Adapting to High Temperatures? The Increased Use of Climate-Resilient Crop Varieties in West Africa

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Abstract

This study investigates the impact of extreme temperatures on the adoption of climate-resilient groundnut varieties among smallholder farmers in West Africa. Using household panel data from Ghana, Mali, and Nigeria, matched with high-resolution temperature data, we show that exposure to extreme heat, measured by extreme heat degree days (EHDDs) increases the probability of adoption and area under adoption of climate-resilient groundnut varieties. This adaptive response is accompanied by a reduction in land allocated to non-improved varieties. Conversely, exposure to optimal growing temperatures reduces adoption and area under adoption. Heterogeneity analysis shows the strongest impacts in Nigeria, and among non-poor and low production farmers. Moreover, we find that extreme heat increases the likelihood of sustained adoption and the area under adoption for sustained adopters, indicating the importance of promoting long-term use of climate-resilient varieties. These findings are robust to alternative specifications, estimation methods, and measures of adoption.

Keywords: High temperatures, Climate Resilient, Groundnut, West Africa
JEL Codes: O13, Q12, Q15.

1. Introduction

Climate change and extreme weather events continue to be important development and environmental challenges plaguing societies. Its effects are quite widespread with visible impacts on the agricultural sector. Here, extreme weather events have been shown to reduce agricultural production (Kakpo et al., 2022) with ensuing implications on food security and livelihoods. Given this, there is a push for adaptation but also mitigation in the agricultural sector through the promotion of climate-smart agriculture (Tabe-Ojong et al., 2023a). Despite some efforts, it is not entirely clear how households adapt to extreme weather and whether they rely on some of these climate-smart agricultural practices especially through the use of inputs especially climate-resilient crop varieties that are developed to be resistant to extreme temperatures and also to pests and diseases. So far, the literature on the impact of extreme weather events is replete with analysis on yields and profits (Sesmero et al., 2017; Maggio et al., 2021; Wing et al., 2021), child nutrition (Blom et al., 2022), as well as risks (Liebenehm et al., 2024), prices (Letta et al., 2022), and market resilience of food supply chains (Hadachek et al., 2024).

We investigate the impacts of extreme temperatures on the adoption of climate-resilient groundnut varieties. We compute different measures of extreme weather (extreme heat degree days (EHDDs) and growing heat degree days (GDDs). By adoption of climate-resilient groundnut varieties, we examine both extensive and intensive margins where we look at both the dichotomous measure of adoption and the extent of adoption. The intensive margin speaks to aspects of land use and expanding crop land. Here, we also estimate some substitution effects by looking at the area of land under landrace and local varieties. Given the reported dis-adoption of some of these climate-resilient crop varieties, we also examine aspects of sustained adoption by looking at how high temperatures could push households to continuously adopt these climate-resilient seeds.

In the interest of explaining these relationships, we perform some heterogeneity analysis where we look at two different sub-groups: poor vs non poor and low production vs high production. Moreover, we conduct a cross-country analysis to examine differences in adoption impacts across the three countries in our sample. We rely on a rich farm household survey from three countries in West Africa: Ghana, Mali, and Nigeria and link this with geospatial weather data. Given the panel nature of our data, we specify different panel data estimators including the Mundlak-Chamberlain device and the household fixed effect estimator. Our identification strategy exploits plausibly quasi-random variations in the distribution of extreme temperatures across space and time. We find that extreme heat measured through EHDDs significantly increases the adoption of climate-resilient groundnut varieties both at the extensive and intensive margins. Specifically, an extra extreme heat degree day in the previous growing season increases the probability of adopting climate resilient groundnut varieties by 0.5 percentage point.

Extreme temperatures also increase the area under these climate-resilient groundnut varieties. An additional EHDD leads to a 1.13% increase in the area under improved varieties. Relatedly, we observe some substitution effects between the area of land under these climate-resilient groundnut varieties and the land under landrace and local varieties. We observe a reduction in land under landrace and local varieties under extreme temperatures. Similarly, we also compute the growing degree days (GDDs) which represents the most ideal temperatures under which groundnut is grown for optimum production. Under this scenario, we find opposing and inverse results suggesting that farmers may not use these climate-resilient varieties under optimum growing conditions. These point to the adaptive role of these climate-resilient varieties as households are using them to respond to extreme weather events.

Our heterogeneity analysis reveals some interesting insights. The cross-country analysis shows the strongest impacts of extreme heat on adoption in Nigeria, followed by Ghana and Mali. Impacts by wealth status indicate both poor and non-poor households increase adoption in response to extreme heat, with stronger effects for non-poor households. By production level, we find larger impacts on adoption for low production households but larger impacts on area for high production households. We also conduct several robustness checks and show that our findings are robust to different identification strategies, estimation models and different measures of extreme temperatures including exposure to extreme temperatures in the pre-planting period.

Our paper adds and contributes to a growing literature on climate change adaptation in agriculture, specifically to climate-smart agriculture in several ways. First, we show that households respond to extreme temperatures by relying on the adoption of climate-resilient groundnut varieties, a typical climate-smart agricultural practices. The relationship between climate change and input use is often overlooked as the focus seems to be more on yields and profits which are not aspects of adaptation. Here, we look at input use and highlight that households are indeed responding to climate change. Most of the existing studies on adapting to extreme weather and shocks have been limited to fertilizers and pesticides which are growing season or within season adaptation practices

(Bareille & Chakir, 2023; Jagnani et al., 2021; Liebenehm et al., 2023b; Maggio et al., 2022; Tambet & Stopnitzky, 2021; Wimmer et al., 2023). Our focus on climate-resilient seeds is different as their use is influenced by previous extreme weather shocks since farmers makes their current seed decisions based on previous shocks. To our knowledge, only Liebenehm et al., (2023) and Wang et al., (2022) 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 that some of the adaptation of households involves 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 where this land expansion is coming from, but it could potentially stem from land reallocation or from increased deforestation. Previous studies have found evidence of such land reallocation and deforestation mechanisms (Aragón et al., 2021; He & Chen, 2022). Our addition here is in showing that negative temperature shocks could induce greater land expansion for 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. The third contribution relates to the observed substitution effects as households are reducing the area of land under landrace/ local varieties to increase the land under these climate-resilient varieties. These substitution effects critically reflect the decision making of farm households but more importantly that households are adapting to extreme temperature shocks through land reallocation.

The fourth contribution relates to the heterogeneity analysis. Here, we explore how the impacts of extreme heat on adoption and area under adoption vary across different subgroups of farmers, categorized by income, production level, education, and age. The heterogeneity analysis shows that the adoption impacts of extreme temperature events are inclusive irrespective of the wealth and production level of the household. The fifth contribution stems from the focus of groundnuts, a legume which has been described as pro-poor and environmentally friendly with the potentials to stir agricultural transformation while simultaneously increasing consumption and food and nutrition security (Tabe-Ojong et al., 2023b). Groundnut is an important stale 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 food security situation in the region, which is both caused by climate change through droughts, the use of climate-resilient groundnut varieties could address these food security issues and improve the livelihoods of smallholder farmers. The final contribution is about the cross-country analysis where we move beyond a single case study to look at three different countries in the region. Most of the existing studies usually focus on just single countries which makes generalization difficult. We bridge this gap by relying on three countries which significantly pushes up our external validity. Akin to this, we also have panel data which enables us to control for unobserved heterogeneity. Moreover, we have geo-referenced data that we merge with weather data from satellite imagery enabling us to move towards causality as we assume plausibly quasi-random variations in the distribution of extreme temperatures across space and time. Our focus on West Africa is also worth mentioning as it is one of the historical warm areas of Africa where maximum temperatures average about 32°C and with high risks of experience intense heat waves (Blom et al., 2022).

2. Context and conceptualization

To structure our understanding of the relationship between extreme temperatures and the adoption of climate-resilient crop varieties, we present a brief conceptual framework where we highlight how households may behaviorally adapt to extreme weather events and what guides this decision. We also explore some of the traits and characteristics of these climate-resilient varieties that make them suited for building adaptation to extreme temperature events. Specifically, we look at how these climate-resilient groundnut varieties are bred to respond to both biotic and abiotic stress. By biotic stress, we refer to stresses that arise from other living organisms such as insects, weeds, fungi, viruses, and pests. Abiotic stress on the other hand refers to environmental stresses such as extreme temperatures, soil salinity and droughts. In many cases, abiotic and biotic stresses are related such that one can be seen as an explanatory mechanism of the other. For instance, extreme weather events could cause the buildup of pests and diseases which could affect plants (Patterson et al., 1999; Rosenzweig et al., 2001).

The climate-resilient varieties we study are different improved varieties that have been developed and disseminated by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) as part of the USAID's Feed the Future program, the Gates Foundation-funded Tropical Legumes I, II, and III projects, and the recent USAID-funded groundnut upscaling project from 2015–2019. Some of these varieties include Samnut 22, Yenyawoso, and Nkatiesari in Ghana;

ICGV 86124 (Niètatiga), ICGV 86015 (Yriwatiga), ICGV 86024 (Bonitiga), and Fleur 11 (Allason) in Mali; and Samnut 23, Samnut 24, Samnut 25, and Samnut 26 in Nigeria (Ajeigbe et al., 2020). These climate-resilient groundnut varieties are considerable different from landraces as they have specialized traits and characteristics that enable them 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 (Tabe-Ojong et al., 2023c); and (3) they are high yielding with ensuing implications for food security (Lokossou et al., 2022). Beyond this biotic and abiotic characteristic, they also have other special characteristics that make them attractive to smallholder households. First, some of these climate-resilient seeds have special market characteristics like better and bigger seed sizes with more nutrient and nutrition security implications (Tabe-Ojong et al., 2022). Talking about market related traits, these climate-resilient groundnut varieties have other production associated traits such as early maturation, easy blanching and harvesting and high shelling percentage and high oil extraction rate.

The adoption of climate-resilient crop varieties as a behavioral adaptation to climate change can be regarded as both an ex-ante and an ex-post strategy. It could be ex-ante in the case when households adopt these climate-resilient crop varieties in response to previous extreme temperature and droughts. In this case, households also undertake land (re)allocation decisions by changing the crop allocation decisions of different crops but also the different varieties of the crops (Kusunose et al., 2020; Liebenehm et al., 2023). In contrast, one could also view the adoption of climate-resilient groundnut varieties as an ex-post response if we assume that farmers will only use these climate-resilient varieties after experiencing the deleterious effect of extreme temperatures and droughts, keeping everything constant. In this sense, adaptation can be looked upon as a risk reduction strategy where households self-insure themselves against potential extreme temperature events to avert livelihood losses.

Given the yield related traits as well as the pest and disease tolerance of these climate-resilient varieties, we expect these groundnut varieties to be increasingly adopted under extreme temperatures and drought as a means of increasing agricultural productivity. Of course, increasing agricultural productivity under extreme temperatures and droughts also requires investments in other productive investments such as fertilizers as well as defensive investments such pesticides

(Jagnani et al., 2021). However, the climate-resilient seeds have some of these traits such as being resistant to pests and diseases especially the groundnut rosette virus and aflatoxin. In terms of productivity, they are high yielding and even important for soil fertility and soil health. Being a legume, groundnut is important for the synthesis of atmospheric nitrogen and making nitrogen available both for itself and other crops through biological nitrogen fixation.

3. Data

3.1. Farm household Data

Our analysis draws from a rich panel dataset, spanning the years 2017 through 2019, collected from households in Ghana, Mali, and Nigeria. The survey was launched in 2017 with an extensive outreach, involving 900 households in Ghana, 1,350 in Mali, and 2,500 in Nigeria. As the study progressed, financial and stability concerns, notably in the Mopti region of Mali, necessitated the reduction of the sample sizes. This strategic adjustment led to a final collection of data from 498 households in Ghana, 840 in Mali, and 1,530 in Nigeria for the conclusive phase of the project. Despite the hurdles faced, the survey succeeded in sustaining low attrition rates in all three countries – 8% in Ghana, 7% in Mali, and 4% in Nigeria. Despite these low attrition rates, we estimated some attrition probit regressions where we show that attrition is not an issue with the analysis. The final dataset involves a total of 2,868 households giving a sample size of 8,604 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.

3.2. Weather Data

We match the household panel data 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 NOAA PSL. Minimum and maximum temperature values are extracted at the district level[2] and used to determine exposure to harmful and optimal temperatures by generating the extreme heat degree days (EHDD) and the growing degree days (GDD) for the growing season prior to each survey year. EHDD measures

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

[2] We were unable to collect temperature data at the household level since we did not have information on household GPS locations. Although our data is at the household level, households living in the same district experience similar temperature shocks due to the idiosyncratic nature of climate anomalies. As such, we expect district-level temperature shocks to produce similar results as household level ones.

the cumulative amount of time temperature exceeds a given threshold (we use 32°C[3] as the threshold for the EHDD for our analysis), whereas GDD measures the cumulative exposure to temperatures within the optimal range for crop growth. We also measure exposure to precipitation using the cumulative rainfall during the previous growing season and its square. Rainfall data comes from the Climate Hazards Group InfraRed Precipitation (CHIRPS)[4] and is collected at the 0.05x0.05 degree resolution. Although some regions in Ghana and Nigeria have two rainy seasons, we adopted the May-September period as the relevant growing season for this study, as most of our households live in the northern part of these countries (Appendix Figure A1), where only one rainy season (that begins in May and lasts until September) prevails. Similarly, Mali only experiences one rainy season, spanning from May to September.

Figure 1 depicts the distribution of daily temperature by year (panel a) and by country (panel b). The figure shows there is ample variability in daily temperature across years and countries. Nigeria exhibits the greatest variability in temperature, with peak percentages spanning temperature ranges of 26-30°C. In contrast, Ghana has the highest, sharpest peak around 28-29°C, indicating this is the most frequent and consistent temperature range for the country. Mali falls somewhere in between, with discernible peaks but exhibiting more variability than Ghana. These differences suggest varying degrees of temperature fluctuations experienced across the different geographic regions and time periods in our sample. Notably, the most frequent temperatures hover around 28-30°C across countries and years, demonstrating how households in our sample might be subject to very high temperatures on a regular basis.

Panel a: By year   *Panel b*: By country

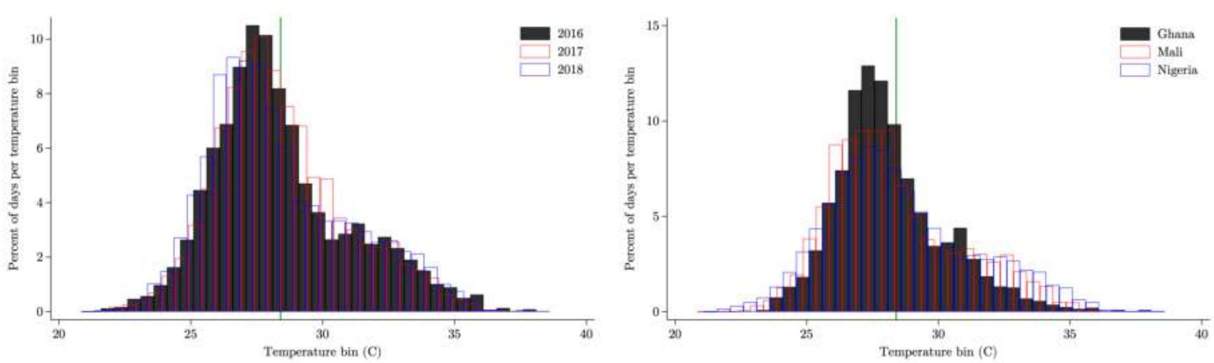

Figure 1: Distribution of daily temperature by year and by country

[3] See section 4.1 for a complete description of the approach used to determine this threshold.
[4] https://data.chc.ucsb.edu/products/CHIRPS-2.0/

Notes: Panel a displays the distribution of daily temperatures over time and Panel b displays the distribution of daily temperatures across the three countries. Each bar represents the percentage of days falling within a one-degree Celsius temperature bin. The green vertical line represents the average temperature in our sample (28 °C).

To further examine the extent of exposure to extreme heat across countries and over time, we calculate the average EHDD for each country and year in our sample, shown in Figure 2. Over the years, Nigeria consistently experienced the highest average EHDD values, followed by Mali and Ghana. Ghana's average EHDD remained relatively stable across the years, while Mali showed more fluctuations. In contrast, Nigeria's average EHDD increased from 2017 to 2019. This suggests that, on average, Nigerian households in the sample were exposed to more intense and increasing extreme heat over the years compared to those in Ghana and Mali.

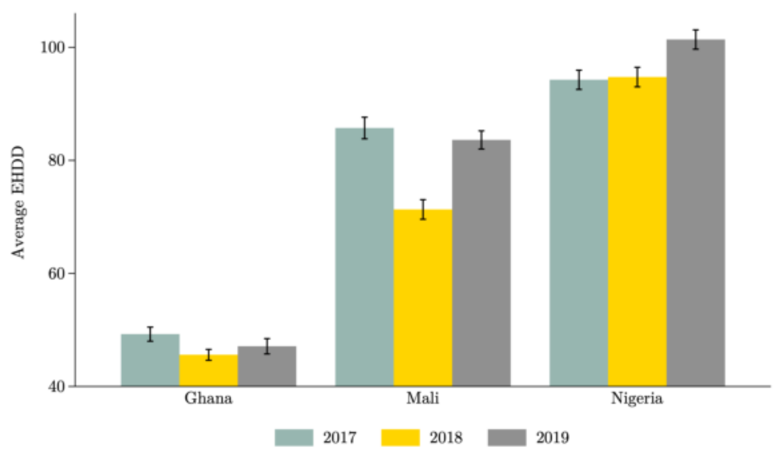

Figure 2: Average EHDD by country and year

Notes: Each thick bar represents the average EHDD in a given country by year. The black thin bars shows 95% confidence intervals. The EHDD is calculated using 32°C as threshold for harmful temperature.

Table 1 presents summary statistics for the variables included in the analysis. Panel A shows the outcome variables related to groundnut adoption: an indicator variable used to measure the adoption decision, the area cultivated with improved groundnut varieties, which measures the intensity of adoption and an alternative measure of the adoption decision: willingness to adopt improved seeds.

On average, 39% of households adopted improved groundnut seeds, with adoption rates increasing from 37% in 2017 to 42% in 2019. The mean area under improved seeds is 0.55 hectares, also increasing over time. Willingness to adopt fluctuated, from 45% in 2017 down to 33% in 2018 and back up to 46% in 2019. Panel B summarizes key weather variables. Extreme Heat Degree Days (EHDD) averaged 83 over the full sample but declined from 2017-2019. Growing Degree Days

(GDD), averaged 900 and saw an inverted U-shape over time. Mean rainfall was 789 mm, dipping in 2018 but rebounding to the highest level in 2019 at 886 mm.

Table 1: Summary statistics

	2017 (N=2,868)	2018 (N=2,868)	2019 (N=2,868)	Total (N=8,604)
Panel A: Outcome Variables				
Adoption (1=yes)	0.37	0.38	0.42	0.39
	(0.48)	(0.49)	(0.49)	(0.49)
Area under improved seeds (ha)	0.53	0.52	0.60	0.55
	(1.04)	(1.04)	(1.01)	(1.03)
Willingness to adopt	0.45	0.33	0.46	0.41
	(0.50)	(0.47)	(0.50)	(0.49)
Panel B: Weather Variables				
EHDD	83.94	79.35	86.76	83.35
	(33.90)	(34.52)	(34.91)	(34.57)
GDD	902.66	910.53	887.20	900.13
	(80.19)	(71.48)	(72.73)	(75.51)
Rainfall	771.92	709.70	886.53	789.38
	(171.29)	(128.70)	(144.63)	(166.23)
Panel C: Household Characteristics				
Household size	11.02	11.02	11.76	11.27
	(6.88)	(6.88)	(8.89)	(7.61)
Membership to Association (1=yes)	0.27	0.27	0.16	0.24
	(0.45)	(0.45)	(0.37)	(0.42)
Training on groundnut production (1=yes)	0.39	0.39	0.28	0.35
	(0.49)	(0.49)	(0.45)	(0.48)
Number of visits from public extension agents	1.99	1.99	2.03	2.00
	(2.61)	(2.61)	(2.03)	(2.43)
Number of visits from private extension agents	0.93	0.93	1.22	1.03
	(1.43)	(1.43)	(1.44)	(1.44)
Access to credit (1=yes)	0.02	0.02	0.04	0.03
	(0.14)	(0.14)	(0.20)	(0.16)
Dependency ratio	1.66	1.66	1.83	1.72
	(1.21)	(1.21)	(1.46)	(1.30)
Rented land (1=yes)	0.03	0.03	0.04	0.04
	(0.18)	(0.18)	(0.19)	(0.18)
Access to off-farm income (1=yes)	0.09	0.09	0.12	0.10
	(0.29)	(0.29)	(0.32)	(0.30)
Farmers perception on soil quality (1=Bad)	0.02	0.02	0.07	0.04
	(0.15)	(0.15)	(0.26)	(0.20)

Notes: Standard deviations are in parentheses.

Panel C presents household characteristics. Average household size is 11, ranging from 11 to nearly 12 over the 3 years. Most households hold membership in agricultural associations and had received past training on groundnut production, though association membership declined while training became less common over time. Households received around 2 annual visits from public extension agents, increasing slightly over time, and 1 visit from private agents. About 3% of households have access to credit or off-farm income-generating activities. The rented land rate and perception of poor soil quality increased from 2017-2019.

Figure 3 depicts a comparison of improved seeds adoption rates among the three countries overtime. Nigeria consistently exhibits the highest adoption rates among the three countries, with a steady increase from approximately 49% in 2017 to 53% in 2018 and a further rise to around 55% in 2019. Ghana has the second-highest adoption rates, but the adoption rate fluctuates over the three years, decreasing from around 34% in 2017 to 29% in 2018, then increasing to 32% in 2019. Mali has the lowest adoption rates, with the rate floating around 17% in both 2017 and 2018 followed by an increase to 24% in 2019. Despite the fluctuations in Ghana's adoption rates, both Nigeria and Mali display consistent growth in the adoption of improved seeds over the three-year period, while Ghana's adoption rate decreases initially but recovers in 2019.

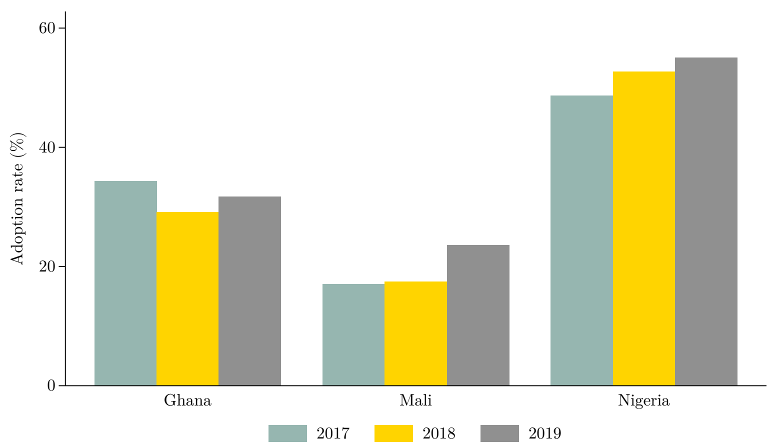

Figure 3: Adoption rate of improved groundnut varieties by year and by country

Figures 4 and 5 shed light on the area allocated to improved groundnut varieties. Figure 4 illustrates the distribution of area under improved seeds across all countries and years, revealing a strong rightly-skewed distribution, with 58% of households having zero area under improved seeds. Figure 5 shows the average area under improved seeds in hectares (ha) for each country and year, highlighting notable differences among the three countries. Nigeria has the highest average area under improved seeds in all 3 years, ranging from approximately 0.75 ha in 2017 to 0.9 ha in 2019.

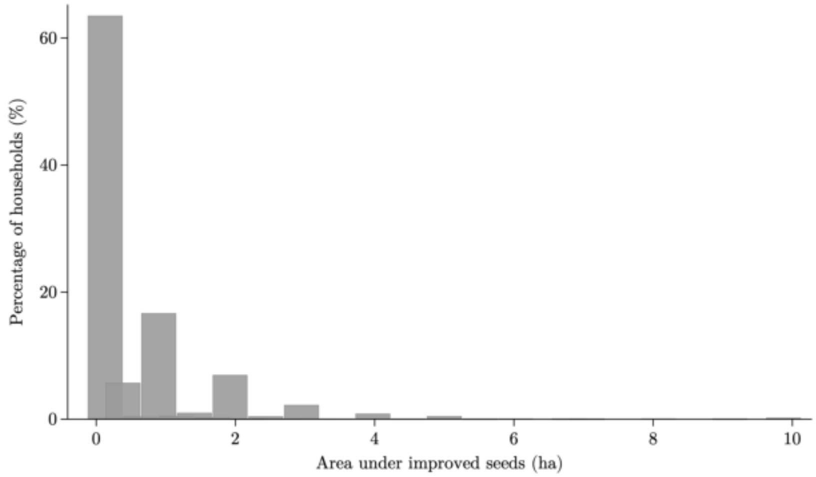

Figure 4: Distribution of area under improved seeds

Ghana's average area under improved seeds fluctuated over the three years, starting at around 0.4 ha in 2017, decreasing to about 0.25 ha in 2018, and then increasing to roughly 0.35 ha in 2019. Mali exhibits the lowest average area under improved seeds among the three countries, with values of approximately 0.25 ha in 2017 and 2018, followed by an increase to around 0.3 ha in 2019.

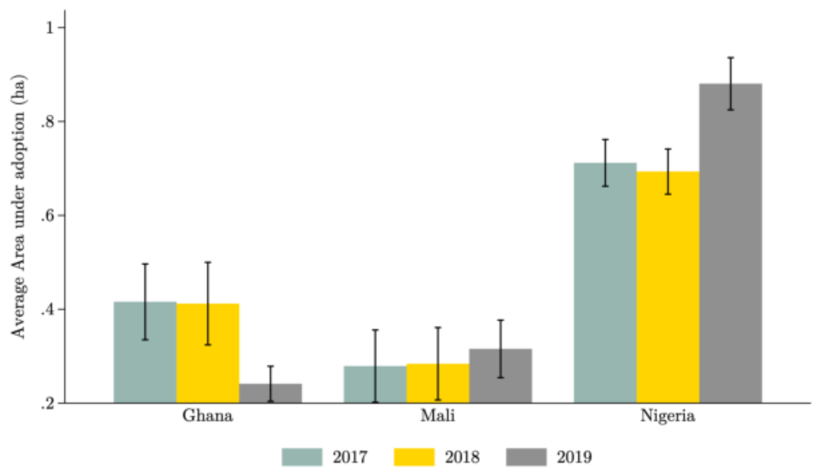

Figure 5: Average area groundnut varieties by year and by country

Notes: Each thick bar represents the average of area under improved seeds in a given country by year. The black thin bars shows 95% confidence intervals.

4. Estimation Strategy

This section presents our estimation strategy for examining the effects of extreme heat and optimal growing temperatures on the adoption of improved groundnut varieties at both the extensive and intensive margins. Our approach consists of two main steps. First, we employ a data-driven method to determine the threshold for harmful temperature, which we use to calculate the EHDD and GDD. In the second step, we estimate the effects of EHDD and GDD on adoption and area under adoption using a two-part model.

4.1. Estimating the threshold for harmful temperature

We estimate the threshold for harmful temperature using a data-driven approach (Aragon et al., 2021). First, we bin our daily average temperature variable into thirteen 1°C bins (from < 24°C to >35°C)[5]. We then generate the proportion of days which fall within each temperature bin during the growing season. Next, we estimate the relationship between temperature bins and our two outcome variables (adoption dummy and area under adoption) using equation 1.

$$Y_{ijt} = \alpha_0 + \sum_{k=1}^{M} \gamma_k \boldsymbol{TB_{itk}} + \boldsymbol{X'_{ijt}\alpha_1} + \delta_t + \mu_i + \varepsilon_{ijt} \qquad (1)$$

Where Y_{ijt} is a vector of outcome variables, which includes a dummy for adoption and the area under adoption in hectares (ha) for household i, in district j and growing season t. $\boldsymbol{TB_{itk}}$ is a vector of 1°C temperature bins. We use the last temperature bin (>35°C) as benchmark and omit it from our estimation. $\boldsymbol{X'_{ijt}}$ is a vector of household controls including 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, rainfall, and farmer's perception of their soil quality. 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. We estimate equation (1) using Ordinary Least Squares (OLS) and cluster standard errors at the household level.

4.2. Estimating the effects of extreme heat and optimal growing temperature

We exploit the quasi-random variation in extreme temperatures across space and time to estimate the effect of household's exposure to extreme heat and optimal growing temperatures on adoption at the extensive and intensive margins. Specifically, our study aims to capture the lagged effects of temperature shocks on adoption and area under adoption. Our focus on lagged temperature effects is justified by the fact that households are likely to make input use decisions before the start

[5] We used <24°C and >35°C as the first and last bins respectively because the percentage of days that fall within those bins are the smallest.

of the agricultural season and based on their most recent exposure to weather shocks (Jain et al., 2015).

Given the nature of our dependent variables, we employ a two-part model to estimate the effects of temperature shocks on adoption and area under adoption. First, we specify the following linear probability model (LPM) to investigate the relationship between temperature shocks and adoption at the extensive margin:

$$I_{ijt} = \beta_0 + \beta_1 EHDD_{ijt-1} + \beta_2 GDD_{ijt-1} + \boldsymbol{X'_{ijt}}\beta_3 \ + \delta_t + \mu_i + \varepsilon_{ijt} \qquad (2)$$

Where I_{ijt} is an indicator variable for adoption, which takes on the value 1 if the household has adopted improved groundnut varieties in growing season t, and 0 otherwise. $EHDD_{ijt-1}$ refers to the extreme heat degree day in the previous growing season, and measures exposure to harmful temperature. To account for non-linear effects of temperature on adoption, we control for exposure to optimal growing temperature by employing the growing degree days in the previous growing season: GDD_{ijt-1}. Similar to equation (1), we include household demographic controls, household, and year fixed effects. We estimate equation (2) employing household fixed effects, and we cluster standard errors at the household level. We check the robustness of our results using spatially corrected Conley standard errors (Conley, 1999). In this LPM set up, the coefficients of interest, β_1 and β_2, measure the change (in percentage points) in the probability of adoption and area under adoption as a result of one additional extreme heat degree day and one additional growing degree day, respectively.

In the second part of our two-part model, we estimate the effects of temperature shocks on the area under adoption, conditional on adoption, still using the household fixed effect estimator with the untransformed dependent variable. This approach is consistent with the recommendations of Mullahy & Norton (2024) for handling non-negative, skewed outcomes with a mass at zero. We estimate the following equation to examine the effects of temperature on adoption at the intensive margin:

$$A_{ijt} = \alpha_0 + \alpha_1 EHDD_{ijt-1} + \alpha_2 GDD_{ijt-1} + \boldsymbol{X'_{ijt}}\alpha_3 + \theta_t + \lambda_i + \omega_{ijt} \qquad (3)$$

Where A_{ijt} is the area allocated to improved groundnut varieties by household i, in district j and growing season t. This regression includes household demographic variables and controls for household and year FE. Estimates for the parameters in equation 3 are presented in table 3, with our preferred specification in column 4. α_1 and α_2 measure the change in area under adoption due to an extra EHDD and an extra GDD, respectively.

5. Main Results

5.1 Threshold for Harmful Temperature

Estimation results for equation (1) reveal a non-linear relationship between temperature and adoption of climate resilient groundnuts both at the extensive and intensive levels (Figure 6)[6]. Notably, the effect of temperature on adoption and area under adoption is positive for lower temperature bins (below 24-25°C), suggesting that a slight increase in temperature from lower levels may initially encourage adoption of climate-resilient groundnut varieties. However, as temperature rises further, the effect on adoption and area under adoption becomes negative, indicating that the incentive to adopt these varieties diminishes as temperature approaches potentially harmful levels. The effect on adoption and area under adoption becomes positive again for the highest temperature bins (above 32°C), with the strongest positive effects observed in this range. Moreover, we find similar non-linear effects between temperature and an alternative measure of adoption (willingness to adopt), with the largest effects being observed for temperature above 32°C (Appendix Figure A2). This suggests that once temperatures reach a critical threshold where crop yields are significantly affected, farmers are more likely to adopt climate-resilient varieties and allocate more land to their cultivation as an adaptation strategy to mitigate the adverse impacts of extreme heat (Di Falco & Veronesi, 2013).

We also show that temperature effects on output become negative above 32°C (figure 7), further reinforcing the notion that farmers adopt climate-resilient varieties as a response to the detrimental impacts of extreme heat on crop yields. We then use 32°C as the threshold for harmful temperature in the calculation of EHDD and we use 22°C[7] as the lower bound of the threshold for optimal temperature.

[6] These estimation results are also presented in Appendix Table A1.

[7] Since the focus of our analysis is to estimate the impacts of extreme heat, we did not determine the lower bound for optimal temperature for groundnut production. Instead, we use the FAO lower-bound threshold for optimal groundnut production.

Panel a: Adoption decision *Panel b*: Area under adoption

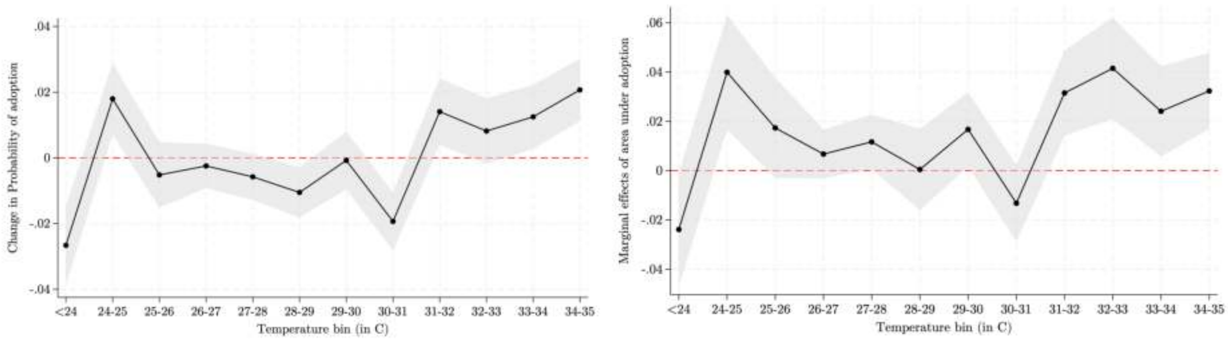

Figure 6: Effects of temperature on adoption decision and area under adoption.

Notes: Panel a shows the impacts of temperature on adoption decision, and panel b shows the impacts of temperature on area under adoption. Full results are presented in column 1 and column 3 of Appendix Table A1, respectively. The circles represent the point estimates, and the gray band 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, rainfall, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors clustered at the household level.

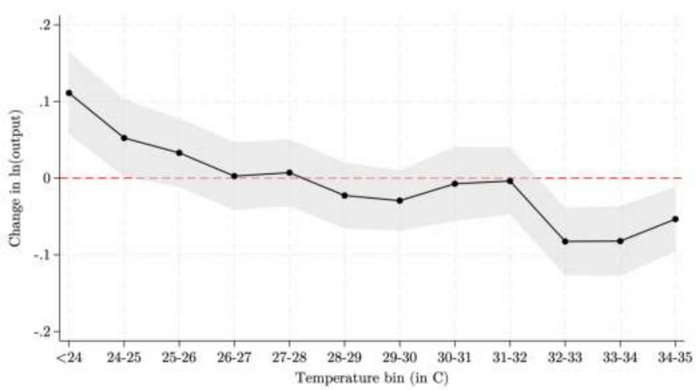

Figure 7: Effects of temperature on output

Notes: Full results are presented in column 4 of Appendix Table A1. The circles represent the point estimates, and the gray band 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, rainfall, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors clustered at the household level.

5.1. Effects of Extreme Heat and Optimal Temperature on Adoption

Table 2 shows the results for the effects of temperature shocks on the adoption decision. Columns (1) and (2) show the results without household controls, with column 2 including both year and household FE, while column 1 only controls for year FE. Columns (3) includes household controls and year FE, but no household FE. Column 4 is our preferred specification, and includes household controls, year FE, and household FE. Our results provide strong evidence that exposure to extreme heat in the previous growing season increases the likelihood of adopting improved groundnut varieties. Specifically, an additional extreme heat degree day in the previous growing season increases the proportion of households using improved groundnut varieties by 0.5 percentage point (Table 1, column 4). These findings align with previous research showing that farmers often adopt climate-resilient crop varieties as an adaptation strategy in response to extreme weather events (Di Falco & Veronesi, 2013).

Our results further show that exposure to optimal growing temperatures in the previous season reduces the likelihood of adoption. An additional growing degree in the previous growing season is associated with a 0.2 percentage point decrease in the probability of adoption. This result is consistent with the idea that farmers may be less inclined to adopt new varieties when they experience favorable growing conditions, as they may perceive less need for adaptation (Burke & Emerick, 2016). Membership in a farmers' group, training on groundnut production, access to extension services (both public and private), access to credit, and access to off-farm income are positively associated with adoption. These factors likely contribute to farmers' awareness, knowledge, and financial capacity to adopt improved varieties (Kassie, Teklewold, Jaleta, et al., 2015; Teklewold et al., 2013). Conversely, household size and rented land have negative or insignificant effects on adoption, possibly due to resource constraints or tenure insecurity (Abdulai & Huffman, 2014).

5.2. Effects of Extreme Heat and Optimal Temperature on Area Under Adoption

The results in Table 3 show that exposure to extreme heat has a positive and statistically significant effect on the area allocated to improved groundnut varieties. One extra extreme heat degree day increases the area under improved varieties by 0.006 hectare (Table 3, Column 4). Given that the average area under adoption in 2017 is 0.53 hectare, our point estimates imply that an extra extreme heat degree day increases the area under adoption by 1.13%. These findings are consistent with our earlier results on the adoption decision and provide further evidence that farmers allocate more land to climate-resilient varieties in response to extreme heat exposure (Aragón et al., 2021; Di Falco & Veronesi, 2013; He & Chen, 2022).

In contrast, the coefficient estimates for GDD are negative and statistically significant in most specifications, suggesting that exposure to optimal growing temperatures reduces the area allocated to improved groundnut varieties. An additional growing degree day in the previous growing season is associated with a 0.003 hectare (or 0.6 %) decrease in the area under improved groundnut varieties (Table 3, Column 4). This finding is consistent with the idea that farmers may perceive less need for adaptation to climate change when growing conditions are optimal (Burke & Emerick, 2016).

Table 2: Linear Probability Model Estimates of the effects of temperature shocks on adoption

	(1)	(2)	(3)	(4)
$EHDD_{t-1}$	0.002***	0.003***	0.004***	0.005***
	(0.000)	(0.001)	(0.000)	(0.001)
GDD_{t-1}	-0.001***	-0.001	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8,604	8,604	7,726	7,726
R-squared	0.031	0.009	0.114	0.052
Controls	No	No	Yes	Yes
Household FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. Dependent variable is adoption dummy. All regressions include year dummies. Robust standard errors clustered at the household level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%. 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, rainfall, and farmer's perception of their soil quality.

Table 3: OLS Estimates of the Effects Temperature Shocks on Area under Adoption

	(1)	(2)	(3)	(4)
$EHDD_{t-1}$	0.003***	0.003**	0.006***	0.006***
	(0.001)	(0.002)	(0.001)	(0.002)
GDD_{t-1}	-0.003***	-0.000	-0.004***	-0.003**
	(0.000)	(0.001)	(0.000)	(0.001)
Observations	8,604	8,604	7,726	7,726
R-squared	0.031	0.009	0.114	0.052
Controls	No	No	Yes	Yes
Household FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. Dependent variable is area allocated to improved groundnut varieties in ha. All regressions include year dummies. Robust standard errors clustered at the household level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%. 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, rainfall, and farmer's perception of their soil quality.

5.4 Heterogeneity analysis
5.4.1 Cross-country analysis

While our main results provide valuable insights into the overall effects of extreme heat on the adoption and area under adoption of improved groundnut varieties, it is crucial to recognize that these impacts may vary across different geographical contexts. Our unique dataset allows us to explore this heterogeneity and gain a more nuanced understanding of how farmers in different regions respond to extreme heat. In this section, we present a cross-country analysis of the impacts of EHDD and GDD on adoption and area under adoption, by emphasizing the similarities and differences in farmers' adaptation strategies across the three West African nations.

Table 4 presents the results of our cross-country analysis, where we find heterogenous variations in magnitudes and statistical significance on the impact of extreme heat on adoption and area under adoption. However, the baseline insights are maintained as we find consistent effects in all the three countries. The lone exception is for Mali where the intensive adoption of climate-resilient seeds is not statistically different from zero. This suggests that farmers in the three countries are highly responsive to extreme heat and adopt improved groundnut varieties and allocating more land to these varieties as a coping mechanism though at varying rates.

These nuanced cross-country differences in the impacts of extreme heat on adoption and area under adoption may be attributed to factors, such as differences in agro-ecological conditions, institutional support, access to information and resources, and cultural practices (Makate, 2019; Wossen et al., 2017). For instance, the stronger response of Nigerian farmers to extreme heat could be due to the country's higher exposure to climate risks or the presence of more effective extension services that promote the adoption of climate-resilient varieties (Wossen et al., 2017). Our cross-country analysis demonstrates the importance of considering the heterogeneity in farmers' responses to extreme heat when designing and implementing policies and interventions aimed at promoting climate change adaptation in smallholder agriculture. Tailoring these efforts to the specific needs and contexts of different regions and countries can help ensure their effectiveness in building the resilience of farming communities to the challenges posed by rising temperatures.

Table 4: Cross-Country Analysis of Extreme Heat Impact on Adoption and Area under Adoption

	Ghana		Mali		Nigeria	
	Adoption	Area	Adoption	Area	Adoption	Area
$\mathrm{EHDD}_{\mathrm{t}-1}$	0.021***	0.014*	0.005*	0.006	0.013***	0.017***
	(0.005)	(0.007)	(0.002)	(0.008)	(0.002)	(0.003)
$\mathrm{GDD}_{\mathrm{t}-1}$	-0.007***	-0.006***	-0.005*	-0.008	-0.007***	-0.010***
	(0.001)	(0.001)	(0.002)	(0.006)	(0.001)	(0.002)
Observations	1,363	1,363	2,287	2,287	4,076	4,076
R-squared	0.135	0.086	0.226	0.125	0.128	0.089
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents estimates from equation 2 (Adoption column) and equation 3 (Area column), for each country. All regressions include controls, and household and year fixed effects. Robust standard errors clustered at the household level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

5.4.2. Heterogeneity Analysis by Wealth and Production level

As argued in our conceptual framework, agricultural technology adoption decisions depend on households' financial liquidity and endowments level. To better understand how these factors influence households' responses to temperature shocks, we explore the heterogeneous effects of EHDD and GDD on adoption and area under adoption by wealth. Additionally, we investigate heterogeneous effects by production level to better understand how households' adaptive capacity may vary depending on their output level. To do so, we compute the average income and production for each household across the three years of our panel and use these values to determine the top and bottom terciles of total household income and total output.

Table 5 presents the results of our heterogeneity analysis by wealth, comparing the effects of extreme heat on adoption and area under adoption for poor households (bottom tercile of average total household income) and non-poor households (top tercile). We find that both poor and non-poor households increase their adoption and area under adoption in response to extreme heat, with the effect being higher for non-poor households. This means that while both groups are responsive to extreme heat, non-poor households may have a greater ability to adopt improved varieties due to their higher income and better access to resources (Dercon & Christiaensen, 2011; Deressa et al., 2009; Fentie & Beyene, 2019).

Table 5: Heterogenous effects of EHDD and GDD on adoption and area under adoption by wealth

	Adoption		Area	
	Poor	Non-poor	Poor	Non-poor
EHDD_{t-1}	0.007***	0.008***	0.006***	0.016***
	(0.001)	(0.002)	(0.001)	(0.006)
GDD_{t-1}	-0.002***	-0.004***	-0.002**	-0.010***
	(0.001)	(0.001)	(0.001)	(0.004)
Observations	2,574	2,580	2,574	2,580
R-squared	0.104	0.092	0.087	0.057
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents estimates from equation 2 (Adoption column) and equation 3 (Area column) for poor versus non-poor households. Poor households are those who fall within the bottom tercile of the average total household income, and non-poor households are those within the top tercile. All regressions include controls, household, and year fixed effects. Robust standard errors clustered at the household level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Similarly, we find positive and statistically significant effects of EHDD on area under adoption across both groups, with the effect being larger for non-poor households. This shows that non-poor households are able to allocate more land to improved varieties in response to extreme heat, possibly due to their larger landholdings and greater financial capacity to invest in climate-resilient technologies (Di Falco & Veronesi, 2013; Teklewold et al., 2019).

With regards to production level heterogeneity (Table 6), we show larger effects for households with high production levels. The larger EHDD effects on area under adoption for households with higher production levels can be explained by several factors. First, households with higher production levels may have larger landholdings, which allows them to allocate more land to improved varieties in response to extreme heat without compromising their overall crop portfolio (Sesmero et al., 2018; Michler et al., 2019). Second, these households could have more financial resources, which enables them to invest in the necessary inputs and technologies required to expand the cultivation of improved varieties (Kassie et al., 2015; Manda et al., 2020). Finally, households with higher production levels may have better access to information, extension services, and input markets, which can provide them with the knowledge, support, and resources needed to effectively increase the area under improved varieties when faced with adverse weather conditions (Aragon et al., 2021; Jain et al., 2015).

Table 6: Heterogenous effects of EHDD and GDD on adoption and area under adoption by production level

	Adoption		Area	
	Low Production	High Production	Low Production	High Production
$EHDD_{t-1}$	0.009***	0.003**	0.005***	0.013**
	(0.001)	(0.002)	(0.001)	(0.005)
GDD_{t-1}	-0.002***	-0.002**	-0.001	-0.009**
	(0.001)	(0.001)	(0.001)	(0.003)
Observations	2,572	2,574	2,572	2,574
R-squared	0.148	0.072	0.135	0.045
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents estimates from equation 2 (Adoption column) and equation 3 (Area column) for poor versus non-poor households. Households with low output are those who fall within the bottom tercile of the average groundnut output, and households with high output are those within the top tercile of average groundnut production. All regressions include controls, household, and year fixed effects. Robust standard errors clustered at the household level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

5.5 Substitution Effects

Our analysis so far has focused on the impact of extreme heat on the adoption and area under adoption of improved groundnut varieties. However, it is important to consider how these changes in adoption patterns may affect the allocation of land to non-improved (local) varieties. While some studies have shown that farmers may increase their total cultivated area as an adaptation strategy to cope with extreme weather events (Aragón et al., 2021; Taraz, 2017), our analysis reveals that, farmers may be expanding the area under improved varieties at the expense of land allocated to non-improved varieties.

To investigate these substitution effects, we estimate the impact of extreme heat and optimal growing temperatures on the area allocated to non-improved groundnut varieties, which is equal to the total area allocated to groundnut cultivation minus the area under adoption of improved groundnut varieties. Table 7 presents the results of this analysis. Our preferred specification (column 4) shows a positive and strong statistically significant effect of EHDD on area under non-improved seeds. An additional EHDD leads to a 0.012 hectare (or approximately 1.2 %)[8] decrease in the area under non-improved groundnut varieties. This finding suggests that as farmers

[8]The average area allocated to non-improved seeds in 2017 is 1.04. As such, this point estimates implies that an extra EHDD increases the area under non-improved seeds by (0.012/1.04) *100 $\approx$ 1.2%.

experience more extreme heat, they not only adopt improved varieties and allocate more land to them but also reduce the area allocated to local varieties. This substitution effect may be driven by farmers desire to maximize yields and minimize the risk of crop failure under adverse weather conditions, as improved varieties are often bred to be more resilient to abiotic stresses (Fisher & Carr, 2015; Kassie et al., 2015).

Conversely, one extra growing degree day is associated with a 0.008 hectare (or 0.8%)[9] increase in the area allocated to non-improved groundnut varieties, with this estimate also being significant at the 1% level. This result indicates that when farmers experience more optimal growing temperatures, they tend to allocate more land to non-improved groundnut varieties. This may be because farmers perceive less need for the stress-tolerant traits of improved varieties under favorable weather conditions and may prefer to cultivate local varieties that are better adapted to their specific agro-ecological contexts and have desirable culinary or cultural properties (Waldman et al., 2014).

Table 7: Effects of Extreme Heat on area with non-improved groundnut varieties

	Area with non-improved groundnut varieties			
	(1)	(2)	(3)	(4)
EHDD_{t-1}	-0.002*	-0.007***	-0.007***	-0.012***
	(0.001)	(0.002)	(0.001)	(0.002)
GDD_{t-1}	-0.000	0.003**	0.001**	0.008***
	(0.000)	(0.001)	(0.001)	(0.001)
Observations	8,604	8,604	7,726	7,726
R-squared	0.012	0.006	0.089	0.064
Controls	No	No	Yes	Yes
Household FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents the estimates of equation 4. The dependent variable is the area under no adoption of improved seeds, which is equal to the total area allocated groundnut cultivation minus the area under adoption of improved seeds. Our preferred specification is in column 4, and includes controls, year and household FEs. All regressions include year fixed effects. Robust standard errors clustered at the household level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

These substitution effects have important implications for agricultural development and climate change adaptation strategies. While the adoption of improved varieties can enhance farmers resilience to extreme heat, it is crucial to ensure that this does not come at the cost of reduced area under non-improved seeds, as local varieties may have valuable genetic diversity and unique traits that are important for long-term adaptation and food security (Atlin et al., 2017; Qaim, 2020). 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. Furthermore, the positive impact of optimal growing temperatures on the area under non-improved seeds highlights the importance of considering the heterogeneous effects of weather conditions on farmers' varietal choices. Extension services and agricultural development programs should tailor their recommendations and support to the specific needs of farmers under different weather scenarios, promoting improved varieties where they are most needed while also recognizing the value of local varieties under favorable conditions.

5.6. Sustained Adoption

One critical concern in the adoption of climate-resilient agricultural technologies is the potential for disadoption, where farmers may initially adopt improved varieties but later discontinue their use (Fentie & Beyene, 2019; Michler et al., 2019; Maggio et al., 2022; Tabe-Ojong et al., 2023c). 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 this challenge, we investigate the effects of extreme heat and optimal temperatures on sustained adoption, both in terms of the likelihood of continued adoption and the area under adoption for those who adopt consistently.

Table 8 presents the results of our analysis of sustained adoption, with columns (1) and (2) focusing on the probability of adoption for two and three years, respectively, and columns (3) and (4) examining the impact on area under adoption for households that have adopted for two and three years, respectively. Our findings here suggest that exposure to extreme heat not only encourages initial adoption but also promotes the sustained use of improved varieties over time.

Table 8: Effects of EHDD and GDD on sustained adoption

	Adoption		Area	
	2 years	3 years	2 years	3 years
$EHDD_{t-1}$	0.001***	0.002***	0.020***	0.007**
	(0.000)	(0.000)	(0.008)	(0.003)
GDD_{t-1}	-0.001***	-0.001***	-0.016***	-0.001
	(0.000)	(0.000)	(0.004)	(0.002)
Observations	7,726	7,726	1,240	1,641
R-squared	0.044	0.156	0.303	0.024
Controls	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	Yes

Year FE	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents estimates of equation 2 (Adoption column) and equation 3 (Area column) for households who have i) adopted improved groundnut varieties for 2 out of the 3 years of our panel and ii) households who have adopted all 3 years. In the adoption column, the dependent variables are indicator variables for whether a household adopts improved seeds for 2 out of the 3 years of our panel (2 years sub-column), or whether the household adopts for all 3 years (3 years sub-column). In the area column, we estimate equation 3 for the sub-group of households who have adopted improved seeds for 2 out of the 3 years of our panel (2 years sub-column), or whether the household adopts for all 3 years (3 years sub-column). All regressions include year fixed effects. Robust standard errors clustered at the household level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%

Taken together, these findings suggest that the experience of extreme heat events not only triggers initial adoption but also encourages farmers to continue using improved varieties over multiple growing seasons. Sustained adoption is 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 & Sumner, 2012; Rippke et al., 2016). The findings also 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).

5.7. Robustness checks

We conducted several robustness checks to confirm and bolster the validity of our estimates.

First, we re-estimated our preferred specification using the Correlated Random Effects (CRE) approach, also known as the Mundlak device (Appendix Table A4, Columns 1 and 2). The CRE model allows for the correlation between the unobserved heterogeneity and the explanatory variables, thus addressing potential endogeneity issues (Mundlak, 1978). By including the means of the time-varying covariates as additional regressors, the CRE approach captures the between-individual effects while still controlling for unobserved heterogeneity. Our results remain robust to this alternative specification.

Second, we employ Probit and Tobit models with CRE (Appendix Table A4, columns 3 and 4) to account for the binary nature of the adoption decision and the censored nature of the area under adoption, respectively. The Probit model is a non-linear probability model that estimates the likelihood of adoption, addressing the limitations of the LPM in terms of predicted probabilities falling outside the [0,1] range (Wooldridge, 2010). The Tobit model, on the other hand, is designed to handle censored dependent variables, such as the area under adoption, which has a lower limit of zero (Tobin, 1958). Our findings are robust to these alternative estimation methods.

We also check the robustness of our adoption results using an alternative measure of adoption: willingness to adopt (Appendix Table A4, column 5). This measure captures farmers' intention to adopt improved varieties, which may be less affected by short-term constraints such as access to credit (Adesina & Zinnah, 1993; Doss, 2006). Our findings are consistent to this alternative measure of adoption.

In addition, we also estimate a Heckman selection model to account for the potential selection bias arising from the fact that the area under improved varieties is only observed for adopters (Appendix Table A6). The Heckman model estimates a two-stage process: first, a selection equation that determines the likelihood of adoption, and second, an outcome equation that estimates the area under adoption conditional on being an adopter (Heckman, 1979). By modeling the selection process explicitly, the Heckman approach addresses the potential bias caused by the non-random selection of adopters. Our results remain robust to this alternative specification.

Next, we conduct a placebo test using EHDD from the pre-planting period of the same growing season instead of the previous growing season (Columns 6 and 7). As expected, the contemporaneous effects of extreme temperature on adoption and area under adoption are statistically insignificant. This test serves two important purposes. First, it allows us to rule out the possibility that exposure to extreme heat right before the growing season might affect adoption and area under adoption. Second, the placebo test highlights the importance of the lagged effects of temperature shocks on adoption decisions. By showing that the coefficient on the pre-planting EHDD variable is insignificant, we show that farmers indeed make adoption decisions based on their past exposure to extreme heat, rather than on current weather conditions.

Moreover, the insignificant EHDD results from the placebo test underscore the fact that given the financial implications of adoption, it might be hard for farmers to adopt improved varieties shortly after experiencing temperature shocks. Adopting new technologies often involves significant upfront costs, such as purchasing fertilizers, pesticides, and other inputs (Duflo et al., 2011; Foster & Rosenzweig, 2010). In the face of immediate weather shocks, farmers may prioritize short-term coping strategies, such as adjusting labor allocation or drawing down savings, rather than investing in long-term adaptation measures like adopting improved varieties (Dercon, 2002; Morduch, 1995). The lagged effects captured in our main specification suggest that farmers need time to mobilize resources and make informed decisions about adopting new technologies in response to past weather shocks.

Finally, we use the Conley (1999) standard errors with thresholds of 500 km, 1000 km, and 2000 km (appendix table A5). Conley standard errors account for potential spatial correlation in our outcome variables or covariates, which may arise due to unobserved factors that are geographically clustered (Conley, 1999; Hsiang, 2010). Our results remain robust to this correction for spatial correlation, with the coefficients on EHDD and GDD remaining significant and of similar magnitude across all distance thresholds.

7. Conclusion

This study investigates the impacts of extreme heat on the adoption of improved groundnut varieties among smallholder farmers in West Africa. Using panel data from household surveys conducted in 2017, 2018, and 2019, we employed a fixed effects model to estimate the effect of extreme heat degree days (EHDD) and growing degree days (GDD) on the likelihood of adoption and the area allocated to improved varieties. Our findings reveal that exposure to extreme heat in the previous growing season significantly increases both the probability of adoption and the area under adoption of improved groundnut varieties. Conversely, exposure to optimal growing conditions, as measured by GDD, reduces the likelihood of adoption and the area allocated to these varieties.

We explore treatment effects heterogeneity across various socioeconomic dimensions, including production levels, and income. Our analysis of heterogeneity by wealth reveals that both poor and non-poor households increase their adoption and area under adoption in response to extreme heat, with the effect being more pronounced for non-poor households. This suggests that while both groups are responsive to extreme heat, non-poor households may have a greater ability to adopt improved varieties and allocate more land to them due to their higher income and better access to resources. Regarding production levels, we found larger extreme heat effects on adoption for households with low production levels, while the effect on area under adoption was larger for households with high production levels.

Our findings have important implications for climate change adaptation in the context of smallholder 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 (Asfawa 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. The results also suggest that policies should focus not only on promoting initial adoption but also on supporting sustained adoption, as the benefits of climate-resilient varieties are found to increase with the duration of adoption. 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.

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Appendix

Table A1: Effects of temperature on Adoption, Area under adoption, and Output

	Adoption	Access	Area under adoption	Ln(output)
$T^{<24}$	-0.0266***	-0.00241	-0.0239*	0.111***
	(0.00607)	(0.00568)	(0.0118)	(0.0276)
T^{24-25}	0.0180**	0.0406***	0.0399***	0.0525*
	(0.00553)	(0.00555)	(0.0118)	(0.0257)
T^{25-26}	-0.00519	0.0107*	0.0173	0.0330
	(0.00509)	(0.00519)	(0.0104)	(0.0228)
T^{26-27}	-0.00245	0.0137***	0.00673	0.00273
	(0.00345)	(0.00306)	(0.00508)	(0.0226)
T^{27-28}	-0.00577	0.00728*	0.0117*	0.00716
	(0.00358)	(0.00332)	(0.00564)	(0.0223)
T^{28-29}	-0.0105**	-0.0122**	0.000492	-0.0226
	(0.00391)	(0.00412)	(0.00842)	(0.0220)
T^{29-30}	-0.000762	0.0219***	0.0168*	-0.0293
	(0.00448)	(0.00421)	(0.00768)	(0.0201)
T^{30-31}	-0.0193***	0.000477	-0.0132	-0.00723
	(0.00453)	(0.00445)	(0.00789)	(0.0247)
T^{31-32}	0.0141**	0.00480	0.0315***	-0.00366
	(0.00517)	(0.00520)	(0.00884)	(0.0224)
T^{32-33}	0.00817	0.0128*	0.0415***	-0.0825***
	(0.00508)	(0.00497)	(0.0105)	(0.0225)
T^{33-34}	0.0125*	0.0364***	0.0241**	-0.0821***
	(0.00498)	(0.00532)	(0.00935)	(0.0233)
T^{34-35}	0.0207***	0.0210***	0.0323***	-0.0534*
	(0.00485)	(0.00495)	(0.00787)	(0.0215)
Observations	7726	7726	7726	7726
R-squared	0.0507	0.0052	0.0403	0.0139
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents the effects of temperature captured using dummies for temperature bins (T^{24}, T^{24-25}, …, T^{34-35}) where each bin represents the proportion of days in the growing season with average daily temperature within that bin. Column 1 shows the marginal effects of each temperature bin on the adoption decision. In column 2, we show the results for an alternative measure of adoption: the willingness to adopt improved groundnut varieties. Column 3 presents the marginal effects of each temperature bin on area under adoption and Column 4 shows the marginal effects of each bin on output. All regressions include controls, household and year fixed effects. Robust standard errors clustered at the household level are in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%

Table A2: Robustness checks: Alternative specifications and measures of our key variables

	(1) Adoption CRE	(2) Area CRE	(3) Probit CRE Adoption	(4) Tobit CRE Area	(5) Willingness To Adopt	(6) Pre-Planting Adoption	(7) Pre-Plantin g Area
$EHDD_{t-1}$	0.005***	0.007***	0.024***	0.025***	0.003***		
	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)		
GDD_{t-1}	-0.003***	-0.004***	-0.013***	-0.013***	-0.003***		
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)		
$EHDD_{t}$						0.000	-0.002*
						(0.000)	(0.001)
GDD_{t}						-0.001***	-0.001
						(0.000)	(0.001)
Observations	7,726	7,726	7,726	7,726	7,726	7,726	7,726
R-squared	0.2801	0.1403	-	-	0.074	0.081	0.052
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents the results of our robustness checks using alternative estimation methods and alternative measures of our treatment and outcome variables. Column 1 and 2 show robustness using the Correlated Random Effects (CRE) approach. Columns 3 and 4 show the results of our robustness using Probit and Tobit for adoption and intensity of adoption, respectively. Column 5 presents robustness results using Willingness to adopt (as an alternative measure of adoption). Columns 6 and 7 presents the results of our Placebo tests where we use the Pre-Panting EHDD and GDD of the same growing season. All regressions include controls, household and year fixed effects. *** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors are clustered at the household level.

Table A3: Robustness Checks: Spatial Correction Using Conley S.E.

	500 km		1000 km		2000 km	
	Adoption	Area	Adoption	Area	Adoption	Area
$EHDD_{t-1}$	0.005**	0.006**	0.005**	0.006**	0.005**	0.006**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
GDD_{t-1}	-0.002***	-0.003**	-0.002***	-0.003**	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Observations	7,726	7,726	7,726	7,726	7,726	7,726
R-squared	0.703	0.655	0.703	0.655	0.703	0.655
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents estimates from equation 2 (Adoption column) and equation 3 (Area column), using the Conley (1999) standard errors with thresholds 500 km, 1000 km and 2000 km. All regressions include controls, household and year fixed effects. *** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors are clustered at the household level.

Table A4: Robustness check using Heckman Selection Model

	(1)	(2)
	Area	Adoption
Ln ($EHDD_{t-1}$)	0.304***	1.440***
	(0.097)	(0.119)
Ln (GDD_{t-1})	-2.410***	-8.918***
	(0.434)	(0.597)
Observations	7,726	7,726
Controls	Yes	Yes
Household FE	Yes	Yes
Year FE	Yes	Yes

Notes: Sample includes all three panel years: 2017, 2018, and 2019. The table presents estimates of the Heckman selection model. A random-effects Probit model is used to estimate the adoption equation and an OLS is used to estimate the outcome (Area) equation. All regressions include controls, and household and year fixed effects. *** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors are clustered at the household level.

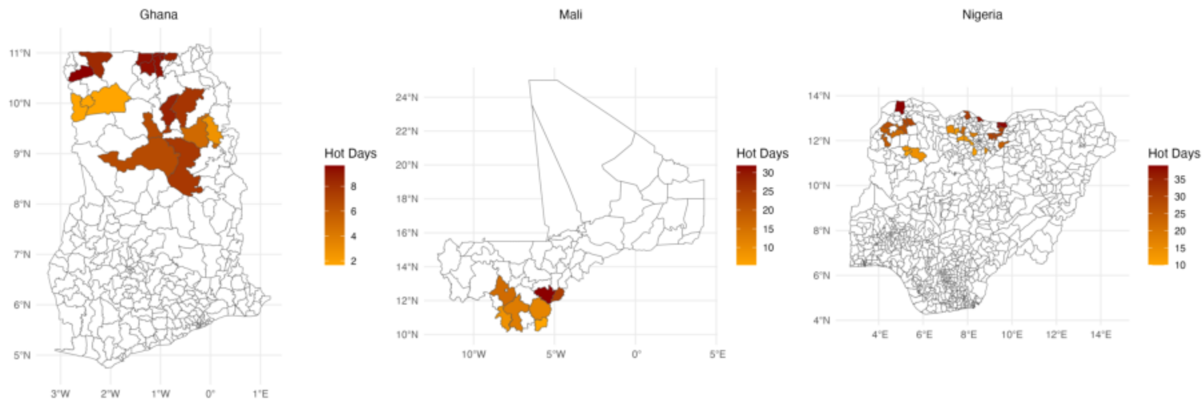

Figure A1: Spatial distribution of hot days

Notes: This map shows the distribution of hot days in districts where households in our sample live. Hot days are days with average temperature above 32°C.

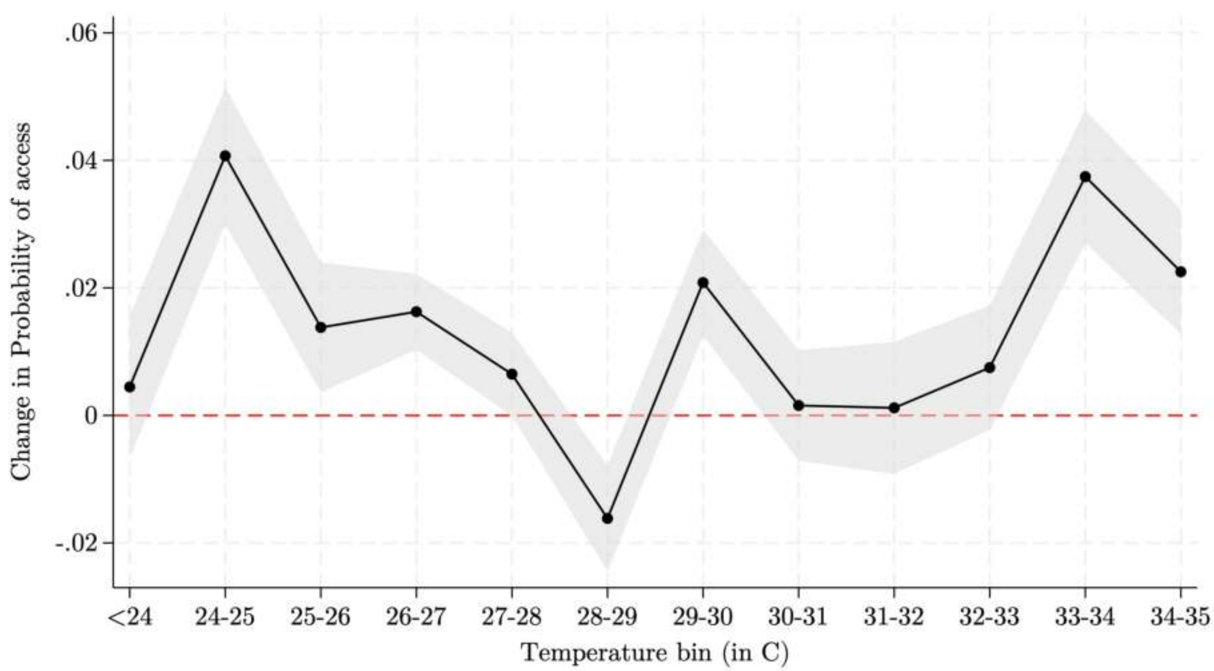

Figure A2: Effects of temperature on willingness to adopt.

Notes: Full results are presented in column 2 of Appendix Table A1. The circles represent the point estimates, and the gray band 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, rainfall, and farmer's perception of their soil quality. Regression also includes household and year fixed effects. Robust standard errors clustered at the household level.

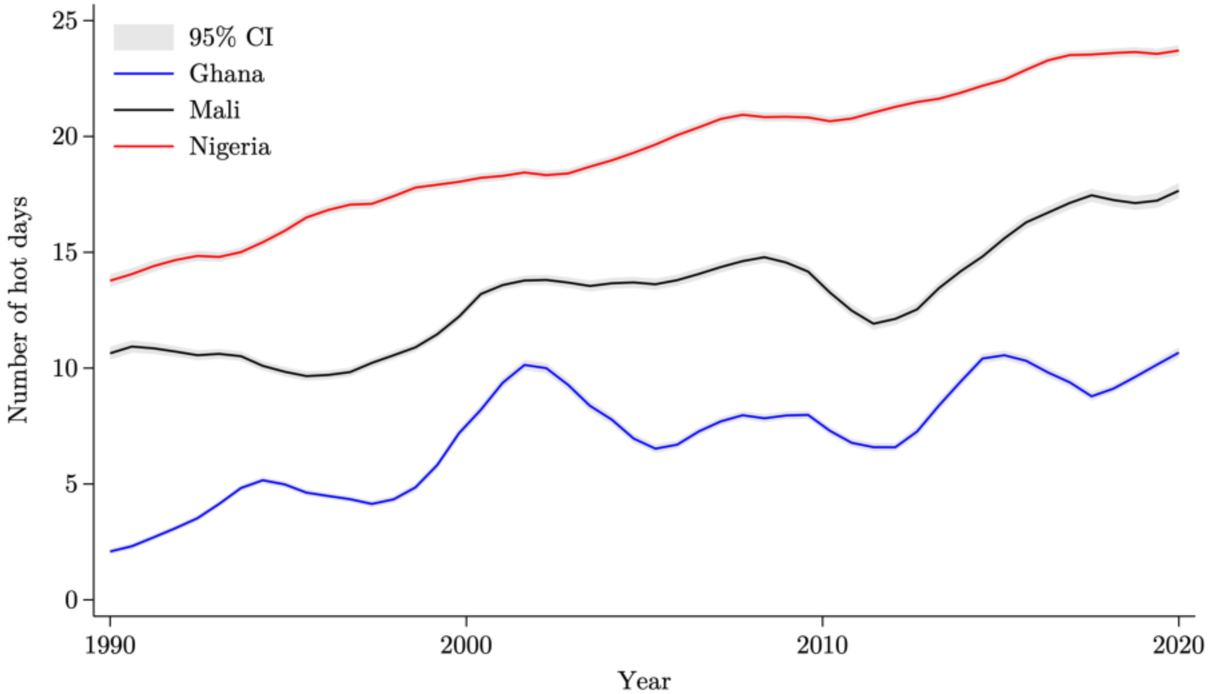

Figure A2: Temporal distribution of hot days: 1990 – 2020.

Notes: This graph shows the historical (1990 – 2020) temporal distribution of hot days. Hot days are days with average temperature above 32°C.

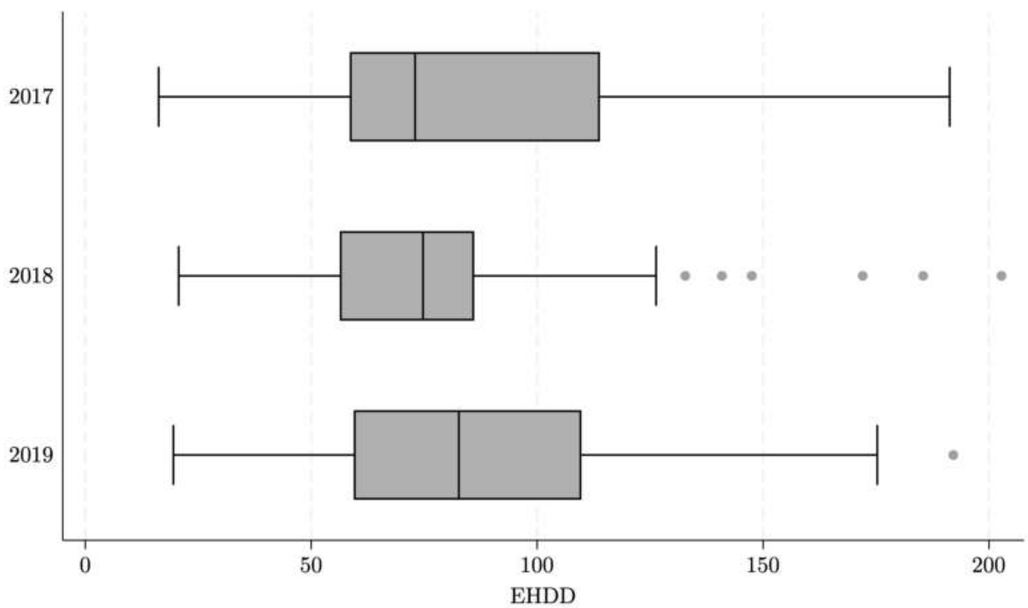

Figure A3: Box plot of EHDD by year

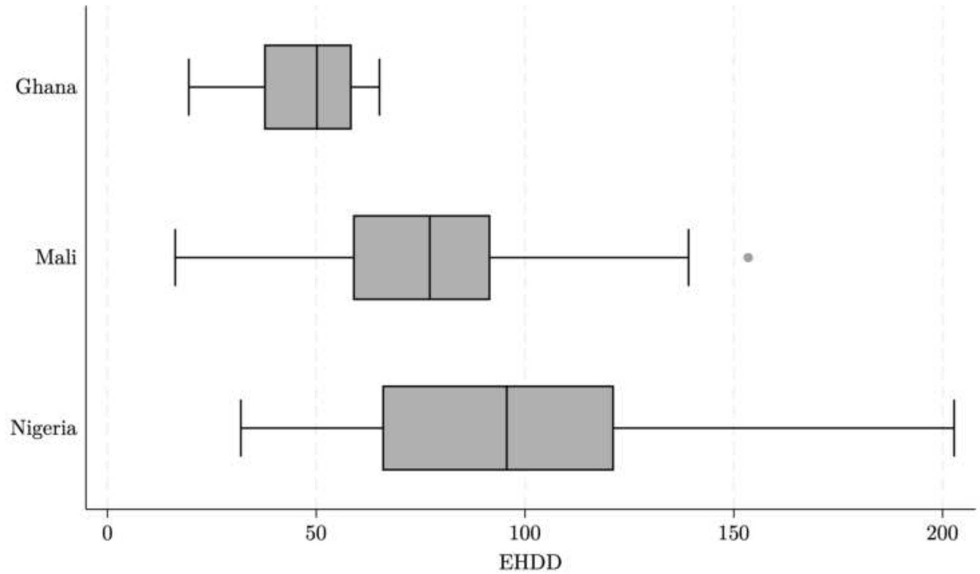

Figure A6: Box plot of EHDD by country

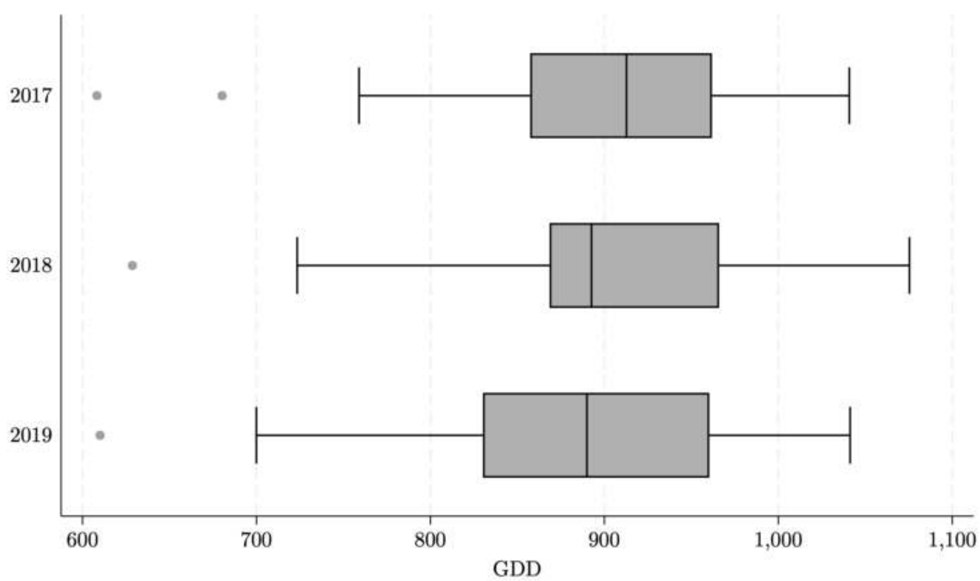

Figure A4: Box plot of GDD by year

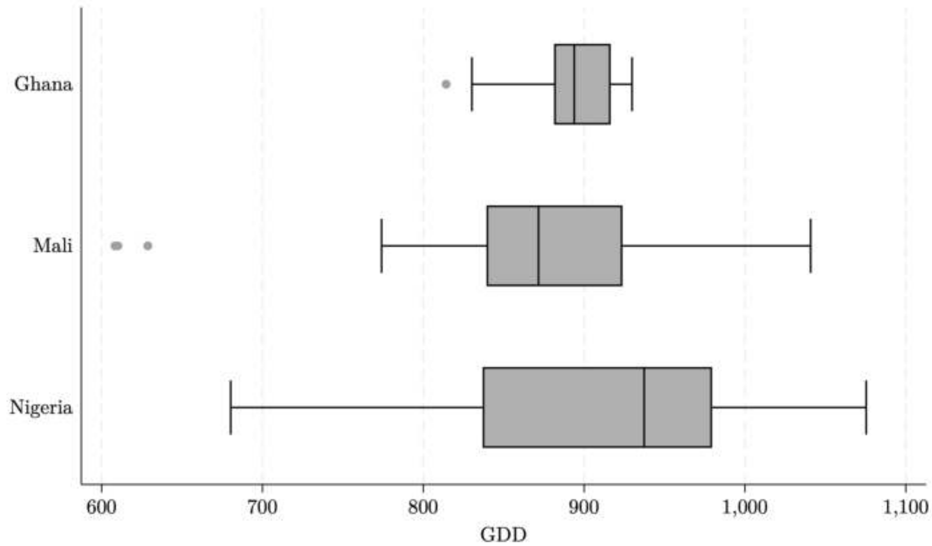

Figure A5: Box plot of GDD by country

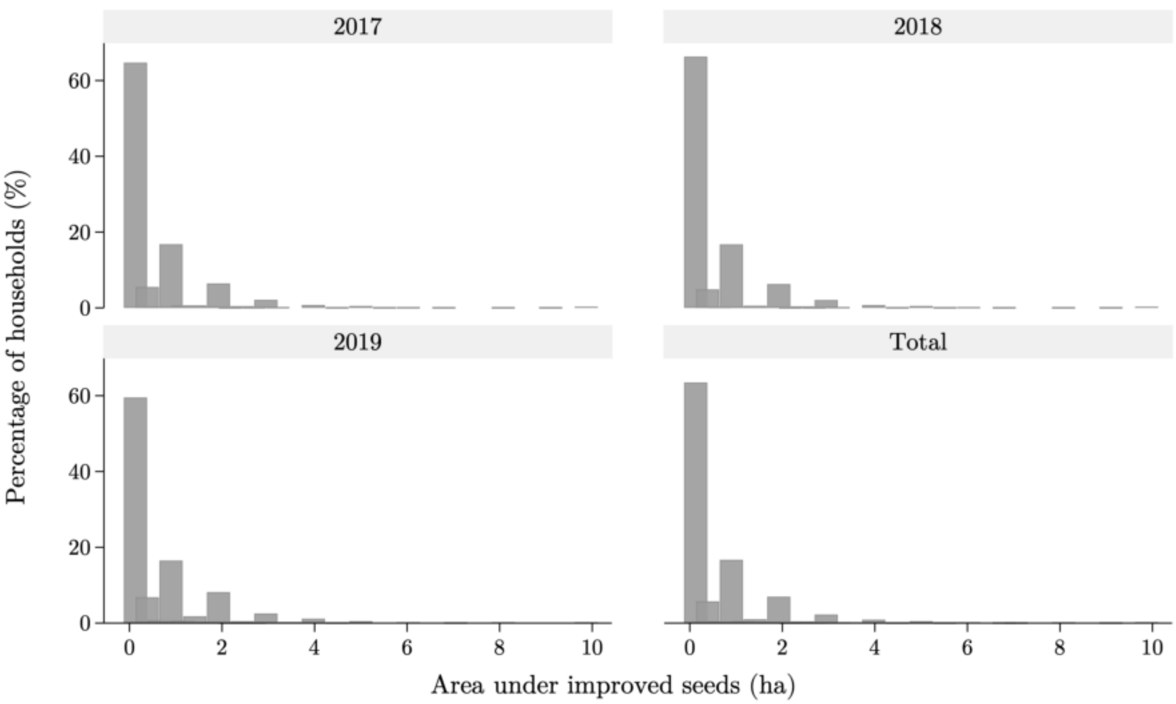

Figure A6: Distribution of area under improved seeds by year

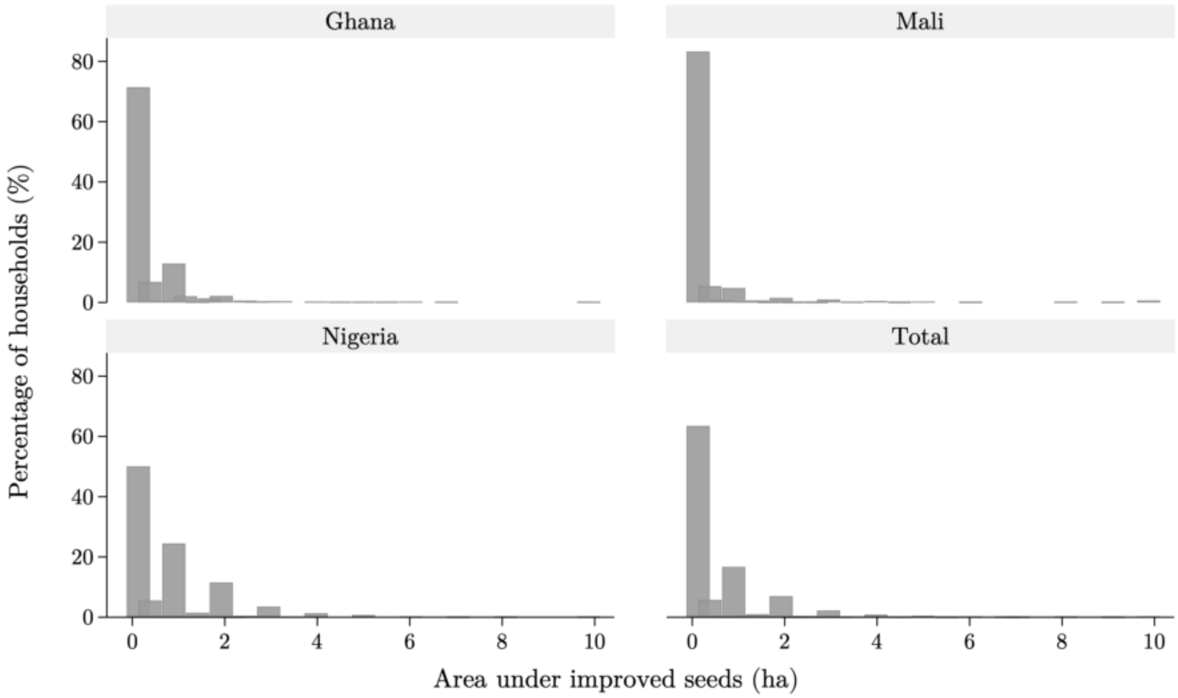

Figure A7: Distribution of area under improved seeds by country