.07	40.72
Potato pesticide intensity (kg/ha)	4.15	3.07	0.01	17.23
Cotton pesticide intensity (kg/ha)	22.74	12.12	0.90	50.33
Sugar pesticide intensity (kg/ha)	10.60	5.27	0.20	22.49
Oil-bearing pesticide intensity (kg/ha)	3.52	2.25	0.14	11.62
Vegetable and fruit pesticide intensity (kg/ha)	26.19	12.02	2.19	76.37
Grain crop ratio (%)	63.60	21.39	0	100
Potato crop ratio (%)	4.45	9.94	0	100
Cotton crop ratio (%)	2.44	7.98	0	100
Sugar crop ratio (%)	1.35	5.35	0	100
Oil-bearing crop ratio (%)	5.04	9.66	0	100
Vegetable and fruit ratio (%)	23.85	18.66	0	100
Climatic variables				
Growing season average temperature (℃)	19.85	2.26	8.75	26.02
Growing season average precipitation (mm)	3.27	1.51	0.02	13.07
Number of counties	2657			

Table 2 Baseline results for climate change on pesticide use

Variable	OLS	Fixed effect		
	(1)	(2)	(3)	(4)
Growing season average temperature(°C)	1.1020***	0.1419***	0.1419***	0.1419***
	(0.0279)	(0.0250)	(0.0468)	(0.0453)
Growing season average temperature(°C)-Quadratic	-0.0223***	-0.0039***	-0.0039***	-0.0039***
	(0.0007)	(0.0006)	(0.0012)	(0.0011)
Growing season average precipitation(mm)	0.5424***	0.0135	0.0135	0.0135
	(0.0141)	(0.0096)	(0.0184)	(0.0176)
Growing season average precipitation(mm)-Quadratic	-0.0579***	-0.0049***	-0.0049**	-0.0049**
	(0.0018)	(0.0011)	(0.0022)	(0.0020)
Constant	-1.5180***	11.1581***	11.1581***	11.1581***
	(0.2644)	(0.2445)	(0.4749)	(0.4512)
Time trend	Yes	Yes	Yes	Yes
County fixed effect	No	Yes	Yes	Yes
County effect	No	No	Yes	Yes
City-by-year effect	No	No	No	Yes
R-squared	0.2228	0.0484	0.0484	0.8961
Number of counties	2657	2657	2657	2657

Notes: Significance codes are *10% level, **5% level, *** 1% level. Standard errors are in parentheses.

Table 3 Robustness checks for different starting temperatures

Variable	Growing season average temperature starts from			
	6°C	7°C	9°C	10°C
	(1)	(2)	(3)	(4)
Growing season average temperature(℃)	0.0556	0.1110***	0.1429***	0.1534***
	(0.0351)	(0.0401)	(0.0468)	(0.0552)
Growing season average temperature(℃)-Quadratic	-0.0016*	-0.0031***	-0.0038***	-0.0039***
	(0.0009)	(0.0010)	(0.0012)	(0.0013)
Growing season average precipitation(mm)	0.0142	0.0146	0.0106	0.0065
	(0.0188)	(0.0181)	(0.0174)	(0.0162)
Growing season average precipitation(mm)-Quadratic	-0.0054**	-0.0052**	-0.0045**	-0.0037**
	(0.0022)	(0.0021)	(0.0020)	(0.0018)
Constant	11.9616***	11.4773***	11.1053***	10.9590***
	(0.3341)	(0.3884)	(0.4714)	(0.5650)
Time trend	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
R-squared	0.8960	0.8961	0.8960	0.8960
Number of counties	2657	2657	2657	2657

Notes: Significance codes are *10% level, **5% level, *** 1% level. Standard errors are in parentheses.

Table 4 Heterogenous analysis over regions

Variable	North	Northeast	East	Central	South	Southwest	Northwest
Growing season average temperature(℃)	0.5726***	0.5386	0.1595***	0.1181***	1.1611**	0.1419	-0.0433
	(0.1861)	(0.3297)	(0.0581)	(0.0453)	(0.5172)	(0.0872)	(0.1161)
Growing season average temperature(℃)-Quadratic	-0.0132***	-0.0127	-0.0053***	-0.0035***	-0.0262**	-0.0035	0.0004
	(0.0047)	(0.0088)	(0.0016)	(0.0013)	(0.0116)	(0.0024)	(0.0033)
Growing season average precipitation(mm)	0.1478	0.3729***	-0.0398	0.0388	0.0490	-0.1712***	0.0454
	(0.0910)	(0.0898)	(0.0270)	(0.0327)	(0.0778)	(0.0483)	(0.0801)
Growing season average precipitation(mm)-Quadratic	-0.0360*	-0.0480***	-0.0024	-0.0097**	-0.0009	0.0155***	-0.0052
	(0.0192)	(0.0122)	(0.0027)	(0.0045)	(0.0074)	(0.0059)	(0.0133)

Notes: Notes: Significance codes are *10% level, **5% level, *** 1% level. Standard errors are in parentheses.

Table 5 Decompose the impact of temperature on pesticide usage

	(1) Intensive effect†				(2) Structural effect				(3) Extensive effect			
	Estimated coefficient		$\frac{\partial PI_i}{\partial W} \cdot SI_i \cdot L$	**Percent**	**Estimated coefficient**		$\frac{\partial SI_i}{\partial W} \cdot PI_i \cdot L$	**Percent**	**Estimated coefficient**		$\frac{\partial L}{\partial W} \cdot PI_i \cdot SI_i$	**Percent**
	Linear	Quadratic	**(kg)**	**%**	Linear	Quadratic	**(kg)**	**%**	Linear	Quadratic	**(kg)**	**%**
Grain crop	0.0210	-0.0004	1091.9207	-19.13	-0.0277	0.0006	-1066.0469	-61.76			-771.5444	36.12
Potato crop	-0.1513	0.0047	552.6042	-9.68	0.0051	-0.0001	-93.5711	-5.42			-34.4644	1.61
Cotton crop	-0.0961	0.0026	828.3848	-14.52	0.0020	-0.0001	-815.0670	-47.22	-0.0043	0.0000	-103.7388	4.86
Sugar crop	0.0491	-0.0016	-376.6409	6.60	0.0001	0.0000	-78.4135	-4.54			-26.7108	1.25
Oil-bearing crop	0.1385	-0.0034	94.3551	-1.65	0.0025	-0.0001	-135.0095	-7.82			-33.0910	1.55
Vegetable and fruit	0.0624	-0.0021	-7897.4697	138.39	0.0017	0.0000	3914.3301	226.76			-1166.7389	54.62
Subtotal			-5706.8459	100			1726.2222	100			-2136.2883	100

Notes: † The marigal effects are measured at sample average.

Table 6 Decompose the impact of precipitation on pesticide usage

	(1) Intensive effect				(2) Structural effect				(3) Extensive effect			
	Estimated coefficient		$\frac{\partial PI_i}{\partial W} \cdot SI_i \cdot L$	**Percent**	**Estimated coefficient**		$\frac{\partial SI_i}{\partial W} \cdot PI_i \cdot L$	**Percent**	**Estimated coefficient**		$\frac{\partial L}{\partial W} \cdot PI_i \cdot SI_i$	**Percent**
	Linear	Quadratic	**(kg)**	**%**	Linear	Quadratic	**(kg)**	**%**	Linear	Quadratic	**(kg)**	**%**
Grain crop	-0.0210	-0.0009	-6138.4790	39.18	0.0075	-0.0016	-1084.6921	63.65	0.0255	-0.0023	2381.0457	36.12
Potato crop	-0.0028	0.0001	-39.8317	0.25	0.0001	0.0000	85.2994	-5.01			106.3599	1.61
Cotton crop	-0.0555	0.0026	-3411.5996	21.78	0.0028	-0.0003	1035.0940	-60.74			320.1461	4.86
Sugar crop	0.0365	-0.0013	587.2892	-3.75	-0.0012	0.0000	-527.4634	30.95			82.4315	1.25
Oil-bearing crop	-0.1157	0.0138	-345.3545	2.20	-0.0020	0.0002	-67.6258	3.97			102.1215	1.55
Vegetable and fruit	0.0093	-0.0042	-6317.8262	40.33	-0.0107	0.0015	-1144.6495	67.17			3600.6465	54.62
Subtotal			-15665.8018	100			-1704.0374	100			6592.7510	100

Notes: † The marigal effects are measured at sample average.

Appendix

Table A1 Differences between yearly aggregated observed and recovered pesticide usage using maximum entropy program over counties

Year	Difference (%)
1998	2.57
1999	3.08
2000	1.32
2001	1.00
2002	3.09
2003	1.20
2004	2.35
2005	3.31
2006	1.25
2007	1.90
2008	2.08
2009	-0.03
2010	0.67
2011	0.18
2012	-2.42
2013	-1.29
2014	-1.09
2015	-1.97
2016	-0.29

Table A2 Coefficients for temperature bins

	[4, 6)	[6, 8)	[8, 10)	[10, 12)	[12, 14)	[14, 16)	[16, 18)	[18, 20)	[20, 22)	[22, 24)	[24, 26)	[26, 28)	[28, 30)	[30, 32)	[32, 34)	>=34
Days of growing season average	-0.0046	0.0004	0.0031***	0.0011	-0.0004	0.0008	0.0001	0.0006	-0.0011*	0.0002	0.0022***	0.0006	0.0021**	-0.0004	-0.0024	-0.0068
temperature (°C)	(0.0052)	(0.0019)	(0.0009)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0009)	(0.0011)	(0.0027)	(0.0104)
Number of counties	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657

Notes: Significance codes: *10% level, **5% level, *** 1% level. Standard errors are in parentheses. All other cofounding varialbles are the same as Table 2.

Table A3 Coefficients for precipitation bins

	[0, 2)	[2, 4)	[4, 6)	[6, 8)	[8, 10)	[10, 12)	[12, 14)	[14, 16)	[16, 18)	[18, 20)	[20, 22)	[22, 24)	[24, 26)	[26, 28)	>=28
Days of growing season average precipitation(mm)	-0.0014**	-0.0021**	-0.0021**	-0.0026**	-0.0019	-0.0011	0.0010	-0.0019	-0.0056***	-0.0079***	-0.0042**	-0.0066***	-0.0021	-0.0046*	-0.0049***
	(0.0006)	(0.0008)	(0.0010)	(0.0011)	(0.0013)	(0.0015)	(0.0016)	(0.0016)	(0.0019)	(0.0021)	(0.0021)	(0.0024)	(0.0025)	(0.0026)	(0.0014)
Number of counties	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657

Notes: Significance codes: *10% level, **5% level, *** 1% level. Standard errors are in parentheses. All other cofounding varialbles are the same as Table 2.

Table A4 Impact of climate change on pesticide intensity

Variable	(1) Grain crop	(2) Potato	(3) Cotton	(4) Sugar crop	(5) Oil-bearing crop	(6) Vegetable and fruit
Growing season average temperature (°C)	0.0210	-0.1513	-0.0961***	0.0491	0.1385**	0.0624*
	(0.0458)	(0.1080)	(0.0345)	(0.0610)	(0.0677)	(0.0361)
Growing season average temperature (℃)-Quadratic	-0.0004	0.0047*	0.0026***	-0.0016	-0.0034**	-0.0021**
	(0.0011)	(0.0027)	(0.0009)	(0.0015)	(0.0017)	(0.0009)
Growing season average precipitation (mm)	-0.0210	-0.0028	-0.0555***	0.0365*	-0.1157***	0.0093
	(0.0152)	(0.0422)	(0.0171)	(0.0205)	(0.0262)	-0.0138
Growing season average precipitation (mm)-Quadratic	-0.0009	0.0001	0.0026	-0.0013	0.0138***	-0.0042***
	(0.0016)	(0.0039)	(0.0016)	(0.0022)	(0.0027)	(0.0016)
Constant	1.0041**	1.6737	4.2444***	1.5067**	-0.3194	2.5717***
	(0.4576)	(1.0641)	(0.3501)	(0.6084)	(0.6757)	(0.3463)
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of counties	2657	2657	2657	2657	2657	2657

Notes: Significance codes: *10% level, **5% level, *** 1% level. Standard errors are in parentheses.

Table A5 Impact of climate change on cropping pattern

Variable	(1) Grain crop	(2) Potato	(3) Cotton	(4) Sugar crop	(5) Oil-bearing crop	(6) Vegetable and fruit
Growing season average temperature (℃)	-0.0277***	0.0051	0.0020*	0.0001	0.0025	0.0017
	(0.0104)	(0.0035)	(0.0012)	(0.0017)	(0.0035)	(0.0077)
Growing season average temperature (℃)-Quadratic	0.0006**	-0.0001	-0.0001**	-0.0000	-0.0001	0.0000
	(0.0003)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0002)
Growing season average precipitation (mm)	0.0075*	0.0001	0.0028**	-0.0012**	-0.0020	-0.0107***
	(0.0040)	(0.0014)	(0.0011)	(0.0005)	(0.0013)	(0.0030)
Growing season average precipitation (mm)-Quadratic	-0.0016***	0.0000	-0.0003***	0.0000	0.0002*	0.0015***
	(0.0005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)
Constant	0.9346***	-0.0016	0.0064	0.0170	0.0363	0.1443**
	(0.0996)	(0.0355)	(0.0108)	(0.0151)	(0.0348)	(0.0730)
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of counties	2657	2657	2657	2657	2657	2657

Notes: Significance codes: *10% level, **5% level, *** 1% level. Standard errors are in parentheses.

Table A6 Impact of climate change on total planted area

Variable	Total planted area
Growing season average temperature (℃)	-0.0043
	(0.0328)
Growing season average temperature (℃)-Quadratic	0.0000
	(0.0008)
Growing season average precipitation (mm)	0.0255**
	(0.0125)
Growing season average precipitation (mm)-Quadratic	-0.0023
	(0.0015)
Constant	3.4202***
	(0.3253)
Time trend	Yes
County fixed effect	Yes
Number of counties	2657

Notes: Significance codes: *10% level, **5% level, *** 1% level. Standard errors are in parentheses.

Table A7 Decomposion of climate change on pesticide usage

	Intensive effect		Structural effect		Extensive effect		Total effect		
							Equation (5)	Equation (3)	Difference†
	kg/°C, kg/mm	Share of impact (%)	kg/°C, kg/mm	Share of impact (%)	kg/°C, kg/mm	Share of impact (%)	kg/°C, kg/mm	kg/°C, kg/mm	%
Growing season average temperature (°C)	-5706.85	93.30	1726.22	-28.22	-2136.29	34.92	-6116.91	-6676.20	8.38
Growing season average precipitation (mm)	-15665.80	145.36	-1704.04	15.81	6592.75	-61.17	-10777.09	-10860.76	0.77

Notes: † We compare the aggregate impact of climate change over the three types of effects based on Equation (5) with the direct impact based on Equation (3).