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Impacts of Climate Change on Agricultural Chemical Inputs: Evidence from Pesticide Usage in China

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ABSTRACT

Pesticides are commonly used for pest control to improve crop yield and quality. Global warming has been suggested to influence pest pressure and optimal pesticide utilization. This study systemically assesses the impacts of rising temperatures on pesticide usage based on novel panel data from China during 1998–2016. Estimation results show a nonlinear relationship between pesticide usage and temperature. This effect is notably more pronounced in southern China compared to the north, especially under extremely hot weather conditions. The overall influence of temperature on pesticide usage is further broken down into three components: pesticide usage intensity, crop mix, and total planted area. Owing to the limited potential for expanding cultivation in China, the intensity effect dominates the impacts of temperature on pesticide usage. Our findings suggest that the rising temperature over the past two decades has led to a moderate reduction in pesticide usage in China.

JEL Classification: O13, Q16, Q54

1 | Introduction

Climate change has altered surface temperatures, making agriculture one of the most vulnerable sectors to rising temperatures (IPCC 2019). Using exogenous variations in weather conditions over time within a specific region, recent studies have demonstrated that high temperatures increase the risks to crop yields (Burke and Emerick 2016; Kawasaki 2023; Mérel and Gammans 2021; Schlenker and Roberts 2009; Dell et al. 2014). These studies specifically highlight the existence of a temperature threshold, beyond which further heat exposure results in significant yield losses.

Adapting agriculture to climate change, through measures such as adopting irrigation, implementing soil conservation practices, and adjusting productivity-enhancing inputs (Sesmero et al. 2018), is crucial for mitigating its negative impacts (Chen and Gong 2021; Kawasaki 2019; McCarl et al. 2016) and has remarkable implications for policy design. Examining how climate change affects production factors helps us better understand farmers' decision-making regarding adaptation. However, agricultural input portfolios vary in terms of climate change across regions. For example, the use of chemical inputs fluctuates annually based on weather conditions and soil spatial variability (Hollinger and Hoeft 1986; Raun and Johnson 1999; Tremblay et al. 2012). Understanding how climate change affects yields through its impact on input usage is essential for evaluating current adaptation strategies and guiding future approaches in agricultural development (Chen and Gong 2021).

Aiming to enhance productivity and food security, agriculture has become increasingly dependent on pesticides. These chemicals are released into the atmosphere, pedosphere, and hydrosphere. Their regular inflow and high persistence can lead to high pesticide concentrations in environmental compartments over time, negatively affecting non-target species (Koleva and Schneider 2009) and damaging the environment (e.g., water and air quality) and human health (e.g., chronic and infectious diseases) (Larsen and Noack 2017). For example, three out of every 100 agricultural workers experience acute pesticide poisoning, leading to thousands of fatalities, with developing countries accounting for 99% of these deaths while using only 25% of the world's pesticides (Chakraborty and Newton 2011). Managing pesticide usage in the context of climate change is crucial for policymakers and requires a well-structured approach for a deeper understanding.

The 2018 IPCC report on the impacts of global warming of 1.5°C indicates that adaptation strategies based on increased pesticide usage may increase risks to human health, oceans, and water accessibility. These impacts may be influenced by climate change because pest pressure and the optimal pesticide application rates vary with changing climate conditions (Olesen and Bindi 2002; Koleva and Schneider 2009; Noyes et al. 2009). Additionally, global warming can accelerate the degradation of chemical components due to accelerated microbial and chemical reaction rates, and pesticides are no exception to this phenomenon (Delcour et al. 2015). Harvell et al. (2002) indicated that pest activities are likely to increase under climate change, prompting farmers to apply more pesticides during growing seasons to protect crops from pests and diseases. At the same time, climate change may also reduce pesticide usage. Biological studies have shown that warm and dry conditions can enhance plant resistance to pest infections, thereby reducing the need for pesticide usage (Patterson et al. 1999). In addition, climate change impacts crop growth, which in turn influences the adaptive behaviors of farmers, including pesticide usage. For example, changes in the spatiotemporal distribution of temperature and precipitation can alter crop mixes across different regions, encouraging the adoption of highly adaptable varieties and subsequently reducing overall pesticide usage. These mixed results in the current literature call for a systematic investigation into the effects of rising temperatures on pesticide usage.

Aiming to fully capture the effect of rising temperatures on pesticide usage, we construct a panel dataset covering 2479 counties in China from 1998 to 2016. Our analysis reveals the complex relationship between temperature and pesticide usage, offering new insights into the overall impacts of climate change. We systematically assess regional variations in how temperature impacts pesticide usage and further decompose the aggregate effects into three components: pesticide usage intensity, crop mix, and total planted area. In addition, we explore the long-term effects of temperature increases on pesticide usage.

Our results show that pesticide usage is drastically affected by temperature. In particular, a highly nonlinear relationship exists between growing season temperature and pesticide usage. Various specifications (piecewise linear, polynomial, and step functions) consistently demonstrate that, during the growing stage of crops, the relationship between pesticide usage and temperature varies; it is positive at low temperatures, negative at moderate temperatures, and positive again at high temperatures, before turning negative again under extremely high temperatures. Pesticide usage in southern China is found to be relatively more responsive to temperature changes, especially under extremely high temperatures. Over the past two decades, the observed increase in China's temperature, approximately 85-degree days, has led to a reduction of approximately 0.5% in total pesticide usage. Furthermore, estimations based on long-difference approaches indicate that temperature has a minor long-term effect on pesticide usage, plausibly because the adjustments in pesticide usage are generally cost-efficient and do not require extensive planning.

This study contributes to the literature on agricultural adaptation to climate change by exploring its nonlinear effects on total pesticide usage. A growing body of research focuses on individual-level adaptation strategies to climate change, such as changing crop mixes (Seo and Mendelsohn 2008; Kaminski et al. 2013; Yang and Shumway 2016; Sesmero et al. 2018), shifting from single-cropping systems to double-cropping systems (Kawasaki 2019), adjusting planting and harvest timings (Cui and Xie 2022), varying inputs, including planted area, labor, irrigation, and fertilizer (Kurukulasuriya and Mendelsohn 2007; Sesmero et al. 2018; Aragón et al. 2021; Jagnani et al. 2021), and diversifying income sources (Sesmero et al. 2018). Due to limited data availability, only a few studies have examined how farmers adjust pesticide usage in response to increasing temperatures. Jagnani et al. (2021) report that Kenyan maize farmers increase pesticide usage due to heat-induced biotic stress from diseases and pests. Möhring et al. (2022) find that extreme heat reduces insecticide use among Colorado potato farmers. Although pesticide applications are less responsive to weather changes, Bareille and Chakir (2024) investigate how farmers adjust pesticide applications for wheat, barley, and rapeseed in response to weather conditions during the growing season in the French department of Meuse. These studies generally rely on individual-level data and focus on a particular crop. In contrast, this study exploits intertemporal and spatial variations in rich county-level panel data to systematically explore the overall effect of temperature changes on pesticide usage on the entire agricultural sector.

To the best of our knowledge, our study is most closely related to Bareille et al. (2024), despite notable differences. They examined pesticide purchases as a specific adaptation strategy for coping with weather shocks, using zip code-level data from France between 2014 and 2019. While their study is pioneering in performing an econometric assessment of pesticide use intensity in response to weather shocks, it does not explore whether warmer temperatures will increase total pesticide use in the agricultural sector. We examine the nonlinear relationship between temperature and total pesticide use, accounting for changes in acreage and crop mix. Second, the impacts identified by Bareille et al. (2024), based on 6 years of data, are short-term in nature and do not inform the long-term adaptation to climate change. Therefore, this study addresses the aforementioned gap in this field.

Another contribution of this study is the identification of the dominant effects of temperature changes on total pesticide usage by constructing a decomposition framework that considers intensity, structure, and overall changes in cultivated area. Existing studies often focus on some specific aspects, such as crop-specific yields (Deschênes and Greenstone 2007; McCarl et al. 2008; Schlenker and Roberts 2009; Miller et al. 2021), planting acreage (Miao et al. 2016), and total planted area (Aragón et al. 2021). Notably, relying solely on crop yields to assess the challenges posed by climate change assumes fixed crop mix. However, if the planted area increases with temperature, then the yield loss may be overestimated (Aragón et al. 2021). Thus, this study aims to disentangle the various intertwining forces by decomposing the overall effects, which informs policymakers' policy design and decision making with respect to future challenges posed by climate change.

Finally, this study also makes a methodological contribution. We develop a maximum entropy (ME) procedure to impute county-level crop-specific pesticide usage intensity, which is essential for our analysis, using province-level aggregated data. Conventional ME studies for this type of imputation normally consider only equality constraints. Building on recent developments in convex analysis and interior-point optimization methods (e.g., Boyd and Vandenberghe 2004), we develop a procedure that accommodates equality (in terms of province level average) and inequality constraints (in terms of known pesticide use intensity bounds). Our simulations demonstrate that the proposed method reliably imputes crop- and county-specific pesticide usage based on aggregated data.

The remainder of this study is organized as follows: Section 2 briefly reviews the literature on how temperature affects pesticide usage and examines trends in pesticide usage in China over the past few decades. Section 3 outlines the empirical estimation strategies, while Section 4 describes the data used in our analysis. Section 5 reports the estimated impacts of temperature on overall pesticide usage, explores regional variations in these effects, presents robustness checks with alternative specifications and weather variables, discusses the decomposition results, and estimates the long-term effect. Section 6 concludes this paper. A Supplemental Appendix includes some technical details and additional estimation results.

2 | Background

2.1 | Temperature and Pesticide Usage

Pesticides play an important role in modern agriculture by reducing pest damage, thereby minimizing crop losses and contributing to the doubling of agricultural yields over the past 40 years (Larsen and Noack 2017; Tilman et al. 2002; Waterfield and Zilberman 2012). However, their effectiveness and impact may be sensitive to temperature (Olesen and Bindi 2002). Temperature can influence pesticide usage through multiple channels. First, high temperatures can reduce pesticide concentrations due to increased volatilization and accelerated degradation, both of which are strongly affected by high moisture content, elevated temperatures, and direct exposure to sunlight (Wu and Nofziger 1999; Noyes et al. 2009; Delcour et al. 2015). Consequently, global warming may accelerate the degradation of chemicals, driven by increased microbial and chemical reaction rates and reduce pesticide concentrations in the environment (Bloomfield et al. 2006; Delcour et al. 2015).

Second, high temperatures may create a highly favorable environment for insect and pathogen attacks (Bale et al. 2002; Bloomfield et al. 2006; Rosenzweig et al. 2001). By contrast, warm winters can reduce winter kill, leading to increased insect populations in subsequent growing seasons (Singh et al. 2013). Furthermore, droughts can alter the physiology of host species, lowering their resistance to invasive insects, while simultaneously reducing the populations of beneficial insects (Rosenzweig et al. 2001).

Third, temperature can influence the growth rate of crops, which, in turn, affects pesticide usage. High temperatures and increased CO_2 concentrations, which notably alter photosynthesis activity, promote plant growth and expansion. A high growth rate can dilute the concentration of absorbed pesticides in plants, thereby reducing pesticide residue (Patterson et al. 1999; Delcour et al. 2015). Conversely, a longer active growing season may allow for increased farming activities, potentially leading to higher pesticide usage.

Fourth, temperature changes can lead to shifts in phenology and geographic distribution across a wide range of ecosystems. Some studies have found that pest infestations often coincide with modifications in temperature conditions (Rosenzweig et al. 2001). Temperature not only affects 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, warm winters may encourage many insect species to expand their geographical ranges to high latitudes and altitudes (Bale et al. 2002).

The impacts of temperature on pesticide usage are further complicated by the adaptive behaviors of farmers. In the short term, farmers are likely to adjust pesticide usage or irrigation methods to reduce the impacts of climate change (Woods et al. 2017). In the long term, farmers may adopt more drastic measures such as altering crop mixes or land use, which also affect pesticide usage (Rosenzweig and Parry 1994; Olesen and Bindi 2002). The overall impacts of temperature change on pesticide usage are complex, necessitating a systematic analysis and careful estimation, which is the primary goal of this study.

2.2 | Pesticide Usage in China

China has experienced a rapid increase in pesticide usage over the past decades. The total amount of pesticides applied annually grew from 0.76 million tons in 1990 to 1.5 million tons in 2018, as shown in Figure 1. During the same period, the intensity of pesticide usage increased from 5 to 9 kg/ha, which is 3.1 times the global average[1].

In 2015, China's Ministry of Agriculture introduced the "Action Plan to Zero Growth in Pesticide Use (ZGPU) by 2020" to address the severe non-point pollution resulting from pesticide overuse. The objective of the ZGPU plan was to maintain pesticide use per unit of land area below the average levels observed between 2016 and 2019, aiming to achieve zero growth in total pesticide use by 2020. Total pesticide use has gradually decreased. Given the increase in total planted area in recent decades and the stability of crop mix, the recent reduction in pesticide usage is largely attributed to improved efficiency in pesticide-intensive

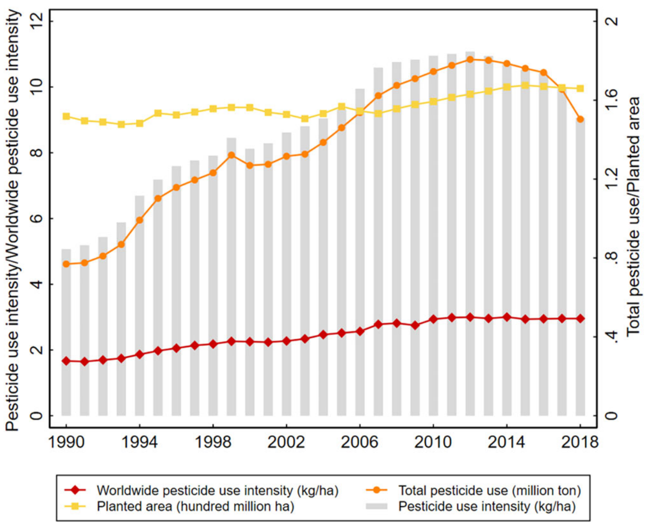

FIGURE 1 | Pesticide usage in China. *Source*: The data are from China's National Bureau of Statistics and Food and Agriculture Organization.

crops, such as fruits and vegetables, which account for 14% of the planted area. For example, between 2012 and 2018, pesticide usage for apples and vegetables decreased by one-fourth and one-fifth, respectively.

3 | Empirical Strategies

This section first presents the empirical models used to estimate the relationship between temperature and pesticide usage, employing a standard panel fixed effects estimation. Second, we explore the channels through which temperature affects pesticide usage by decomposing its effects on the total pesticide usage. Finally, we examine the long-term responses of total pesticide usage using a two-period panel of long differences approach.

3.1 | Impact of Temperature on Total Pesticide Use

As Horowitz and Lichtenberg (1994) indicated, the effect of pesticide depends on the correlation between random factors such as weather and pest/disease levels and their marginal contributions to crop outputs and no unambiguous theoretical predictions can be made (e.g., Dorschner et al. 1986; Schiedek et al. 2007; Maxmen 2013; Möhring et al. 2020). The scientific literature reviewed in Section 2.1 also implies that rising temperature can affect pesticide usage in different directions. Aiming to investigate the complicated impacts of climate change on farm household production behavior, many studies rely on empirical models (e.g., Kawasaki 2019; Aragón et al. 2021; Jagnani et al. 2021; Cui and Xie 2022).

In this study, we opt to rely on empirical investigation to explore this important topic. An important strand of literature models the pesticide usage of individual farmers using structural approaches (e.g., Carpentier and Letort 2012; Kaminski et al. 2013; Bareille and Chakir 2024). Due to the lack of micro-level data on Chinese farmers, we conduct reduced-form analysis of pesticide usage, leveraging the temporal and spatial variations in the panel data to estimate the impacts of temperature on pesticide usage. Our empirical model is as follows:

$$\text{Ln } P_{it} = \beta_0 + \sum_{k=1}^{K} f_k(T_{it}; \beta_k) + X_{it}\gamma + \phi_i + \mu_t + u_{it}, \quad (1)$$

where P_{it} denotes the total pesticide usage in county i in year t. The key explanatory variables $\sum_{k=1}^{K} f_k(T_{it}; \beta_k)$ include K terms of temperature variable T_{it} during growing seasons[2]. This parametrization provides the desired flexibility. Given that the underlying relationship between pesticide usage and temperature is likely nonlinear (e.g., Schlenker and Roberts 2009; Kawasaki 2019), using a single term based on average temperature runs the risk of oversimplification and may lead to inconsistent estimates.

We use piecewise linear functions $f_k(T_{it}; \beta_k)$ to capture the potentially nonlinear effects of temperature on pesticide usage. Additionally, we explore alternative functional forms such as step functions and Chebyshev polynomials, to assess the sensitivity of our results to functional form specifications (reported in the following section and in Appendix A.1 of the Supporting Information). Our experiments indicate that the estimation results are robust with respect to functional form specifications. For brevity, we focus on estimations based on piecewise linear functions in our discussion. Following Schlenker and Roberts (2009), we set the knots of the piecewise linear functions, which correspond to the threshold degree days at 11°C, 21°C, and 29°C, according to the best-fitting model with the highest R^2 value[3]. Aiming to capture detailed information on diurnal variation in daily temperature T_{it}, we calculate the degree days using sinusoidal interpolation between daily maximum and minimum temperatures.

The covariate X_{it} includes daily average precipitation, sunlight duration, relative humidity, and wind speed. A time-invariant county fixed effect ϕ_i is included to control for heterogeneity due to differences in factors such as soil quality, land topography, and agricultural production practices. We use μ_t to capture year fixed effects that account for technical advancements related to pesticide usage, such as the introduction of new pesticide varieties and the adoption of genetically modified crops. The error term is denoted by u_{it} and the parameters β and γ are to be estimated. We use a fixed-effects model, controlling for county and year fixed effects, to estimate the panel data Model (1). Panel data approaches generally capture within-season, short-run responses to weather fluctuations. Additionally, we apply a two-period panel data model based on the long-difference approach to examine the long-term effects of rising temperatures. The approach is introduced in Section 3.3.

The error terms are likely spatially and serially correlated across counties and years. High degree of spatial dependency arises mainly from the natural spatial autocorrelation of weather variables and other factors influencing pesticide use, such as the extent of agricultural collective services and agri-environmental policies in surrounding areas. In China, prefecture-level cities serve as the primary administrative units, comprising multiple counties that share similar geographic features and environmental policy patterns. Therefore, we cluster the standard errors at the county level and the prefectural city-by-year level to account for spatial and temporal correlations[4], following Cameron et al. (2011) and Zhang et al. (2017). Clustering standard errors at a larger group level is a common method for addressing spatial correlations across smaller units (Conley 1999; Wooldridge 2003) and is widely used in the literature (Dell et al. 2012; Burke and Emerick 2016; Olper et al. 2021). Alternatively, we also employ the spatial heteroscedasticity and autocorrelation consistent (HAC) estimator of the variance–covariance matrix, as introduced by Conley (1999), to correct for spatial dependence in the estimation results[5].

3.2 | Decomposition of Temperature Effects on Pesticide Use

Decomposing aggregate pesticide usage can provide deeper insights into the effects of temperatures. Previous studies have examined the impacts of climate change on pesticides, finding that the impacts of rising temperatures vary across crops (Chen and McCarl 2001; Rhodes and McCarl 2020). We decompose total pesticide usage as follows to explore the channels through which temperature affects pesticide usage:

$$P = \sum_j P_j = \sum_j \frac{P_j}{L_j} \cdot \frac{L_j}{L} \cdot L = \sum_j PI_j \cdot S_j \cdot L\,, \tag{2}$$

where P is the total pesticide usage in a specific region, P_j is the pesticide usage for crop j, L is the total planted area for crop production, L_j denotes the cultivated land area for crop j, PI_j refers to pesticide intensity of crop j, and S_j is the share of crop j according to planting area.

Taking the derivative of P with respect to temperature T then yields

$$\frac{\partial P}{\partial T} = \underbrace{\sum_j \frac{\partial PI_j}{\partial T} \cdot S_j \cdot L}_{\text{Intensive effect}} + \underbrace{\sum_j \frac{\partial S_j}{\partial T} \cdot PI_j \cdot L}_{\text{Structural effect}} + \underbrace{\sum_j \frac{\partial L}{\partial T} \cdot PI_j \cdot S_j}_{\text{Extensive effect}}. \tag{3}$$

According to this model, changes in total pesticide usage depend on the intensive, structural, and extensive effects of rising temperatures. Section 2 has described the complexity of the effects of rising temperatures on total pesticide usage, including the agronomic mechanisms of pest and disease development and crop growth, as well as the mechanism of farmers' adaptive behaviors. However, because adaptive adjustments themselves alter pesticide use, the two types of mechanisms are not completely independent. Consequently, few studies could have explicitly identified the direct impact of temperature changes on total pesticide use under observed weather and agricultural production conditions as well as crop simulation models. The decomposition of Equation (3) provides an economic framework for quantitatively identifying the overall impacts of temperature on total pesticide use. It ensures the completeness and exclusivity of decomposing temperature impacts within the framework of farmers' economic decision-making via the intensive, structural, and extensive margins.

Under the assumption of no transaction costs, all three of these effects are likely to play a role. However, once the transaction costs of adjustment are taken into account, the intensive effect is likeliy to dominate in the short run. This is because the fixed costs of adjusting crop structure and sowing area, including farmers' skills and infrastructure, are high while the cost of changing the intensity of pesticide use by farmers is considerably lower. This is especially true in China as the potential arable lands have been depleted.

We utilize the following estimations based on agriculture-weather panel data to evaluate the decomposition of the total climate effects on pesticide usage intensity, crop mix, and total planted area:

$$\mathrm{Ln}P\, I_{j,it} = \alpha_{j,10} + \sum_{k=1}^{K} f_k\left(T_{it}; \alpha_{j,1k}\right) + X_{j,it}\gamma_{j,1} + \phi_{j,i} + \mu_t + \varepsilon_{j,it}, \tag{4}$$

$$S_{j,it} = \frac{\exp\left(\alpha_{j,20} + \sum_{k=1}^{K} f_k\left(T_{it}; \alpha_{j,2k}\right) + X_{j,it}\gamma_{j,2} + \phi_{j,i} + \mu_t\right)}{\sum_{h=1}^{6} \exp\left(\alpha_{h,20} + \sum_{k=1}^{K} f_k\left(T_{it}; \alpha_{h,2k}\right) + X_{h,it}\gamma_{h,2} + \phi_{j,i} + \mu_t\right)}, \tag{5}$$

$$L_{it} = \alpha_{30} + \sum_{k=1}^{K} f_k\left(T_{it}; \alpha_{3k}\right) + X_{it}\gamma_3 + \phi_i + \mu_t + \upsilon_{it}, \tag{6}$$

where $PI_{j,it}$ and $S_{j,it}$ denote pesticide intensity and planted area-based share of crop j in county i in year t, respectively, and L_{it} is the total planted area of county i in year t. We divide all crops into six categories and use $j = 1, \ldots, 6$ to denote grain crops, potatoes, cotton, sugar crops, oil-bearing crops, and vegetables and fruits[6]. h has the same domain as j.$[\varepsilon_{it}\ \upsilon_{it}]$ is a vector of error terms and α and γ are the parameter vectors to be estimated. Pesticide intensity PI_j, crop share S_j, and total planted area L, along with estimated parameters, capture the intensive, structural, and extensive effects of temperature on pesticide usage, as explained in Equation (3).

We use a multinomial logit model, as given by Equation (5), to estimate the effect of weather on the probability of alternative crop planted areas. We estimate the crop mix effects using a modified multinomial logit model, as outlined in Parks (1980), Kala et al. (2012), and Cho and McCarl (2017), to ensure that $S_{j,it}$ is a proper probability residing between 0 and 1. Further details are presented in Appendix A.3 of the Supporting Information. Moreover, to address potential interdependencies between crop choices, we introduce a key control by including certain crop prices, along with the prices of alternative crops in $X_{j,it}$, in addition to the weather variables in Equation (5). This approach enables us to account for the alternative relationships between different crop choices.

3.3 | Long-Term Effect on Pesticide Use

Quantifying the long-term effect of temperature changes on pesticide usage is useful for both researchers and policymakers. So far our estimation and subsequent decomposition temperature effects on pesticide usage have been based on short-term weather fluctuations. However, this decomposition may overstate the impacts of climate change, as farmers alter their expectations on climate change based on weather history and adapt their farming practices accordingly, such as changing their crop mix response to realized and/or expected climate changes over time.

Aiming to examine the long-term effect of climate change on pesticide usage, we conduct a two-period panel to utilize the long-difference approach introduced by Burke and Emerick (2016). This approach helps avoid potential bias due to the presence of within-region time-varying unobservables that are correlated with temperature and pesticide usage such as technological advancements and local environmental regulations. The two-period long-difference panel model for the estimation of long-term effects is as follows:

$$\Delta \mathrm{Ln}P_{it} = \sum_{k=1}^{K} \beta_k \Delta GDD_{it}^{k} + \Delta X_{it}\gamma + \delta_t + \rho_i + \Delta u_{it} \ , \quad (7)$$

where $t = 1, 2$ denote the two subperiods. In this estimation, β_k captures the effect of county i's k th term of GDD in year t. δ_t accounts for the year fixed effects, and ρ_i denotes unobserved differences in average county-level trends. The other weather control variables in the vector X are constructed similarly. We retain the same specification of four temperature variables with thresholds at 11°C, 21°C, and 29°C. Standard errors are clustered at the county and prefectural city-by-year levels. We also consider another common long-difference approach, originally proposed by Burke and Emerick (2016) as a robustness check for the long-term analysis; the results are reported in Section A.4 of the Supporting Information.

4 | Data

4.1 | Economic Data

Agricultural production data, including county-level total pesticide usage, planted area, and crop share, are sourced from the Institute of Agricultural Information at the Chinese Academy of Agricultural Sciences (CAAS). Our sample includes 167 and 2479 counties located to the south and north of the Tropic of Cancer, respectively. The areas south of the Tropic of Cancer typically experience year-round agricultural production, complicating our analysis because we need to include winter as an additional growing season. In contrast, counties located north of the Tropic of Cancer do not engage in active agricultural production during the winter months. For simplicity, we focus on the 2479 counties located north of the Tropic of Cancer, which cover 30 provinces/municipalities in mainland China from 1998 to 2016. Summary statistics for our sample are provided in Table 1[7], with further details presented in Table A1 of the Supporting Information.

An obstacle to our empirical analysis is the lack of crop-specific pesticide usage data and corresponding total pesticide usage for crop production at the county level. While crop-specific pesticide usage data are available only at the provincial level, the CAAS reports aggregate pesticide usage across all crops for each county, although local ecological management differences are typically minor. In order to tackle this challenge, we develop an ME procedure to impute crop-specific pesticide usage for each county. Details of this procedure and the estimation results are provided in Appendix A.5 of the Supporting Information.

The proposed novel ME procedure imputes crop-specific pesticide usage given limited provincial-level pesticide intensity and county-level upper bounds for aggregate pesticide usage. In the absence of actual county-level pesticide use data, we conduct numerical simulations that emulate the real-world situations considered in this study. The experiment proceeds as follows: (1) we consider a hypothetical province with six crops and 83 counties (which is the average number of counties per province in our sample). Each county's area is randomly generated based on a uniform distribution with a minimum of 5 ha and a maximum of 185,000 ha (the range corresponds to the sample range of county size). The average pesticide usage for each crop at the province level is randomly generated from a uniform distribution between 2 and 30 kg/ha (which corresponds to the sample range of pesticide usage). (2) For each crop, pesticide usage at the county level is generated based on a uniform distribution supported between 0.5 and 1.5 times the provincial average usage. In total, we generate $6 \times 83 = 498$ pesticide usage observations, one for each crop/county. We then divide these observations by their total sum, transforming them into probabilities that can be estimated using the proposed ME method. (3) We calculate the total pesticide usage per crop (6 measurements) and total pesticide usage per county (83 measurements). Consider the crop/county pesticide data as a 6×83 contingency table. Our ME imputation aims to estimate the entire table using only limited $(6 + 83)$ aggregated measurements, which correspond to the row and column sums of the contingency table.

This procedure is repeated 1000 times. We use two criteria to gauge the quality of the ME imputation. The first metric measures the correlation between the true proportions and the estimated proportions. Panel A of Table A2 of the Supporting Information shows that the estimated proportions of pesticide usage for each crop closely align with the real proportions, with a mean correlation value as high as 0.99. We also calculate the Hellinger distance between these two probability vectors. A Hellinger distance value of 0 indicates perfect agreement, while a value of 1 indicates maximum discrepancy. The average Hellinger distance is as small as 0.02, with a maximum at 0.03. These results demonstrate that the proposed method reliably imputes a matrix of nearly 500 entries using fewer than 90 measurements. Panel B in Table A2 of the Supporting Information reports simulation results for a "large" province with 2500 counties, following the same design. The results are consistent with those from the 83-county case, demonstrating that the quality of the ME imputation is not affected by the number of geographical units considered. Overall, our simulations show that the proposed ME procedure can reliably impute crop-specific pesticide usage at the county level based on aggregated data at the province level.

Additionally, the differences between the yearly observed aggregate pesticide usage and those recovered by the ME procedure across counties are less than 5% (Table A3 of the Supporting Information). Given the remarkably small scale of individual farms in China, county-level data are suitable for investigating pesticide usage. As suggested by Larsen and Noack (2017), in highly homogeneous agricultural regions dominated by a small number of crops, county-level cropland can serve as an appropriate metric for studies where crop and pesticide data are limited in spatial resolution.

TABLE 1 | Summary statistics.

Variables A. Economic variables	Obs.	Mean	S.D.	Min	Max
Total pesticide usage (1000 kg)	44,350	563.06	586.92	4.74	5558.52
Pesticide intensity for grain crops (kg/ha)	43,977	6.38	6.03	0.07	40.72
Pesticide intensity for potatoes (kg/ha)	24,851	4.16	3.13	0.01	17.23
Pesticide intensity for cottons (kg/ha)	20,255	22.70	12.24	0.90	50.33
Pesticide intensity for sugar crops (kg/ha)	17,931	10.53	4.97	0.20	22.49
Pesticide intensity for rapeseeds (kg/ha)	27,697	3.51	2.27	0.14	11.62
Pesticide intensity for vegetables and fruits (kg/ha)	43,005	26.27	12.23	2.19	76.37
Share of grain crops (%)	44,350	63.68	21.14	0	100
Share of potatoes (%)	44,350	4.61	10.13	0	100
Share of cottons (%)	44,350	2.59	8.20	0	100
Share of sugar crops (%)	44,350	0.90	3.90	0	86.04
Share of rapeseeds (%)	44,350	5.31	9.86	0	100
Share of vegetables and fruits (%)	43,009	22.91	17.99	0.01	100
Total planted area (1000 ha)	44,350	53.87	46.56	0	619.90
Price of grain crops (CNY/kg)	44,350	1.37	0.35	0.01	4.03
Price of potatoes (CNY/kg)	23,491	0.86	0.29	0.23	2.00
Price of cottons (CNY/kg)	30,936	11.76	3.83	1.88	55.26
Price of sugar crops (CNY/kg)	23,747	0.26	0.12	0.03	1.08
Price of rapeseeds (CNY/kg)	29,653	2.69	0.81	0.14	7.09
Price of vegetables and fruits (CNY/kg)	42,828	1.37	0.55	0.23	5.54
Average price of labor (CNY/day)	44,350	27.34	12.66	0.69	121.10
Average price of pesticide (CNY/kg)	44,350	42.64	26.44	0.81	316.50
B. Climatic variabls					
$GDD_{5°C–11°C}$ (D)	44,350	1401.07	214.64	0	1650
$GDD_{11°C–21°C}$ (D)	44,350	1696.41	452.20	0	2623.42
$GDD_{21°C–29°C}$ (D)	44,350	533.20	265.18	0	1352.22
$GDD_{\geq 29°C}$ (D)	44,350	68.01	59.72	0	339.65
Precipitation (mm/day)	44,350	2.94	1.59	0.01	10.83
Average wind speed (m/s)	44,350	2.10	0.63	0.58	6.71
Average relative humidty (%)	44,350	68.50	9.69	30.10	88.65
Total sunlight duration (1000 h)	44,350	1.61	0.40	0.59	2.78

Note: This table shows summary statistics for the key variables from 1998 to 2016 across all counties. Data on the price of labor, pesticides, and agricultural products are provided at the provincial level. All prices are adjusted using the Consumer Price Index, with average prices weighted by planting areas. Temperature and weather variables are constructed for the growing season from March to November.

4.2 | Climate Data

The climate data used in this study are obtained from the China Meteorological Data Sharing Service System. These data include the daily minimum and maximum temperatures, average temperature, precipitation, humidity, wind speed, and sunlight duration from 825 weather stations across China. The detailed daily weather data facilitate accurate estimation of the weather conditions experienced by crops during their growing seasons.

The distribution of weather stations does not exactly align with county designation. Some counties have more than one station, while others have none. Aiming to address this problem, we converted the station-level weather data and used spatial interpolation to impute the weather data for each county. The process follows the steps outlined below. First, the meteorological variables were spatially interpolated using the inverse distance weighting (IDW) method, which interpolates meteorological variables at the station level onto a grid with a 500 m spacing. This method is commonly used for spatial estimation of meteorological or pollution data (Currie and Neidell 2005; Schlenker and Walker 2016; Yi et al. 2016). This method calculates a weighted average of the daily observations from weather stations within a 100 km radius of each grid point, with the weights determined by the inverse of the distance between the stations and the grid point (Hatono et al. 2022; Lyu et al. 2024). Second, the grid-level weather data were aggregated to the county level, which was obtained by averaging across all grid points within the administrative boundaries of each county. Counties represent the penultimate level of China's administrative hierarchy and typically cover small homogeneous areas. Thus, the aggregation bias at this level is minimal, as suggested by Ortiz-Bobea (2021). Overall, this process resulted in a comprehensive set of county-level weather variables (i.e., temperature, relative humidity, precipitation, wind speed, and sunshine duration).

Our temperature variables are constructed based on a fixed growing season to ensure comparability of weather conditions across years. The northern region tends to plant later than the southern region, and planting dates may vary each year depending on weather conditions. Hence, we define the growing season as spanning from March to November in the baseline model, and examine its robustness with three alternative specifications. We also follow Schlenker and Roberts (2009) in assuming that temperature follows a sine curve, which interpolates between the minimum and maximum temperatures of each day in every grid. In particular, we generate a series of points at 15 min intervals to measure temperature exposure, and the averages of these points are used in our analysis.

Daily average precipitation, sunlight duration, relative humidity, and wind speed were incorporated into the regression analysis of pesticide usage (Zhang et al. 2017). Pesticide usage is influenced by factors such as precipitation and humidity. Elevated soil moisture contents and increased precipitation levels accelerate pesticide degradation (Noyes et al. 2009), while wet conditions also promote the germination of spores, the spread and activity of zoospores, and the proliferation of fungi and bacteria (Rosenzweig et al. 2001). Conversely, droughts can affect the physiology of host species, weakening their resistance to pest infestations. Wind speed has been suggested to affect the effectiveness of pesticide application (Desmarteau et al. 2020), and the spread of pathogens (Patterson et al. 1999). Finally, sunlight duration could also affect pesticide usage due to rapid pesticide volatilization, which is mainly attributed to elevated temperatures and direct sunlight exposure (Otieno et al. 2013). In addition, sunlight may impact the reproduction and survival of pests and pathogens. Overall, incorporating these variables helps account for the effects of other climate/weather conditions, allowing for a clear assessment of how temperature specifically affects pesticide usage.

5 | Results and Discussions

This section first reports the nonlinear effects of temperature increase on pesticide usage and regional differences. It then assesses the aggregate change in pesticide usage over the last two decades due to temperature changes based on our empirical findings. Furthermore, this section compares the heterogeneous effects across regions and examines the robustness of the estimation results with various alternative specifications. Finally, the decomposition results and estimates of long-term effects are presented.

5.1 | Nonlinear Effects of Temperature

As the temperature increases, pesticide usage follows two phases of rising and declining. Panel (a) of Figure 2 presents estimates based on piecewise linear functions, along with their 95% confidence bands that take into account serial and spatial correlations. During the first phase, the effect of temperature on pesticide usage peaks at around 10°C, which corresponds to a critical period in crop planting. This finding aligns with agronomic science, which indicates that crops are particularly susceptible to pests, diseases, and weeds during the early stages of planting and growth. Farmers often apply pesticides shortly after planting as a preventive measure and control method. During the subsequent growing season, when temperatures range from approximately 10°C–20°C, an increase in temperature can positively impact the growth of thermophilic crops such as cotton, promoting their rapid growth and enhancing their natural defenses against diseases (Shahzad et al. 2021). Once temperatures reach 21°C, pesticide usage experiences a second phase of increase and decline as the temperature rises. The knot effectively captures nonlinear patterns supported by agronomic evidence. For instance, the pesticide application response near 21°C is consistent with temperature-driven changes in pest population dynamics. As demonstrated by Kenis et al. (2023), the fall armyworm, a typical pest of maize and cereal crops, has the highest larval survival rates between 26°C and 30°C, with optimal temperatures (≈30°C) boosting fecundity because females can produce up to 1500 eggs. However, the negative effect of temperature on pesticide application begins at 29°C, indicating that extreme heat reduces pesticide use. This finding may be due to the fact that extremely high temperatures can negatively impact specific pest species (Das et al. 2011).

Aiming to confirm that the above results remain valid in the presence of other control variables, we report detailed estimation results using piecewise linear functions in Table 2. Additional weather variables, including wind speed, relative humidity, sunlight duration, and their squars, are incrementally included in Columns (2) and (3). The coefficients and significances of the temperature variables are barely affected. In Column (4), we also controlled for market relative prices in relation pesticide usage. Adding the price ratios of the product to pesticide and the price ratio of the product to labor does not significantly affect the results for the temperature variable. In addition, we control for county-level planted area in the estimation (Column [5] in Table 2), and the estimates remain consistent with those obtained without controlling for agricultural area. While planted area is a key input factor in agricultural production, it can be substantially affected

TABLE 2 | Estimated results based on piecewise linear functions.

	(1)	(2)	(3)	(4)	(5)
$GDD_{5°C–11°C}$ (10D)	0.0050***	0.0053***	0.0050***	0.0048***	0.0044***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0014)
	[0.0017]	[0.0017]	[0.0017]	[0.0016]	[0.0014]
$GDD_{11°C–21°C}$ (10D)	−0.0043***	−0.0045***	−0.0043***	−0.0043***	−0.0036***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	−0.0012
	[0.0014]	[0.0014]	[0.0014]	[0.0013]	[0.0020]
$GDD_{21°C–32°C}$ (10D)	0.0074***	0.0078***	0.0080***	0.0080***	0.0059***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0017)
	[0.0021]	[0.0021]	[0.0021]	[0.0021]	[0.0019]
$GDD_{\geq 29°C}$ (10D)	−0.0172***	−0.0155***	−0.0189***	−0.0181***	−0.0163***
	(0.0034)	(0.0036)	(0.0036)	(0.0036)	(0.0031)
	[0.0039]	[0.0042]	[0.0042]	[0.0041]	[0.0036]
Precipitation (mm/day)	0.0125	0.0151	0.0012	0.0074	−0.0134
	(0.0212)	(0.0228)	(0.0226)	(0.0223)	(0.0196)
	[0.0237]	[0.0252]	[0.0251]	[0.0247]	[0.0216]
Precipitation (mm/day)—Squared	−0.0053**	−0.0063**	−0.0041	−0.0044*	−0.0022
	(0.0025)	(0.0027)	(0.0026)	(0.0026)	(0.0023)
	[0.0028]	[0.0029]	[0.0029]	[0.0028]	[0.0025]
Average wind speed (m/s)		0.0894	0.0500	0.0490	0.1086
		(0.0873)	(0.0865)	(0.0855)	(0.0779)
		[0.0814]	[0.0805]	[0.0792]	[0.0740]
Average wind speed (m/s)—Squared		−0.0067	0.0020	0.0019	0.0010
		(0.0189)	(0.0188)	(0.0185)	(0.0166)
		[0.0172]	[0.0171]	[0.0168]	[0.0155]
Average relative humidty (%)		−0.0282*	−0.0596***	−0.0497***	−0.0283**
		(0.0149)	(0.0164)	(0.0162)	(0.0143)
		[0.0141]	[0.0155]	[0.0155]	[0.0137]
Average relative humidty (%)—Squared		0.0002**	0.0005***	0.0004***	0.0002**
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
		[0.0001]	[0.0001]	[0.0001]	[0.0001]
Total sunlight duration (1000 h)			1.3671***	1.3451***	1.0635***
			(0.2385)	(0.2324)	(0.2022)
			[0.2426]	[0.2349]	[0.2084]
Total sunlight duration (1000 h)—Squared			−0.3886***	−0.3780***	−0.3102***
			(0.0719)	(0.0700)	(0.0604)
			[0.0726]	[0.0704]	[0.0624]
Price ratio for product and pesticide				0.1651***	0.1623***
				(0.0561)	(0.0548)
				[0.0527]	[0.0515]
Price ratio for product and labor				−0.0110	0.0008
				(0.0159)	(0.0146)
				[0.0152]	[0.0137]
Total planted area (1000 ha)					0.0142***
					(0.0007)

(Continues)

TABLE 2 | (Continued)

	(1)	(2)	(3)	(4)	(5)
					[0.0006]
Year fixed effect	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes
R-squared	0.9012	0.9013	0.9016	0.9050	0.9227
Number of observations	44,350	44,350	44,350	44,336	44,336

Note: This table shows the coefficient estimates for a set of temperature variables fitted using a piecewise linear regression model with four splines. The dependent variable is the logarithmic aggregate pesticides. Columns (2)–(5) evaluate the sensitivity of the results from Column (1) under alternative specifications. All regressions account for county and year fixed effects. Standard errors (in parentheses) are two-way clustered by counties and prefectural city-by-year pairs, with Conley standard errors reported in brackets. The significance levels are ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

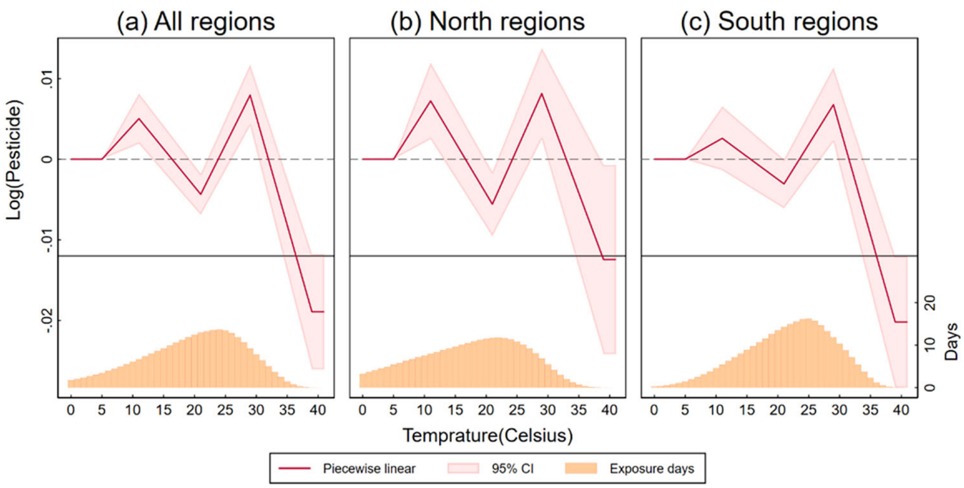

FIGURE 2 | Effects of temperature on pesticide usage. The figures show the estimated temperature effects on pesticide usage for the entire country sample, northern China, and southern China. In each panel, the solid line represents changes in the logged total pesticide usage in relation to temperatures, modeled using piecewise linear functions. The light red areas indicate the 95% confidence band, and the histogram of growing season temperature is displayed at the bottom. All regressions account for precipitation, wind speed, relative humidity, sunlight duration, county fixed effects, and year fixed effects. Standard errors are clustered at the county and prefectural city-by-year levels.

by weather conditions. Therefore, we focus on the estimates in Column (3) of Table 2 for the subsequent analysis[8].

Notably, the initial positive relationship between temperature and pesticide usage, as revealed by our estimation, is consistent with the finding of Jagnani et al. (2021). In addition, our results indicate that heat stress may reduce pesticide usage, a conclusion also supported by Möhring et al. (2022). Zhang et al. (2018) report somewhat different results. Since their study relies on coarser province-level data, their results are not directly comparable to ours, which are based on more detailed county-level data.

To assess the robustness of the above results, we estimated the effect of temperature on total pesticide use in Equation (1) using other empirical scenarios or choices, including (1) the measurement of temperature during the growing season (Appendices A.1 and A.2.1 of the Supporting Information); (2) the estimation of bounds for pesticide intensity using the ME procedure (Section A.2.2 of the Supporting Information); (3) alternative definition of growing seasons (Section A.2.3 of the Supporting Information); and (4) the inclusion of flexible weather controls (Section A.2.4 of the Supporting Information). These robustness checks used the same model setup as the baseline estimates, without any further modifications, and demonstrate that our main results are robust to these alternatives.

5.2 | Aggregate Impact

We next explore how rising temperatures affect total pesticide usage, which has important policy implications. The effects of climate change are usually calculated by adjusting daily temperature data according to some hypothesized warming scenario (e.g., Cui 2020; Perry et al. 2020; Miller et al. 2021). This calculation involves increasing the daily minimum and maximum temperatures incrementally (e.g., by +1°C) and then re-interpolating the data to calculate growing degree days. The implicit assumption of uniform warming in this approach may not align with the actual pattern of historical rising temperatures. Figure A2 of the Supporting Information shows that the temperature distribution based on a uniform 1°C warming in 1998 differs notably from

TABLE 3 | County-level aggregate effect of temperature on pesticides.

GDD intervals	ΔGDD		Pesticide use change[a]	
Panel A. All samples	**Value (D)**	**Percent (%)**	**Value (kg)**	**Percent (%)**
$GDD_{5°C-11°C}$	18.78	21.90	5331.17	−176.25
$GDD_{11°C-21°C}$	51.72	60.32	−12657.84	418.48
$GDD_{21°C-29°C}$	13.57	15.83	6083.88	−201.14
$GDD_{\geq 29°C}$	1.67	1.95	−1781.93	58.91
Subtotal	85.74	100	−3024.72	100
Panel B. North regions				
$GDD_{5°C-11°C}$	32.71	38.31	11739.24	642.13
$GDD_{11°C-21°C}$	55.44	64.93	−15308.58	−837.36
$GDD_{21°C-29°C}$	3.62	4.24	1463.26	80.04
$GDD_{\geq 29°C}$	−6.38	−7.47	3934.26	215.20
Subtotal	85.39	100	1828.19	100
Panel C. South regions				
$GDD_{5°C-11°C}$	11.51	10.37	1924.75	−15.88
$GDD_{11°C-21°C}$	58.38	52.58	−11477.61	94.67
$GDD_{21°C-29°C}$	29.31	26.40	12785.77	−105.46
$GDD_{\geq 29°C}$	11.83	10.65	−15356.71	126.67
Subtotal	111.03	100	−12123.80	100

Note: The table shows the estimates and aggregate impacts on pesticide usage for the entire country, as well as for the northern and southern regions, under each *GDD* interval change (5°C–11°C, 11°C–21°C, 21°C–29°C, and ≥ 29°C, respectively) from 1998 to 2016. The differences between each *GDD* interval are calculated using moving averages from 1998 to 2000 and from 2014 to 2016. The aggregate impacts are calculated based on the weight of each *GDD* interval relative to the total warming and the average county-level data of pesticides, while the estimates are obtained from baseline regressions. The north and South regions comprise 1324 and 1155 counties, respectively.

[a]The percentage columns are calculated by dividing the change in value of Δ*GDD* or pesticide use by the corresponding subtotal values in each panel.

the actual temperature distribution observed between 1998 and 2016[9]. Given the nonlinearity of temperature impacts on pesticide usage, the magnitudes of *GDD* in different temperature, intervals are critical for determining the overall effect on pesticide use. To avoid drawing misleading conclusions from unrealistic scenarios, we used historical temperature data from 1998 to 2016 to estimate the total effect of temperature on pesticide use (Panel [b] of Figure A2 of the Supporting Information).

First, we measure the changes in *GDD* s for each of the four temperature intervals: $[5°C, 11°C)$, $[11°C, 21°C)$, $[21°C, 29°C)$, and $\geq 29°C$, during the sample period from 1998 to 2016. By multiplying these changes by the corresponding estimated coefficients reported in Column (3) of Table 2, we calculate the total estimated change in pesticide usage associated with temperature change between 1998 and 2016.

Panel A of Table 3 reports the aggregate effects of temperature on total pesticide usage using the entire samples. During the sample period, the temperature generally increased, with $\Delta GDD_{11°C-21°C}$ accounting for around 60% of the total increase in *GDD*. Consequently, the reduction in pesticide usage associated with the increase in $GDD_{11°C-21°C}$ presents the primary effect of temperature change. Although extremely high temperatures only account for 2% of the total *GDD* increase, their substantial marginal effects lead to a disproportionate reduction in pesticide usage. Overall, an increase of more than 80°C days in *GDD* measured between 1998 and 2016, based on observed historical temperature trends in China, results in a net decrease of slightly above 0.5% in pesticide usage at the county level.

5.3 | Heterogeneous Effects Across Regions

Our sample contains 1324 and 1155 counties from northern and southern China and 1155 counties respectively. A substantial climatic difference exists between northern and southern China, separated by the Huai-River–Qin-Mountain line at latitude 33°. The climate in the south is subtropical, while northern China is considerably cooler (Figure A3 of the Supporting Information). Recent studies have demonstrated substantial differences in the impacts of climate change on China's agriculture between the northern and southern regions (e.g., Wu et al. 2021; Chen et al. 2023).

Table 4 reports estimation results on regional differences in temperature effects, using piecewise linear functions. The estimated coefficients and their statistical significance, for the interactions between temperature and regional dummy variables, indicate similar effects of rising temperatures on total pesticide usage in

TABLE 4 | Response heterogeneity between northern and southern regions.

	(1)	(2)	(3)	(4)
North × $GDD_{5°C–11°C}$ (10D)	0.0061***	0.0067***	0.0072***	0.0069***
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
North × $GDD_{11°C–21°C}$ (10D)	−0.0043**	−0.0049**	−0.0056***	−0.0058***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
North × $GDD_{21°C–29°C}$ (10D)	0.0060**	0.0067**	0.0082***	0.0085***
	(0.0029)	(0.0029)	(0.0029)	(0.0028)
North × $GDD_{\geq 29°C}$ (10D)	−0.0109*	−0.0107*	−0.0124**	−0.0111*
	(0.0058)	(0.0059)	(0.0060)	(0.0059)
South × $GDD_{5°C–11°C}$ (10D)	0.0032	0.0033	0.0026	0.0028
	(0.0021)	(0.0021)	(0.0020)	(0.0020)
South × $GDD_{11°C–21°C}$ (10D)	−0.0038**	−0.0038**	−0.0031**	−0.0030**
	(0.0016)	(0.0016)	(0.0015)	(0.0015)
South × $GDD_{21°C–29°C}$ (10D)	0.0076***	0.0080***	0.0068***	0.0065***
	(0.0023)	(0.0024)	(0.0024)	(0.0023)
South × $GDD_{\geq 29°C}$ (10D)	−0.0187***	−0.0167***	−0.0202***	−0.0193***
	(0.0040)	(0.0041)	(0.0042)	(0.0040)
Precipitation (mm/day)	0.0164	0.0178	0.0055	0.0122
	(0.0216)	(0.0229)	(0.0228)	(0.0225)
Precipitation (mm/day)—Squared	−0.0058**	−0.0066**	−0.0046*	−0.0049*
	(0.0026)	(0.0027)	(0.0026)	(0.0026)
Average wind speed (m/s)		0.0909	0.0528	0.0519
		(0.0875)	(0.0868)	(0.0857)
Average wind speed (m/s)—Squared		−0.0071	0.0016	0.0017
		(0.0190)	(0.0189)	(0.0186)
Average relative humidty (%)		−0.0274*	−0.0569***	−0.0467***
		(0.0157)	(0.0169)	(0.0167)
Average relative humidty (%)—Squared		0.0002**	0.0005***	0.0004***
		(0.0001)	(0.0001)	(0.0001)
Total sunlight duration (1000 h)			1.4406***	1.4322***
			(0.2442)	(0.2379)
Total sunlight duration (1000 h)—Squared			−0.4088***	−0.4023***
			(0.0736)	(0.0717)
Price ratio for product and pesticide				0.1658***
				(0.0562)
Price ratio for product and labor				−0.0120
				(0.0159)
Constant	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes
R-squared	0.9012	0.9013	0.9017	0.9051
Number of observations	44,350	44,350	44,350	44,336

Note: This table presents the coefficients associated with the temperature interacting with the northern/southern region indicator. The dependent variable is the logarithmic aggregate pesticides. All regressions include county and year fixed effects. Standard errors in parentheses are two-way clustered by counties and by prefectural city-by-year pairs. The significance levels are ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

both regions. These results are plotted in Panels (b) and (c) of Figure 2 to facilitate visual inspection. Two key findings emerge from the analysis. First, when the temperature rises from 5°C to 29°C, the northern region exhibits a stronger response to temperature increases compared to the southern region, with larger and more significant regression marginal coefficients. This finding indicates that the impacts of warming are more concentrated in the cooler northern region, consistent with the findings of Chen et al. (2023). Second, the converse holds under extremely high temperatures. Compared to the northern region, the impact of temperature changes on total pesticide usage is substantially higher in the southern region. This finding is mainly attributed to the extensive cultivation of crops with high pesticide demands, such as rice. Rice growth is highly sensitive to temperature and particularly vulnerable to heat stress, which may cause pesticide usage in southern China to be strongly influenced by high temperatures.

We report the aggregate effects for the northern and southern regions in Panels B and C of Table 3, using the estimates in Column (3) of Table 4, respectively. As previously mentioned, the temperature increase in $GDD_{11^\circ C-21^\circ C}$ is critical, consistently showing the substantial changes in pesticide use across both regions. Additionally, the temperature increase in $GDD_{\geq 29^\circ C}$ plays a crucial role, especially in the southern region, indicating that temperature change has a stronger effect on reducing pesticide usage in this area.

5.4 | Decomposition Results

We decompose the aggregate effect of temperature on pesticide usage into the effects of usage intensity, crop mix, and total planted area, as described in Equation (3) in Section 3.2. The estimation details are provided in Appendix of the Supporting Information. We use a data-driven method to determine the functional form of how increasing temperatures affect pesticide usage intensity, crop formation, and overall planted area. Extremely high temperatures tend to have a larger marginal effect; thus, we compare two piecewise linear models: one using a single threshold of 29°C and another using the same three thresholds (11°C, 21°C, and 29°C) from the baseline model based on some information criteria. The statistical test results, shown in Table A11 of the Supporting Information, favor the second specification with four linear splines for the pesticide intensity of crops.

Another challenge is defining one-degree increase in GDD. Using two linear splines as an example, the effects of a degree increase in temperature differ between lower (<29°C) and higher (≥ 29°C) temperatures. Thus, we construct weights based on the total increase in growing degree days from 1998 to 2016. The average GDD from 1998 to 2000 is used to represent the 1998 level, while the average GDD from 2014 to 2016 denotes the value in 2016. The ratio of the change in $GDD_{5^\circ C-29^\circ C}$ to the total increase in GDD from 1998 to 2016 is used as the weight for a one-degree increment of $GDD_{5^\circ C-29^\circ C}$. A similar method is applied to measure the weight for $GDD_{\geq 29^\circ C}$. The weights for the model using four linear splines are constructed similarly. These weights are then applied to measure the marginal effect of a one-unit increase in GDD on pesticide usage across various channels based on Equation (3) using the estimates for intensity, cropping structure, and planted area from Tables A12, A13, and A14 of the Supporting Information, respectively.

We report the contributions of the three components to the total impact of temperature on pesticide usage in Figure 3 and their respective marginal effects in Table 5. The response of total cropland area to temperature change is not statistically significant, whether we control for time fixed effects or provincial time trends, so we exclude extensive effects from our calculations[10]. The intensive effects contribute most to the impact of temperature on pesticide usage at the national and regional levels. We report the impact of the temperature on pesticide intensity for each crop in Table 5. Our findings demonstrate that temperatures drastically alter pesticide intensity but not uniformly across crops. Grain crops are the main driver of changes in pesticide intensity, possibly because they require notably more pesticides than other crops and account for 64% of the total planted area. In addition, after accounting for year fixed effects and the relevant economic variables, such as the price of alternative crops, our results indicate that while changes in total planted area do not contribute to variations in the total amount of pesticides used (Table A14 of the Supporting Information), evidence of notable adjustments in pesticide application intensity is obtained for specific crops (Table A12 of the Supporting Information). These results underscore that the observed changes in total pesticide usage predominantly mirror adjustments in application intensity rather than area changes, providing important insight into how agrochemical inputs respond to temperature changes.

5.5 | Long-Term Effect

Table 6 presents the estimates with a two-period panel of long differences suggested by Burke and Emerick (2016), aiming to capture the long-term effects of temperature on pesticide use over time. Aiming to perform differencing, we define two subperiods: 1998–2007 and 2007–2016. We calculate the endpoints as 3-year averages to capture the change in average temperature and pesticide usage over time. For example, for the year 1998, we take the average for each variable over the period 1998–2000, and the other three endpoints are calculated similarly. For the sub-sample 1998–2007, we calculate the difference between 1998 and 2007 for each variable. Similarly, we applied the same difference between the observations in 2007 and those in 2016. The coefficients for almost all temperature terms in Table 6 are not statistically significant, indicating that rising temperatures have little long-term effect on pesticide usage. Furthermore, these conclusions are consistent with those obtained similarly using the direct long-difference method initially proposed by Burke and Emerick (2016). The estimation results are reported in Table A15 of the Supporting Information, with additional descriptions provided in Section A.4 of the Supporting Information.

The results on the lack of long-term effect can be explained in terms of both adaptive pesticide usage and shifts in crop mix. First, farmers may improve the efficiency of pesticide use by adapting more appropriate types of pesticides or timing of applications in response to climate change. For example, agronomists have observed that prolonged drought leads to an increase in insect pests and a decrease in weeds (Peters et al. 2014). As a result, the use of insecticides will increase and the use of herbicides will

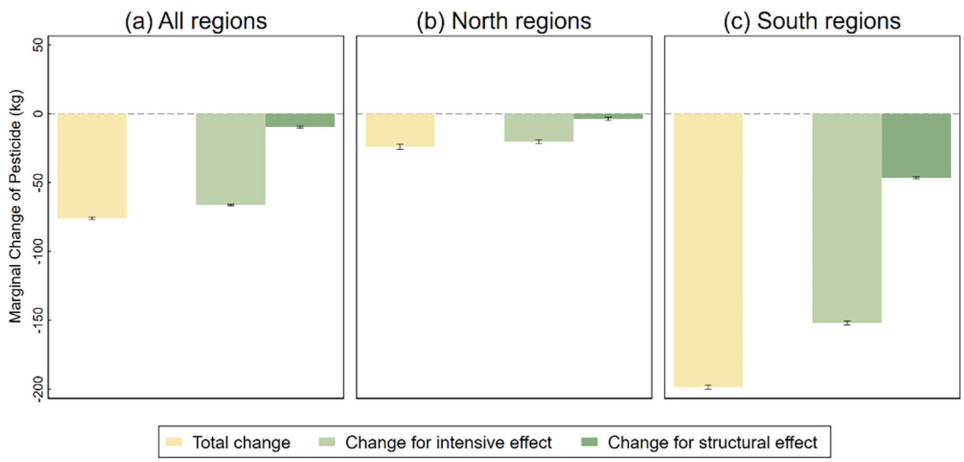

FIGURE 3 | Decomposition of the effects of temperature change on pesticide usage at the county level. The figure presents the marginal effect of temperature change on pesticide usage, excluding the extensive effect, for a 1 GDD increase at the county level between 1998 and 2016. The 95% confidence interval is derived from 1000 bootstrap repetitions. For each bootstrap replication, a bootstrap sample is constructed by sampling with replacements from the observed data. The bootstrap samples are clustered at the county level, preserving all within-county correlations. For each bootstrap sample, we estimate our main specification using Equations (4) and (5), and calculate the marginal impacts using Equation (3).

TABLE 5 | Decomposition of the marginal effects of temperature on pesticide usage based on one unit GDD increase.

	(1) Intensive effect		**(2) Structural effect**	
	$\frac{\partial PI_i}{\partial T} \cdot SI_i \cdot L$ **(kg)**	**Percent %**	$\frac{\partial SI_i}{\partial T} \cdot PI_i \cdot L$ **(kg)**	**Percent %**
Grain crops	−23.39	35.29	1.19	−12.28
Potatoes	−10.01	15.10	−2.27	23.43
Cottons	−4.15	6.26	−3.19	32.92
Sugar crops	−7.66	11.56	0.29	−2.99
Rapeseeds	−0.57	0.86	−2.16	22.29
Vegetables and fruits	−20.50	30.93	−3.55	36.64
Subtotal	−66.28	100	−9.69	100

Note: The marginal effects are evaluated at the sample means for the period 1998–2006 using Equation (3) in Section 3.2.
The percentage columns are calculated by dividing the change in pesticide usage (in kilograms) by the corresponding subtotal values in each column. Standard errors are obtained via bootstrapping with 1000 replications, using a method similar to that in Figure 3. The coefficients for the intensive and structural effects are statistically significant at the 1% level.

decrease, and this structural change will lead to a decrease in the total use of pesticides. Second, it is widely recognized that warming temperatures reduce yields for a wide range of crops (Hasegawa et al. 2021; Zhu et al. 2022), and therefore subsequent crop restructuring due to changes in relative returns may reduce pesticide demand. This indirect effect may not be immediate as structural adjustments are often costly. We also note that this result is to some degree consistent with the key finding from our decomposition analysis: the primary effect of temperature change on pesticide usage occurs through adjustments on pesticide use intensity, while its indirect effects through crop mix and land use are rather minor in short term.

Another possible reason is the relatively short span of our data. Kelly et al. (2005) indicated that climate change entails a prolonged learning and adaptation process for farmers. Studies on the long-term effects of climate change generally consider time spans of more than 30 years, testing the stability of regression coefficients over time, which naturally requires relatively long panels (e.g., Burke and Emerick 2016; Mérel and Gammans 2021; Ortiz-Bobea 2021). In contrast, the current study is based on a sample period of only 19 years.

6 | Concluding Remarks

The threats posed by climate change to farming and agricultural production are considered one of the greatest challenges to the global food supply. Against this backdrop, identifying the total impacts of climate change on pesticide usage, along with a detailed decomposition of its mechanisms, can increase our understanding of the impacts of climate change on agriculture. Unlike previous studies based on pesticide use intensity, this paper is more concerned with sustainable development from the

TABLE 6 | Long-term impacts on pesticides under panel long differences.

	1999–2011 2003–2015		1999–2012 2002–2015		1999–2013 2001–2015	
	(1)	(2)	(3)	(4)	(5)	(6)
$GDD_{5°C-11°C}$ (10D)	0.0010	0.0031	−0.0032	−0.0007	−0.0058	−0.0049
	(0.0042)	(0.0042)	(0.0045)	(0.0046)	(0.0039)	(0.0040)
$GDD_{11°C-21°C}$ (10D)	−0.0003	−0.0010	0.0005	−0.0008	0.0015	0.0010
	(0.0030)	(0.0029)	(0.0027)	(0.0027)	(0.0026)	(0.0027)
$GDD_{21°C-29°C}$ (10D)	−0.0039	−0.0024	−0.0038	−0.0022	−0.0054	−0.0059
	(0.0040)	(0.0040)	(0.0039)	(0.0038)	(0.0040)	(0.0040)
$GDD_{\geq 29°C}$ (10D)	0.0134	0.0120	0.0120	0.0094	0.0076	0.0098
	(0.0091)	(0.0087)	(0.0094)	(0.0091)	(0.0105)	(0.0100)
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes
Other weathers	No	Yes	No	Yes	No	Yes
Economic variables	No	Yes	No	Yes	No	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.7966	0.8077	0.8704	0.8783	0.8823	0.8902
Number of observations	4512	4510	4538	4536	4494	4492

Note: The dependent variables in all regressions is the difference in the log of smoothed pesticides. The controls are all similar to those in the main specification of Table 2. Data in Columns (1)–(6) represent a two-period panel with 12-, 13-, and 14-year differences. The long difference for each period is calculated as the average of the first three years and the last three years. All regressions include county and year fixed effects. Standard errors (in parentheses) are two-way clustered by counties and by prefectural city-by-year pairs. The significance levels are ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

perspective of the impact of increasing temperatures on total pesticide use. We systematically explore the complex phased impact of temperature rise on pesticide use based on a large-scale cross-regional data study in China and provide new insights into the impact of rising temperatures on pesticide use. In addition, this study innovatively presents a decomposition framework for analyzing the impacts of climate change on total inputs of agricultural production, including three types of impacts: intensity, structure, and planted area. Third, climate change research is often challenged by missing data on pesticide use across regions and crops. We develop a mathematical method based on entropy maximization for data imputation to address this problem.

Our investigation reveals a nonlinear relationship between temperature increase and pesticide usage, indicating that extremely high temperatures are likely to reduce pesticide usage. Pesticide usage in northern China, which is cooler than southern China, is more responsive to rising temperatures as they increase from 5°C to 29°C. The effect of temperature change on pesticide usage is relatively mild under extreme heat compared to that in the southern region. Calculation based on our estimation results indicates that China's pesticide usage decreased by approximately 0.5% in response to an increase of more than 80°C days in *GDD*, as measured by historical temperature trends during the study period. We further decompose the impacts of temperature on total pesticide usage into intensive, structural, and extensive effects. The results show that the main impact of temperature on pesticide usage is through its effect on changes in pesticide intensity. Moreover, the long-term effect of temperature increase on pesticide usage is insignificant.

There are several policy implications of this study. First, the process of agricultural green transformation warrants more attention, especially for the main grain-producing areas in northern China with mild temperatures, as there is considerable uncertainty about the impact of sustained temperature increases on the demand for pesticides. Second, pesticide research and development needs to take into account the impacts of climate change. Because of the nonlinear response of pesticides to rising temperatures, research and development of pesticides can benefit from factoring in the characteristics of local climate change. Third, governments can design policies to reduce the impact of climate change on the pesticide supply system. For example, as temperatures rise, the demand for herbicides and fungicides may decrease while the demand for insecticides increases. Timely public dissemination of relevant weather forecast and market information can contribute to a stable and resilient supply chain of pesticides and other critical agricultural inputs.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Endnotes

[1] The data are available at http://www.fao.org/faostat/en/#data.

[2] In our study, we defined the growing season as a fixed period (typically corresponding to the warm months of the year). In addition, we introduced a seasonal temperature variable into Equation (1) to better capture the effect of seasonal temperature changes on pesticide use. The results show that total pesticide use responds to temperature changes in a manner that is generally consistent with the baseline estimates. Specifically, temperature changes during the spring (March to May) and summer (June to August) had a substantial effect on pesticide use, while the effect of fall (September to November) temperatures was less pronounced. These results are available upon request.

[3] We also experimented with a single knot specification as in Schlenker and Roberts (2009). The overall results are similar, although the three-knot model consistently outperforms the one-knot model in terms of goodness-of-fit (e.g., lower AIC/BIC). These results are available upon request.

[4] For robustness checks, we re-estimated the baseline model with two-way clustered standard errors at the county level and province-by-year level. The key temperature coefficients remain stable. Since the province is the principal administrative division in China, with the prefecture being the level between the province and the county, we do not cluster by province because our data includes only 30 provinces, which is relatively few for effective clustering (Angrist and Pischke 2009; Zhang et al. 2017). The regression results are available upon request.

[5] The Conley covariance matrix is a weighted average of spatial autocovariances, with weights determined by the product of Bartlett kernels in two dimensions. We selected a cutoff radius, which represents the distance at which spatial dependence is assumed to be zero. We choose a cutoff of approximately 100 km (Dell et al. 2012) and assumed 5 lags for serial correlation. Choosing other cut points produces qualitatively similar results. Due to space limits, we only reported Conley standard errors (shown in brackets) in Table 2. The Conley standard errors of other tables are available upon request.

[6] The grain crops include rice, wheat, soybean, and corn.

[7] Due to its special natural environment and incomplete data, Tibet is not included in our analysis.

[8] Controlling a dummy variable for the ZGPU program does not significantly change the major estimation.

[9] To make the two scenarios comparable, we normalized the historical temperature changes from 1998 to 2016 to match the temperature change size in the +1°C uniform warming scenario. First, we calculated the sum of the temperature changes in each degree interval under the +1°C uniform warming scenario, and then divided the sum of the temperature changes in each degree interval from 1998 to 2016 to obtain a multiplier factor. Second, we expanded all the temperature change values for each temperature interval of the period 1998–2016 by multiplying the above multiplier factor to make the uniform warming scenario comparable with the historical temperature increase from 1998 to 2016.

[10] Including the extensive effect does not affect our main conclusions and the intensive effect remains the dominant factor. The results are available upon request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

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