Extreme Heat, Induced Innovation and Cropland Expansion

Ange T. Kakpo[1] and Martin Paul Jr. Tabe-Ojong[2,3]

[1]Prime Economics, Prime Science, Amazon, Seattle, Washington, USA. Email: atkakpo@gmail.com

[2]World Bank, Washington, DC, USA

[3]Disaster Management Training and Education Centre for Africa, Bloemfontein, South Africa

Abstract

We examine how extreme heat impacts the adoption of an induced innovation in agriculture - climate-resilient seeds and cropland expansion. Using high-resolution temperature and micro data from Nigeria, we find that each additional hot day in the prior season increases adoption by 2% and cropland by 1.1%. These varieties are adopted by both poor and non-poor households, but poorer households expand cropland more. High-productivity and older farmers are more responsive to adoption and cropland expansion. While adoption persists, sustained cropland expansion is less evident. Our findings highlight economic and demographic disparities in adaptation, with important implications for equitable climate policy.

JEL Classification: O13, Q12, Q15

Keywords: Extreme Heat, Adoption, Cropland Expansion, Climate Resilient, Groundnut.

1. Introduction

Climate change and extreme weather events continue to be important development and environmental challenges plaguing societies (Lobell et al., 2011a; Burke and Emerick, 2016). Its effects are quite widespread with visible impacts on the agricultural sector. Extreme weather events have been shown to reduce agricultural production, growth, and productivity (Kakpo et al., 2022; Ortiz-Bobea et al., 2021; IPCC, 2022) with ensuing implications on food security and livelihoods(Fanzo et al., 2018; Blom et al., 2022). Given this, there is a push for adaptation and mitigation in the agricultural sector through the promotion of climate-smart agriculture (Rippke et al., 2016; Aragón et al., 2021; Tambet and Stopnitzky, 2021; Tabe-Ojong et al., 2023a; Wimmer et al., 2023). This involves the use of various practices, inputs, and innovations that increase productivity, reduce emissions, and build resilience to climate change (Arslan et al., 2014; Teklewold et al., 2019; Sitko et al., 2024). Understanding how households adapt to extreme weather events by using these climate-smart agricultural practices is crucial for designing policies on climate adaptation and mitigation but considerable knowledge gaps prevail (Aragón et al., 2021; Wimmer et al., 2023).

We investigate the impact of extreme temperatures on the adoption of climate-resilient groundnut varieties and cropland expansion proxied using the area under adoption of these climate-resilient groundnut varieties. Climate-resilient seeds represent a form of induced innovation in agriculture that emerges in response to environmental challenges such as drought, extreme heat, and pest infestations (Moscona and Sastry, 2023). These seeds are developed through intensive breeding and genetic advancements, leading to greater productivity and contributing to improved livelihoods and food security (Ajeigbe et al., 2020; Gollin et al., 2021; Lokossou et al., 2022). They have been argued to support adaptation and mitigate yield losses under extreme temperatures (Byerlee, 1996; Walker and Alwang, 2015; Simtowe et al., 2019; Boucher et al., 2024). These climate-resilient varieties are usually bred to be high yielding and resistant to many pests and diseases (Ajeigbe et al., 2020; Acevedo et al., 2020; Tabe-Ojong et al., 2022). To proxy for the adoption of climate-resilient groundnut varieties, we examine both the adoption of these resilient varieties as well as cropland expansion. Given the reported dis-adoption of some of these climate-resilient crop varieties (Simtowe and Mausch, 2019; Lokossou et al., 2022), we also examine aspects of sustained adoption by looking at how extreme temperatures could push households to sustainably adopt these climate-resilient seeds and induce cropland expansion. In the interest of explaining these relationships, we perform some heterogeneity

analyses along poverty, productivity and demographic lines exploring age and gender dynamics (Pignède, 2025).

We develop a simple theoretical framework to formalize how households adapt to extreme weather events and what guides their decision making (Aragón et al., 2021; Wimmer et al., 2023; Mayorga et al., 2025).The framework builds on agricultural household models under risk (Singh et al., 1986), the literature on climate-sensitive production (Schlenker and Roberts, 2009; Lobell et al., 2011b), and work on induced innovation/technology adoption (Moscona and Sastry, 2023). We derive two key testable predictions that guide our empirical analysis: (i) extreme heat increases adoption at the extensive margin and (ii) extreme heat promotes land reallocation at the intensive margin. We explore some of the traits and characteristics of these climate-resilient varieties that make them suited for building adaptation and resilience to extreme temperatures (Ajeigbe et al., 2020; Acevedo et al., 2020). These climate-resilient groundnut varieties are considerably different from landraces as they have specialized traits and characteristics that enable them to respond to both biotic and abiotic stress in a number of ways: (1) they are drought and heat resistant and able to withstand the extreme temperatures and drought related events in the Sahel region: (2) they are pest and disease resistant especially with respect to common groundnut pests and diseases such as the root rot, rust, aflatoxin, and the rosette virus (Ajeigbe et al., 2020); and (3) they are high yielding with ensuing implications for food security (Lokossou et al., 2022; Tabe-Ojong et al., 2023a).

We merge a panel micro data (about 4000 households) from Nigeria with daily minimum and maximum temperature data collected at the 0.05x0.05 (approximately 5 km x 5 km) degree resolution, from the Climate Prediction Center[1] (CPC) Global Unified Temperature data, provided by the National Oceanic and Atmospheric Administration's Physical Science Library (NOAA PSL). From this, we construct a flexible measure of exposure to extreme heat in two steps. First, we define thirteen 1°C bins, ranging from below 24°C to above 35°C. Next, we determine the number of days falling into each temperature bin in the growing season prior to each survey year. We use below 24°C to above 35°C as first and last bin respectively, because these bins have the lowest number of days, as shown in Figure 1. Our measure of extreme heat follows a large precedence in the literature on extreme heat for the growing season (Chen and Gong, 2021; Aragón et al., 2021). Our identification strategy exploits plausibly quasi-random variations in the distribution of extreme temperatures across space and time.

[1] https://www.cpc.ncep.noaa.gov/

In response to extreme temperature, we find that households increase the adoption of climate-resilient groundnut varieties both at the extensive and intensive margins (cropland expansion). Specifically, any additional hot day in the previous growing season increases the probability of adopting climate resilient groundnut varieties by 2%. Extreme temperatures also increase the area under these climate-resilient groundnut varieties by about 1.1 %, largely suggestive of cropland expansion effects. These point to the adaptive role of these climate-resilient varieties especially as we find suggestive evidence that households are using them as a response strategy to extreme weather events. We also find evidence of sustained adoption of these climate-resilient groundnut varieties, however, we find little or no evidence of sustained cropland expansion. We also look at long term exposure to extreme heat to address any concerns with using the previous season exposure to heat. We find insights confirming that households resort to the adoption of climate-resilient varieties with implications for cropland expansion. These results are robust across a wide range of sensitivity analyses. We show that the findings hold when using alternative estimation methods (including Probit and Tobit Correlated Random Effects models), alternative measures of adoption such as the share of land under climate-resilient varieties, and when using the area allocated to local (landrace) varieties as an outcome. The results also remain stable when accounting for spatial correlation using Conley (1999) standard errors.

Finally, we examine how adaptation responses vary across key socioeconomic and demographic groups. We document three main findings. First, both poor and non-poor households increase adoption of climate-resilient groundnut varieties in response to extreme heat, indicating broad inclusivity at the extensive margin. However, poor households exhibit larger cropland expansion responses, suggesting greater reliance on land reallocation following heat shocks. Second, households with higher baseline productivity show stronger adoption and land-expansion responses, consistent with greater capacity to scale cultivation. Third, our results reveal reveal that while adult-headed households display statistically significant increases in both adoption and land allocation, youth-headed households exhibit positive but statistically insignificant responses. Formal tests indicate no statistically significant differences between age groups.

Our paper adds and contributes to a growing literature on climate change adaptation in agriculture, specifically climate-smart agriculture in three main ways. First, we show that households respond to extreme temperatures by relying on the adoption of climate-resilient crop varieties, a typical climate-smart agricultural practice (Arslan et al., 2014; Walker and Alwang, 2015;

Simtowe et al., 2019; Teklewold et al., 2019; Sitko et al., 2024; Boucher et al., 2024). The relationship between climate change and input use is often overlooked as the focus seems to be more on yields and profitability. Here, we look at input use and highlight that households are indeed responding to climate change by alternating their input use. Existing studies on input use adaptation to extreme weather and climate shocks have been limited to fertilizers and pesticides which are more or less growing season or within season adaptation practices (Bareille and Chakir, 2023; Jagnani et al., 2021; Liebenehm et al., 2023; Maggio et al., 2022; Tambet and Stopnitzky, 2021; Wimmer et al., 2023). Our focus on climate-resilient seeds is different as their use is influenced or at best informed by previous extreme weather shocks since farmers make their current seed decisions based on previous shocks. To our knowledge, only Liebenehm et al. (2023) and Wang et al. (2022b) have examined the implications of extreme temperatures on the adoption of drought resistant crop varieties. Using two common staples, rice, and maize, both studies found contrasting results suggesting that the implications of extreme temperatures and dry anomalies may be context and farm system dependent.

Second and related to the first, we show significant evidence of cropland expansion. Farmers faced with extreme temperature may behaviorally adapt by adopting climate-resilient crop varieties and by expanding the land under which these crops are cultivated. We do not explore the source of this land expansion, but it could potentially stem from land reallocation or from increased deforestation (Zaveri et al., 2020; Aragón et al., 2021). Previous studies have found evidence of such land reallocation and deforestation mechanisms (Figari, 2025; He and Chen, 2022). Our addition here is in showing that negative temperature shocks could induce the cultivation of an important legume, groundnut which has been highlighted to be pro-poor and environmentally friendly with immense food and nutrition security implications (Ajeigbe et al., 2020; Lokossou et al., 2022; Tabe-Ojong et al., 2023b). Groundnut is an important staple crop that is both consumed and marketed by smallholder households in many rural areas of West Africa. It is used as a less costly replacement of the usually expensive alternative protein sources such as meat and fish. Given the widespread food security situation in the region, the use of climate-resilient groundnut varieties could play a critical role in strengthening food systems and improving the livelihoods of smallholder farmers (Tabe-Ojong et al., 2023a).

The final contribution of the paper is to show how adaptation to extreme heat varies across key economic and demographic dimensions, and what these patterns reveal about the structure of climate-adaptation constraints. Although our results show that both poor and non-poor

households adopt climate-resilient varieties in response to extreme heat, we find that poor households exhibit larger cropland expansion responses, consistent with the idea that land reallocation may serve as an important self-insurance mechanism when formal risk-management tools are limited. We also show that households with higher productivity scale adaptation more effectively, highlighting the role of complementary resources in enabling land reallocation and technology use. Demographic patterns further reveal that cropland expansion is concentrated among adult-headed households, reflecting structural barriers that youth face in accessing land and other productive assets (Quisumbing et al., 2001; Meinzen-Dick et al., 2019; Kumeh and Omulo, 2019; Zulu et al., 2021; Sitko et al., 2024; Pignède, 2025). We also show evidence of sustained adoption of climate-resilient varieties in response to extreme temperatures. This finding supports extant work on the adoption and disadoption dynamics of climate-smart crop varieties (Simtowe and Mausch, 2019; Lokossou et al., 2022; Tabe-Ojong et al., 2023b).

2. Climate-Resilient Groundnut Varieties as Induced Innovation

Climate-resilient seeds are a prominent illustration of an induced innovation in agriculture prompted by direct responses to environmental stressors such as prolonged drought, extreme temperatures, and increased pest pressure (Moscona and Sastry, 2023; Boucher et al., 2024). The creation of these seeds requires substantial investments in advanced breeding techniques and genetic engineering to ensure they can withstand and perform well under harsh climatic conditions (Ajeigbe et al., 2020). By incorporating traits that help crops survive and thrive despite these adverse factors, climate-resilient seeds not only lead to higher yields but also play a critical role in supporting rural livelihoods, strengthening household welfare, and bolstering overall food security (Lokossou et al., 2022; Wang et al., 2022b; Tabe-Ojong et al., 2023b).

Climate-resilient groundnut varieties have been developed and disseminated across West Africa through multi-decade breeding programs led by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in collaboration with national research systems. These efforts have occurred under large-scale initiatives, including USAID's Feed the Future program, the Gates Foundation–funded Tropical Legumes I–III projects, and the Groundnut Upscaling Project (Ajeigbe et al., 2020; Lokossou et al., 2022; Tabe-Ojong et al., 2023a,b). The improved varieties released through these programs differ markedly from local landraces in their ability

to withstand both abiotic and biotic stresses, and they incorporate a suite of traits designed to enhance productivity, marketability, and resilience under climatic variability.

A central feature of these improved varieties is their enhanced tolerance to environmental stressors. From an abiotic standpoint, they exhibit substantial resistance to heat stress and drought: two climatic shocks that have become increasingly prevalent in the Sahel due to rising temperatures and more erratic rainfall patterns (Acevedo et al., 2020). Heat stress during critical phenological stages, such as flowering and pegging, can severely reduce crop yields; improved varieties are bred to maintain seed set and pod development even at high temperature thresholds. They also possess superior drought-tolerance mechanisms, including deeper or more efficient root systems and increased transpiration efficiency, enabling them to withstand prolonged dry spells.

These abiotic advantages are complemented by strong resistance to major biotic threats. Several climate-resilient varieties carry genetic resistance to groundnut rosette virus, aflatoxin contamination, early and late leaf spot, rust, and root rot (Tabe-Ojong et al., 2022). The prevalence and severity of many of these diseases increase following extreme weather conditions (Patterson et al., 1999; Rosenzweig et al., 2001), making resistance traits particularly valuable under a warming climate. Disease resistance also reduces the need for chemical pesticides, lowering production costs and improving environmental outcomes.

Beyond stress tolerance, improved varieties are characterized by multiple traits that enhance their agronomic performance and market appeal. They typically mature earlier than local landraces, reducing exposure to late-season heat or rainfall deficits. Their growth habit often includes stronger branching architecture, improved pod-filling capacity, higher shelling percentage, and elevated oil extraction rates (Ajeigbe et al., 2020). These traits translate into higher and more stable yields across heterogeneous and challenging production environments.

Several improved varieties additionally possess market-preferred characteristics, including larger kernel size, brighter seed color, and higher nutritional value. These traits enhance the marketability of the crop and strengthen incentives for adoption, particularly among households with commercial production objectives (Lokossou et al., 2022). As legumes, groundnuts contribute to biological nitrogen fixation, improving soil fertility and providing important rotational benefits in mixed cropping systems (Simtowe et al., 2019). Improved varieties have been shown to maintain or even enhance these soil fertility contributions, helping restore soil organic matter

and promoting long-term productivity on smallholder farms.

Taken together, these agronomic, ecological, and market-oriented characteristics make climate-resilient groundnut varieties particularly suitable for adaptation in smallholder systems facing rising heat and drought stress. When households experience extreme temperatures—either through direct yield losses or through updated expectations of future heat—the relative attractiveness of stress-tolerant varieties increases (Wang et al., 2022b; Liebenehm et al., 2023; Boucher et al., 2024). The varieties' capacity to buffer against yield losses, resist pests and diseases, and deliver stable returns under variable conditions positions them as a key instrument for short-run and medium-run adaptation. Understanding the behavioral responses of farm households to extreme temperatures—and the extent to which such shocks trigger adoption or changes in land allocation—is therefore critical for the design of climate-resilient agricultural policies and seed systems.

3. Theoretical Framework

We develop a simple theoretical framework to formalize the effect of extreme heat on the adoption and allocation of land to climate–resilient groundnut varieties. The framework builds on agricultural household models under risk (Singh et al., 1986), the literature on climate-sensitive production (Schlenker and Roberts, 2009; Lobell et al., 2011b), and work on induced innovation and technology adoption under uncertainty and incomplete insurance (Dercon and Christiaensen, 2011; Gollin et al., 2021; Moscona and Sastry, 2023). Climate-resilient seeds are an example of induced innovation in agriculture, created in response to challenges like drought, heat, and pests (Boucher et al., 2024; Moscona and Sastry, 2023). Developed through advanced breeding and genetics, they boost productivity and help improve welfare and food security. We derive two key testable predictions that guide our empirical analysis: (i) extreme heat increases adoption at the extensive margin and (ii) extreme heat promotes land reallocation at the intensive margin.

3.1. Model setup and expected utility problem.

We start with a household that produces groundnut using two possible varieties: a local (landrace) variety indexed by $v = 0$ and a climate–resilient variety indexed by $v = 1$. Let $L_v \geq 0$

denote land allocated to variety v, and let

$$A = \bar{A} + E \tag{1}$$

denote total cultivated land, where $\bar{A}$ is endowed land and $E \geq 0$ captures cropland expansion (e.g. clearing, borrowing, or renting additional plots). Land must satisfy

$$L_0 + L_1 \leq A. \tag{2}$$

Let θ denote exposure to extreme temperature during the growing season. Output for variety v is

$$Y_v(\theta) = A_v(\theta)\, f_v(L_v, x_v), \tag{3}$$

where $A_v(\theta)$ is a climate-sensitive total factor productivity term and x_v is a vector of other inputs. We impose the following three assumptions:

Assumption 1 (Climate damage) *Extreme heat reduces productivity for each variety:*

$$\frac{\partial A_v(\theta)}{\partial \theta} < 0 \quad \textit{for } v \in \{0, 1\}.$$

Assumption 1 captures the well-documented convex relationship between temperature and crop yields, whereby yield losses accelerate once temperatures exceed critical thresholds (Schlenker and Roberts, 2009; Lobell et al., 2011b; Burke et al., 2015).

Assumption 2 (Heat-tolerance advantage) *The climate–resilient variety is less heat-sensitive than the local variety:*

$$\left|\frac{\partial A_1(\theta)}{\partial \theta}\right| < \left|\frac{\partial A_0(\theta)}{\partial \theta}\right|.$$

Assumption 2 reflects the explicit agronomic design of stress-tolerant varieties, which are bred to maintain seed set and pod development even under high temperatures (Lybbert and Carter, 2015; Emerick et al., 2016). While resilient varieties may perform similarly to landraces under normal conditions, they suffer significantly smaller losses when heat shocks occur.

Per-hectare profits for variety v are

$$\pi_v(\theta) = p_y \frac{Y_v(\theta)}{L_v} - \frac{p_{x_v}^{\top} x_v}{L_v}, \tag{4}$$

and the relative profit advantage of the climate–resilient variety is

$$\Delta\pi(\theta) = \pi_1(\theta) - \pi_0(\theta). \tag{5}$$

Assumption 3 (Monotone relative advantage) *The profit advantage of the climate–resilient variety increases with extreme heat:*

$$\frac{\partial\,\Delta\pi(\theta)}{\partial\theta} > 0.$$

Assumption 3 stresses the dual benefits of stress-tolerant varieties documented in the literature: they deliver larger relative yield gains in adverse states of nature and reduce downside risk by limiting catastrophic losses. Consequently, as heat becomes more extreme, both expected returns and risk protection tilt more strongly in favor of the resilient variety.

To connect heat-sensitive production in (3) to technology adoption and land-use decisions, we consider a household that chooses whether to pay a fixed cost to access the resilient variety and how to allocate cultivated land (including the possibility of expanding land) before the season's heat realization is observed. Let consumption be:

$$C(\theta) = p_y\big(Y_0(\theta) + Y_1(\theta)\big) - p_{x_0}^{\top}x_0 - p_{x_1}^{\top}x_1 - p_E(E)\ - F_1\mathbf{1}\{L_1 > 0\} + M, \tag{6}$$

where p_y is the output price, p_{x_v} is the input price vector, $p_E(E)$ is the (possibly increasing) cost of land expansion, $F_1 > 0$ is a fixed cost of adopting the resilient variety (learning, information, seed package purchase (Foster and Rosenzweig, 2010)), and M is exogenous nonfarm income. The household chooses (L_0, L_1, E, x_0, x_1) to maximize expected utility

$$\max_{L_0,L_1,E,x_0,x_1}\ \mathbb{E}_\theta\big[u(C(\theta))\big] \quad \text{s.t.} \quad (1),\ (2). \tag{7}$$

Assuming risk-neutral[2] preferences (i.e. $u(C) = C$), the problem in (7) is equivalent to maximizing expected profits:

$$\max_{L_0,L_1,E}\ \mathbb{E}\Big[\pi_0(\theta)L_0 + \pi_1(\theta)L_1\Big] - p_E(E) - F_1\mathbf{1}\{L_1 > 0\} + M \quad \text{s.t.} \quad L_0 + L_1 \le \bar{A} + E. \tag{8}$$

We solve this problem in two steps, deriving optimality conditions for (i) adoption (extensive margin), and (ii) cropland expansion (intensive margin) in the face of extreme heat.

[2]We focus on the risk-neutral case in the main text for analytical clarity and tractability. However, substantial evidence shows that poor and smallholder households typically exhibit strong risk-averse preferences (Binswanger, 1980; Liu, 2013; Yesuf and Bluffstone, 2009), and that exposure to adverse climatic shocks can further heighten risk aversion (Callen, 2015; Cassar et al., 2017; Liebenehm et al., 2023). In Appendix A, we extend the model to incorporate risk aversion under CARA utility and normally distributed shocks. Under these conditions, the same qualitative predictions hold, and risk aversion strengthens the relative attractiveness of the climate-resilient variety by reducing downside risk.

3.2. Adoption Under Fixed Land

We first abstract from land expansion by setting $E = 0$, so that total cultivated land is fixed at $A = \bar{A}$. The household then chooses whether to adopt the climate–resilient variety (an extensive-margin decision) and, conditional on adoption, how much land to allocate to it. In what follows, the extensive margin corresponds to whether $L_1 > 0$, while the intensive margin corresponds to the total area planted with the resilient variety, $L_1 = s_1\bar{A}$.

Define the land share allocated to the resilient variety:

$$s_1 \equiv \frac{L_1}{\bar{A}} \in [0, 1].$$

Then

$$L_1 = s_1\bar{A} \quad \text{and} \quad L_0 = (1 - s_1)\bar{A}.$$

Under risk neutrality, and with $E = 0$, the expected utility maximization in (8) is equivalent to:

$$\max_{L_0, L_1} \mathbb{E}\Big[\pi_0(\theta)L_0 + \pi_1(\theta)L_1\Big] - F_1\mathbf{1}\{L_1 > 0\} + M \quad \text{s.t.} \quad L_0 + L_1 = \bar{A}.$$

Substituting $L_0 = (1 - s_1)\bar{A}$ and $L_1 = s_1\bar{A}$ yields

$$\begin{aligned}
\mathbb{E}\big[\pi_0(\theta)L_0 + \pi_1(\theta)L_1\big] &= \mathbb{E}\Big[\pi_0(\theta)(1 - s_1)\bar{A} + \pi_1(\theta)s_1\bar{A}\Big] \\
&= \bar{A}\Big\{(1 - s_1)\mathbb{E}[\pi_0(\theta)] + s_1\mathbb{E}[\pi_1(\theta)]\Big\} \\
&= \bar{A}\Big\{\mathbb{E}[\pi_0(\theta)] + s_1\big(\mathbb{E}[\pi_1(\theta)] - \mathbb{E}[\pi_0(\theta)]\big)\Big\}. \qquad (9)
\end{aligned}$$

Using the definition $\Delta\pi(\theta) = \pi_1(\theta) - \pi_0(\theta)$ implies

$$\mathbb{E}[\pi_1(\theta)] - \mathbb{E}[\pi_0(\theta)] = \mathbb{E}[\pi_1(\theta) - \pi_0(\theta)] = \mathbb{E}[\Delta\pi(\theta)].$$

Hence expected profits conditional on adoption ($s_1 > 0$, which triggers payment of F_1) can be written as

$$\Pi^{\mathrm{A}}(s_1) = \bar{A}\Big\{\mathbb{E}\big[\pi_0(\theta)\big] + s_1\,\mathbb{E}\big[\Delta\pi(\theta)\big]\Big\} - F_1 + M. \qquad (10)$$

Under non-adoption, the household sets $L_1 = 0$ (equivalently, $s_1 = 0$), so all land is allocated to the local variety and the fixed cost is not paid. Expected profits are therefore

$$\Pi^{\mathrm{N}} = \bar{A}\,\mathbb{E}\big[\pi_0(\theta)\big] + M. \qquad (11)$$

The household adopts if there exists some $s_1 \in (0,1]$ such that $\Pi^{\mathrm{A}}(s_1) \geq \Pi^{\mathrm{N}}$. Using (10)–(11), this inequality is

$$\bar{A}\Big\{\mathbb{E}\big[\pi_0(\theta)\big] + s_1\,\mathbb{E}\big[\Delta\pi(\theta)\big]\Big\} - F_1 + M \;\geq\; \bar{A}\,\mathbb{E}\big[\pi_0(\theta)\big] + M,$$

which simplifies (by canceling common terms) to

$$\bar{A}\,s_1\,\mathbb{E}\big[\Delta\pi(\theta)\big] \geq F_1. \tag{12}$$

Condition (12) characterizes the extensive margin of adoption: households adopt climate–resilient seeds when the expected profit gains under extreme heat are large enough to offset the fixed adoption cost.

Proposition 1 (Extreme heat increases adoption and land share) *Under Assumptions 1–3, a shift in the distribution of θ toward higher extreme heat (in the sense of first-order stochastic dominance) increases (i) the probability that condition (12) is satisfied and the household adopts the resilient variety ($L_1 > 0$).*

3.3. Intensity of Adoption: Land Allocated to Climate–Resilient Seeds

We now characterize the *intensive margin* of technology use: how much land is allocated to climate–resilient groundnut seeds among adopters. In our empirical analysis, this margin corresponds to the total area planted with the resilient variety, L_1, which can vary from zero to the household's total groundnut land.

3.3.1. Optimal Land Share with fixed cultivated land ($E = 0$)

We continue to abstract from land expansion and maintain $E = 0$ so that total cultivated land is fixed at $A = \bar{A}$. In this environment, the household's within-groundnut land allocation can be summarized by the share

$$s_1 \equiv \frac{L_1}{\bar{A}} \in [0,1], \quad \text{so that} \quad L_1 = s_1\bar{A}.$$

Recall from (10) that, under fixed land and risk neutrality, expected profits conditional on adoption can be written as

$$\Pi^{\mathrm{A}}(s_1) = \bar{A}\Big\{\mathbb{E}\big[\pi_0(\theta)\big] + s_1\,\mathbb{E}\big[\Delta\pi(\theta)\big]\Big\} - F_1 + M,$$

where $\Delta\pi(\theta) = \pi_1(\theta) - \pi_0(\theta)$. Conditional on adoption (i.e. paying F_1 and choosing $s_1 > 0$), the household chooses $s_1 \in [0, 1]$ to maximize $\Pi^{\mathrm{A}}(s_1)$. Differentiating with respect to s_1 yields

$$\frac{\partial \Pi^{\mathrm{A}}(s_1)}{\partial s_1} = \bar{A}\,\mathbb{E}\big[\Delta\pi(\theta)\big]. \tag{13}$$

Because (13) does not depend on s_1, the objective is linear in s_1 and the optimum is characterized by a corner solution:

$$s_1^\star = \begin{cases} 1 & \text{if } \mathbb{E}\big[\Delta\pi(\theta)\big] > 0, \\ 0 & \text{if } \mathbb{E}\big[\Delta\pi(\theta)\big] < 0, \\ \text{any } s_1 \in [0,1] & \text{if } \mathbb{E}\big[\Delta\pi(\theta)\big] = 0. \end{cases} \tag{14}$$

Under Assumption 3 and a shift toward hotter realizations of θ, the expected profit advantage $\mathbb{E}[\Delta\pi(\theta)]$ increases, implying that $s_1^\star = 1$: the household allocates total cultivated land to the climate-resilient variety. Equation (14) is a benchmark implication of a parsimonious setup in which land shares are governed solely by expected per-hectare profit differences. In practice, adjustment costs, learning frictions, input/credit constraints, or plot-level heterogeneity can generate *partial* allocation to the resilient variety, i.e. $0 < s_1 < 1$, even when $\mathbb{E}[\Delta\pi(\theta)] > 0$. As a result, the model predicts that hotter climates unambiguously increase the *share* of land allocated to the resilient variety. Adjustment costs, credit constraints, or plot-level heterogeneity may prevent the corner solution $s_1^\star = 1$ from being reached, but they do not reverse the *direction* of the response: an interior share that satisfies the first-order condition still rises with θ.

Proposition 2 (Extreme heat increases the intensity of adoption) *Under Assumptions 1–3, a shift in the distribution of θ toward higher extreme heat increases the optimal land allocated to the resilient variety, $L_1^\star = s_1^\star \bar{A}$, in the sense that it (weakly) increases $s_1^\star$ and therefore (weakly) increases $L_1^\star$.*

3.3.2. Optimal Land Share with Positive Cropland Expansion ($E > 0$)

We now consider the case in which the household expands cultivated land so that $E > 0$ and total cultivated land is $A = \bar{A} + E$. Although the household chooses both (s_1, E) prior to the realization of extreme heat, the empirical analysis does not separately model the expansion decision. Instead, we focus on a key theoretical implication that is robust to expansion: *conditional on any given expansion level $E > 0$, hotter climates tilt the household's optimal allocation toward the climate-resilient variety.* Accordingly, in this subsection we treat $E > 0$ as given and solve for the optimal share $s_1^\star(E)$.

Under risk neutrality, expected profits can be written as

$$\Pi(s_1, E) = (\bar{A} + E)\big\{\mathbb{E}\pi_0(\theta) + s_1\mathbb{E}\Delta\pi(\theta)\big\} - p_E(E) - F_1\mathbf{1}\{s_1 > 0\} + M, \tag{15}$$

where $\Delta\pi(\theta) \equiv \pi_1(\theta) - \pi_0(\theta)$ denotes the per-hectare profit advantage of the resilient variety. For a *given* $E > 0$, the terms $p_E(E)$ and $(\bar{A}+E)\mathbb{E}\pi_0(\theta)$ are constants with respect to s_1. Conditional on choosing $s_1 > 0$ (i.e., adopting), the household pays the fixed cost F_1. Therefore, for a given $E > 0$, the adoption-conditional choice of s_1 solves

$$\max_{s_1 \in (0,1]} (\bar{A} + E)\Big\{\mathbb{E}\pi_0(\theta) + s_1\,\mathbb{E}\Delta\pi(\theta)\Big\} - p_E(E) - F_1 + M. \tag{16}$$

Dropping terms that are constant in s_1 yields the equivalent problem

$$\max_{s_1 \in (0,1]} (\bar{A} + E)\, s_1\, \mathbb{E}\Delta\pi(\theta). \tag{17}$$

Differentiating (17) with respect to s_1 gives:

$$\frac{\partial}{\partial s_1}\Big[(\bar{A} + E)\, s_1\, \mathbb{E}\Delta\pi(\theta)\Big] = (\bar{A} + E)\, \mathbb{E}\Delta\pi(\theta). \tag{18}$$

Because the first-order condition with respect to s_1 does not depend on s_1 itself, the optimal allocation is the same corner solution obtained in the $E = 0$ case ($s_1^\star = 1$): the household then chooses to allocate all cultivated land to the climate-resilient variety. As discussed above, interior solutions may arise in practice due to adjustment costs, learning frictions, or diversification motives that are not explicitly modeled here. Allowing for cropland expansion therefore does not alter the qualitative prediction for the intensive margin: conditional on adoption, hotter climates tilt incentives toward allocating a larger share of cultivated land to climate-resilient varieties.

3.4. Heterogeneous Responses To Extreme Heat

The framework abstracts from household heterogeneity in wealth, land access, and production capacity in order to deliver transparent predictions about how extreme heat affects adoption and land allocation decisions on average. In practice, households would differ in their exposure to risk, access to land and credit, and ability to smooth consumption. These differences may shape the magnitude of responses to extreme heat. Rather than imposing theoretical predictions for specific subgroups, we treat heterogeneous responses as an empirical question. In the empirical analysis, we therefore explore differential effects by wealth and productivity, allowing the data

to reveal how households with varying economic capacity adjust adoption and land allocation decisions in response to heat stress.

4. Data

We rely on two different unique and rich datasets for the analysis. In the first place, we use a geocoded panel farm household dataset from Nigeria. We combine this with daily minimum and maximum temperature data collected at 0.05x0.05 degree resolution (approximately 5 km x 5 km), from the Climate Prediction Center [3] (CPC) Global Unified Temperature data, provided by the National Oceanic and Atmospheric Administration Physical Science Library (NOAA PSL). We discuss both datasets below.

4.1. Panel data

Our analysis draws on a rich household panel dataset, covering the years 2017 through 2019, collected from farm households in Nigeria as part of the USAID-funded groundnut upscaling project. The survey started in 2017 with an extensive outreach that included 2,500 households. As the study progressed, financial and stability concerns required a reduction of sample sizes. In 2018, 1,600 households were re-sampled with 70 households dropping out in 2019, resulting in a final collection of data from 1,530 households for the conclusive phase of the project (a 4% attrition rate). The final dataset involves a total sample size of 4950 observations. The household survey collected a wide range of information, including household demographic characteristics (age, gender, education, marital status, household size, etc.), income generating activities (groundnut production, off-farm activities), adoption of improved groundnut varieties and access to extension services.

4.2. Sample Attrition

Despite the low attrition rate, there is a potential concern that attrition may introduce selection bias if the households that drop out of the panel differ systematically from those that remain. Specifically, if attrition is correlated with past weather shocks or household characteristics, our estimates could be biased. To assess the extent of this concern, we estimate a probit model to predict the probability of attrition as a function of pre-baseline weather conditions and household characteristics:

[3] https://www.cpc.ncep.noaa.gov/

$$Pr(\text{Attrition}_i = 1) = \Phi(\beta_0 + \beta_1 \mathbf{W}_i + \beta_2 \mathbf{X}_i + \epsilon_i) \tag{19}$$

where Attrition_i is a binary variable equal to 1 if household i dropped out before the final round of the survey, $\mathbf{W}_i$ captures pre-baseline weather conditions including a measure for exposure to extreme temperature (number of days in the 2016 growing season - year before baseline - with temperature above 32°C) and a measure for exposure to rainfall in 2016 (defined as cumulative and squared cumulative rainfall in the 2016 grpwing season). $\mathbf{X}_i$ includes household demographic controls. The function $\Phi(.)$ represents the cumulative distribution function of the standard normal distribution. Our results indicate that attrition is not significantly correlated with pre-baseline weather conditions (Appendix Table A1), suggesting that household dropouts are unlikely to be systematically driven by prior climate shocks. Additionally, we find no evidence that attrition is correlated with household characteristics. This mitigates concerns about sample selectivity bias affecting our estimates.

4.3. Weather data

We match the household panel data with daily gridded minimum and maximum temperature data collected at the 0.05x0.05 (approximately 5 km x 5 km) degree resolution, from the Climate Prediction Center (CPC) Global Unified Temperature data, provided by the NOAA PSL. Minimum and maximum temperature values are extracted at the grid level and used to construct a flexible measure of exposure to extreme heat in two steps. First, we define thirteen 1°C bins, ranging from below 24°C to above 35°C. Next, we determine the number of days falling into each temperature bin in the growing season prior to each survey year. We use below 24°C to above 35°C as first and last bin respectively, because these bins have the lowest number of days (see Figure 1). We also match our household data with gridded daily rainfall data collected at the 0.05x0.05 degree resolution. Rainfall data comes from the Climate Hazards Group InfraRed Precipitation (CHIRPS)[4] and is used to construct positive and negative rainfall shock indicators. A household is said to experience a negative (positive) rainfall shock if total rainfall in the growing season of year t is one standard deviation below (above) long-term (30 years) average. We adopt the May-September period as the relevant growing season for this study, given that households in our sample are located in northern Nigeria, where only one rainy season (that begins in May and lasts until September) prevails.

Figure 1 depicts the distribution of the number of days per temperature bin for the growing

[4] https://data.chc.ucsb.edu/products/CHIRPS-2.0/

seasons preceding each survey year and for the full sample. We notice a rightward shift of the yearly temperature distribution overtime, indicating farmers' increasing exposure to high temperatures. In 2016, most days fell within a moderate temperature range (26-30°C) but by 2018, there was a clear shift towards more frequent occurrences of temperatures above 30°C. The full sample distribution confirms this trend, with households being exposed to temperature exceeding 30°C (86°F) for more than 30 days on average across the 3-year period.

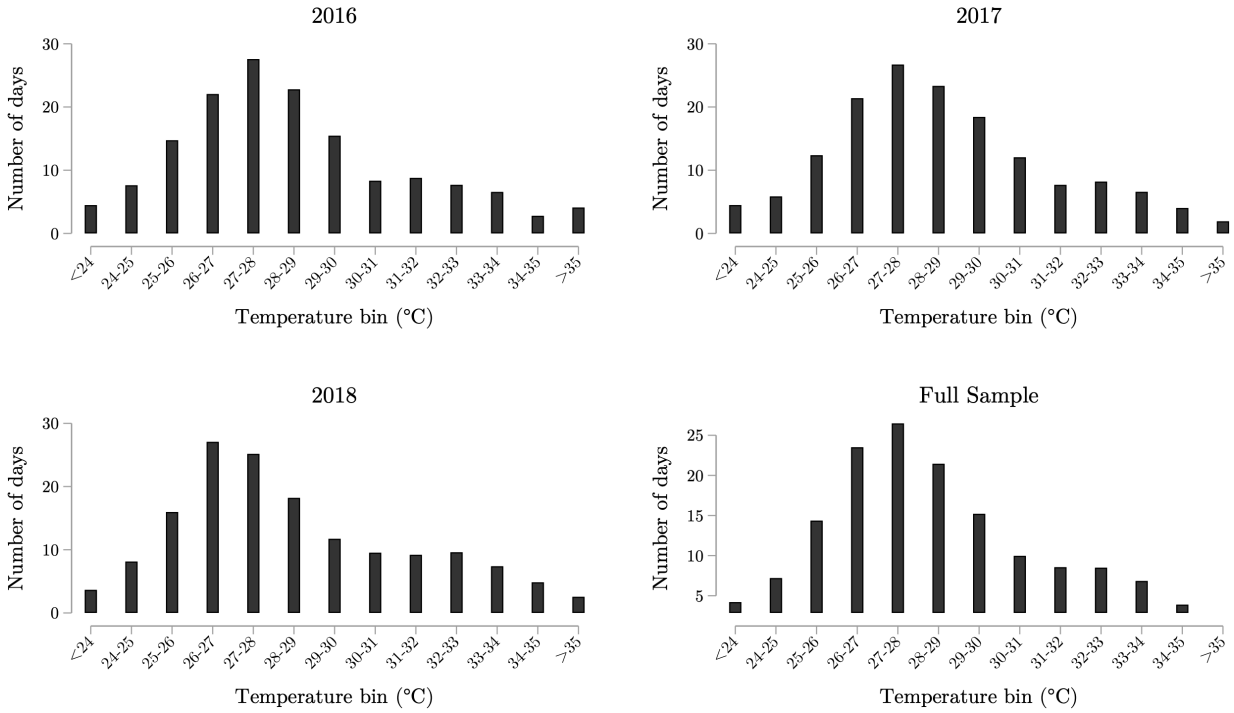
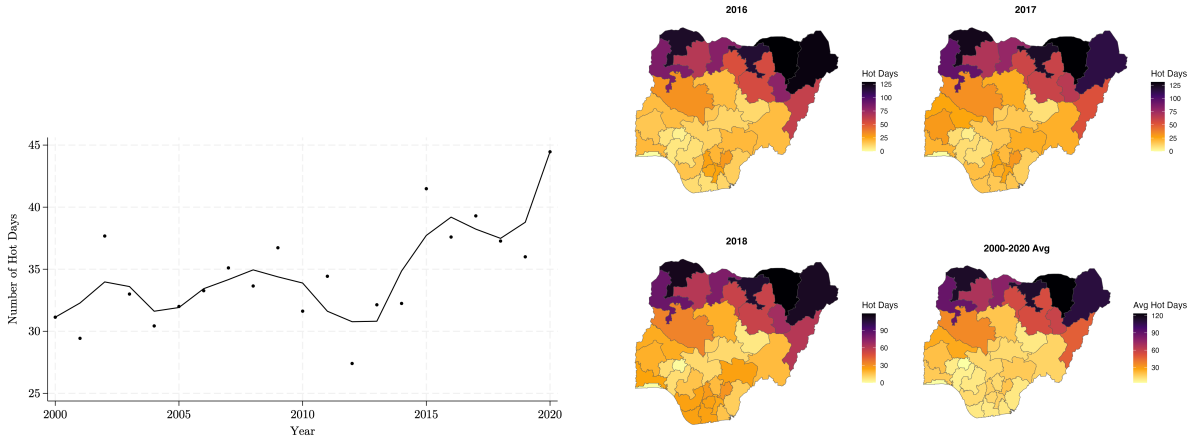


Figure 1: Number of days per temperature bin

To further examine the extent of exposure to extreme heat across space and over time, we plot the spatial and temporal distribution of hot days (days with average daily temperature greater than 32°C). Panel (a) of Figure 2 presents the temporal trend (from 2000 to 2020), and highlights an increase in the frequency of hot days over the years (including the study period). This upward trend suggests that extreme heat events are becoming more frequent overtime, further reinforcing the concern that households in our sample are facing prolonged periods of high temperatures during the growing season. Additionally, this trend underscores the temporal variation in households' exposure to extreme heat within our sample. Panel (b) illustrates the spatial distribution of hot days across different regions of Nigeria. The map reveals significant heterogeneity in temperature exposure, with northern districts (where our

households are located) experiencing a much higher concentration of hot days than southern ones. Further, the graph also displays variation even within northern regions, with some areas experiencing significantly more hot days than others. This highlights the spatial heterogeneity in households' exposure to extreme heat within our sample.



(a) Temporal trend in hot days (2000–2020)

(b) Spatial distribution of hot days

Figure 2: Temporal and Spatial Distribution of Extreme Heat in Nigeria

Notes: Panel A shows the national average number of hot days per year in Nigeria from 2000 to 2020, where a hot day is defined as a day with average temperature exceeding 32°C. Panel B displays the spatial distribution of hot days across Nigeria, measured as the long-run average number of hot days at the grid level over the sample period.

4.4. Descriptive Statistics

4.4.1. Summary of key Variables

Appendix Table A2 presents summary statistics for key variables used in the analysis, organized by survey year (2017-2019) and for the total sample. The adoption of climate-resilient groundnut varieties shows a steady increase over the study period, rising from 49% in 2017 to 55% in 2019, with an overall adoption rate of 52% across all years. Similarly, the area under adoption increased from 0.71 hectares in 2017 to 0.88 hectares in 2019, and averaged 0.76 hectares for the full sample. The average household in our sample is about 46 years old, predominantly male (97%), and lives in a household that has approximately 9 members. Membership in farmer associations is relatively common at 62%, though it declined from 68% in 2017-2018 to 50% in 2019. Participation in training on groundnut production was limited overall, with only 23% of households reporting access to such training across the full sample. This share increased from 19% in 2017 and 2018 to 31% in 2019. Access to extension service remains

limited, with households receiving an average of 1.66 visits from public extension and 0.72 visits from private extension services annually. Access to credit is particularly constrained with only 2% of households reporting access across the full sample. Access to off-farm income increases modestly from 16% in 2017 to 21% in 2019, averaging 17% overall. Rainfall shock indicators reveal significant year-to-year variation; the percentage of households that experienced negative rainfall shocks increased from 9% in 2016 to 16% in 2017, before falling to negligible levels in 2018. In contrast, while almost no households experienced positive rainfall shocks in 2016 and 2017, this percentage rose to 35% in 2018.

4.4.2. Patterns of Area Allocation of Climate-Resilient Varieties

Figure 3 presents the distribution of land area allocated to climate-resilient groundnut varieties for each survey year and for the full sample. In all years, the distribution is right-skewed, with 51% of households in 2017, 47% in 2018 and 48% in 2019 allocating no land to climate-resilient groundnut seeds. On average, roughly 48% of households allocate no land to climate-resilient seeds in the full sample. The majority of adopters allocate less 2 hectares of land to climate resilient seeds, while about 15% of households cultivate more than 2 hectares in the full sample.

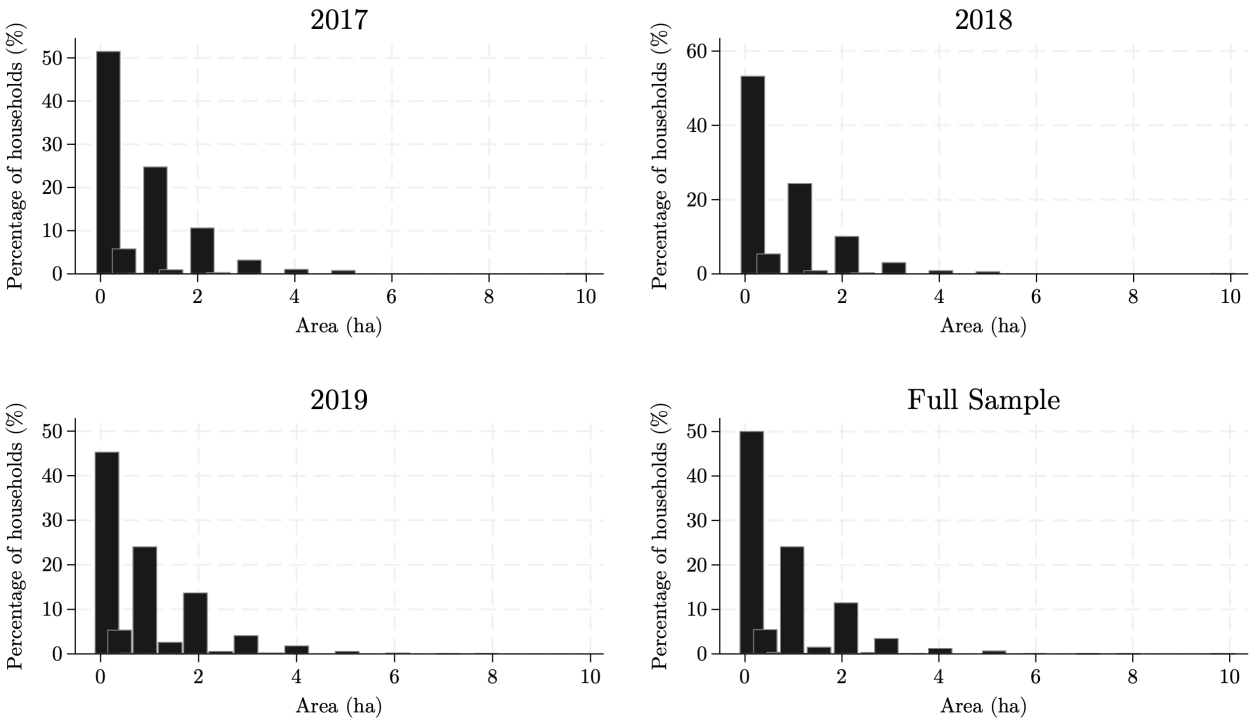


Figure 3: Distribution of area under climate-resilient seeds

5. Empirical Strategy

We exploit the temporal and spatial variation in extreme temperatures to estimate the effect of household exposure to extreme heat on adoption at the extensive and intensive margins. Specifically, we estimate the lagged effects of temperature shocks on adoption and area under adoption of climate-resilient groundnut varieties. Our focus on lagged temperature effects is justified by the fact that households are likely to make seed use decisions before the start of the agricultural season and based on their most recent exposure to weather shocks (Jain et al., 2015). However, households' adoption decisions may also be shaped by long-term adaptation to extreme heat rather than just short-term weather shocks (Burke and Emerick, 2016). As a result, we also examine the effects of prolonged exposure to extreme temperatures on adoption and cropland expansion.

We employ a two-part model to estimate the effects of temperature shocks on adoption and area under adoption. First, we investigate the relationship between temperature shocks and adoption at the extensive margin using the following flexible regression model:

$$I_{ijt} = \sum_{k=1}^{13} \gamma_k \mathbf{TB}_{kij,t-1} + X'_{ijt}\beta_1 + f(\text{rain}_{ij,t-1}) + \delta_t + \mu_i + \epsilon_{ijt} \tag{1}$$

Where I_{ijt} is an indicator variable for adoption, which takes on the value 1 if household i in grid j has adopted climate-resilient groundnut varieties in growing season t, and 0 otherwise. $\mathbf{TB}_{kit-1}$ is a vector of thirteen 1°C temperature bins from growing season $t-1$ defined as follows: $< 24°\text{C}, 24°\text{C} - 25°\text{C}, 25°\text{C} - 26°\text{C}, \ldots, > 35°\text{C}$. We estimate separate γ_k coefficients for each bin k. We use the first temperature bin ($< 24°\text{C}$) as the benchmark, interpreting the coefficients of the other bins relative to this reference point. For example, the coefficient of the $34°\text{C} - 35°\text{C}$ bin is the marginal effect on adoption of an additional day with average temperature between 34°C and 35°C relative to a day with average temperature less than 24°C. X'_{ijt} is a vector of household controls that includes household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, and farmer's perception of their soil quality. $f(\text{rain}_{ij,t-1})$ includes negative and positive rainfall shock indicator variables. As a robustness check, we use rainfall and quadratic rainfall from a previous growing season and we also estimate specifications that exclude rainfall controls altogether to test the sensitivity of our findings. δ_t represents year fixed effects and captures time-varying determinants of adoption and area under adoption. μ_i controls for time-invariant

household heterogeneity, and ϵ_{ijt} is the error term.

In the second part of our two-part model, we estimate the effects of temperature shocks on cropland expansion using the following specification:

$$A_{ijt} = \sum_{k=1}^{13} \alpha_k \mathbf{TB}_{kij,t-1} + X'_{ijt}\beta_2 + f(\text{rain}_{ij,t-1}) + \theta_t + \lambda_i + \omega_{ijt} \tag{2}$$

Where A_{ijt} is the area allocated to climate-resilient groundnut seeds by household i, in grid j, and growing season t. Equation 2 includes household demographic variables and controls for household and year fixed effects. To investigate the effects of exposure to extreme temperature, we estimate a parsimonious version of Equation 1 and Equation 2 with an upper threshold of 31°C [5], as follows:

$$Y_{ijt} = \gamma_1 T(> 31°C)_{ij,t-1} + X'_{ijt}\beta_3 + f(\text{rain}_{ij,t-1}) + \delta_t + \mu_i + \epsilon_{ijt} \tag{3}$$

Where Y_{ijt} represents our outcome of interest (adoption or area under adoption) and $T(> 31°C)_{ij,t-1}$ is the number of days in the previous growing season with average daily temperature above $31°C$.

We estimate all equations using the household fixed effect estimator and cluster standard errors at the grid level. As an additional robustness check, we also employ Conley (1999) standard errors, to account for potential spatial autocorrelation within specified distance thresholds. We also assess the robustness of our findings to alternative estimation methods and variable definitions. Specifically, we estimate Probit and Tobit models with the correlated random effects (CRE) to account for the binary and censored nature of adoption and area under adoption, respectively. Additionally, we test the sensitivity of our results to alternative baseline temperature bin to ensure that our main findings are not sensitive to the chosen baseline. Finally, we consider an alternative measure of adoption by examining the share of total land allocated to climate-resilient groundnut varieties.

[5] We explain the choice of this threshold in section 6.3.

6. Results and Discussions

6.1. Extreme Temperature and Adoption of Climate Resilient Varieties

Estimation results for equation (1) are shown in Figure 4 and also presented in Appendix Table A5. We show that the relationship between extreme heat and the adoption of climate-resilient groundnut varieties is distinctly nonlinear. Adoption responds weakly to moderate increases in temperature but rises sharply once the number of hot days exceeds a threshold. This is consistent with well-documented nonlinearities in crop responses to temperature. Agronomic research shows that groundnut experiences disproportionately large yield losses once temperatures exceed critical physiological thresholds—typically around 33–35°C during the sensitive flowering and pegging stages (Vara Prasad et al., 2000; Craufurd et al., 2003). Recent evidence confirms that even short episodes of heat stress during these windows can severely impair fruit set and final pod weight (Lai et al., 2024; Aravind et al., 2024).

These agronomic thresholds shape how farmers adjust their production decisions. When heat shocks are mild, expected yield losses are limited, and households have little incentive to incur the fixed costs associated with adopting a new variety. However, once temperatures exceed the crop's tolerance range, expected losses rise sharply, and the relative advantage of climate-resilient varieties increases substantially (Emerick et al., 2016; Lybbert and Carter, 2015). This makes adoption more attractive only at higher levels of heat exposure. These findings are consistent with previous literature showing that farmers adopt climate-resilient crop varieties as an adaption strategy in response to extreme heat (Di Falco and Veronesi, 2013). Similar studies in Sub-Saharan Africa and South Asia have documented that exposure to extreme heat induces a behavioral shift towards climate-adaptive technologies (Di Falco and Veronesi, 2013; Wang et al., 2022b; Liebenehm et al., 2023).

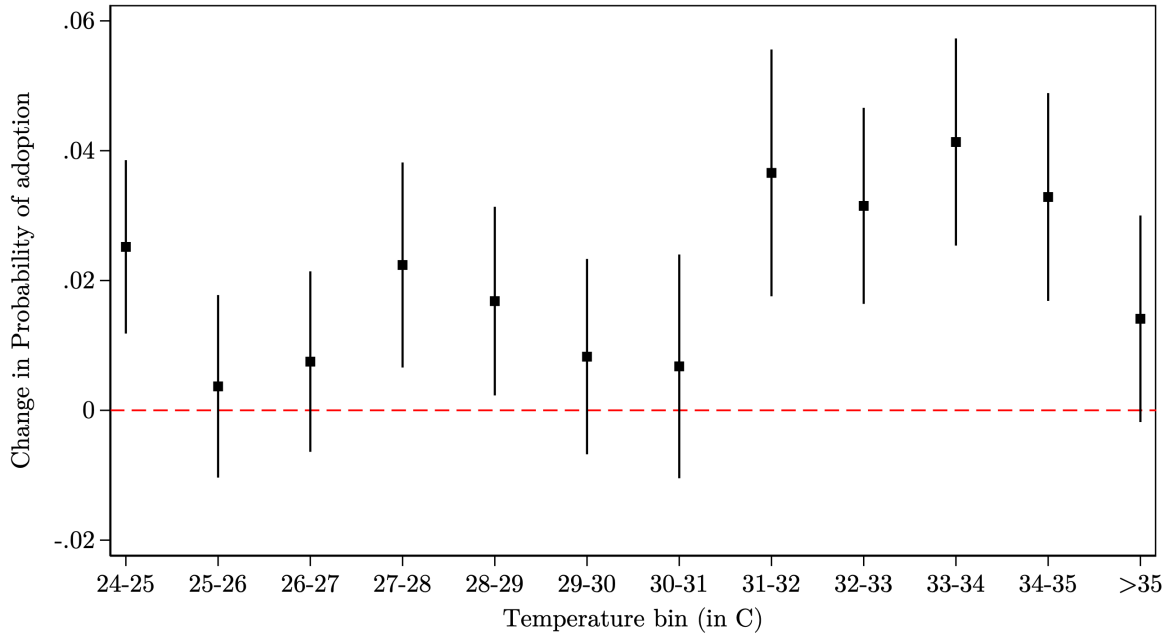


Figure 4: Effects of Temperature Shocks on Adoption of Climate-Resilient Varieties

Notes: The graph shows the effects of temperature shocks on the likelihood of adoption. Full results are presented in column 1 of Appendix Table A5. The squares represent the point estimates, and the bars indicate 95% confidence intervals. Additional controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall shock indicators, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors clustered at the grid level.

6.2. Extreme Temperature and Cropland Expansion

Figure 5 shows the results of the effect of temperature shocks on cropland expansion. We again observe a nonlinear response: cropland expansion remains largely unchanged at lower levels of heat exposure but increases sharply once temperatures reach the upper end of the distribution. In particular, statistically significant increases in cropland expansion emerge only in the 32–33°C and 33–34°C bins, indicating that households adjust land allocation only when heat exposure becomes sufficiently severe to alter the relative profitability of cultivating climate-resilient groundnut varieties.

Cropland expansion is a fundamentally different decision from seed adoption because it may involve clearing new land, negotiating access to communal or borrowed plots, reallocating land across crops, or securing permission from family or community authorities. These actions entail non-trivial labor, time, and social coordination costs (Bardhan, 2000; Macours and Vakis,

2014). As a result, households do not adjust land area in response to mild heat shocks that generate only modest expected losses. Instead, expansion occurs only when extreme heat makes the expected gains from reallocating land large enough to justify these adjustments. Extreme heat provides such a trigger. Once temperatures exceed the crop's tolerance range, the expected profitability of local varieties declines sharply, and the relative returns to allocating more land to climate-resilient varieties rise. At this point, the benefits of expanding cultivated area outweigh the fixed or lumpy costs associated with doing so, consistent with evidence that extreme weather shocks induce discrete changes in land use, including shifts into more resilient crops or expansion into new plots, when the expected gains from adaptation become large enough (Aragón et al., 2021; He and Chen, 2022; Wang et al., 2022a).

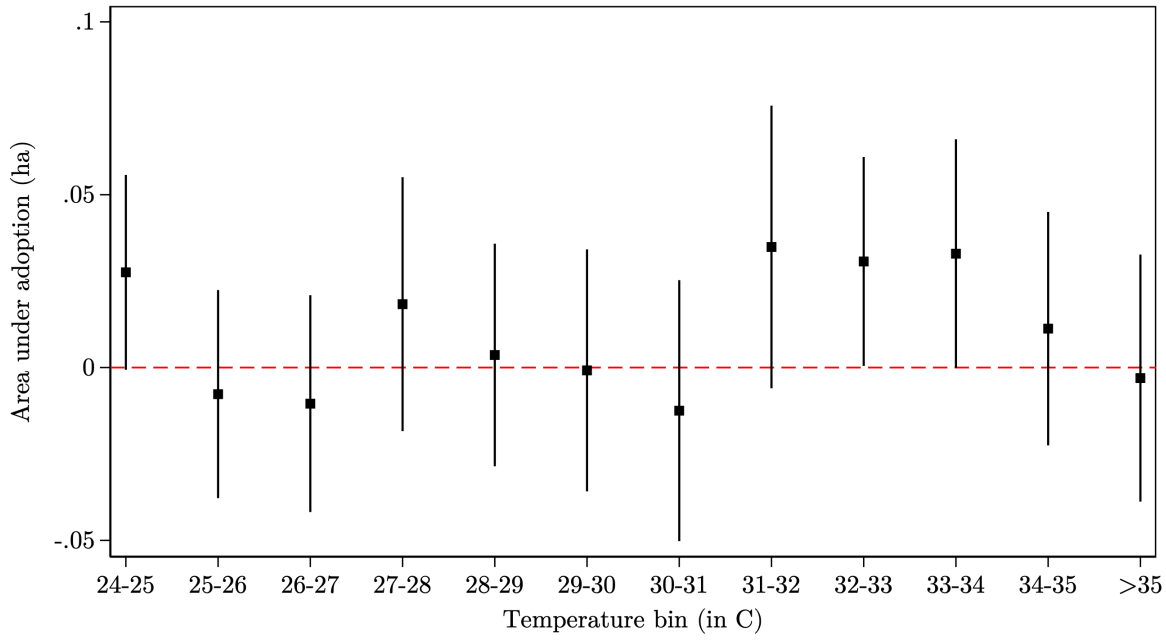


Figure 5: Effects of Temperature on Area under Adoption

Notes: The graph shows the effects of temperature shocks on area under adoption of climate-resilient seeds. Full results are presented in column 2 of Appendix Table A5. The squares represent the point estimates, and the bars indicate 95% confidence intervals. Additional controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall shock indicators, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors clustered at the grid level.

6.3. Parsimonious Results

After showing the binned effect of extreme temperatures on adoption and cropland expansion, we forge ahead to show some parsimonious insights where we estimate the average effects of temperature above 31°C. We run this parsimonious regression to specifically estimate the effects

of exposure to extreme temperatures. We set 31°C as the threshold for extreme temperatures based on the findings in Figure 4 and Figure 5, which show a visible jump in the magnitude of adoption and area effects at this point. The results, presented in Table 1, confirm that exposure to extreme heat has a positive and statistically significant effect on the adoption of climate-resilient groundnut varieties and the area allocated to climate-resilient groundnut varieties. An additional day with temperature above 31°C increases the adoption of climate-resilient groundnut varieties by about 2 %. Relatedly, we observe an increase in the area under climate-resilient groundnut seeds by about 1.1 % [6].

Table 1: Effects of Temperature on Adoption and Area under Adoption (Parsimonious Results)

	Adoption		Area	
	(1)	(2)	(3)	(4)
$\mathbf{T}(> 31°\mathbf{C})$	0.010***	0.010***	0.008***	0.007***
	(0.001)	(0.001)	(0.002)	(0.002)
Observations	4,076	4,076	4,076	4,076
R-squared	0.087	0.085	0.052	0.050
Household controls	Yes	Yes	Yes	Yes
Rainfall controls	Yes	No	Yes	No
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table shows the effects of exposure to extreme temperature (temperature over 31°C) on adoption and area under adoption of climate resilient groundnut seeds. All regressions include year dummies. Columns 1 and 3 include both households and rainfall controls. Columns 2 and 4 include household controls but exclude rainfall controls. Robust standard errors clustered at the grid level are in parentheses. *** significant indicate statistical significance at the 1% level. Controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall indicators, and farmer's perception of their soil quality.

Given that households in our sample have experienced about 30 days with temperature above 31°C on average per year (see Appendix Table A4), these estimates imply that exposure to extreme temperatures leads to an overall 60 % increase in adoption and an approximate 33 % increase in cropland expansion. These magnitudes are substantial given the importance of groundnut for both nutritional and ecological benefits (Tabe-Ojong et al., 2023b). These findings are consistent with earlier results on the adoption of climate-resilient crop varieties (Di Falco and Veronesi, 2013; Wang et al., 2022b; Liebenehm et al., 2023) and provide further evidence that farmers respond to extreme heat exposure by both adopting climate-resilient seeds varieties and expanding the area allocated to them (Figari, 2025; Di Falco and Veronesi, 2013; He and

[6] We calculate these percentages by dividing our point estimates by the average baseline (2017) adoption rate and baseline area under adoption.

Chen, 2022).

6.4. Effects of Long-term Exposure to Extreme Heat

So far we have estimated the positive effect of previous season exposure to extreme temperature on the adoption of climate-resilient groundnut varieties and cropland expansion. However, it may be that long term exposure to extreme heat is the primary driver of these behavioral adaptations. We investigate this possibility by constructing a household-specific measure that captures the gradual warming trend experienced by each farmer during the decades preceding the survey. Specifically, we estimate the linear trend in extreme heat over the thirty growing seasons that end immediately before the survey year for every household. For grid cell j and survey year t, we run the separate regression:

$$d_{ijt} = \gamma_{0jt} + \gamma_{1jt} \cdot T + \varepsilon_{jt}, \qquad T = 1, \ldots, 30, \tag{20}$$

where d_{ijt} is the number of days with temperature above 31 °C in growing season of survey year t and T represents a linear time trend for the 30-year window preceding this survey year (1 oldest, 30 most recent). The coefficient $\hat{\gamma}_{1jt}$ measures the average number of additional hot days gained per year during the 30-year window and is stored as $\texttt{LT_trend}_{ij,t-1}$. It varies both across grid cells (cross-sectional heterogeneity in warming speed) and across survey waves (year-to-year updates as the window shifts), providing the variation needed to estimate long-term historical impacts. We then run our parsimonious panel specification in (3) using $\texttt{LT_trend}_{ij,t-1}$ as the main variable of interest:

$$Y_{ijt} = \beta^{Long} \texttt{LT_trend}_{ij,t-1} + X'_{ijt}\gamma_2 + f(\text{rain}_{ij,t-1}) + \mu_i + \delta_t + \varepsilon_{ijt}, \tag{21}$$

β^{Long} measures the change in adoption (or area) when a household's local climate trend adds one additional hot day per year. Table 2 presents estimates with and without our household and rainfall controls. We find results that are consistent with short-term temperature responses. Exposure to extreme heat over the long term significantly increases both the likelihood of adoption and the area allocated to climate-resilient groundnut varieties. These findings highlight the importance of long-term climatic trends in shaping agricultural decision-making. Farmers appear to adjust not only in reaction to recent temperature extremes but also in response to persistent heat exposure over time. This aligns with evidence from other contexts showing that adaptation to climate change is often a gradual process influenced by cumulative exposure (Figari, 2025).

Table 2: Long-Term Effects of Extreme Heat on Adoption and Area under Adoption

	Adoption		Area	
	With Controls	Without Controls	With Controls	Without Controls
Extra ≥31°C days per year (30-yr trend)	0.957**	2.532***	2.155**	3.455***
	(0.480)	(0.449)	(0.982)	(1.037)
Observations	4,076	4,590	4,076	4,590
R-squared	0.079	0.020	0.053	0.021
Additional controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: All columns report household fixed-effects estimates. The explanatory variable is the slope of a regression of the number of days with average temperature ≥ 31 °C in growing season t on a linear time trend estimated separately for each grid cell and survey wave (1987-2016 for 2017, 1988-2017 for 2018, 1989-2018 for 2019). "With Controls" additionally includes lagged rainfall shocks, household size, cooperative membership, training, extension visits, credit access, dependency ratio, land tenure, off-farm income, and farmer's soil-quality perception. Robust standard errors clustered at the 0.05° grid-cell level are shown in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

6.5. Sustained Adoption

One critical concern in the adoption of climate-resilient agricultural technologies is the potential disadoption, where farmers may initially adopt climate-resilient varieties but later discontinue their use (Fentie and Beyene, 2019; Michler et al., 2019; Maggio et al., 2022; Tabe-Ojong et al., 2023b). Disadoption can undermine the long-term effectiveness of these technologies in helping farmers adapt to climate change and may limit the realization of their full benefits (Chinseu et al., 2019). To better understand and probe this issue, we investigate the effect of temperature shocks on sustained adoption, both in terms of the likelihood of continued adoption and the area under adoption for those who adopt consistently. We look at both sustained adoption for two consecutive years as well as three consecutive years. We do this by re-estimating Equation 1 and Equation 2 for the sample of households with two consecutive years of adoption and those with three consecutive years.

Figure 6 presents the results of these estimations, which are also reported in appendix Table A6. Panels A and B show the sustained adoption and cropland expansion for two years following extreme temperatures while Panels C and D show impacts for 3 years sustained adoption. As shown in these figures, extreme temperatures increase the likelihood of both two-year and three-year sustained adoption of climate-resilient crop varieties. We also find evidence of increased cropland expansion among households that adopt for two consecutive years, but we do not observe a statistically significant effect on cropland expansion for those who sustain adoption over three consecutive years.

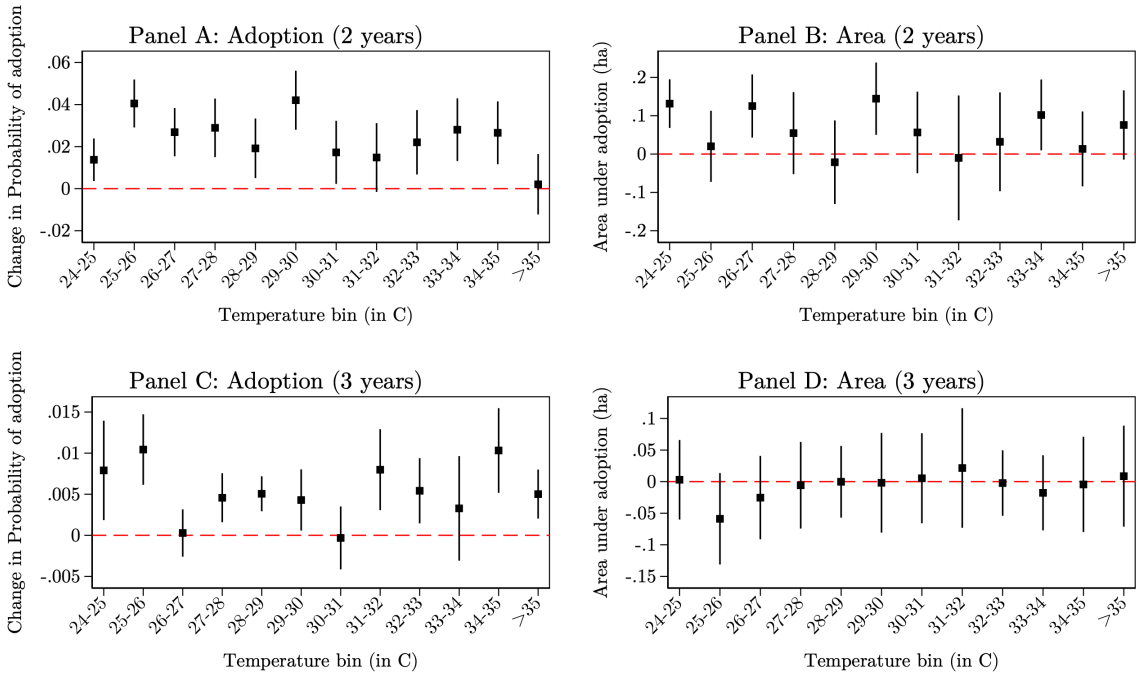


Figure 6: Effects of Temperature Shocks on Sustained Adoption

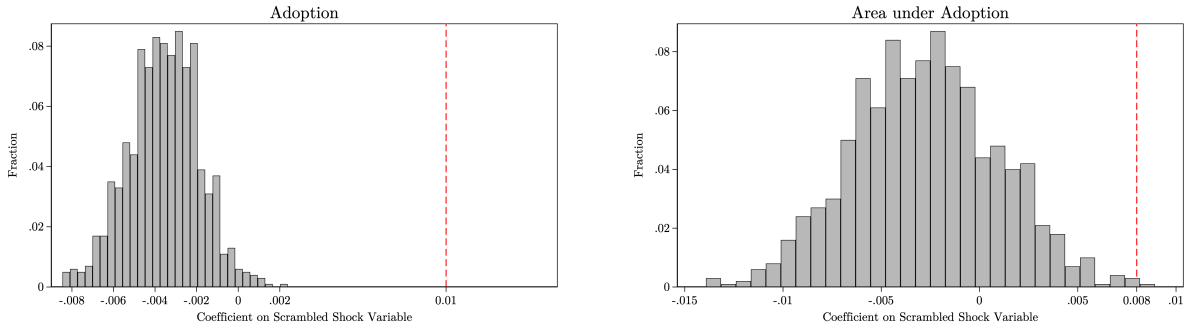
Notes: The graph shows the effects of temperature shocks on the likelihood of sustained adoption (Panel A and Panel C) and on sustained cropland expansion (Panel B and Panel D). Full results are presented in Appendix Table A6. The squares represent the point estimates, and the bars indicate 95% confidence intervals. Controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall shock indicators, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors clustered at the grid level.

Overall, these findings suggest that the experience of extreme heat events not only triggers initial adoption but also encourages farmers to continue using climate-resilient crop varieties for two consecutive growing seasons. Sustained adoption in this case may be crucial for building the resilience of smallholder farming systems to the impacts of climate change and ensuring the long-term food security and livelihoods of rural communities (Lybbert and Sumner, 2012; Rippke et al., 2016).

6.6. Placebo Test

Since our study employs a short three-year panel, we perform a falsification test to validate our findings and verify that the observed effects are indeed attributable to extreme temperature shocks ($T > 31°C$), rather than being driven by spurious year-to-year variation. To conduct this check, we generated 1,000 random sets of the extreme temperature variable. For each set, we randomly reassigned the observed extreme temperature values across time and space (scrambling the data) and then re-estimated the main adoption and area under adoption specifications using

these randomized "placebo" shocks. If our estimated coefficients are robust and truly reflect the impact of extreme heat, the scrambled data should yield results that are statistically insignificant and different from our true estimates. As shown in Figure 7, the resulting coefficients from the 1,000 randomized datasets were smaller and statistically insignificant compared to our main estimates. Critically, our true estimated coefficients lie at the far-right tail of the placebo distribution, meaning they are mostly rare under the null hypothesis of no true effect. The resulting placebo p-values were < 0.001 for adoption and < 0.1 for area under adoption. This suggests significant differences between the true estimates and the placebo distribution, and strengthens our confidence that the observed increase in improved-seed adoption and cropland reallocation of area is a direct and robust response to the extreme heat events.



(a) Adoption

(b) Area under adoption

Figure 7: Placebo tests for extreme heat effects

Notes: This figure reports placebo distributions obtained from 1,000 randomized reassignments of extreme heat exposure across space and time. Panel A shows placebo coefficients for adoption of climate-resilient groundnut varieties, while Panel B shows placebo coefficients for land allocated to these varieties. The vertical line denotes the true estimated coefficient from the parsimonious specification.

6.7. Heterogeneity analysis

6.7.1. Heterogeneity Analysis by Wealth

To better understand factors driving households' adoption and cropland expansion decisions in the face of temperature shocks, we explore heterogeneous effects by wealth level. We classify households as *poor* or *non-poor* based on baseline (2017) per-capita daily income relative to the international extreme poverty line of \$1.90. Using baseline income avoids potential endogeneity concerns that would arise if contemporaneous income were itself affected by temperature shocks. While extreme heat may influence income dynamics over time, temperature exposure in the growing season prior to the survey year is unlikely to affect poverty status measured at baseline.

We estimate the following specification:

$$Y_{ijt} = \alpha_{np} T(>31^{\circ}C)_{ij,t-1} + \alpha_p \left(T(>31^{\circ}C)_{ij,t-1} \times \text{Poor}_i\right) + \alpha_c X_{ijt} + \mu_i + \lambda_t + \varepsilon_{ijt}, \quad (22)$$

where Poor_i is an indicator equal to one for households classified as poor at baseline. In this specification, α_{np} captures the effect of extreme heat for non-poor households, α_p measures the differential response of poor households relative to non-poor households, and $\alpha_{np} + \alpha_p$ gives the implied effect for poor households. We formally test for heterogeneity using the null hypothesis $H_0 : \alpha_p = 0$.

Table 3 reports the results. We find that both poor and non-poor households increase adoption of climate-resilient groundnut varieties in response to extreme heat. The point estimates indicate a larger adoption response among poor households, although the difference is statistically significant at conventional levels only for land allocation. In particular, the area under climate-resilient varieties increases significantly more for poor households than for non-poor households. This pattern suggests that while adoption at the extensive margin responds broadly to heat stress across wealth groups, poor households exhibit a stronger intensive-margin response once adoption occurs. One possible explanation is that poorer households, facing greater vulnerability to yield losses and limited access to formal insurance, rely more heavily on reallocating land toward climate-resilient technologies as a self-insurance mechanism (Dercon and Christiaensen, 2011; Di Falco and Veronesi, 2013). These results are consistent with evidence that climate risk can induce disproportionately strong behavioral responses among more vulnerable households (Deressa et al., 2009; Fentie and Beyene, 2019).

6.7.2. Heterogeneity Analysis by productivity level

To examine whether baseline productive capacity influences farmers' responses to extreme heat, we categorize households into top and bottom terciles based on their baseline groundnut yields. Households in the top tercile are classified as high-productivity and those in the bottom tercile as low-productivity. We then estimate our main specification including an interaction term between extreme heat exposure (days with temperature above 31°C) and an indicator for low-productivity households. presents the results. High-productivity households exhibit significant responses at both the extensive and intensive margins: an additional day above 31°C increases adoption by 1.0 percentage point and expands area under climate-resilient varieties by 1.2 hectares (both significant at the 1% level) (Table 4). In contrast, low-productivity house-

Table 3: Heterogeneous Effects of Extreme Heat by Household Wealth

	Adoption	**Area**
Non-poor	0.0070***	0.0011
	(0.0021)	(0.0041)
Poor	0.0117***	0.0122**
	(0.0034)	(0.0057)
Difference (Poor − Non-poor)	0.0047*	0.0111**
	(0.0027)	(0.0057)
p-value: equality of effects ($H_0 : \alpha_p = 0$)	0.084	0.050
Household fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Additional controls	Yes	Yes
Observations	4,076	4,076

Notes: The table reports heterogeneous effects of extreme heat exposure on adoption of climate-resilient groundnut varieties and land allocated to these varieties. "Extreme heat" is measured as the number of days with average temperature above 31°C during the growing season prior to survey year t. The Non-poor row reports α_{np}, the Poor row reports $\alpha_{np} + \alpha_p$, and the Difference row reports α_p. Robust standard errors clustered at the grid level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

holds show a marginally significant adoption response of 0.7 percentage points, but their area expansion effect of 0.5 hectares is not statistically significant. The formal test indicates that the difference in area expansion between the two groups is statistically significant (though the adoption difference is not).

These findings complement our wealth heterogeneity results and highlight that households with greater productive capacity are better positioned to scale up adoption in response to extreme heat. High-productivity farmers likely possess larger landholdings, stronger financial capacity, and better access to information and input markets, enabling them to expand cultivation of climate-resilient varieties more effectively (Michler et al., 2019; Kassie et al., 2015; Manda et al., 2020; Aragón et al., 2021; Jain et al., 2015). This suggests that while adoption of improved varieties may be relatively accessible across productivity levels, translating adoption into meaningful cropland expansion requires access to complementary resources that are more readily available to high-productivity households.

6.7.3. Heterogeneity by Age

We further explore demographic heterogeneity by examining whether the effects of extreme heat on adoption of climate-resilient groundnut varieties and land allocation differ by the age of the

Table 4: Heterogeneous Effects of Extreme Heat by Productivity Level

	Adoption	**Area**
Higher-productivity (reference)	0.0071***	0.0051*
	(0.0015)	(0.0026)
Low-productivity	0.0159	0.0144
	(0.0024)	(0.0047)
Difference (Low-productivity − Higher-productivity)	0.0088***	0.0093
	(0.0029)	(0.0061)
p-value: equality of effects (H_0 : no difference)	0.002	0.124
Household fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Additional controls	Yes	Yes
Observations	4,076	4,076

Notes: The table reports heterogeneous effects of extreme heat exposure on adoption of climate-resilient groundnut varieties and land allocated to these varieties by baseline productivity level. "Extreme heat" is measured as the number of days with average temperature above 31°C during the growing season prior to survey year t. Higher-productivity households (top tercile of baseline yields) form the reference group. The Low-productivity row reports the implied effect for bottom-tercile households (computed using `lincom`), and the Difference row reports the interaction effect. Robust standard errors clustered at the household level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

household head. Following the African Union's definition, we classify household heads aged 15 to 34 as youth and those older than 34 as adults. Similar to wealth and productivity heterogeneity analysis, we test differential age effects by estimating a pooled regression model that includes an interaction term between extreme heat exposure and a youth indicator variable. Table 5 presents the results. For adult-headed households, exposure to extreme heat is associated with a statistically significant increase in both adoption of climate-resilient groundnut varieties and land allocated to these varieties. For youth-headed households, the corresponding point estimates are positive but not statistically significant for either outcome. Moreover, the differences in estimated effects between youth and adult households are not statistically significant, indicating no evidence of differential responses to extreme heat by age group. These results suggest that age of the household head does not systematically mediate households' adaptation responses to extreme heat in this setting. While younger farmers may face well-documented constraints related to land access or capital, our estimates do not indicate that these constraints translate into significantly different adoption or land allocation responses to climate stress. Instead, the findings point to broadly similar behavioral responses across age groups, with other dimensions of heterogeneity-such as wealth and productive capacity playing a more prominent role in shaping differential adaptation outcomes.

Table 5: Heterogeneous Effects of Extreme Heat by Age Group

	Adoption	**Area**
Adult	0.0096***	0.0068***
	(0.0013)	(0.0022)
Youth	0.0130	0.0168
	(0.0033)	(0.0060)
Difference (Youth − Adult)	0.0034	0.0100
	(0.0035)	(0.0066)
p-value: equality of effects ($H_0 : \alpha_{youth} = 0$)	0.333	0.128
Household fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Additional controls	Yes	Yes
Observations	4,076	4,076

Notes: The table reports heterogeneous effects of extreme heat exposure on adoption of climate-resilient groundnut varieties and land allocated to these varieties by age group. "Extreme heat" is measured as the number of days with average temperature above 31°C during the growing season prior to survey year t. Adults (age >34) form the reference group. The Adult row reports α_{adult}, the Youth row reports $\alpha_{adult} + \alpha_{youth}$, and the Difference row reports α_{youth}. Robust standard errors clustered at the household level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

6.8. Robustness Checks

We conduct several robustness and sensitivity checks to confirm and bolster the validity of our estimates. These checks include alternative model specifications and functional forms, as well as the use of non-linear models. In addition to these checks, we examine alternative definitions of our outcome variables, especially cropland expansion. Finally, to account for potential spatial correlation, we re-estimated our main models using Conley (1999) standard errors.

6.8.1. Alternative Specifications

We test the sensitivity of our results to alternative model specifications by re-estimating Equation 1 using different functional forms. These alternative specifications include variations in how we control for rainfall including a non-linear specification where both rainfall and its squared term from the previous growing season are included. In a separate specification, we exclude all rainfall controls to verify if rainfall can explain away the results. These results are presented in Appendix Figure A3. Panel A shows the results with the quadratic rainfall controls while panel B shows the results when rainfall controls are excluded. In both cases, we find that extreme heat leads to increased adoption of climate-resilient crop varieties and cropland expansion. Last, we re-estimated the binned temperature specification using the median temperature bin (28-29°C) as the reference category. The results remain highly consistent: adoption and area under re-

silient varieties increase sharply in the highest temperature bins, while moderate-temperature bins remain close to zero (Figure A4).

6.8.2. Alternative estimation methods

As a third robustness check, we assess the sensitivity of our results using alternative econometric models. So far, we have relied on linear models to estimate the impacts of extreme temperature on climate-resilient groundnut varieties and cropland expansion. However, the binary and censored nature of our outcome variables suggests that non-linear models may also be appropriate. Given this, we estimate a Probit model for adoption and Tobit model for cropland expansion. For both models we estimate the correlated random effects (CRE) to account for time invariant unobserved heterogeneity. As shown in Appendix Figure A5, our main baseline estimates on the positive impact of extreme temperatures on climate-resilient groundnut varieties and cropland expansion holds. These findings further bolster our main results in the paper.

6.8.3. Alternative measures of adoption

In our main analysis, cropland expansion is measured using the area allocated to climate-resilient groundnut varieties. As a robustness check, we use the share of groundnut area allocated to climate-resilient varieties, rather than the absolute area. Additionally, we leverage data on the area under local (landrace) varieties to investigate whether increased adoption of improved varieties comes at the expense of local ones. Appendix Figure A6 presents these results. We find that exposure to extreme temperatures increases the share of land allocated to climate-resilient groundnut varieties, while reducing the share under landrace varieties. These findings are interesting as they not only confirm the positive impact of extreme temperatures on cropland expansion, but are also indicative of some substitution effects between the climate-resilient seeds and the local seeds. This highlights a potential reallocation of land toward more climate-resilient technologies in the face of extreme heat. We further examine whether extreme heat leads households to adjust their total groundnut cultivation area. As shown in Figure A7, we find that total groundnut cultivation area decreases in response to previous-season extreme temperatures. This finding reinforces our main story: even as farmers reduce their overall exposure to groundnut cultivation under heat stress, they strategically allocate a greater share of their remaining land to the more heat-resilient varieties. Thus, increases in improved-seed adoption are not driven by expansion of groundnut cultivation but by within-crop reallocation toward more heat-tolerant technologies.

6.8.4. Conley Standard Errors

Our final robustness check addresses the potential for spatial correlation in the data. Since the assumption of independence across observations may be violated when geographically proximate households experience similar unobserved shocks, we estimate standard errors using the spatial correction approach proposed by Conley (1999), with distance thresholds of 100 km and 200 km (Appendix Figure A8). The results as shown in Figure A8 are maintained, suggesting that they are robust to spatial correlation. This again, confirms our findings that in response to extreme temperatures, households resort to the adoption of climate-resilient groundnut varieties with implications for cropland expansion.

7. Conclusion

We investigate the impacts of extreme heat on the adoption of climate-resilient groundnut varieties and cropland expansion in Nigeria. Using panel data from a three-wave household survey (2017, 2018, and 2019) combined with high-resolution temperature data, we develop a theoretical framework grounded in agricultural household models under risk and induced innovation theory, and employ fixed effects models to estimate the causal impact of temperature shocks. We show that exposure to extreme heat increases both the likelihood of adopting climate-resilient crop varieties and the area allocated to them. Specifically, an additional day with temperatures above 31°C in the previous growing season increases adoption by 2 percentage points and expands cropland allocated to these varieties by 1.1 percentage points. These findings point to the adaptive nature of households in building resilience to extreme temperature events through behavioral adoption of induced agricultural innovations. Importantly, we find that extreme heat not only drives initial adoption but also promotes sustained adoption over two consecutive years, although the effects on sustained cropland expansion over three years are more limited.

Our heterogeneity analyses yield several important insights into the distributional dimensions of climate adaptation. Regarding wealth, both poor and non-poor households significantly adopt climate-resilient varieties in response to extreme heat, demonstrating broad inclusivity at the extensive margin. However, poor households exhibit significantly larger cropland expansion responses than non-poor households, suggesting they may rely more heavily on land reallocation as a self-insurance mechanism. Similarly, high-productivity farmers respond more strongly than low-productivity farmers at both margins, indicating that productive capacity and access to complementary resources enable more effective scaling of adaptive responses. Demographic analyses by age reveal that while adult-headed households show statistically significant increases in both adoption and land allocation, the estimated effects for youth-headed households are imprecisely estimated and not statistically significant, despite larger point estimates. Formal tests indicate no significant differences between age groups, suggesting that age per se may not be a binding constraint once economic factors are controlled for. These findings suggest that economic constraints such as wealth, productivity, and access to resources, are more consistent determinants of adaptive capacity than demographic characteristics alone, though the two dimensions are often interrelated.

Our findings have important implications for climate change adaptation in the context of small-

holder agriculture. The increase in likelihood of adoption and area under adoption as responses to extreme heat highlights the potential of climate-resilient crop varieties as a key strategy for enhancing the adaptive capacity of smallholder farmers in the face of climate change (Asfaw et al., 2016). As temperatures continue to rise and the frequency and intensity of extreme heat events increase, the development and dissemination of improved varieties that can withstand these harsh conditions will become increasingly crucial. Our findings underscore the importance of policies and interventions that promote the breeding, release, and adoption of such varieties, as well as those that address potential barriers to adoption and area allocation, such as lack of access to information, credit, or input markets. Our findings also imply that policies and interventions should aim to promote a balanced approach that encourages the adoption of improved varieties while also supporting the conservation and sustainable use of local crop diversity.

Moreover, the results highlight the importance of designing policies and interventions that not only promote initial adoption but also support sustained use of climate-resilient technologies. This may involve providing ongoing extension services, facilitating access to inputs and markets, and creating an enabling institutional environment that encourages long-term investment in climate change adaptation (Acevedo et al., 2020). By facilitating the widespread adoption of climate-resilient varieties, these efforts can help build the resilience of smallholder agricultural systems and safeguard the livelihoods of millions of farmers in the face of a changing climate.

References

Acevedo, M., Pixley, K., Zinyengere, N., Meng, S., Tufan, H., Cichy, K., Bizikova, L., Isaacs, K., Ghezzi-Kopel, K., and Porciello, J. (2020). A scoping review of adoption of climate-resilient crops by small-scale producers in low- and middle-income countries. *Nature Plants*, 6(10).

Ajeigbe, H. A., Vabi, M. B., Inuwa, A. H., Abdulazeez, T., and Akinseye, F. M. (2020). *Handbook on improved agronomic practices of groundnut production in north east Nigeria*. USAID Feed the Future Nigeria Integrated Agriculture Activity, International Institute of Tropical Agriculture.

Aragón, F. M., Oteiza, F., and Rud, J. P. (2021). Climate change and agriculture: Subsistence farmers' response to extreme heat. *American Economic Journal: Economic Policy*, 13(1).

Aravind, B., Shreeraksha, R., Poornima, R., Ravichandran, D., Krishnaraj, P., Chimmad, V., Mirajkar, K. K., Bagewadi, B., Janila, P., Pandey, M. K., et al. (2024). Impact of heat stress on physiological characteristics and expression of heat shock proteins (hsps) in groundnut (arachis hypogaea l.). *Physiology and molecular biology of plants*, 30(10):1691–1706.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., and Cattaneo, A. (2014). Adoption and intensity of adoption of conservation farming practices in zambia. *Agriculture, Ecosystems and Environment*, 187.

Asfaw, S., Di Battista, F., and Lipper, L. (2016). Agricultural technology adoption under climate change in the sahel: Micro-evidence from niger. *Journal of African Economies*, 25(5).

Bardhan, P. (2000). Irrigation and cooperation: An empirical analysis of 48 irrigation communities in south india. *Economic Development and cultural change*, 48(4):847–865.

Bareille, F. and Chakir, R. (2023). Structural identification of weather impacts on crop yields: Disentangling agronomic from adaptation effects. *American Journal of Agricultural Economics*.

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural india. *American journal of agricultural economics*, 62(3):395–407.

Blom, S., Ortiz-Bobea, A., and Hoddinott, J. (2022). Heat exposure and child nutrition: Evidence from west africa. *Journal of Environmental Economics and Management*, 115:102698.

Boucher, S. R., Carter, M. R., Flatnes, J. E., Lybbert, T. J., Malacarne, J. G., Mareyna, P. P., and Paul, L. A. (2024). Bundling genetic and financial technologies for more resilient and productive small-scale farmers in africa. *The Economic Journal*, 134(662):2321–2350.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, 8(3).

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.

Byerlee, D. (1996). Modern varieties, productivity, and sustainability: Recent experience and emerging challenges. *World Development*, 24(4):697–718.

Callen, M. (2015). Catastrophes and time preference: Evidence from the indian ocean earthquake. *Journal of Economic Behavior & Organization*, 118:199–214.

Cassar, A., Healy, A., and Von Kessler, C. (2017). Trust, risk, and time preferences after a natural disaster: experimental evidence from thailand. *World Development*, 94:90–105.

Chen, S. and Gong, B. (2021). Response and adaptation of agriculture to climate change: Evidence from china. *Journal of Development Economics*, 148.

Chinseu, E., Dougill, A., and Stringer, L. (2019). Why do smallholder farmers dis-adopt conservation agriculture? insights from malawi. *Land Degradation and Development*, 30(5).

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics*, 92(1).

Craufurd, P., Prasad, P. V., Kakani, V., Wheeler, T., and Nigam, S. (2003). Heat tolerance in groundnut. *Field Crops Research*, 80(1):63–77.

Dercon, S. and Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from ethiopia. *Journal of Development Economics*, 96(2).

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., and Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the nile basin of ethiopia. *Global Environmental Change*, 19(2).

Di Falco, S. and Veronesi, M. (2013). How can african agriculture adapt to climate change? a counterfactual analysis from ethiopia. *Land Economics*, 89(4).

Emerick, K., De Janvry, A., Sadoulet, E., and Dar, M. H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, 106(6):1537–1561.

Fanzo, J., Davis, C., McLaren, R., and Choufani, J. (2018). The effect of climate change across food systems: Implications for nutrition outcomes. *Global food security*, 18:12–19.

Fentie, A. and Beyene, A. D. (2019). Climate-smart agricultural practices and welfare of rural smallholders in ethiopia: Does planting method matter? *Land Use Policy*, 85.

Figari, S. (2025). Climate change response: Input adjustment in agriculture. *Journal of Development Economics*, page 103472.

Foster, A. D. and Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, 2.

Gollin, D., Hansen, C. W., and Wingender, A. M. (2021). Two blades of grass: The impact of the green revolution. *Journal of Political Economy*, 129(8):2344–2384.

He, X. and Chen, Z. (2022). Weather, cropland expansion, and deforestation in ethiopia. *Journal of Environmental Economics and Management*, 111.

IPCC (2022). Climate change 2022: Impacts, adaptation and vulnerability. Technical report. Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.

Jagnani, M., Barrett, C. B., Liu, Y., and You, L. (2021). Within-season producer response to warmer temperatures: Defensive investments by kenyan farmers. *Economic Journal*, 131(633).

Jain, M., Naeem, S., Orlove, B., Modi, V., and DeFries, R. S. (2015). Understanding the causes and consequences of differential decision-making in adaptation research: Adapting to a delayed monsoon onset in gujarat, india. *Global Environmental Change*, 31.

Kakpo, A., Mills, B. F., and Brunelin, S. (2022). Weather shocks and food price seasonality in sub-saharan africa: Evidence from niger. *Food Policy*, 112.

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., and Erenstein, O. (2015). Production risks and food security under alternative technology choices in malawi: Application of a multinomial endogenous switching regression. *Journal of Agricultural Economics*, 66(3).

Kumeh, E. M. and Omulo, G. (2019). Youth's access to agricultural land in sub-saharan africa: A missing link in the global land grabbing discourse. *Land use policy*, 89:104210.

Lai, H., Li, X., Chen, Y., and Liu, Z. (2024). Mitigating heat-induced yield loss in peanut: Insights into 24-epibrassinolide-mediated improvement in antioxidant capacity, photosynthesis, and kernel weight. *Field Crops Research*, 316:109521.

Liebenehm, S., Jaretzky, H., and Waibel, H. (2023). Extreme weather and agricultural management decisions among smallholder farmers in rural thailand and vietnam. *Agricultural Economics (United Kingdom)*, 54(5).

Liu, E. M. (2013). Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in china. *Review of Economics and Statistics*, 95(4):1386–1403.

Lobell, D. B., Bänziger, M., Magorokosho, C., and Vivek, B. (2011a). Nonlinear heat effects on african maize as evidenced by historical yield trials. *Nature climate change*, 1(1):42–45.

Lobell, D. B., Schlenker, W., and Costa-Roberts, J. (2011b). Climate trends and global crop production since 1980. *Science*, 333(6042):616–620.

Lokossou, J. C., Affognon, H. D., Singbo, A., Vabi, M. B., Ogunbayo, A., Tanzubil, P., Segnon, A. C., Muricho, G., Desmae, H., and Ajeigbe, H. (2022). Welfare impacts of improved groundnut varieties adoption and food security implications in the semi-arid areas of west africa. *Food Security*, 14(3).

Lybbert, T. J. and Carter, M. R. (2015). Bundling drought tolerance and index insurance to reduce rural household vulnerability to drought. In *Sustainable economic development*, pages 401–414. Elsevier.

Lybbert, T. J. and Sumner, D. A. (2012). Agricultural technologies for climate change in developing countries: Policy options for innovation and technology diffusion. *Food Policy*, 37(1).

Macours, K. and Vakis, R. (2014). Changing households' investment behaviour through social interactions with local leaders: Evidence from a randomised transfer programme. *The Economic Journal*, 124(576):607–633.

Maggio, G., Mastrorillo, M., and Sitko, N. J. (2022). Adapting to high temperatures: Effect of farm practices and their adoption duration on total value of crop production in uganda. *American Journal of Agricultural Economics*, 104(1).

Manda, J., Khonje, M. G., Alene, A. D., Tufa, A. H., Abdoulaye, T., Mutenje, M., Setimela, P., and Manyong, V. (2020). Does cooperative membership increase and accelerate agricultural

technology adoption? empirical evidence from zambia. *Technological Forecasting and Social Change*, 158.

Mayorga, J., Villacis, A. H., and Mishra, A. K. (2025). Farm-level agricultural productivity and adaptation to extreme heat. *American Journal of Agricultural Economics*.

Meinzen-Dick, R., Quisumbing, A., Doss, C., and Theis, S. (2019). Women's land rights as a pathway to poverty reduction: Framework and review of available evidence. *Agricultural systems*, 172:72–82.

Michler, J. D., Baylis, K., Arends-Kuenning, M., and Mazvimavi, K. (2019). Conservation agriculture and climate resilience. *Journal of Environmental Economics and Management*, 93.

Moscona, J. and Sastry, K. A. (2023). Does directed innovation mitigate climate damage? evidence from us agriculture. *The Quarterly Journal of Economics*, 138(2):637–701.

Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., and Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, 11(4):306–312.

Patterson, D. T., Westbrook, J. K., Joyce, R. J. V., Lingren, P. D., and Rogasik, J. (1999). Weeds, insects, and diseases. *Climatic Change*, 43(4).

Pignède, E. (2025). Who carries the burden of climate change? heterogeneous impact of droughts in sub-saharan africa. *American Journal of Agricultural Economics*.

Quisumbing, A. R., Payongayong, E., Aidoo, J., and Otsuka, K. (2001). Women's land rights in the transition to individualized ownership: Implications for tree-resource management in western ghana. *Economic development and cultural change*, 50(1):157–181.

Rippke, U., Ramirez-Villegas, J., Jarvis, A., Vermeulen, S. J., Parker, L., Mer, F., Diekkrüger, B., Challinor, A. J., and Howden, M. (2016). Timescales of transformational climate change adaptation in sub-saharan african agriculture. *Nature Climate Change*, 6(6).

Rosenzweig, C., Iglesius, A., Epstein, P. R., and Chivian, E. (2001). Climate change and extreme weather events - implications for food production, plant diseases, and pests. *Global Change & Human Health*, 2(2).

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

Simtowe, F., Amondo, E., Marenya, P., Sonder, K., Erenstein, O., et al. (2019). Impacts of drought-tolerant maize varieties on productivity, risk, and resource use: Evidence from uganda. *Land use policy*, 88:104091.

Simtowe, F. and Mausch, K. (2019). Who is quitting? an analysis of the dis-adoption of climate smart sorghum varieties in tanzania. *International Journal of Climate Change Strategies and Management*, 11(3):341–357.

Singh, I., Squire, L., and Strauss, J. (1986). Agricultural household models: Extensions, applications, and policy.

Sitko, N., Cavatassi, R., Staffieri, I., Heesemann, E., Rossi, J., Becerra Valbuena, L., Rajagopalan, P., Kluth, J., and Azzarri, C. (2024). The unjust climate.

Tabe-Ojong, M. P., Aihounton, G. B. D., and Lokossou, J. C. (2023a). Climate-smart agriculture and food security: Cross-country evidence from west africa. *Global Environmental Change*, 81.

Tabe-Ojong, M. P., Smale, M., Jamora, N., and Azevedo, V. (2022). Genebanks and market participation: evidence from groundnut farmers in malawi. *CABI Agriculture and Bioscience*, 3(1).

Tabe-Ojong, M. P. J., Lokossou, J. C., Gebrekidan, B., and Affognon, H. D. (2023b). Adoption of climate-resilient groundnut varieties increases agricultural production, consumption, and smallholder commercialization in west africa. *Nature Communications*, 14(1):5175.

Tambet, H. and Stopnitzky, Y. (2021). Climate adaptation and conservation agriculture among peruvian farmers. *American Journal of Agricultural Economics*, 103(3).

Teklewold, H., Gebrehiwot, T., and Bezabih, M. (2019). Climate smart agricultural practices and gender differentiated nutrition outcome: An empirical evidence from ethiopia. *World Development*, 122.

Vara Prasad, P. V., Craufurd, P. Q., Summerfield, R. J., and Wheeler, T. R. (2000). Effects of short episodes of heat stress on flower production and fruit-set of groundnut (arachis hypogaea l.). *Journal of experimental botany*, 51(345):777–784.

Walker, T. S. and Alwang, J. (2015). *Crop improvement, adoption, and impact of improved varieties in food crops in sub-Saharan Africa*. Cabi.

Wang, J., Zhang, J., and Zhang, P. (2022a). Rising temperature threatens china's cropland. *Environmental Research Letters*, 17(8):084042.

Wang, R., Rejesus, R. M., Tack, J. B., Balagtas, J. V., and Nelson, A. D. (2022b). Quantifying the yield sensitivity of modern rice varieties to warming temperatures: Evidence from the philippines. *American Journal of Agricultural Economics*, 104(1).

Wimmer, S., Stetter, C., Schmitt, J., and Finger, R. (2023). Farm-level responses to weather trends: A structural model. *American Journal of Agricultural Economics*.

Yesuf, M. and Bluffstone, R. A. (2009). Poverty, risk aversion, and path dependence in low-income countries: Experimental evidence from ethiopia. *American Journal of Agricultural Economics*, 91(4):1022–1037.

Zaveri, E., Russ, J., and Damania, R. (2020). Rainfall anomalies are a significant driver of cropland expansion. *Proceedings of the National Academy of Sciences*, 117(19):10225–10233.

Zulu, L. C., Djenontin, I. N., and Grabowski, P. (2021). From diagnosis to action: Understanding youth strengths and hurdles and using decision-making tools to foster youth-inclusive sustainable agriculture intensification. *Journal of Rural Studies*, 82:196–209.

A. Theoretical Framework: Risk–Averse Households

We extend the benchmark risk-neutral model to allow for risk-averse preferences. The stochastic structure, technology, and Assumptions 1–3 remain exactly as before. The household now maximises expected utility of consumption, where the utility index satisfies $u' > 0$, $u'' < 0$. Throughout we impose CARA (constant-absolute-risk-aversion) utility and normally distributed profit shocks. Under these two assumptions the certainty-equivalent (CE) representation of the expected-utility problem is exact and algebraically tractable; all comparative-static predictions obtained under risk neutrality continue to hold, and risk aversion merely strengthens the relative attractiveness of the climate-resilient variety by penalising the higher downside variance of the local variety.

A.1. Model set-up and certainty-equivalent problem

Let the per-hectare profit of variety v be decomposed as

$$\pi_v(\theta) = \mathbb{E}\pi_v(\theta) + \varepsilon_v, \qquad \varepsilon_v \sim \mathcal{N}(0, \sigma_v^2), \quad \mathrm{Cov}(\varepsilon_0, \varepsilon_1) = \sigma_{01}.$$

Assumption 2 (heat-tolerance) implies that the resilient variety has both a higher mean and a lower variance under hotter θ:

$$\frac{\partial\, \mathbb{E}\Delta\pi(\theta)}{\partial\theta} > 0 \quad \text{and} \quad \sigma_1^2 \le \sigma_0^2 \text{ with strict inequality for large } \theta.$$

With CARA utility, $u(C) = -\mathrm{e}^{-\alpha C}$, $\alpha > 0$, the certainty-equivalent of stochastic consumption is:

$$\mathrm{CE}(C) = \mathbb{E}C - \frac{\alpha}{2}\mathrm{Var}(C).$$

Expected utility maximisation is therefore equivalent to maximising

$$\max_{L_0, L_1, E} \; \mathbb{E}[\pi_0(\theta)L_0 + \pi_1(\theta)L_1] - \frac{\alpha}{2}\mathrm{Var}[\pi_0(\theta)L_0 + \pi_1(\theta)L_1] - p_E(E) - F_1\mathbf{1}\{L_1 > 0\} + M$$

subject to the same land constraints (1)–(2). Denote the variance of total profit by

$$\mathrm{Var}(\Pi) = L_0^2\sigma_0^2 + L_1^2\sigma_1^2 + 2L_0L_1\sigma_{01}.$$

The household's objective becomes

$$\max_{L_0,L_1} \underbrace{\mathbb{E}[\pi_0(\theta)]L_0 + \mathbb{E}[\pi_1(\theta)]L_1}_{\text{expected profit}} - \underbrace{\frac{\alpha}{2}\Big(L_0^2\sigma_0^2 + L_1^2\sigma_1^2 + 2L_0L_1\sigma_{01}\Big)}_{\text{risk penalty}} - F_1\mathbf{1}\{L_1 > 0\} + M. \tag{23}$$

Because $\sigma_1^2 < \sigma_0^2$, the risk-penalty term reinforces the mean-profit advantage of the resilient variety. All subsequent steps parallel the risk-neutral derivation, with $\mathbb{E}[\Delta\pi(\theta)]$ replaced by the risk-adjusted profit advantage $\Delta^\alpha\pi(\theta)$, where:

$$\Delta^\alpha\pi(\theta) \equiv \mathbb{E}\Delta\pi(\theta) - \frac{\alpha}{2}\Big[\sigma_1^2 - \sigma_0^2\Big] - \alpha(\sigma_{01} - \sigma_0^2)(1 - s_1)\bar{A},$$

which is strictly increasing in θ under the same Assumption 3.

A.2. Adoption under fixed land (extensive margin)

Set $E = 0$ and define $s_1 = L_1/\bar{A}$. The certainty-equivalent of adoption is:

$$\Pi^{\mathrm{A}}(s_1) = \bar{A}\Big\{\mathbb{E}\pi_0(\theta) + s_1\mathbb{E}\Delta\pi(\theta)\Big\} - \frac{\alpha}{2}\bar{A}^2\Big\{(1-s_1)^2\sigma_0^2 + s_1^2\sigma_1^2 + 2s_1(1-s_1)\sigma_{01}\Big\} - F_1 + M \tag{24}$$

while non-adoption yields

$$\Pi^{\mathrm{N}} = \bar{A}\mathbb{E}\pi_0(\theta) - \frac{\alpha}{2}\bar{A}^2\sigma_0^2 + M.$$

The household adopts if there exists $s_1 \in (0, 1]$ such that $\Pi^{\mathrm{A}}(s_1) \geq \Pi^{\mathrm{N}}$. After simplification the adoption condition becomes:

$$\bar{A}s_1\Big[\mathbb{E}\Delta\pi(\theta) - \frac{\alpha}{2}\bar{A}\big(\sigma_1^2 + \sigma_0^2 - 2\sigma_{01}\big)s_1 + \alpha\bar{A}(\sigma_0^2 - \sigma_{01})\Big] \geq F_1. \tag{25}$$

The left-hand side is strictly larger than the risk-neutral expression $\bar{A}s_1\mathbb{E}\Delta\pi(\theta)$ because $\sigma_0^2 > \sigma_1^2$ and $\sigma_{01} \leq \sigma_0^2$. Hence risk aversion lowers the adoption threshold: the resilient variety is adopted under milder heat exposure than required under risk neutrality.

Proposition 3 (Extreme heat increases adoption under risk aversion) *Under Assumptions 1–3 and CARA-normal shocks, a first-order stochastically dominant shift toward hotter θ increases the probability that condition (25) is satisfied, so the household adopts the resilient variety ($L_1 > 0$).*

A.3. Intensity of adoption and cropland expansion

Conditional on adoption, the household chooses s_1 to maximise (23). The first-order condition yields

$$\frac{\partial \Pi^{\mathrm{A}}}{\partial s_1} = \bar{A}\mathbb{E}\Delta\pi(\theta) - \alpha\bar{A}^2\Big[s_1(\sigma_1^2+\sigma_0^2-2\sigma_{01}) - (\sigma_0^2-\sigma_{01})\Big].$$

Because the second-order condition is negative, the optimal share $s_1^\star$ is interior and satisfies

$$s_1^\star = \frac{\mathbb{E}\Delta\pi(\theta) + \alpha\bar{A}(\sigma_0^2-\sigma_{01})}{\alpha\bar{A}(\sigma_1^2+\sigma_0^2-2\sigma_{01})} \;\in\; (0,1). \tag{26}$$

Equation (26) is strictly increasing in $\mathbb{E}\Delta\pi(\theta)$ and therefore strictly increasing in θ. Consequently, hotter climates raise the optimal land share allocated to the resilient variety even when farmers are risk-averse and land is fixed.

Finally, we re-introduce cropland expansion ($E > 0$). Total land is $A = \bar{A} + E$, and the certainty-equivalent objective (conditional on adoption) is:

$$\Pi^{\mathrm{A}}(s_1) = A\big\{\mathbb{E}\pi_0(\theta)+s_1\Delta\pi(\theta)\big\} - \frac{\alpha}{2}A^2\Big[(1-s_1)^2\sigma_0^2+s_1^2\sigma_1^2+2s_1(1-s_1)\sigma_{01}\Big] - p_E(E) - F_1 + M. \tag{27}$$

Differentiating (27) with respect to s_1 (holding E fixed) gives:

$$\frac{d\Pi^{\mathrm{A}}}{ds_1} = A\mathbb{E}\Delta\pi(\theta) - \alpha A^2\Big[s_1(\sigma_1^2+\sigma_0^2-2\sigma_{01}) - (\sigma_0^2-\sigma_{01})\Big]. \tag{28}$$

Setting (28) equal to zero and solving for s_1 yields the same closed-form solution as in the fixed-land case:

$$s_1^\star = \frac{\mathbb{E}\Delta\pi(\theta) + \alpha A(\sigma_0^2-\sigma_{01})}{\alpha A(\sigma_1^2+\sigma_0^2-2\sigma_{01})}, \quad \text{with} \quad A = \bar{A} + E. \tag{29}$$

Because $\mathbb{E}\Delta\pi(\theta)$ is strictly increasing in θ (Assumption 3) and $A > 0$ is held constant when differentiating (29), we obtain

$$\frac{ds_1^\star}{d\theta} = \frac{1}{\alpha A(\sigma_1^2+\sigma_0^2-2\sigma_{01})}\frac{\partial\mathbb{E}\Delta\pi(\theta)}{\partial\theta} > 0.$$

Therefore **proposition 3** is verified: a hotter climate raises the optimal share of land allocated to the climate-resilient variety even under risk aversion and total cropland expansion.

Table A1: Checking Attrition Bias

	(1)	(2)	(3)
T($>32°$C)	-0.007		-0.006
	(0.006)		(0.007)
Rainfall 2016	-0.003		-0.001
	(0.003)		(0.003)
(Rainfall 2016)^2	0.000		0.000
	(0.000)		(0.000)
Sex of household head (male=1)		0.162	0.149
		(0.421)	(0.421)
Age (years)		0.003	0.003
		(0.006)	(0.006)
Education (years)		0.012	0.011
		(0.012)	(0.012)
Experience in groundnut production (years)		0.003	0.002
		(0.006)	(0.006)
Household size		-0.005	-0.004
		(0.011)	(0.011)
Dependency ratio		-0.055	-0.059
		(0.037)	(0.038)
Access to credit in cash (yes=1)		0.079	0.076
		(0.264)	(0.267)
Access to credit in kind (yes=1)		-0.098	-0.095
		(0.187)	(0.188)
Crop-mixture (1=yes)		0.043	0.037
		(0.117)	(0.120)
Crop rotation (1=yes)		0.182	0.175
		(0.127)	(0.128)
Log household distance to urban market		-0.017	-0.014
		(0.061)	(0.059)
Access to off-farm income (1=yes)		-0.052	-0.052
		(0.144)	(0.145)
Observations	1,600	1,600	1,600

Notes: The table presents results from attrition bias checking. Column (1) includes only weather variables, while Columns (2) and (3) introduce household and farm characteristics. Robust standard errors clustered at the grid level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A2: Summary statistics

	2017		2018		2019		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Adoption (1=yes)	0.49	0.50	0.53	0.50	0.55	0.50	0.52	0.50
Area under adoption (ha)	0.71	0.99	0.69	0.96	0.88	1.11	0.76	1.03
Age of household head (years)	45.14	10.78	46.14	10.78	47.14	10.78	46.14	10.81
Gender of household head (male=1)	0.97	0.16	0.97	0.16	0.97	0.16	0.97	0.16
Household size	8.54	4.48	8.54	4.48	8.68	5.01	8.59	4.66
Membership to Association (1=yes)	0.68	0.99	0.68	0.99	0.50	0.90	0.62	0.96
Training on groundnut farming (1=yes)	0.19	0.39	0.19	0.39	0.31	0.46	0.23	0.42
Number of visits from public extension service	1.70	2.71	1.70	2.71	1.58	1.96	1.66	2.49
Number of visits from private extension service	0.70	1.10	0.70	1.10	0.75	0.99	0.72	1.07
Access to credit (1=yes)	0.02	0.13	0.02	0.13	0.04	0.19	0.02	0.15
Dependency ratio	1.76	1.35	1.76	1.35	1.98	1.70	1.83	1.48
Rented land (1=yes)	0.03	0.18	0.03	0.18	0.04	0.20	0.04	0.18
Access to Off-farm income (1=yes)	0.16	0.36	0.16	0.36	0.21	0.40	0.17	0.38
Negative Rainfall Shock in Year t-1 (1=yes)	0.09	0.29	0.16	0.37	0.00	0.06	0.09	0.28
Positive Rainfall Shock in Year t-1 (1=yes)	0.00	0.05	0.01	0.09	0.35	0.48	0.12	0.33
Farmers' perception of soil quality (1=yes)	0.02	0.14	0.02	0.14	0.06	0.24	0.04	0.19

Table A3: Summary Statistics for Temperature Bins

	2016		2017		2018		Total	
Temperature Bin	Mean	SD	Mean	SD	Mean	SD	Mean	SD
$T^{<24}$	4.48	5.18	4.49	5.63	3.65	4.92	4.21	5.26
T^{24-25}	7.62	6.29	5.85	3.93	8.13	6.99	7.20	5.97
T^{25-26}	14.75	5.79	12.36	5.61	15.97	8.34	14.36	6.86
T^{26-27}	22.05	7.23	21.40	6.98	27.06	4.24	23.50	6.78
T^{27-28}	27.59	5.17	26.72	7.84	25.16	6.02	26.49	6.52
T^{28-29}	22.80	5.63	23.33	7.28	18.20	6.10	21.44	6.77
T^{29-30}	15.46	7.09	18.43	4.78	11.74	2.94	15.21	5.89
T^{30-31}	8.33	4.03	12.04	4.65	9.52	3.25	9.96	4.30
T^{31-32}	8.79	2.12	7.68	2.58	9.19	2.60	8.55	2.52
T^{32-33}	7.69	2.88	8.19	2.28	9.59	1.86	8.49	2.51
T^{33-34}	6.56	4.19	6.57	2.08	7.39	4.02	6.84	3.58
T^{34-35}	2.78	2.97	4.02	2.94	4.86	4.46	3.89	3.63
$T^{>35}$	4.10	7.73	1.92	7.11	2.55	7.00	2.85	7.34

Notes: The table shows the average number of days per temperature bin in the growing seasons prior to each survey year and for the full sample. Bins are constructed such that the upper limit is excluded from the range of possible temperature values. For instance, a day with average temperature of $25°C$ falls in the $25 - 26°C$ bin and not in the $24 - 25°C$ range.

Table A4: Summary Statistics for number of days with temperature over 31°C

	2017		2018		2019		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
T($>31°$ C)	29.92	10.18	28.39	9.91	33.57	9.74	30.63	10.18

Notes: The table shows the average number of days with temperature above 31°C for the growing seasons prior to each survey year and for the full sample.

Table A5: Effects of Previous-Season Temperature Shocks on Adoption and Cropland Expansion

	Previous Season Shocks	
	Adoption	Area
T^{24-25}	0.025***	0.028*
	(0.007)	(0.014)
T^{25-26}	0.004	-0.008
	(0.007)	(0.015)
T^{26-27}	0.008	-0.010
	(0.007)	(0.016)
T^{27-28}	0.022***	0.018
	(0.008)	(0.019)
T^{28-29}	0.017**	0.004
	(0.007)	(0.016)
T^{29-30}	0.008	-0.001
	(0.008)	(0.018)
T^{30-31}	0.007	-0.012
	(0.009)	(0.019)
T^{31-32}	0.037***	0.035*
	(0.010)	(0.021)
T^{32-33}	0.032***	0.031**
	(0.008)	(0.015)
T^{33-34}	0.041***	0.033*
	(0.008)	(0.017)
T^{34-35}	0.033***	0.011
	(0.008)	(0.017)
$T^{>35}$	0.014*	-0.003
	(0.008)	(0.018)
Observations	4,076	4,076
R-squared	0.114	0.071
Household controls	Yes	Yes
Rainfall controls	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes

Notes: This table reports the effects of previous growing season temperature shocks on the adoption of climate-resilient groundnut varieties and the area allocated to these varieties. T^{24-25}, T^{25-26}, ..., $T^{>35}$ denote the number of days with average daily temperature falling within each bin during the previous growing season, with the omitted category being the median temperature bin. All regressions include household-level controls, rainfall controls, household fixed effects, and year fixed effects. Robust standard errors clustered at the grid level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A6: Effect of Extreme Temperature Shocks on Sustained Adoption

	2 Years		**3 Years**	
	Adoption	Area	Adoption	Area
T^{24-25}	0.014***	0.132***	0.008**	0.003
	(0.005)	(0.032)	(0.003)	(0.032)
T^{25-26}	0.041***	0.020	0.010***	-0.059
	(0.006)	(0.047)	(0.002)	(0.037)
T^{26-27}	0.027***	0.125***	0.000	-0.025
	(0.006)	(0.042)	(0.001)	(0.034)
T^{27-28}	0.029***	0.055	0.005***	-0.006
	(0.007)	(0.055)	(0.002)	(0.035)
T^{28-29}	0.019***	-0.021	0.005***	-0.000
	(0.007)	(0.056)	(0.001)	(0.029)
T^{29-30}	0.042***	0.144***	0.004**	-0.002
	(0.007)	(0.048)	(0.002)	(0.040)
T^{30-31}	0.017**	0.056	-0.000	0.005
	(0.008)	(0.054)	(0.002)	(0.036)
T^{31-32}	0.015*	-0.010	0.008***	0.022
	(0.008)	(0.083)	(0.003)	(0.048)
T^{32-33}	0.022***	0.032	0.005***	-0.002
	(0.008)	(0.066)	(0.002)	(0.026)
T^{33-34}	0.028***	0.102**	0.003	-0.018
	(0.008)	(0.047)	(0.003)	(0.030)
T^{34-35}	0.027***	0.013	0.010***	-0.004
	(0.008)	(0.050)	(0.003)	(0.038)
$T^{>35}$	0.002	0.076	0.005***	0.009
	(0.007)	(0.046)	(0.002)	(0.041)
Observations	4,076	907	4,076	1,210
R-squared	0.435	0.489	0.333	0.099
Household controls	Yes	Yes	Yes	Yes
Rainfall controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table shows the effects of temperature shocks on sustained adoption. T^{24-25}, T^{25-26}, ..., $T^{>35}$ represent the number of days with average daily temperature within that bin. Columns 1 and 2 show the effects for households with two consecutive years of adoption, while columns 3 and 4 show the effects for households with three consecutive years of adoption. All regressions include controls, household and year fixed-effects and year fixed effects. Robust standard errors clustered at the grid level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

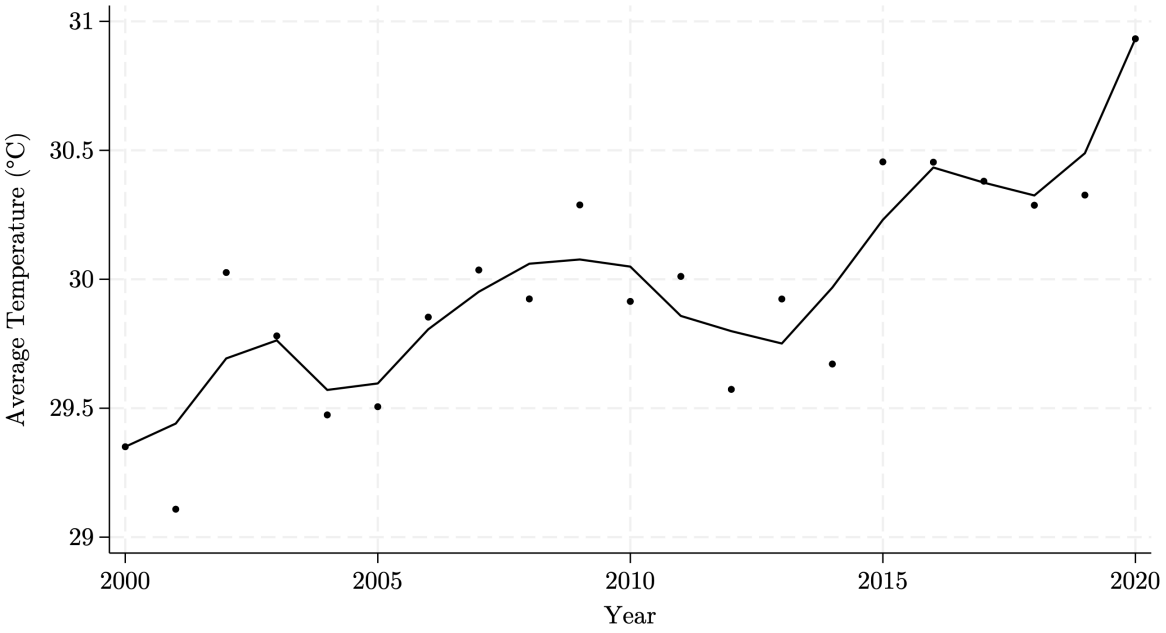


Figure A1: Trend of Average Temperature (2000-2020)

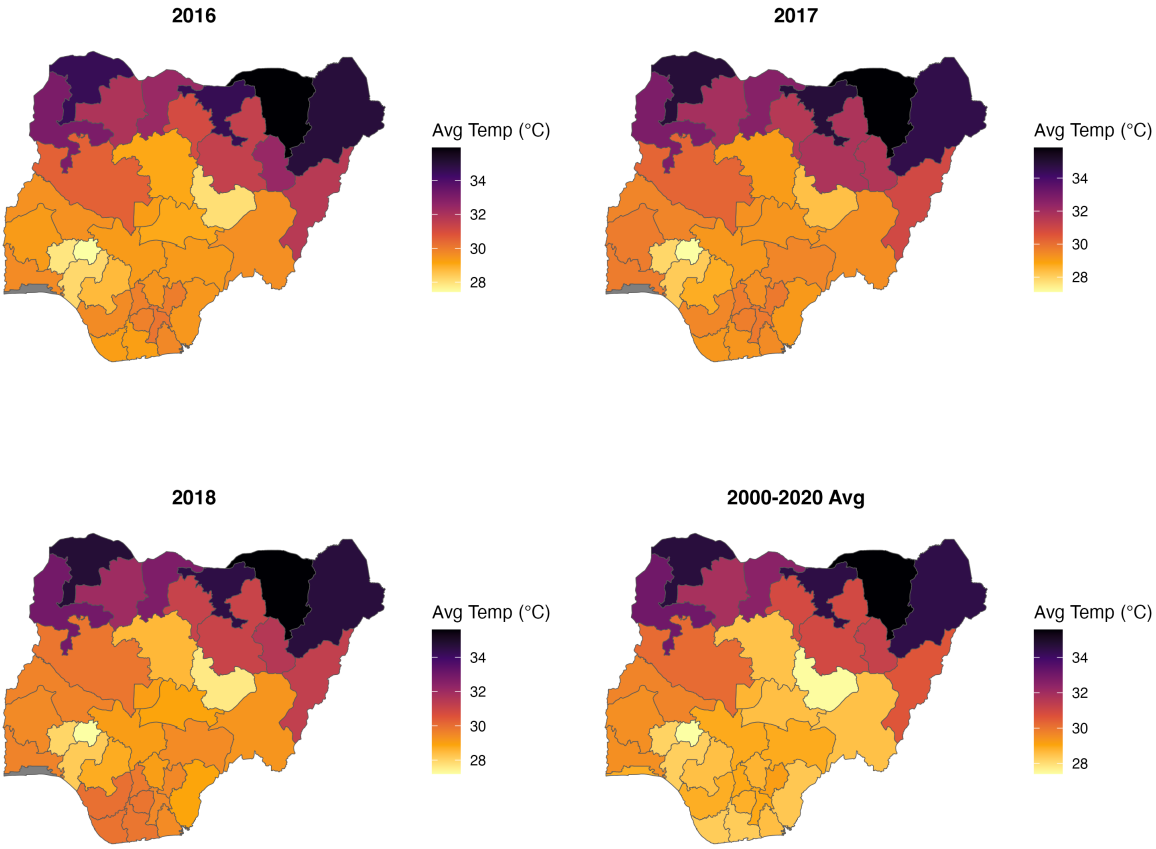


Figure A2: Spatial Distribution of Average Temperature (2000-2020)

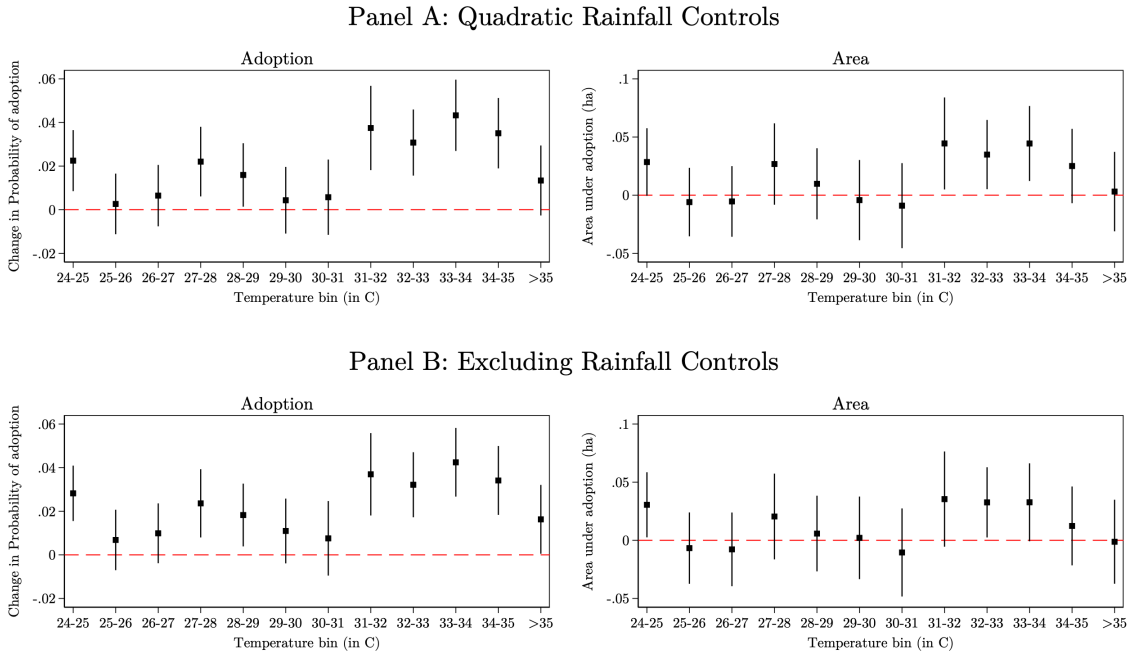


Figure A3: Robustness Checks: Alternative Specifications

Notes: This graph shows robustness results using alternative specifications. Panel A shows the results for a specification that includes quadratic rainfall measures, and Panel B shows specifications that exclude rainfall controls altogether. The squares represent point estimates and the bars are 95% confidence intervals. Additional controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall shock indicators, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors are clustered at the grid level.

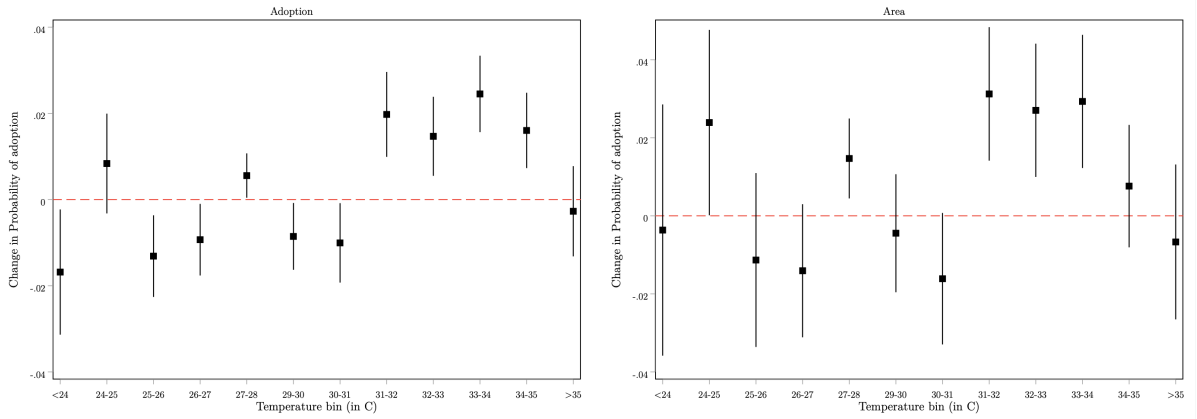


Figure A4: Using the Median Temperature bin (28 - 29 C) as Baseline

Notes: This figure reports coefficient estimates from the binned temperature specification using the median temperature bin (28–29 °C) as the reference category. The outcome variables are (Panel A) adoption of climate-resilient groundnut varieties and (Panel B) area allocated to these varieties. Each point represents the estimated effect of exposure to a given temperature bin relative to the 28–29 °C bin, with vertical bars denoting 95% confidence intervals. The estimates show that both adoption and area under resilient varieties increase sharply at higher temperature ranges, while effects at moderate temperatures remain close to zero, confirming that the main results are not driven by the choice of baseline bin.

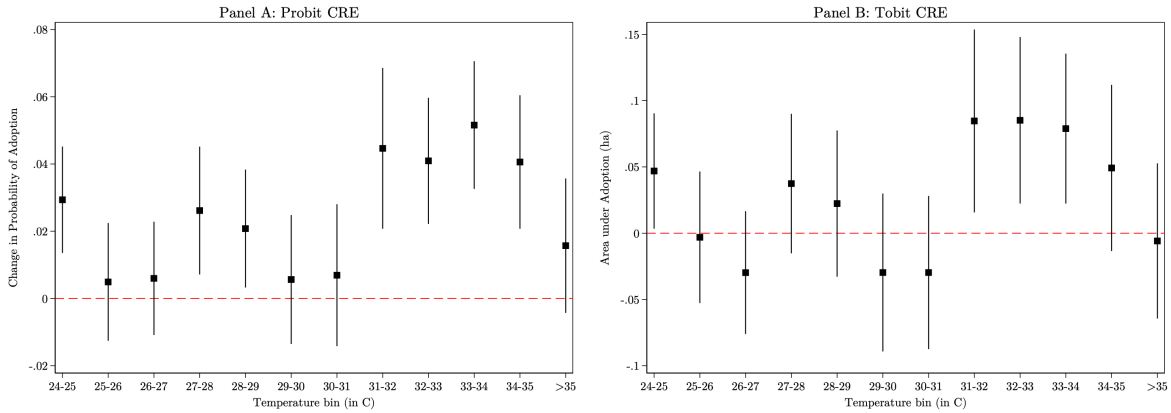


Figure A5: Alternative Estimation Methods – Probit CRE and Tobit CRE

Notes: This graph shows robustness results using alternative estimation methods. Panel A shows adoption results using the Probit CRE estimator and Panel B shows area results using the Tobit CRE estimator. The squares represent point estimates and the bars are 95% confidence intervals. Additional controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall shock indicators, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors are clustered at the grid level.

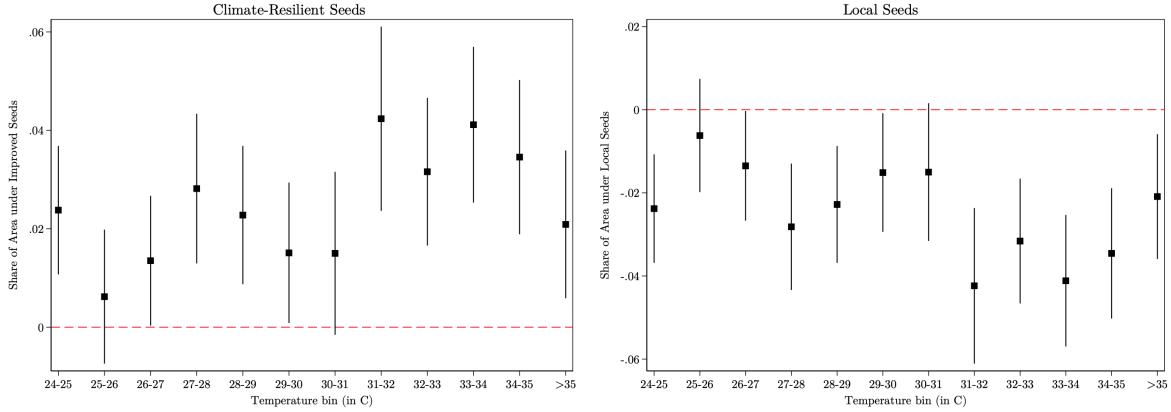


Figure A6: Robustness: Share of land allocated to climate-resilient seeds

Notes: This graph shows the effects of temperature shocks on the share of land allocated to climate-resilient seeds (Panel A) and the share of land allocated to local varieties (Panel B). The squares represent the point estimates, and the bars indicates 95% confidence intervals. Additional controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall shock indicators, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors are clustered at the grid level.

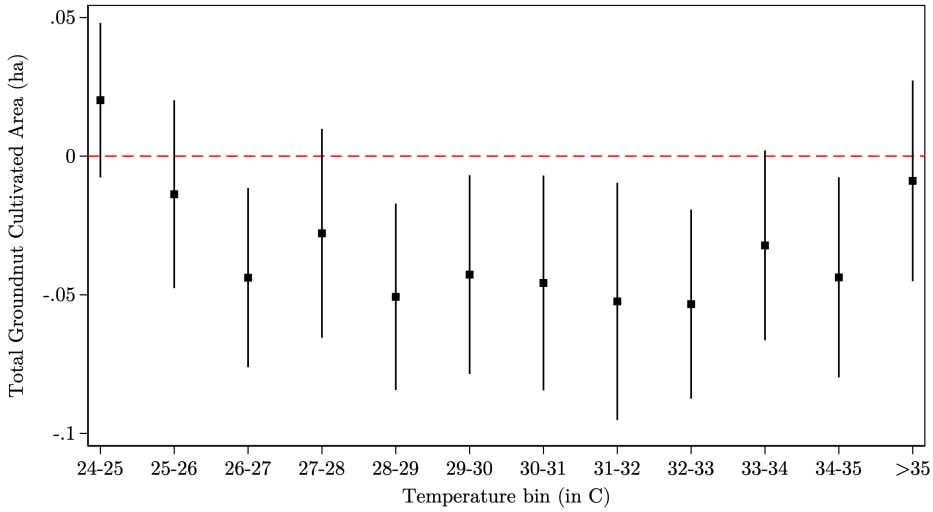


Figure A7: Effects of Extreme Heat on Total Groundnut Area

Notes: This graph shows the effects of temperature shocks on total groundnut cultivated area. The squares represent the point estimates, and the bars indicates 95% confidence intervals. Additional controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall shock indicators, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors are clustered at the grid level.

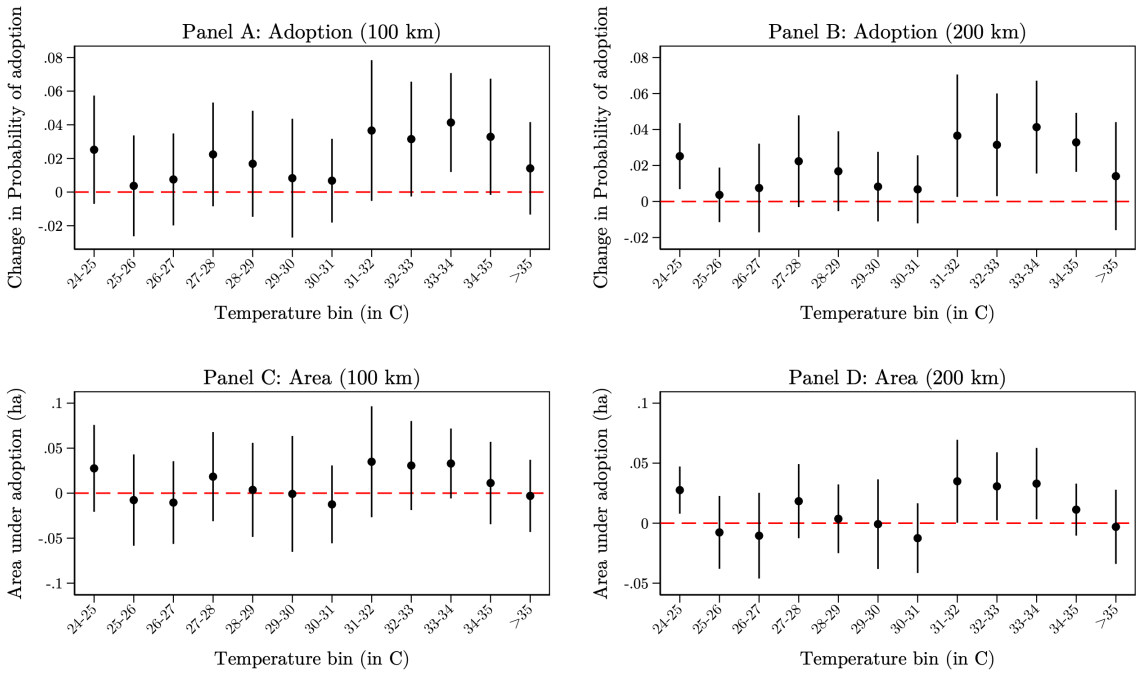


Figure A8: Conley Standard Errors

Notes: This graph shows robustness results using the Conley (1999) standard errors at 100 km distance thresholds (Panel A and Panel C) and 200 km distance thresholds (Panel B and Panel D). The squares represent the point estimates, and the bars indicates 95% confidence intervals. Additional controls include household size, cooperative membership, training in groundnut production, number of visits from public extension agents, number of visits from private extension agents, access to credit, dependency ratio, land tenure, access to off-farm income, positive and negative rainfall shock indicators, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors are clustered at the grid level.