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Climate Risks and Damage Abatement Effects of Pesticides: Evidence Based on Four-Wave Panel Data in Nigeria

Hiroyuki Takeshima

Hyacinth O. Edeh

Akeem O. Lawal

Johnson E. Oniybe

Christogonus K. Daudu

Kwaw S. Andam

Innovation Policy and Scaling

Development Strategies and Governance

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

AUTHORS

Hiroyuki Takeshima (H.takeshima@cgiar.org) is a Senior Research Fellow in the Innovation Policy and Scaling Unit of the International Food Policy Research Institute (IFPRI).

Hyacinth O. Edeh (H.edeh@cgiar.org) is a Country Program Manager in the Development Strategy and Governance Unit of the International Food Policy Research Institute (IFPRI).

Akeem O. Lawal (aolawal10@yahoo.co.uk) is a Department Head in the Agricultural Engineering, Department of the National Agricultural Extension & Research Liaison Services, Federal Ministry of Agricultural & Rural Development, Zaria, Nigeria.

Johnson E. Oniybe (jeonyibe@yahoo.com) is a Policy, Agriculture & Agribusiness Specialist National Agricultural Extension and Research Liaison Services (NAERLS), Ahmadu Bello University, Zaria, Nigeria.

Christogonus K. Daudu (chrisdaudu@yahoo.com) is a professor of the National Agricultural Extension Research & Liaison Services, Ahmadu Bello University, Zaria Nigeria.

Kwaw S. Andam (k.andam@cgiar.org) is a Country Program Leader in the Development Strategy and Governance Unit of the International Food Policy Research Institute (IFPRI).

Notices

ABSTRACT

Managing biotic stress, such as pests, diseases, and weeds, remain critical in enhancing the productivity of agrifood systems in developing countries, including Nigeria. The public sector continues to seek solutions for efficient and effective measures for addressing these biotic stresses, ranging from varietal technologies, improved crop husbandry, and the application of agrochemicals. The field-level evidence remains scarce regarding the effectiveness of these measures in developing countries like Nigeria. Furthermore, increasing climate uncertainty poses further challenges in identifying effective measures. This study assesses the damage abatement effects of agrochemicals in Nigeria and how these effects are affected by weather shocks. We extend the standard damage abatement framework to 4 waves of farm panel data to minimize the potential bias due to the endogeneity in agrochemical use decisions. Our results indicate that weather shocks have significant effects. In particular, rising nighttime minimum temperatures above 20 °C have significantly increased damage abatement effects of pesticides in Nigeria. This is possibly because of increased pest activities induced by the warmer nighttime temperatures, which, in the absence of pesticide uses, would cause more significant damage to crops. These results hold for all crops combined, as well as individual crops, including cowpea and maize, for which Nigeria has intensified its effort in pest control through both agrochemicals and Bt varieties in recent years.

Keywords: pesticides, climate change, damage abatement framework, panel data, maximum likelihood estimation, Nigeria

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1 Background

Management of biotic shocks, including pests and disease controls, is critical for enhancing the productivity of agrifood systems in developing countries, including Nigeria. Globally, pests and diseases reduce major food crop production by about 20 percent, albeit with significant variations across locations (Savary et al., 2019). In developing regions outside Africa South of the Sahara (SSA), management of biotic shocks became increasingly intensive since the 1970s through the shifting breeding focus from yield enhancement to pest resistance (Evenson & Gollin 2003) and increased agrochemical use (Barker et al. 1985), among others. The recent growth of the global agrochemical market, partly induced by increased production of generic products in China and elsewhere, can also make agrochemicals less costly and more accessible in Africa (e.g., Haggblade et al. 2017, 2022, 2023).

However, pests and diseases remain significant challenges for agricultural productivity and global food security due to various emerging factors, including increased migration that induces spatial pests movement and reduced biodiversity, among others (Ristaino et al. 2021). Another potentially important factor is climate change. An increasing body of experimental evidence suggests that climate conditions can significantly affect crop pest activities (e.g., Jackai et al. 1990; Jackai & Inang 1992; Bottenberg et al. 1997; Adati et al. 2004; Hassan 2007; Kumar et al. 2017; Ba et al. 2019; Venter et al. 2019; Singh et al. 2022; Díaz-Álvarez et al. 2023). Evidence is, however, limited at the field level regarding the effects of climate change on the effectiveness of crop pest management. This is despite the improved knowledge of such effectiveness under more statistic cases, including evidence that has been accumulated through the damage abatement framework (e.g., Lichtenberg & Zilberman 1986; Babcock et al. 1992; Carrasco-Tauber et al. 1992; Qaim 2003; Qaim & De Janvry 2005; Shankar & Thirtle 2005; Horna et al. 2008; Salazar et al. 2010; Cavatassi et al. 2011).[1]

This study partly fills this knowledge gap by providing relevant farm-level evidence from Nigeria. Specifically, we estimate damage abatement effects of agrochemicals (primarily pesticides) on agricultural productivity using farm plot-level data from four waves of nationally representative farm household data in Nigeria. We then assess how these effects are associated with climate shocks, including temperatures, droughts, and rainfall. Using the four waves of nationally representative data, we conduct robust analyses that also account for potential endogeneity of agrochemical uses, and also exploiting rich spatial and temporal variations in these climate outcomes.

Nigeria is a particularly important case to study the climate change-pest management nexus. Nigeria is the largest country in SSA regarding population and agricultural land use. It is also characterized by diverse agroclimatic regimes, ranging from humid tropics to arid- and semi-arid production systems. Furthermore, supporting effective pest management has been an essential policy area for the government in recent years (Government of Nigeria 2021), which has promoted various pest management technologies, including varietal technologies (e.g., genetically modified pest-resistant cowpeas and maize), integrated pest management, and agrochemicals. Furthermore, access to and the use of agrochemicals, although growing, can vary considerably both across space and over time in developing countries like Nigeria, which

[1] Here we refer to a damage-abatement framework as an empirical framework generally characterized in the literature, which differentiates agrochemicals as inputs that reduce inefficiency, unlike all the other inputs that relate more with production frontier. Intuitively, damage abatement effects refer to the effectiveness of agrochemicals in reducing the production losses due to pests and diseases.

facilitate the analyses of the damage abatement effects of agrochemicals and its interactions with weather shocks.[2]

The paper contributes to the various strands of literature. The study extends the long literature of damage abatement effects of agrochemicals (Lichtenberg & Zilberman 1986; Babcock et al. 1992; Carrasco-Tauber et al. 1992; Qaim 2003; Qaim & De Janvry 2005; Shankar & Thirtle 2005; Horna et al. 2008; Salazar et al. 2010; Cavatassi et al. 2011), by incorporating climate shocks as some of the factors driving the heterogeneity in damage abatement effects. The paper also contributes to growing literature on agrochemical use in Africa including Nigeria (Haggblade et al. 2017, 2022, 2023; Zhang et al. 2018), by shedding light at micro-level into how climate shocks affect returns to (and thus the demand for) agrochemicals. The paper further contributes to the growing literature investigating the effects of climate change on agricultural productivity in West Africa including Nigeria (e.g., Akossou et al. 2016; Adam et al. 2020; Yobom & Le Gallo 2022; Amare & Balana 2023; Joseph et al. 2023), by adding evidence on returns to agrochemical as one of the impact pathways.

The remainder of this paper is structured as follows. Section 2 describes potential linkages between climate and pests. Section 3 discusses empirical methods. Section 4 describes data. Section 5 presents and interprets results. Finally, section 6 concludes.

[2] Among other factors, such volatility can be attributed to the fact that the pesticide market in Nigeria is still thin, albeit with significant growth in recent years, especially since the mid-2010s (Haggblade et al. 2022). As is shown in the later section, the share of farmers using pesticides in Nigeria has been around 20%. Most pesticide importers in West Africa, including Nigeria, still lack the capacity to establish stable distributor networks, so the supply chain for agrochemicals remains fragmented, especially for reliable-quality agrochemical products (Haggblade et al. 2022, 2023). The thinness of markets, especially in rural areas, can raise the transaction costs for sourcing agrochemicals when sudden shocks lead to the exit or discontinuation by local informal dealers/retailers from supplying agrochemical products.

2 Weather shocks, pests, and agrochemicals

Climate shocks have significant effects on the population and activities by various pests, which can have implications on the effects of pest control technologies, including agrochemicals.

Temperature

Nighttime temperature is one of the factors that affect pests prevalence. Importantly, in West Africa including Nigeria, minimum temperature has risen faster than average temperature in recent years (Barry et al. 2018). Generally speaking, where the nighttime minimum temperature starts exceeding around 20 °C, it induces greater pests prevalence, by stimulating more mating activities (Jackai et al. 1990; Hassan 2007), facilitating larvae development (Jackai & Inang 1992; Adati et al. 2004), and extending periods at night when host-seeking flight activity, and feeding take place (Venter et al. 2019).[3] The potentially enhanced pests activities under warmer nighttime temperature may enhance the relative importance of pest controls because the damage in the absence of pest controls can be greater. However, higher nighttime temperature can also reduce general yield potentials (e.g., Peng et al. 2004; Welch et al. 2010; Musa et al. 2021; Tofa et al. 2021).[4] Depending on the effects on yield potentials, the effectiveness of pest controls under higher nighttime temperature can be mixed.

The effects of changes in growing degree days (GDD) and harmful degree days (HDD) on pest prevalence is also somewhat mixed. For example, while pod borer population shows significant positive correlation with maximum temperature in India (Kumar et al. 2018c), other studies find that temperature above 34 °C is less suitable for egg development (Adati et al. 2004; Ba et al. 2019).

Similarly, higher temperatures are also found to induce pests' activities for other crops. For example, higher temperature stimulates the growth / population of fall armyworms for maize (e.g., Early et al. 2018; Singh et al. 2021; Díaz-Álvarez et al. 2023), pests for other major crops like whitefly, brown streak virus or mealybug for cassava (Bellotti et al. 2012), or major cereals like wheat and rice (Schneider et al. 2022). Other studies also suggest that higher temperatures generally lead to increased pest activities and population for a variety of crops (Pereira 2017; Skendžić et al. 2021).

Rainfall, drought in relation to humidity

Greater humidity generally facilitates the growth of pests. In general soil insects are more prevalent in moist conditions than in drier conditions. Greater moisture may provide an ideal condition for the multiplication and development of most soil insects (e.g., Villani & Wright 1990). In China, soil humidity helps overwintering behavior of soybean pod borer (Qin et al. 2015). Pod borers have been considered endemic only in the more humid coastal areas of Southern Benin, Nigeria and Ghana (Bottenberg et al. 1997; Adati et al. 2004). In the drier north,

[3] For various legume pod borer pests, mating activity takes place between the fourth and twelfth hour of darkness when temperatures range between 20 and 25 °C and relative humidity is greater than 80% (Jackai et al. 1990; Hassan 2007). Temperatures between 19.5 °C and 29.3 °C seem most suitable for the development of M. vitrata larvae (Jackai & Inang 1992; Adati et al. 2004). In Southern Africa, at nocturnal temperatures below 20 °C, host-seeking flight activity, and feeding will be condensed into the three hours immediately after sunset. Once nocturnal temperatures increase above 20 °C, host-seeking and flight activity, and the risk of virus transmission, will be extended over longer periods and not be restricted to a one- to three-hour period after sunset (Venter et al. 2019).

[4] For example, high night temperature (minimum temperature in the range of 22–25 °C) could contribute to the lower yield of maize crops grown in the humid tropics because of higher rate of respiration (Tofa et al. 2021).

the flight activity of moths is only observed during the rainy season when cowpea is flowering (Ba et al. 2009; Baoua et al. 2011). Greater humidity and rainfall season may also extend the number of generations of pest population. At the same time, however, drier conditions may make certain soils lighter, easing the emergence of adults from pupae and their movements within the soil, often observed for pod borers among non-cowpea crops (Anitha 1992). In addition, greater (and particularly excessive) rainfall can increase flood incidence that can induce inter-plots movement of pests (e.g., Urama & Hodge 2004).

3 Empirical methods

This paper extends the conventional damage abatement framework into multiple-period panel data context.

3.1 Model assuming the exogeneity of agrochemical use

Specifically, the general specification of our empirical models is the following. We estimate

$$\begin{aligned} \ln Y_{ijt} = \alpha_Y + \ln G\left(X_{ijt}, W_{jt}\right) + \beta_K \cdot K_{ijt} + \beta_Z \cdot Z_{ijt} + \beta_W \cdot W_{jt} + c_j \\ + \varepsilon_{ijt} \\ G\left(X_{ijt}\right) = \left[1 + \exp\left(\alpha_G - \beta_X X_{ijt} - \beta_{XW} X_{ijt} \cdot W_{jt}\right)\right]^{-1} \\ \ln G\left(X_{ijt}\right) = -\ln\left[1 + \exp\left(\alpha_G - \beta_X X_{ijt} - \beta_{XW} X_{ijt} \cdot W_{jt}\right)\right]. \end{aligned} \tag{1}$$

Y_{ijt} is the production value per area on plot i for household j in year t, X_{ijt} is the amount of agrochemicals used per area, K_{ijt} is the amount of other inputs, Z_{ijt} is the set of other time-variant exogenous factors, and W_{jt} is the variable that captures weather anomaly in t where j is located. $G(\cdot)$ is a function that captures the damage abatement effect as a function of X_{ijt} and W_{jt} as described. Our specification of damage abatement function $G(\cdot)$ follows a logistic damage abatement model, which has been considered reasonably flexible and reliable in the literature (e.g., Shankar & Thirtle 2005; Cavatassi et al. 2011).[5] Notation c_j refers to farm household fixed effects. Notations α, β's, are estimated parameters, and ε_{ijt} is an idiosyncratic error term. Adding the interaction term $X_{ijt} \cdot W_{jt}$ captures how the weather anomalies affect the damage abatement effect of agrochemicals. Similar approaches have been used in past studies to model the heterogeneity of damage abatement effects as functions of other covariates (e.g., Skevas et al. 2012; Qiao 2015). Under the assumptions that agrochemical use X_{ijt} is exogenous given K_{ijt}, Z_{ijt} , W_{jt} and c_j, equation (1) can be estimated through a standard nonlinear least square (NLS) method.

The parameter β_X and β_{XW} is related to the marginal effects of agrochemical X_{ijt}, and W_{jt} on Y_{ijt} through

$$\begin{aligned} \frac{\partial\left\{-\ln\left[1 + \exp\left(\alpha_G - \beta_X X_{ijt} - \beta_{XW} X_{ijt} \cdot W_{jt}\right)\right]\right\}}{\partial X_{ijt}} \\ = \left(\beta_X + \beta_{XW} W_{jt}\right) \\ - \frac{\left(\beta_X + \beta_{XW} W_{jt}\right)}{1 + \exp\left(\alpha_G - \beta_X X_{ijt} - \beta_{XW} X_{ijt} \cdot W_{jt}\right)} \end{aligned} \tag{2}$$

[5] We show in later section that results are robust when using exponential damage abatement function, another commonly used functional form, where by $G\left(X_{ijt}\right) = \left[1 - \exp\left(\alpha_G - \beta_X X_{ijt} - \beta_{XW} X_{ijt} \cdot W_{jt}\right)\right]$ in equation (1).

$$\frac{\partial^2\{-\ln[1+\exp(A)]\}}{\partial X_{ijt}\,\partial W_{jt}} = \\ = \beta_{XW} - \frac{\beta_{XW}}{1+\exp(A)} - \frac{(\beta_X + \beta_{XW}W_{jt})\cdot(\beta_{XW}X_{ijt})\cdot\exp(A)}{[1+\exp(A)]^2} \quad (3) \\ A = \alpha_G - \beta_X X_{ijt} - \beta_{XW}X_{ijt}\cdot W_{jt}.$$

Extension to a panel framework

Our model converts all variables through within-transformation, which is equivalent to including farm household j dummy variables. Similar approaches of controlling for various types of unobserved fixed effects have been used in various other studies that focused on damage abatement models in the panel data framework (e.g., Lansink & Carpentier 2001; de Mey et al. 2012; Skevas et al. 2013; Qiao 2015; Huffman et al. 2018; Qiao & Huang 2020).

3.2 Model addressing the potential endogeneity of agrochemical use

X_{ijt} can still be endogenous if it can be correlated with idiosyncratic shock ε_{ijt}.[6] In this case, instrumental variable (IV) approaches can be used, whereby X_{ijt} is regressed on other exogenous variables as well as excluded IVs, and residuals from this regression is incorporated in the estimation of the main equation (1). This approach can be implemented either through a two-step method or through a one-step maximum likelihood estimation (MLE) method (Terza et al. 2008; Terza 2017). We implement the MLE method as it is generally more efficient than the two-step method.

In MLE method, however, precise estimation of coefficients for the interaction term (β_{XW}) can become more difficult due to multicollinearity. We therefore employ an approach that avoids estimation through the interaction terms. Specifically, we first split the samples based on waves 1-2 and waves 3-4, and the relative changes of each climate parameter value between these two sub-periods. We then separately estimate

$$\ln Y_{ijT\pm} = \alpha_{T\pm} + \ln G_{T\pm}(X_{ijt\pm}, W_{jT\pm}) + \beta_{K\pm}\cdot\ln K_{ijT\pm} + \beta_{Z\pm}\cdot Z_{ijT\pm} + \beta_{W\pm}\cdot W_{jT\pm} \\ + c_{j\pm} + \varepsilon_{ijT\pm} \\ \ln X_{ijT\pm} = \gamma_{T\pm} + \gamma_{V\pm}\cdot V_{ijT\pm} + \gamma_{K\pm}\cdot K_{ijT\pm} + \gamma_{Z\pm}\cdot Z_{ijT\pm} + \theta_{i\pm} + u_{ijT\pm}. \quad (4)$$

Here T denotes aggregated waves ($T=0$ if wave = 1 or wave = 2; $T=1$ if wave = 3 or wave = 4). The notation $\pm = \{+,-\}$ denotes "+" if the farm household i has been in location that experienced relative increase in weather parameters between $T=0$ and $T=1$, and "–" if experiencing relative decrease. $V_{ijT\pm}$ is the excluded IV, $\theta_{i\pm}$ is farm household fixed effects, and $u_{ijT\pm}$ is the idiosyncratic error term affecting $X_{ijT\pm}$. MLE is then conducted through the likelihood function that is a bivariate normal density function based on two error terms $\varepsilon_{ijt}, u_{ijt}$ as random variables. Estimation is conducted through STATA command `mlexp`. We first estimate equations (4) in two-step, first by regressing bottom equation, and use predicted value of $\ln X_{ijT\pm}$ into the top equation. We then use the estimated coefficients from this two-step

[6]A few past studies in agricultural economics field raised similar concerns regarding the potential endogeneity of agricultural inputs use even after controlling for time-invariant farm-fixed effect, including in more general setting beyond damage-abatement framework (e.g., Shee & Stefanou 2015).

process as the initial values of parameters.[7]

3.3 Variables

The set of control variables K_{ijt} and Z_{ijt} are selected following the related literature (e.g., Pemsl et al. 2011; Huffman et al. 2018). Specifically, K_{ijt} includes a set of other inputs used, namely, labor (both family and hired), expenditures on all the other inputs (seeds, fertilizer, renting of draft animals and machines) per area, and whether irrigation is used, on plot i at year t. K_{ijt} also includes the value of agricultural capital held by the farm household j (which is constant across all plots i for the farm household j). Variables Z_{ijt} include whether improved seed is used, whether mixed cropping is used rather than pure stand on plot i, and whether the farm household received visits by the government extension staff during the past 12 months (which is arguably exogenous compared to the receipt of private extension service). Lastly, Z_{ijt} also includes year dummy variable to control for any other year-specific common shocks.

Instrumental variable

The excluded IV $V_{ijT\pm}$ is the cluster-average which has also been used in past studies where markets for potentially endogenous factors are imperfect and sometimes thin, so that accessibility to them can be spatially heterogeneous and can vary significantly over time (e.g., Benjamin 1992; Le 2010; Ji et al. 2012; Min et al. 2017; Dillon et al. 2019; Dolislager et al. 2021). Specifically, it is the average value of $X_{ijT\pm}$ in Enumeration Area (EA) of j excluding own observation.

[7]Applying within transformation can lead to consistent estimates in MLE under standard regularity conditions, without facing incidental parameter problems (e.g., widely applied in certain MLE models like stochastic frontier model (Wang & Ho 2010; Chen et al. 2014). This is particularly true in linear models including ours. Importantly, our models are essentially linear models that approximate nonlinear component (exp ( ) part) through Taylor-series approximation. Therefore, properties that hold under linear models also apply to our models.

4 Data

4.1 Primary household / plot data

Our primary data are panel farm household data and their plot-level production data from the Living Standard Measurement Study – Integrated Survey on Agriculture (LSMS-ISA) for Nigeria. The data correspond to main production season from 4-waves, i.e., 2010, 2012, 2015 and 2018. Note that the data are panel only at farm household level, whereas different set of plots are cultivated by farms each year. For waves 2010, 2012 and 2015, the same set of 5,000 farm households were interviewed, while in wave 2018, approximately 1,478 of original 5,000 farm households, were interviewed again. Generally, approximately two-thirds of these households engaged in farming. Our exogenous model (1) focuses on a total of 17,710 plots of 5,090 panel households who cultivated their plots in at least two waves (so that farm household-fixed effects can be effectively controlled for), including 5,676 observations of maize-growing plots and 3,469 observations of cowpea/beans-growing plots. Our endogenous model (4) focuses 4,822 plot-level observations from about 1,000 of 1,478 panel households that cultivated their plots in all 4 waves.

4.2 Climate data

In addition to the primary farm household data, we compiled historical climate data for temperature, rainfall and drought and extracted them for geo-referenced locations of farm households in LSMS-ISA data. Historical temperature data are extracted from WorldClim data (Fick & Hijmans 2017) and AgERA5 data (AgERA5 daily mean temperatures developed by the European Centre for Medium-Range Weather Forecasts (Dee et al. 2011). WorldClim are monthly temperature data but are of high resolution, available for 1 km by 1 km grids. In contrast, AgERA5 is daily data, but its spatial resolution is only 6.0 arcminutes (11.1 km at the equator). We therefore follow Li (2023) to combine these two data to generate daily temperature at 1 km by 1 km grids.

In addition, historical monthly rainfall data are taken from The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) by Funk et al. (2015). Historical monthly drought index are extracted from the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010). The SPEI quantifies drought severity in ways that are comparable across time and space. The SPEI is correlated with water balance, and more negative values indicate greater drought severity. For each year between 1981 up to the survey years, we extracted key climate conditions for major cropping season,[8] including total rainfall, and average SPEI scores, as well as two temperature-based parameters, namely Growing Degree Days (GDD) and High Nighttime Temperature (HNT). Following past studies on Nigeria and other developing countries in the tropics (Amare & Balana 2023; Amare et al. 2023), GDD is constructed based on daily average of 8 °C and 32 °C as base and ceiling temperatures, while HDD is constructed based on daily average of 32 °C as base temperatures. For HNT, we count the number of days within the production season when the daytime minimum temperature is

[8]Specifically, major cropping season in Nigeria is defined as follows for each of 6 geopolitical zone, based on the LSMS-ISA data; June – November (North East Zone), June – October (North West), May – October (North Central), April – September (South East and South South), and May – September (South West).

above 20 °C (Musa et al. 2021).[9]

We then compile proxy variables that represent climate anomalies, namely the percentiles of weather outcomes relative to the historical distributions, following the past studies in Nigeria (Takeshima et al. 2020).

4.3 Descriptive results

Table 1 summarizes the key descriptive statistics of pesticide use, use of other inputs, production and farm capital ownership. A majority of samples are smallholders with plot size less than 1 ha, significant of which are under mixed-cropping, and using relatively limited amounts of modern inputs like improved varieties, irrigation.

The use of agrochemicals, including pesticides, is limited to among a relatively minor fraction of farmers. However, among those who use these agrochemicals, typical value of use was about 3,000 Naira, or 3 kg of each of pesticides.

Table 2 shows the historical percentile, z-score, and absolute-values of deviations from the norm. Table 2 confirms that, GDD, HDD and HNT20 have all been rising compared to historical norms of percentile = 50, and z-value = 0. Similarly, 2015/2018 generally experienced relatively more intense drought and lower rainfall (compared to 2010/12 with relatively limited drought and greater rainfall). The absolute values of deviations from the norm (expressed as deviation from 0) also indicate that abnormality in these weather conditions have intensified in 2015/2018 compared to 2010/2012.

[9]We also constructed alternative proxies using other values of minimum nighttime temperature between 21 C ~ 25 C, which are also considered potentially important thresholds in the literature (Tofa et al. 2021). We find that results are generally robust.

5 Results

5.1 Damage abatement effects with exogeneity assumption (standard nonlinear square regression)

Table 3 summarizes the key results based on the exogenous NLS regression (1) (Full results are shown in Table 9). Specifically, Table 3 presents the estimated coefficients for agrochemical variable (β_X) and its interaction with weather shocks (β_{XW}), and corresponding marginal effects. Results for all crops combined (top panel) suggest that agrochemical use has statistically significant damage abatement effects across all specifications. The corresponding elasticity values are generally around 0.07 ~ 0.08, i.e., increasing agrochemical use by 1% leads to about 0.07 ~ 0.08 % increase in outputs holding other inputs unchanged.

Coefficients for interaction terms suggest that weather shocks can significantly affect the damage abatement effects. Higher GDD, HNT, greater incidence of drought, and lower rainfall (relative to historical norms) generally boost the damage abatement effects of agrochemicals. Regarding the impact on elasticity, a one standard deviation increase in respective weather shocks increases damage abatement effects elasticity of agrochemicals by 0.012 ~ 0.047% (equivalent to 17 ~ 63% of average elasticity of around 0.07 ~ 0.08). In contrast, a greater incidence of HDD depresses damage abatement effects. These results are broadly consistent with the discussions in section 2 regarding how climate affects pests' activities and potentially the productivity effects of agrochemicals.

Results are generally similar when focusing on maize and cowpea/beans (lower panels of Table 3), except for generally lower statistical significance and occasionally reversed signs. For maize, using agrochemicals has significant damage abatement effects overall, with elasticity around 0.09. Both greater incidences of HNT and drought relative to historical norms are associated with increased damage abatement effects. A one standard deviation increase in such weather anomalies is associated with about 20 ~ 30% increase in the average damage abatement elasticity. Similarly, greater incidences of HNT and drought are associated with increased damage abatement effects of agrochemicals for cowpea/beans, where a one standard deviation increase in such weather anomalies is associated with about 20 ~ 30% increase in the average damage abatement elasticity. Interestingly, in contrast to the results for maize or other crops, for cowpea, lower rainfall is associated with lower damage abatement effects. For cowpeas/beans, greater moisture due to more rainfall and looseness of soil during drought conditions may be associated with widespread pest presence. Overall, however, the potentially significant effects of weather shocks on damage abatement effects of agrochemicals still hold.

5.2 Damage abatement effects with endogeneity assumption (maximum likelihood estimation)

Table 4 through Table 6 summarize key results based on the MLE (4) that addresses potential endogeneity of agrochemicals use. Most results were obtained in less than 10 iterations of estimations, suggesting that global optimums in log-likelihood function are highly stable.

These results imply that aforementioned results are generally robust. Specifically, in areas that experienced relative increases in anomaly of HNT experienced significant relative increases in the mean damage abatement effects of agrochemicals. This has been driven by the fact that, in areas with relatively normal HNT, the damage abatement elasticity declined between 2010-12 and 2015-18 from 0.215 to 0.003, while the areas with increasingly abnormal HNT saw change of 0.141 to 0.162. As a result, the latter area saw a relative net increase in the damage abatement elasticity of 0.233 (= (0.215 – 0.003) – (0.141 – 0.162)) with statistical significance at 5%, compared to the former area, between 2010/2012 and 2015/2018.

Results also show, albeit to a lesser extent, that damage abatement effects remain statistically significantly positive in throughout the period where GDD, drought or rainfall increased relatively more (decreased relatively less), while the effects become statistically insignificant in 2015-2018 in other areas. These results weakly suggest that rising GDD, and both increasing drought and decreasing rainfall also led to increased damage abatement effects of pesticides.

Results by northern and southern regions

Table 5 provides same sets of results specifically for northern and southern regions of the country, respectively. Table 5 suggests that the patterns observed in Table 4 often hold in both regions, including the effects of more frequent HNT. While the effects of other climate parameters are more or less ambiguous, partly due to the smaller sample sizes, none are statistically significant in opposite directions as those in Table 4.

Results by crop

Results in Table 6 suggest that, results for all crops combined (Table 4) are generally consistent at specific crops, including cowpea and maize. In particular, increased frequency of high nighttime temperature leads to increased damage abatement effects of pesticides.

Droughts and rainfall anomalies have somewhat complex effects for damage abatement effects in maize production. For maize, both drought and greater rainfall may increase the damage abatement effects of pesticides. This possibly reflects the hypotheses in the literature that, while greater rainfall generally induce pests growth, intermittent drought may further induce more pests movement in the soil as the soil dries and loosens. These relatively mixed effects are more in line with the aforementioned discussions based on the literature; droughts and HDD may induce multiple effects in opposite directions which may offset each other in aggregate. Overall, however, results suggest that climate shocks affect damage abatement effects of agrochemicals.

Other robustness checks

As a robustness check, Table 7 presents the same sets of results from Table 4 and Table 6, but splitting the samples using 33 and 67 percentiles of relative changes in weather risks, instead of 50 percentile used for Table 4. Importantly, results in Table 7 are more or less consistent with Table 4 and Table 6, with no signs of statistically significantly conflicting results. In particular, Table 7 suggests that the effects of relative increase in HNT is consistently positive, i.e., rising HNT raises the damage abatement effects of agrochemicals, for both maize and cowpea production as well as for overall crop production.

As was mentioned above, we also checked whether the type of damage abatement function affects our main results. Table 8 shows the same sets of results as Table 3, but using exponential damage abatement function instead of logistic damage abatement function. Statistical significance and signs, as well as abatement effects elasticity in Table 8, are generally fairly consistent with those in Table 3. These results further imply the robustness of our main results.

5.3 Results for other covariates (for all crops combined)

Our primary focuses are on the effects of agrochemical variable and its interaction with weather shocks, and the coefficients for other variables of secondary importance. Table 9 summarizes the full results for exogenous model Table 3, and Table 10 summarizes the signs of significant coefficients corresponding to results for endogenous model Table 4 due to the large numbers of regressions. Table 9 suggests that production value per land is significantly positively affected by greater labor and other expenditure per land, receiving extension visits from the public-sector extension offices, while negatively affected by using mixed-cropping method rather than single-cropping method, and temperature related weather shocks. Table 10 suggests similarly consistent patterns, albeit with some variations; production value per land is generally positively affected by greater labor and other expenditure per land, and public extension, while negatively affected by mixed cropping system and weather shocks. Interestingly, irrigation is negatively associated with production value per land conditional on all the other factors. This may be due to significant reliance on rainfed farming (for which irrigation benefits are relatively small (e.g., Tittonell & Giller 2013)), and/or insufficient knowledge that leads to inefficient irrigation practices and negative outcomes like nutrient erosion or excess saturation, among others (e.g., Comas et al. 2012). Agrochemical use per land is positively affected by labor and other expenditures per land, irrigation, public extension, and greater use by other farmers within the same area, while negatively affected by the use of mixed cropping system. These results are generally consistent with other studies that investigate damage abatement effects of agrochemicals, and thus underscore the validity of our main results.

6 Conclusions

Effective management of biotic shocks like pests is critical for raising agricultural productivity and improving food security in developing countries, including Nigeria. Many factors, including climate change in recent decades, complicate the identification of effective measures and their impacts. This study aimed to fill this knowledge gap by assessing the effects of weather shocks on the damage abatement effects of agrochemicals, including pesticides, for crop production in Nigeria.

Our results indicate that climate change can significantly affect the damage abatement effects of agrochemicals. Among various climate parameters, higher daily minimum temperatures commonly increase the returns to pesticides and agrochemicals. Such patterns are consistent with the hypothesis that higher daily minimum temperature can facilitate pests' activities, especially at night, so that crop productivity would decline more significantly in the absence of pesticides. These patterns broadly hold for the production of specific crops, including cowpea and maize, as well as when all other crops are combined, both at the nationwide level and at the northern/southern zonal levels. Other climate parameters, including higher daytime temperatures, drought, and rainfall, also weakly affect the damage abatement effects of pesticides, albeit in more sporadic manners.

Our results point toward the growing vulnerability of agricultural productivity to biotic shocks including pests in Nigeria, due to emerging climate changes, particularly rising nighttime temperatures, in recent years and the near future. These emerging challenges have important policy implications. The Nigerian government should expand more support for enhancing farmers' capacity for pest controls, including training and extension support on proper agrochemical uses and promoting healthy and competitive development of agrochemical markets to improve access to good quality agrochemicals at affordable prices. The government may also support efforts to increase the demand and efficient supply of other pest control technologies, including varietal technologies like Bt cowpea and Bt maize, especially in areas experiencing higher nighttime temperatures. At the same time, more research continues to be needed to assess the impact of various pest control measures, including their contributions to climate change mitigation within the agrifood systems in Nigeria.

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Table 1. Descriptive statistics (plot level, all four waves combined)

Variables	Mean	Percentiles (5th / 50th / 95th) for nonbinary variables
Use pesticides (%)	17	NA
Pesticides use (Naira)	817.152	0 / 0 / 4800
Pesticides use (Kg)	0.804	0 / 0 / 4
Pesticides use (Naira) among users	4869.407	400 / 2800 / 16000
Pesticides use (Kg) among users	4.807	0.5 / 3 / 12
Production revenue	321,939	2,500 / 34,500 / 320,000
Land (m^2)	6,111	105 / 3,043 / 20,000
Labor (family and hired – person-days)	164	3 / 88 / 558
Capital + livestock (1,000 Naira)	348.798	0.679 / 45.453 / 1431.126
Other expenditures (Naira)	55,897	0 / 3,350 / 44,000
Irrigation (%)	1.6	NA
Improved variety (%)	7	NA
Mixed crops plots (%)	59	NA
Extension from government (%)	3	NA
EA average pesticide use (excluding own-sample)	710.066	0 / 96.429 / 3590.909

Source: Authors based on LSMS-ISA data.
NA = Not applicable.

Table 2. Climate anomalies in waves 1 and 2 (2010/2012) and waves 3 and 4 (2015/2018)

Weather parameters	Unit	Mean (Standard deviation)	Mean (Standard deviation)
		Waves 1 and 2 - 2010/2012	Waves 3 and 4 - 2015/2018
Growing Degree Days	Historical Percentile	62.601 (28.081)	77.219 (26.318)
Harmful Degree Days	Historical Percentile	50.374 (9.478)	54.121 (13.891)
Hight Nighttime Temperature	Historical Percentile	66.882 (23.127)	66.278 (15.698)
Drought	Historical Percentile	35.872 (27.369)	52.516 (33.960)
Rainfall	Historical Percentile	68.165 (19.685)	55.927 (27.340)

Source: Authors.

Table 3. Results assuming the exogeneity of agrochemical use

Crops / variables / parameters	Climate parameters				
	GDD	HDD	HNT	Drought	Lower Rainfall
All crops combined (sample = 17,710)					
Agrochemical use (natural log)	0.142***	0.141***	0.135***	0.152***	0.144***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Agrochemical use (natural log) * weather shocks	0.057***	–0.041***	0.022**	0.063***	0.084***
	(0.009)	(0.007)	(0.009)	(0.008)	(0.010)
Average abatement effects elasticity (1 = 100%)	**0.073**	**0.073**	**0.070**	**0.079**	**0.075**
Effects of 1sd increase in climate shocks on the abatement effects elasticity (1 = 100%)	**0.031**	**–0.022**	**0.012**	**0.034**	**0.047**
Ratio	0.43	–0.30	0.17	0.43	0.63
Maize (sample = 5,676)					
Agrochemical use (natural log)	**0.181*****	**0.188*****	**0.151*****	**0.183*****	**0.189*****
	(0.020)	**(0.021)**	**(0.020)**	**(0.019)**	**(0.021)**
Agrochemical use (natural log) * weather shocks	0.011	–0.008	**0.031***	**0.061*****	**0.026**
	(0.020)	(0.010)	**(0.017)**	**(0.018)**	**(0.020)**
Average abatement effects elasticity (1 = 100%)	**0.092**	**0.094**	**0.075**	**0.091**	**0.095**
Effects of 1sd increase in climate shocks on the abatement effects elasticity	0.006	-0.004	**0.016**	**0.031**	**0.013**
Ratio	0.07	0.04	0.21	0.34	0.14
Cowpea / beans (sample = 3,479)					
Agrochemical use (natural log)	**0.098*****	**0.098*****	**0.091*****	**0.096*****	**0.100*****
	(0.014)	**(0.014)**	**(0.012)**	**(0.013)**	**(0.014)**
Agrochemical use (natural log) * weather shocks	-0.004	0.003	**0.024****	**0.026****	**–0.046*****
	(0.014)	(0.014)	**(0.012)**	**(0.013)**	**(0.013)**
Average abatement effects elasticity (1 = 100%)	**0.049**	**0.049**	**0.046**	**0.048**	**0.050**
Effects of 1sd increase in climate shocks on the abatement effects elasticity	–0.002	0.002	**0.012**	**0.013**	**–0.023**
Ratio	–0.04	0.04	0.26	0.27	0.47

Source: Authors. ***1% **5% *10%.

Numbers in parentheses are heteroskedasticity-robust standard errors.

"Insig" = coefficients on agricultural use * weather shocks statistically insignificant.

GDD = Growing Degree Days; HDD = Harmful Degree Days; HNT = High Nighttime Temperature.

"1sd" = one standard deviation

Table 4. Climate shock effects on the elasticity of damage abatement effects (effects of one-standard deviation change in climate anomalies, estimated by MLE, Nigeria)

Climate parameters	Samples experiencing relative **increase** in climate anomaly		Samples experiencing relative **decrease** in climate anomaly		Net differences = (b) – (a) – [(d) – (c)]	Qualitative differences[a]
	(a)	(b)	(c)	(d)		
	2010-12	2015-18	2010-12	2015-18		
GDD	0.160** (0.081)	0.131** (0.060)	0.219***(0.061)	0.016 (0.042)	0.174 (0.125)	+
Other variables	Included	Included	Included	Included		
Log-likelihood	-3791.5685	-4907.8392	-4108.8327	-5001.4238		
Sample	1,009	1,350	1,096	1,367		
HNT	0.141* (0.078)	0.162**(0.054)	0.215** (0.063)	0.003 (0.031)	0.233** (0.118)	+
Other variables	Included	Included	Included	Included		
Log-likelihood	-2319.9821	-3204.6541	-5582.8107	-6706.7337		
Sample	621	867	1,484	1,850		
Drought	0.201**(0.063)	0.120**(0.055)	0.189***(0.073)	–0.006 (0.051)	0.114 (0.122)	+
Other variables	Included	Included	Included	Included		
Log-likelihood	-4088.515	-4903.2117	-3647.9338	-4871.4279		
Sample	1,043	1,321	1,042	1,357		
Rainfall (lower)	0.160**(0.074)	0.070*(0.043)	0.268***(0.064)	0.026 (0.057)	0.152 (0.121)	+
Other variables	Included	Included	Included	Included		
Log-likelihood	-3834.7019	-5007.5228	-3970.2186	-4711.1496		
Sample	1,034	1,387	1,110	1,291		

Source: Authors. ***1% **5% *10%.

GDD = Growing Degree Days; HNT = High Nighttime Temperature.

[a]Qualitative difference is marked as "positive" because, for example, while coefficients remain statistically significantly positive during the entire period for the sample experiencing relative increase in climate anomaly, coefficients become statistically insignificant in 2015-2018 for the sample experiencing relative decrease in climate anomaly.

Table 5. Results by subregional zones, Nigeria

Climate parameters	Samples experiencing relative **increase** in climate anomaly		Samples experiencing relative **decrease** in climate anomaly		Net differences = (b) – (a) – [(d) – (c)]	Qualitative differences
	(a) 2010-12	(b) 2015-18	(c) 2010-12	(d) 2015-18		
North						
GDD	0.180**(0.085)	0.035 (0.075)	0.122 (0.114)	0.014 (0.042)	-0.037 (0.166)	
HNT	0.117* (0.071)	0.046 (0.087)	0.376***(0.100)	0.000 (0.058)	0.305* (0.161)	+
Drought	0.186** (0.091)	-0.039***(0.006)	0.137* (0.071)	0.057 (0.039)	-0.145 (0.122)	–
Rainfall (Lower)	0.023 (0.079)	0.019 (0.052)	0.048 (0.100)	0.000 (0.046)	0.044 (0.145)	
South						
GDD	-0.049***(0.003)	0.240***(0.078)	-0.060***(0.004)	0.093 (0.146)	0.136 (0.166)	+
HNT	-0.039 (0.029)	0.151** (0.081)	0.280***(0.089)	0.229***(0.104)	0.241 (0.162)	+
Drought	0.158* (0.086)	0.132* (0.074)	0.081 (0.150)	-0.035 (0.031)	0.090 (0.191)	
Rainfall (lower)	0.173 (0.114)	0.216***(0.077)	0.143 (0.148)	0.260** (0.129)	-0.074 (0.240)	

Source: Authors. ***1% **5% *10%.
GDD = Growing Degree Days; HNT = High Nighttime Temperature.

Table 6. Results by crops (Cowpea and maize)

Climate parameters	Samples experiencing relative **increase** in climate anomaly		Samples experiencing relative **decrease** in climate anomaly		Net differences = (b) – (a) – [(d) – (c)]	Qualitative differences
	(a) 2010-12	(b) 2015-18	(c) 2010-12	(d) 2015-18		
Cowpea						
GDD	0.011 (0.170)	-0.027 (0.039)	0.043 (0.119)	-0.041* (0.024)	0.046 (0.213)	+
HNT	0.026 (0.094)	0.234**(0.102)	0.026 (0.094)	-0.053***(0.002)	0.287* (0.168)	+
Drought	0.162 (0.195)	0.023 (0.283)	0.009 (0.218)	-0.036** (0.018)	-0.094 (0.407)	+
Rainfall (lower)	0.083 (0.167)	-0.012 (0.132)	0.019 (0.128)	0.083 (0.167)	-0.159 (0.299)	
Maize						
GDD	0.144 (0.114)	0.315** (0.151)	0.074 (0.207)	0.109 (0.148)	0.136 (0.317)	+
HNT	0.098 (0.106)	0.262* (0.136)	0.154 (0.245)	0.154 (0.163)	0.164 (0.341)	+
Drought	-0.043***(0.005)	0.263* (0.136)	0.259** (0.121)	-0.034***(0.011)	0.599***(0.182)	+
Rainfall (lower)	-0.036* (0.021)	0.148 (0.110)	0.172* (0.100)	-0.033** (0.014)	0.389***(0.151)	+

Source: Authors. ***1% **5% *10%
GDD = Growing Degree Days; HNT = High Nighttime Temperature.

Appendix: Additional Results

Table 7. Results for Table 4 but using 33 and 67 percentiles

Climate parameters	Samples experiencing relative **increase** in climate anomaly		Samples experiencing relative **decrease** in climate anomaly		Net differences = (b) – (a) – [(d) – (c)]	Qualitative differences
	(a)	(b)	(c)	(d)		
	2010-12	2015-18	2010-12	2015-18		
All crops combined						
33 percentiles						
GDD	0.214***(0.057)	0.083** (0.042)	0.042***(0.002)	0.021 (0.042)	–0.110 (0.082)	+
HNT	0.014 (0.083)	0.063**(0.029)	0.220***(0.055)	–0.025 (0.020)	0.294***(0.106)	+
Drought	0.178***(0.055)	0.025 (0.030)	0.119* (0.068)	0.068 (0.052)	–0.102 (0.106)	
Rainfall (lower)	0.196** (0.079)	0.038 (0.033)	0.212***(0.060)	0.029 (0.048)	0.025 (0.115)	
67 percentiles						
GDD	0.128 (0.096)	0.066* (0.040)	0.199***(0.058)	0.051 (0.052)	0.086 (0.130)	+
HNT	0.008 (0.112)	0.103** (0.042)	0.236***(0.052)	0.004 (0.030)	0.327** (0.134)	+
Drought	0.120 (0.075)	0.026 (0.040)	0.237***(0.056)	0.049 (0.034)	0.094 (.107)	+
Rainfall (lower)	0.120* (0.072)	0.038 (0.029)	0.319***(0.067)	0.081 (0.070)	0.156 (0.124)	
Maize						
33 percentiles						
GDD	0.161 (0.111)	0.188 (0.163)	0.050 (0.217)	0.179 (0.130)	–0.102 (0.321)	
HNT	0.174* (0.094)	0.231* (0.121)	0.055 (0.300)	–0.040***(0.005)	0.152 (0.337)	+
Drought	–0.043***(0.004)	0.194 (0.143)	0.272**(0.133)	0.245 (0.162)	0.264 (0.254)	+
Rainfall (lower)	0.139 (0.095)	0.303**(0.148)	0.250 (0.323)	0.115 (0.105)	0.299 (0.382)	+
67 percentiles						
GDD	0.106 (0.186)	0.192* (0.111)	0.104 (0.119)	–0.027* (0.014)	0.217 (0.248)	+
HNT	–0.037**(0.016)	0.151 (0.164)	0.215*(0.121)	0.178 (0.154)	0.225 (0.256)	+
Drought	-0.035 (0.066)	0.299* (0.160)	0.292**(0.115)	–0.036***(0.009)	0.662***(0.208)	+
Rainfall (lower)	-0.042** (0.016)	-0.028* (0.016)	0.134 (0.129)	0.136 (0.116)	0.012 (0.175)	
Cowpea / beans						
33 percentiles						
GDD	0.011 (0.234)	0.448***(0.171)	0.010 (0.151)	-0.049* (0.028)	0.496 (0.328)	+
HNT	–0.026 (0.091)	0.166* (0.090)	–0.041 (0.060)	0.044 (0.358)	0.107 (0.385)	+
Drought	0.154 (0.200)	0.010 (0.203)	0.009 (0.218)	-0.033 (0.023)	-0.102 (0.360)	
Rainfall (lower)	0.013 (0.096)	0.072 (0.122)	0.089 (0.076)	0.099 (0.127)	0.049 (0.214)	
67 percentiles						
GDD	0.011 (0.170)	-0.027 (0.039)	0.044 (0.122)	-0.041* (0.024)	0.047 (0.214)	+
HNT	–0.036 (0.002)	0.166* (0.090)	0.011 (0.103)	–0.053***(0.007)	0.266* (0.137)	+
Drought	-0.051***(0.001)	-0.005 (0.238)	-0.038 (0.042)	-0.042***(0.003)	0.050 (0.242)	+
Rainfall (lower)	0.013 (0.157)	0.033 (0.106)	-0.011 (0.097)	0.085 (0.138)	-0.076 (0.254)	

Source: Authors. ***1% **5% *10%.
GDD = Growing Degree Days; HNT = High Nighttime Temperature.

Table 8. Same set of results for Table 3 but using exponential, rather than logistic, damage abatement formula

	Climate parameters				
	GDD	HDD	HNT	Drought	Lower Rainfall
All crops combined (sample = 17,710)					
Agrochemical use (natural log)	**0.069***** **(0.004)**	**0.070***** **(0.004)**	**0.068***** **(0.004)**	**0.073***** **(0.004)**	**0.064***** **(0.004)**
Agrochemical use (natural log) * weather shocks	**0.026***** **(0.004)**	**–0.019***** **(0.003)**	**0.011**** **(0.004)**	**0.026***** **(0.003)**	**0.024***** **(0.002)**
Average abatement effects elasticity (1 = 100%)	**0.074**	**0.074**	**0.072**	**0.079**	**0.071**
Effects of 1sd increase in climate shocks on the abatement effects elasticity (1 = 100%)	**0.026**	**–0.018**	**0.010**	**0.026**	**0.023**
Ratio	0.35	0.25	0.14	0.33	0.33
Maize (sample = 5,676)					
Agrochemical use (natural log)	**0.082***** **(0.008)**	**0.086***** **(0.008)**	**0.054***** **(0.004)**	**0.076***** **(0.007)**	**0.085***** **(0.008)**
Agrochemical use (natural log) * weather shocks	–0.001 (0.008)	-0.003 (0.004)	**0.007*** **(0.004)**	**0.017***** **(0.001)**	0.006 (0.006)
Average abatement effects elasticity (1 = 100%)	**0.083**	**0.088**	**0.053**	**0.078**	**0.087**
Effects of 1sd increase in climate shocks on the abatement effects elasticity	0.001	0.003	**0.007**	**0.018**	0.006
Ratio	0.01	0.03	0.13	0.23	0.07
Cowpea / beans (sample = 3,469)					
Agrochemical use (natural log)	**0.048***** **(0.007)**	**0.048***** **(0.007)**	**0.042***** **(0.005)**	**0.047***** **(0.006)**	**0.047***** **(0.007)**
Agrochemical use (natural log) * weather shocks	-0.002 (0.007)	0.001 (0.006)	**0.014***** **(0.005)**	**0.012**** **(0.006)**	**-0.021***** **(0.006)**
Average abatement effects elasticity (1 = 100%)	**0.048**	**0.048**	**0.042**	**0.047**	**0.048**
Effects of 1sd increase in climate shocks on the abatement effects elasticity	-0.002	0.001	**0.014**	**0.012**	**0.020**
Ratio	0.04	0.02	**0.32**	**0.26**	**0.43**

Source: Authors. ***1% **5% *10%.

Numbers in parentheses are heteroskedasticity-robust standard errors.

GDD = Growing Degree Days; HNT = High Nighttime Temperature.

Table 9. Full results for Table 3

	Climate parameters				
	GDD	HDD	HNT	Drought	Lower Rainfall
All crops combined					
Agrochemical use (natural log)	0.142***	0.141***	0.135***	0.152***	0.144***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Agrochemical use (natural log) * weather shocks	0.057***	–0.041***	0.022**	0.063***	0.084***
	(0.009)	(0.007)	(0.009)	(0.008)	(0.010)
Labor per land	0.411***	0.410***	0.418***	0.405***	0.404***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Other expenditure per land	0.074***	0.075***	0.074***	0.076***	0.074***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Agricultural capital	-0.014	-0.016	-0.014	-0.011	-0.017
	(0.011)	(0.011)	(0.011)	(0.009)	(0.011)
Irrigation	-0.016	0.001	-0.021	-0.010	-0.018
	(0.095)	(0.093)	(0.095)	(0.094)	(0.094)
Mixed-crop plot	-0.139***	-0.136***	-0.136***	-0.142***	-0.137***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Public extension	0.164***	0.158***	0.169***	0.137**	0.147**
	(0.061)	(0.061)	(0.061)	(0.055)	(0.062)
Improved seeds	0.002	0.008	-0.011	0.041	0.046
	(0.034)	(0.034)	(0.034)	(0.034)	(0.037)
Weather shocks	–0.002***	-0.002***	–0.003***	0.000	0.000
	(0.0004)	(0.001)	(0.000)	(0.000)	(0.000)
Wave dummy	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included
R-square	.350	.351	.350	.350	.352
Sample	17,710	17,710	17,710	17,710	17,710

Source: Authors. ***1% **5% *10%.
GDD = Growing Degree Days; HNT = High Nighttime Temperature.

Table 10. Full results for Table 4 (Signs of coefficients that are statistically significant at 10%)

Climate parameters	GDD				HDD				HNT				Drought				Rainfall			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
First stage (dependent variable = agrochemical use)																				
Labor per land	+	+	+	+	+	+	+	+	+	+	+	+	+		+	+	+	+	+	+
Other expenditure per land	+	+	+	+		+	+	+	+	+	+	+	+		+	+	+	+	+	+
Agricultural capital		+		–					+		–								–	
Irrigation	+	+				+	+				+				+			+	+	–
Mixed-crop plot			–		–	+	–				–				–			+	–	–
Public extension			+				+				+				+				+	
Improved seeds				–																
Weather shocks	–						+	–	+	+			–		+					
Agrochemicals use in EA	+	+	+	+		+	+	+	+	+	+	+			+	+	+	+	+	+
Wave dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Intercept	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Second stage (dependent variable = production value per land)																				
Agrochemicals use per land	+		+				+			+	+		+		+		+	+	+	
Labor per land	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Other expenditure per land	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
Agricultural capital														+						+
Irrigation			–		–				–				–				–			
Mixed-crop plot		–	–	–	–	–		–		–	–	–		–	–	–	–	–		
Public extension	+						+				+				+	–			+	
Improved seeds																				
Weather shocks		–		–										–		–				–
Wave dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Intercept	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Source: Authors.

"(a)", "(b)". "(c)" and "(d)" refer to columns (a) – (d) in Table 4, respectively, for each weather variable.
"+" = statistically significantly positive at 10% significance level or above.
"–" = statistically significantly negative at 10% significance level or above.
Y = included
GDD = Growing Degree Days; HDD = Harmful Degree Days; HNT = High Nighttime Temperature

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IFPRI HEADQUARTERS

1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org