Climate-Induced Innovation in China's Crop Seed Industry: Evidence from Firm-Level Data

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Abstract

This paper examines how the private sector in a middle-income country like China adapts to extreme heat through seed breeding innovation. While most existing research has focused on abiotic stress, such as drought and heat, we extend the analytical framework to include biotic stresses, specifically crop pest and disease exposure, a critical but often overlooked dimension of climate adaptation. We construct novel firm-level, crop-specific exposure measures of extreme heat and crop pests/diseases to investigate how both climate-related abiotic and biotic stressors influence the development of heat/drought-tolerant (HDT) and pest/disease-resistant (PDR) varieties at the firm level. Our results show that Chinese seed firms actively respond to climate pressures, increasing HDT varieties by 2.6% and PDR varieties by 9% for an additional harmful extreme heat degree-day, with significant variations across crops. Maize exhibits comprehensive adaptation across both HDT and PDR, rice focuses on PDR traits, while wheat shows limited responsiveness due to biological complexity and weaker market incentives. Breeding innovation responsiveness is stronger among private firms compared to state-owned enterprises and is most pronounced under the independent innovation model relative to inter-firm collaboration and private-public partnership models. We identify three key pathways driving these responses: increased farmer demand for climate-resilient seeds, heightened pest and disease pressures induced by extreme heat, and government policy signals, proxied by official communications addressing climate- and pest/disease-related issues. Furthermore, the adoption of improved varieties significantly mitigates crop yield loss caused by extreme heat exposure and pest/disease prevalence--PDR varieties reduce pest-related yield losses by 363.72 tons in rice and by 1,342.27 tons in maize. However, adoption and mitigation effects in wheat remain limited due to biological and market constraints. These findings offer valuable policy insights for enhancing agricultural climate resilience.

Keywords: Extreme heat, Seed breeding innovation, Pest- and disease-resistant crop varieties, Chinese, seed firms

1. Introduction

Climate change, particularly the rising frequency and intensity of extreme heat events, poses a substantial threat to global food security, with disproportionate impacts on agricultural systems in low- and middle-income countries (LMICs) (Calzadilla, et al., 2013, Nkonya, 2019). A growing body of empirical studies has identified various adaptation strategies, including adjustments in inputs such as labor, agrochemicals, and machinery (Chen and Gong, 2021, Jagnani, et al., 2021), investments in irrigation infrastructure (Fishman, 2018, Wang, et al., 2024), crop switching (Cui and Tang, 2024, Wang, et al., 2010), and changes in planting timing (Cui and Xie, 2022, Kawasaki, 2018). Among these strategies, the development of climate-resilient seed varieties, specifically heat- and drought-tolerant (HDT) and pest- and disease-resistant (PDR) cultivars, has emerged as a promising long-term adaptation pathway (Wang, et al., 2022, Wang, et al., 2025).

Evidence from high-income countries (HICs) highlights the growing importance of breeding innovation, as variety-level analyses demonstrate significant reallocations of breeding efforts toward crops increasingly exposed to rising temperatures (Moscona and Sastry, 2023). However, critical knowledge gaps remain in understanding the role of seed breeding innovation in LMICs' response to climate stress. Moreover, despite their expanding role in global seed markets and their relevance for smallholder farmers, the adaptive responses of private seed firms in breeding innovation, especially in response to climate-induced pest and disease outbreaks, have been largely overlooked (Deng et al. 2025). Pest and disease pressure driven by climate change are known to severely reduce crop yields (Wang, et al., 2025), yet there is no systematic evidence on PDR innovation as a response.

China offers a compelling context to examine these questions. Over the past two decades, China's seed breeding sector has undergone a significant transformation. Prior to 2000, varietal development was predominantly led by public research institutions. Since 2010, however, private firms have become increasingly dominant, accounting for over 50% of new developed maize varieties and more than 70% of new developed rice varieties by 2022—aligning with the global trend toward privatization of agricultural R&D (Fuglie et al., 2020). Leading companies such as Syngenta Group China and Longping High-Tech have expanded internationally, positioning China as a key player in the global development of climate-resilient seeds (Deng et al., 2025). Understanding how these firms respond to climate stress is thus critical for both national food security and global climate adaptation strategies.

This study addresses these research gaps by investigating four key questions: (1) Did Chinese seed firms develop more HDT and PDR varieties in response to climate stress? (2)

Which types of seed firms (e.g., state-owned vs. private) and which innovation model (e.g., independent R&D vs. public-private collaboration) were more effective in driving climate-related breeding innovation? (3) Through what mechanisms—market demand signals, biophysical stressors like pest outbreaks, or policy priorities—did climate change influence firms' breeding priorities? (4) Did climate-resilient varieties mitigate yield losses from extreme weather, thereby enhancing agricultural resilience?

Leveraging a newly constructed, novel firm-level dataset of 6,335 approved rice, maize, and wheat varieties developed by 1,773 seed firms and 1,984 promoted varieties developed by 795 seed firms between 2003 and 2015, we find strong evidence that Chinese seed firms have developed more climate-resilient varieties, particularly HDT and PDR, in response to extreme heat exposure. We also find distinct crop-specific adaptation patterns: maize breeding exhibited dual adaptation pathways through both HDT and PDR varieties; rice breeding focused heavily on PDR traits, reflecting its vulnerability to heat-induced pest pressures; and wheat breeding showed a positive but statistically insignificant response, possibly due to institutional or technological constraints. Furthermore, consistent with previous studies (Carter, et al., 2018, Cui and Tang, 2024, Lobell, et al., 2011), we find that both extreme heat and pest/disease outbreaks significantly reduced major grain crop yields. However, HDT varieties effectively offset heat-related yield losses, while PDR varieties mitigated losses due to biotic stressors, collectively enhancing agricultural resilience.

We identify three key mechanisms linking extreme heat affects to seed breeding innovation. First, through a demand channel, heat stress significantly amplified farmer demand for climate-resilient varieties, which in turn drove firm-level investment in HDT and PDR varieties. Second, via a biophysical channel, extreme heat intensified pest and disease prevalence, directly increasing the need for PDR varieties. Third, government attention and priority, measured by climate-related content on government websites, reinforced these effects by directing innovation priorities at the firm level. We also explore heterogeneity across firm ownership and innovation models. Private firms exhibited a stronger adaptive response than SOEs, likely due to greater responsiveness to market signals. Independently developed varieties accounted for the majority of climate-resilient innovations, with collaborative public-private R&D playing a complementary role.

This paper offers several contributions to the literature on climate change and agricultural innovation. First, it provides the first systematic firm-level evidence on climate-induced breeding innovation in a LMIC context. While most prior work focuses primarily on HICs (Chemeris, et al., 2022, Moscona and Sastry, 2023), we extend the literature to China, whose seed firms operate in distinct institutional settings and market environments but are increasingly important globally. Unlike short-term adaptation strategies such as agricultural input adjustment, changes in planting time and frequency, crop switching, and irrigation updates, breeding renovation represents a proactive, scalable, and long-term adaption solution. Those short-term responses may be constrained by limited resources and institutional barriers (Chen and Gong, 2021). In contrast, we find that private firms in China responded effectively through independent R&D, often more than through collaborative innovation.

Second, while existing research has emphasized the development of HDT varieties as a key adaptation pathway (Crow, 1998, Kaminski, et al., 2013, Sutch, 2011), we expand this framework to include PDR varieties. This extension is critical given the growing impact of climate-amplified pest pressures. Given the projected increase in pest-related yield losses--46% in wheat, 19% in rice, and 31% in corn (Ma, et al., 2025)—and the fact that pest migration is increasingly climate-driven (Wang, et al., 2025), this extension is timely and important. By unifying HDT and PDR breeding innovation into a unified analytical framework, we provide a more comprehensive view of seed innovation for resilience to both abiotic and biotic stressors.

Third, this study deepens understanding of the mechanisms that drive climate-adaptive agricultural innovation. While prior studies have emphasize either supply-side drivers (e.g., R&D investment, financial subsidies (Gao, et al., 2021, Guo, et al., 2016) or demand-side factors (e.g., market or policy incentives) (Bianchini, et al., 2019, Horbach and Rammer, 2025), few have integrated both. We identify dual channels—market-driven demand and government policy priorities—that together explain the responsiveness of firms to climate shocks.

Finally, this paper contributes methodologically by developing two novel indices to measure climate exposure at the firm and crop levels. The firm-specific extreme heat exposure index addresses the common disconnect between climate impacts and innovation drivers (Long and Wang, 2025). We estimate this index by combining crop-specific county-level heat data, aggregated to the provincial level using planting area weights, with firm-level varietal distribution across provinces. This approach enables mapping from localized climate shocks to firm innovation incentives, improving on prior studies that rely on regional averages (Adhvaryu, et al., 2020, Chen and Yang, 2019, Somanathan, et al., 2021). The crop-specific heat exposure links localized weather extremes to crop planting areas, enabling us to assess how innovations translate into yield protection.

The remainder of this paper proceeds as follows. Section 2 provides the institutional background and conceptual framework. Section 3 describes the data sources and empirical strategy. Section 4 presents the main results, robustness checks, and mechanism analyses. Section 5 concludes with policy implications and directions for future research.

2. Background and literature review

2.1 The Evolution of Seed Breeding Innovation in China and Climate-Adapted Breeding Priorities

Seed breeding innovation serves as a cornerstone of agricultural productivity growth (Jin, et al., 2002). China's seed industry has undergone profound structural transformation since the late 20th century, particularly in the shifting roles of public and private sectors—a central theme in agricultural innovation studies (Morris, et al., 1998, Pray, 2001, Pray, et al., 1991, Price, 1999). Unlike developed economies where private firms dominate R&D, China's pre-2000 breeding landscape was characterized by public-sector dominance, with over 90% of new varieties developed by public institutions, while private firms focused on seed distribution (Bozeman, 2000, Hu, et al., 2011, Moschini, 2010). This public-sector dominance, though effective in achieving yield gains, often overlooked market-oriented traits like stress tolerance and quality improvement.

A pivotal shift occurred with the enactment of the 2000 Seed Law, which was further reinforced by the 2011 initiative to establish a market-oriented breeding system. These institutional reforms significantly accelerated private sector development. Survey data from the China Agricultural Technology Extension Service Center reveal that the number of seed firms with assets exceeding 100 million yuan increased by 59% from 243 in 2013 to 386 in 2019. Notably, nearly 100 firms reported annual R&D expenditure surpassing 10 million yuan during this period. By 2022, private firms accounted for 50% of newly registered maize varieties and 70% of new rice varieties—a dramatic reversal from the pre-2000 period when public institutions dominated variety development.

Climate-adaptive breeding priorities have emerged distinctly across China's major grain crops. Corn breeding has prioritized drought tolerance given that 70% of production occurs in rainfed regions vulnerable to 20-50% yield losses (Li, 2009, Zhang and Bonjean, 2010). Intensifying climate pressures have also elevated resistance traits against emerging threats like ear rot, leaf blight, and Asian corn borer (Dong, et al., 2025, Li, et al., 2019). Rice breeding has adapted to changing water availability patterns. While traditional irrigation infrastructure supported stable production in southern China (Luo, 2010), shifting precipitation has driven adoption of water-saving varieties, now representing over two-thirds of provincial plantings (Heredia, et al., 2022, Xia, et al., 2022). Despite warming trends, heat stress impacts on irrigated rice remain relatively stable (Sun and Huang, 2011, Yu, et al., 2012), with consistent emphasis on blast resistance (Yue, et al., 2020). Wheat breeding reflects regional agro-climatic variation, with northern spring wheat programs emphasizing drought/salt-alkali tolerance and winter wheat regions prioritizing cold resistance (He, 2001). Across all regions, climate change has elevated heat tolerance and pest/disease resistance as key breeding targets. This crop-specific heterogeneity in climate adaptation strategies underscores the need for disaggregated analysis of extreme heat's innovation impacts - a research gap this study addresses through variety-based evidence.

2.2 Literature review

The escalating frequency and intensity of extreme heat events under climate change present profound threats to global food security, with particularly severe consequences for developing countries (Brumbelow and Georgakakos, 2001, Challinor and Wheeler, 2008, Kang, et al., 2009, Mendelsohn, 2009). Extensive research has consistently shown that abiotic stressors, such as drought and heat driven by climate change, exert direct negative effects on crop yields (Gammans, et al., 2017, Schlenker and Lobell, 2010, Schlenker and Roberts, 2009, Wang, et al., 2009). These primary impacts are compounded by significant secondary effects through altered pest and disease epidemiology (Heeb, et al., 2019, Lv, et al., 2023, Ma, et al., 2025, Ma, et al., 2024). Recent estimates reveal that climate-mediated increases in pest pressure may reduce potential yields by 46% for wheat, 19% for rice, and 31% for maize (Ma, et al., 2025), highlighting the multifaceted nature of climate threats to agricultural systems.

China's agricultural sector, as the world's largest, occupies a pivotal position in maintaining global food security. Empirical evidence demonstrates significant climate vulnerability in China's agricultural systems, with documented declines in both agricultural productivity and crop yields (Chen and Gong, 2021, Cui and Tang, 2024, Huang, et al., 2015, Wang, et al., 2024). These impacts are particularly pronounced for staple crops including rice, wheat, and maize (Cui and Tang, 2024, Yin, et al., 2016, Zhang, et al., 2018). Recent findings by Wang et al. (2025) highlight an important but previously underappreciated climate impact pathway — climate-induced pest migrations exert greater influence on China's crop yields than local climate variability alone.

To address these climate challenges, multiple adaptation strategies have been implemented in both research and practice, including adjustments in agricultural inputs (e.g., labor, agrochemicals, machinery) (Chen and Gong, 2021, Jagnani, et al., 2021), crop switching (Cui and Tang, 2024, Wang, et al., 2010), improvements in irrigation (Fishman, 2018, Wang, et al., 2024), modifications to planting time and frequency (Cui and Xie, 2022, Kawasaki, 2018). Empirical evidence from China demonstrates the effectiveness of these adaptation measures. Chen and Gong (2021), for example, documented significant factor substitution, with farmers replacing labor with machinery to maintain productivity under changing climate conditions. Lei et al. (2016) observed a shift from double-cropping rice systems to diversified rotations in Southern China. Wang et al. (2010) identified temperature-driven crop substitutions. Technical adaptations show particular promise, with irrigation offsetting 40% of heat-induced yield losses (Wang, et al., 2024) and planting calendar adjustments preserving up to 9% of projected yields (Cui and Xie, 2022).

However, these conventional adaptation strategies face significant implementation constraints. Farmer resource limitations and institutional barriers substantially reduce their effectiveness (Chen and Gong, 2021) with national food security policies restricting crop switching options and narrowing planting windows (Ding, et al., 2020). While irrigation mitigates drought stress, it also promotes pest proliferation (Ma, et al., 2025) and faces adoption barriers due to high infrastructure costs (Yin, et al., 2016). Biological controls present environmental trade-offs, with climate change exacerbating pesticide resistance (Ma, et al., 2021). Critically, these measures only partially offset yield losses (Burke and Emerick, 2016, Gammans, et al., 2017, Schlenker and Roberts, 2009), serving as reactive coping mechanisms rather than transformative solutions for long-term agricultural resilience.

Seed breeding innovation represents a more sustainable adaptation pathway (Kaminski, et al., 2013, Smithers and Blay-Palmer, 2001), directly addressing climate impacts through genetic improvements (Wahid, et al., 2007). Climate-adapted varieties demonstrate superior performance across diverse agroclimatic conditions (Chhetri and Easterling, 2010, Joseph and Keddie, 2008, Tack, et al., 2016), making breeding innovation fundamental to food security (Sutch, 2011)

However, existing research on climate-induced breeding innovation focuses predominantly on developed countries (Chemeris, et al., 2022, Moscona and Sastry, 2023), leaving critical knowledge gaps regarding developing economies like China. While some studies demonstrate improved drought tolerance in Chinese rice varieties (Liu, et al., 2013, Wang, et al., 2019, Zhang, et al., 2022), they fail to establish causal climate-innovation relationships, particularly for private-sector breeding. This study addresses these gaps by examining firm-level breeding responses to climate change in China's seed market.

3. Data and Key Variables

We construct a comprehensive, novel firm-level panel dataset by integrating multiple sources on climate conditions, seed variety innovation and adoption, crop pest and disease (CPD) prevalence, and agricultural production of major grain crops. This section details the construction and key features of each component.

3.1 Extreme Weather

We obtain daily temperature records—including average, maximum, and minimum temperatures—from the Global Surface Summary of the Day (GSOD) for the period 1973-2023. Using spatial interpolation techniques, we transform station-level data into high-resolution 0.1° × 0.1° gridded data, which is then aggregated to the county level via zonal statistics in ArcGIS. To capture long-run climate exposure relevant for seed breeding innovation, we adopt a 30-year moving average of growing-season temperatures (1981-2015), weighted by crop-specific planting area shares across provinces. This approach, following Cui and Zhong (2024), allows us to construct a robust measure of province-level extreme heat exposure. Below, we outline the procedure to construct this novel firm-specific extreme heat exposure measure that decouples firm location from market reach.

Step 1: Estimating County-level Extreme Heat Exposure

We adopt harmful degree days (HDDs)—defined as the cumulative number of growing-season days (March to October) with temperature exceeding crop-specific physiological thresholds--as our primary measure of extreme heat stress. Consistent with FAO guidelines and agronomic studies (Schlenker and Roberts, 2009), we set thresholds as 34°C for maize, 31°C for rice, and 24°C for wheat, based on temperature-yield response curves that indicate sharp productivity declines above these values. For analyses pooling all major grain crops, we use a composite threshold of 30°C.

County-level level extreme heat exposure is calculated as:

$$CountyExposure_{c,t}^{k} = DegreeDays_{c,t}^{k}\left(T^{k}\right) = \sum_{d \in t} DegreeDays\left(T^{k}; d\right) \quad (1)$$

where $DegreeDays_{\mathrm{c},t}^{k}\left(T^{k}; d\right)$ represents HDDs for crop k in county c during year t, where d denotes the daily temperature and T^{k} represents the crop-specific heat threshold. To isolate persistent climate trends from short-term weather variability, we compute 30-year moving averages of county-level HDDs, using data from 1981 to 2015. These averages are weighted by crop-specific planting areas, allowing us to capture the agronomic significance of extreme heat for different crops across counties. This approach, based on Cui and Zhong (2024), provides a robust measure of long-term, spatially explicit climate stress relevant to agricultural decision-making.

Step 2: Aggregating Count-level Extreme Heat Exposure to the Provincial Level

To construct provincial-level measures of extreme heat exposure, we aggregate county-level HDDs using county-level cropping area as weights:

$$ProvinceExposure_{p,t}^{k} = \sum_{c} \left[\frac{Area_{c,t}^{k}}{\sum_{c \in p} Area_{c,t}^{k}} \cdot CountyExposure_{c,t}^{k} \right] \quad (2)$$

Where $Area_{p,c,t}^{k}$ represents the planting area of crop k in county c of province p in year t. This weighted aggregation approach ensures that counties with larger crop production areas exert greater influence on the provincial-level exposure measure. As a result, the index more accurately reflects the distribution of agricultural activity and associated climate risks across regions, providing a more meaningful input for firm-level exposure calculations in subsequent stages.

Step 3: Estimating Firm-Level Extreme Heat Exposure

We link provincial extreme heat exposure to firm-level innovation activity by constructing adoption-weighted extreme heat exposure at the firm level. Specifically, for each firm i, crop k, and year t, we calculate a weighted average of provincial heat exposure using the firm's total promotion area $AdoptionArea_{i,t,p}^{k}$ in province p as weights:

$$FirmExposure_{i,t}^{k} = \sum_{p}\left[\frac{AdoptionArea_{i,t,p}^{k}}{\sum_{p} AdoptionArea_{i,t,p}^{k}} \cdot ProvinceExposure_{p,t}^{k}\right] \tag{3}$$

This approach accounts for the geographic dispersion of a firm's market presence, thereby aligning climate exposure with the actual environments where its seed varieties are adopted.

This three-step approach yields a rigorous and economically meaningful estimate of firm-specific exposure to extreme heat. By incorporating crop-specific heat thresholds and adoption-based area weights, our exposure metric captures the biophysical conditions seed firms must consider when making R&D decisions, thus enhancing the accuracy of our empirical identification.

3.2 Breeding Innovation and Adoption of Major Grain Crop Seeds

Data on seed breeding innovation, measured by approved varieties, are drawn from the China Seed Industry Big Data Platform, maintained by the National Agricultural Technology Extension Service Center (NATESC) under the Ministry of Agriculture and Rural Affairs (MARA) of China. This platform provides comprehensive records of approved seed varieties from 1977 to 2021, including 15,560 maize, 12,889 rice, and 4,168 wheat approved seed varieties. Each entry includes information on approval year, crop type, varietal traits, breeder details, and applicant information. Information on varietal traits allows us to identify HDT and PDR cultivars. The applicant information helps us identify different innovation models. Specifically, we categorize innovation model into three forms: independent innovation, inter-firm collaborative innovation, and public-private collaboration. An application from a single firm is classified as independent innovation. When applications include two or more firms, this is recognized as inter-firm collaborative innovation. Conversely, an application that encompasses both firms and research institutions is identified as public-private partnership innovation. After obtaining the comprehensive list of companies that have developed new varieties, we search for more detailed information about these companies on the Tianyancha website, which provides the types of enterprises (such as limited liability companies, individual businesses, and state-owned operating units). We define the ownership of firms based on their types. If a firm's capital composition includes state capital and collective capital, we classify it as a state-owned firm; otherwise, it is categorized as a non-state-owned firm. A key institutional feature of China's seed approval system is the dual-track structure: national approvals of new varieties target broad adaptability across agroecological zones, while provincial approvals emphasize the localized performance of varieties. Provincial approvals accounted for 96% of all approvals, reflecting the decentralized nature of varietal evaluation and regulations in China. For our analysis, we focus on 6,335 varieties developed by 1,773 seed firms and approved between 2003–2015.

We distinguish four seed varieties: 1) heat- or drought-tolerant varieties (N = 197), 2) pest- or disease-resistant (PDR) varieties (N = 5,081), 3) stacked varieties that combine HDT and PDR traits (N = 175), and 4) traditional varieties (N = 1,042). The first three types of seed varieties accounted for 83.51%, especially PDR varieties comprised 80.40% of the newly approved varieties developed by private firms during our study period (2003-2015), highlighting the importance of biotic stress mitigation in China's seed markets.

To examine the adoption of seed varieties, we leverage provincial adoption records from the same MARA database, which document the adoption and commercial promotion areas of firm-developed varieties. These data enable us to construct firm-year-province adoption weights, which serve as a key metric for assessing firms' exposure to local climate conditions. Our baseline sample consists of 834 firms whose seed varieties were adopted in at least one province during the study period, thereby ensuring a focus on commercially active firms with incentives to respond to climate-induced agricultural risks.

3.3 Pests and Disease Prevalence and Agricultural Production

Data on CPD prevalence are compiled from province-year-crop panels maintained by the NATESC. These records, based on over 5,000 entries since 2002, allow us to construct a detailed panel of CPD prevalence for each crop. WE focus on major pests and diseases relevant to the traits targeted by PDR varieties, enabling a consistent linkage between biological stressors and firm-level innovation response.

Crop production data are compiled from the County-level Agricultural Database administered by the MARA, which includes annual information on planting area and yield for major grain crops across over 2,400 counties (1981-2015). We integrate province-level statistics on crop planting structure and agricultural output value from the National Bureau of Statistics of China. These data are used to construct climate exposure weights and as control variables in our empirical models. All monetary values are adjusted to constant 2015 RMB using appropriate deflators.

3.4 Government Attention to Climate-Related Agricultural and Environmental Issues

To quantify government attention to climate-related agricultural and environmental issues, we construct novel indices based on text mining of official news released by government websites. Our data collection and index construction proceed in three main steps. We restrict the search queries to official government websites targeted and extract the following information, including the province name, relevant keywords related to climate change or CPD issues. This approach ensures that only content published by verified government entities is included in our dataset. Second, we employ automated web scraping tools to extract metadata for each identified government communication, including publication date, issuing agency, headlines, and content summary. We organize the resulting dataset into a structured panel by province, year, and keyword. Finally, we construct two separate indices of government attention: one for climate change and one for CPD issues. To account for potential skewness in the distribution of raw counts and to enable comparability across provinces and years, we apply a natural logarithmic transformation to the counts. These indices serve as proxies for the salience of climate pressure and CPD stress in provincial-level policy discourse, allowing us to test whether government priorities—reflected in public communications—influence firms' breeding decisions and innovation strategies in response to climate pressures.

Table 1 shows the summary statistics of key variables.

<Table 1 about here>

4.Estimation Strategies and Model Specifications

To assess how seed firms adapt their breeding strategies in response to extreme heat exposure, we employ a two-way fixed effects (TWFE) regression model that accounts for both firm-specific heterogeneity and temporal trends. Our baseline specification is as follows:

$$lnY_{i,t}^{k} = \partial_0 + \partial_1 FirmExposure_{i,t}^{k} + \partial_2 X_{i,p,t} + \gamma_i + \mu_t + \varepsilon_{i,t} \quad (4)$$

Where $Y_{i,t}^{k}$ represents the number of climate-resilient seed varieties for crop k developed by firm i in year t, and $FirmExposure_{i,t}^{k}$ denotes is our key independent variable capturing firm-specific exposure to extreme heat. $X_{i,p,t}$ is a vector of time-varying provincial-level control variables, including total crop planting area and aggregate agricultural output value in firm i's home province. γ_i and μ_t denote firm and year fixed effects, respectively. $\varepsilon_{i,t}$ is the idiosyncratic error term.

The coefficient of firm-specific exposure to extreme heat, ∂_1, measures the marginal effect of extreme heat exposure on the development of climate-resilient varieties. A statistically significant and positive estimate of ∂_1 would provide evidence that seed firms respond to extreme heat through targeted innovation in climate-resilient seeds.

5.The Landscape of Seed Breeding Innovation Priorities in China's Private Sector

This section provides a comprehensive analysis of crop breeding innovation within China's private seed sector. Our evidence demonstrates the private sector's emergence as the major force in crop varietal development. Figure 1 illustrates the temporal evolution of new major grain crop varieties developed by seed firms from 2000 to 2015. In the pre-2000 period, the number and proportion of new crop varieties developed by seed companies was very low, with most seed firms engaged solely in seed production and sales while public institutions dominated innovation. A transformative shift occurred in 2000, marked by a substantial increase in both the quantity and proportion of firm-developed varieties. By 2011, seed firms accounted for over 50% of new crop varieties for the first time——a milestone reflecting their growing innovation capacity. This trajectory aligns with policy reforms, particularly the 2000 Seed Law that initiated commercial breeding and its 2011 amendments that further stimulated private sector growth (Deng et. al, 2025), mirroring global trends in agricultural R&D privatization (Fuglie et al. 2020).

<Figure 1 about here>

Our crop-specific analysis (Figure 2) reveals distinct innovation patterns across major grain crops. Maize has experienced the most dramatic growth, increasing from negligible numbers in 2000 to over 400 varieties annually by 2015, representing 87% of new maize varieties by 2015. Rice shows parallel growth, reaching 233 annual varieties (57% share) by 2015. In contrast, wheat innovation remains limited (10% share pre-2010), with only gradual increases post-2011, likely attributable to biological complexity and weaker market incentives. The results reveal that seed firms have increasingly prioritized maize and rice varietal development, with both quantity and proportion showing remarkable growth. Conversely, wheat varietal development has been more limited, constituting just 10% of annual new varieties prior to 2010. While wheat breeding efforts have gradually intensified since 2011, their scale and market share continue to lag behind maize and rice, potentially reflecting lower market demand, greeter breeding challenges.

<Figure 2 about here>

We next examine commercial breeding priorities of seed firms in response to climate pressures during 2000-2015. Figure 3 displays the quantity and proportion of HDT and PDR varieties developed by seed firms, with panel (a) showing the results for major grain crops, while panels (b), (c), and 3 (d) provide crop-specific results for maize, rice, and wheat, respectively.

<Figure 3 about here>

The results presented in Figure 3 reveals two prominent and divergent trends. First, we observe a consistent but modest investment in HDT varieties, which maintained a stable 5% share of total new varieties developed by seed firms throughout the study period. This trend highlights the ongoing focus that seed firms have maintained on improving heat/drought tolerance within their breeding programs. Second, and more strikingly, we document an exponential growth in pest/disease-resistant varieties, which increased from just 33 varieties (45% share) in 2000 to 609 varieties (88%) by 2015. This surge underscores PDR traits as a core priority in seed firms' breeding strategies, signaling a strong emphasis on biotic stress resistance. Crop-specific trends reveal a uniform pattern in corn and rice varieties (Figure 3 (b) and 3(c)). Maize and rice breeding has heavily prioritized PDR traits, with PDR varieties comprising approximately 15% and 65% of new releases in the early study period, surging to 85% (maize) and 97% (rice) by 2015. It is worth noting that pre-2010 fluctuations in wheat HDT variety proportions were largely driven by the limited scale of wheat breeding programs. Nevertheless, PDR traits dominated, with nearly all new wheat varieties incorporating them. After 2011, wheat varieties expanded, with increasing attention to a broader trait portfolio.

Our findings reveal that climate-resilient traits—particularly PDR— are central to seed industry innovation in major grain crops, surpassing the focus on HDT traits. This prioritization likely arises from PDR's crucial role in enhancing crop stability and adaptability amid escalating climate change and biotic threats—a dimension previously underemphasized in the literature.

6. Results

6.1 Baseline Estimates: Effects of Extreme Heat on Climate-resilient Varieties

Table 2 presents our baseline TWFE regression results, assessing the impacts of extreme heat exposure on the development of three categories of climate-resilient varieties: HDT varieties, PDR varieties, and stacked varieties combining both traits. For comparison, we also assess the effect on varieties that do not exhibit HDT or PDR traits.

As shown in Column 1 of Table 2, extreme heat exposure exhibits a positive and statistically significant effect on climate-related variety innovation. Specifically, each additional HDD above 30°C is associated with an increase of 0.03 HDT varieties, equivalent to a 3% increase, significant at the 1% level. The effect is larger for PDR varieties (Column 2), with an increase of 0.09 varieties, corresponding to an approximately 9% increase, statistically significant at the 5% level. For stacked varieties that combine both HDT and PDR traits, extreme heat exposure increases the number of varieties by 0.03, representing a 3% rise (Column 3), significant at the 1% level. In contrast, as shown in Column (4), extreme heat exposure is not significantly associated with varieties that lack HDT or PDR traits, indicating no evidence of crowding-out effects. These results suggest that seed firms respond to extreme heat exposure by expanding innovation in climate-related varieties without diverting resources away from other breeding efforts. Rather than reallocating R&D investment, firms appear to intensify their overall innovation in response to climate-related stress.

These findings are consistent with and extend the work by Moscona and Sastry (2023), offering new evidence that private sector firms in LMICs actively innovate in response to climate stress by developing both HDT and PDR varieties. Our results highlight two distinct but related adaptation pathways: (1) HDT varieties that address abiotic stresses such as heatwaves and drought, and (2) PDR varieties that mitigate biotic stresses exacerbated by extreme heat, including pests and diseases (Wang, et al., 2022, Wang, et al., 2025). This dual breeding innovation strategy reflects firms' comprehensive effort to adapt to the multifaceted impacts of climate change.

<Table 2 about here>

To further validate our key findings, we conduct a series of robustness tests: 1) including nationally approved seed varieties; 2) applying higher thresholds for extreme heat (32℃ and 34℃ respectively); and 3) incorporating additional control variables, including precipitation exposure. The results across all alternative specifications remain consistent with our baseline estimates. The sustained statistical significance and consistency in effect magnitudes reinforce the robustness of our key finding: seed firms respond to extreme heat exposure by developing more climate-resilient varieties.

6.2 Crop-specific heterogeneity in climate-resilient breeding responses

Building on our findings of climate-induced breeding innovation, we explore crop-specific heterogeneity in breeding responses to extreme heat exposure across maize, rice, and wheat, and present the results in Table 3.

For maize, extreme heat exposure significantly stimulates the development of both HDT and PDR varieties, demonstrating a comprehensive adaptation strategy to both abiotic and biotic stresses under climate volatility. As shown in Columns (1) and (2) in Panel A of Table 3, an additional HDD above 34°C is associated with an increase of 0.019 HDT varieties (a 1.9% increase) and 0.073 PDR varieties (a 7.3% increase). Additionally, extreme heat exposure also stimulates the development of stacked maize varieties incorporating both traits, further highlighting firms' multi-trait innovation response to climate stress.

Rice exhibits a selective adaptation pattern, as shown in Columns (1) and (2) in Panel B of Table 3: extreme heat exposure is significantly associated with an increase of 0.016 PDR varieties (a 1.6% increase), significant at the 5% level, while no statistically significant association is found for HDT varieties. This pattern likely reflects rice's unique cultivation context: 1) extensive irrigation infrastructure mitigates drought stress (Huang, et al., 2006), reducing the demand for HDT traits; and (2) rice tends to be less sensitive to high-temperature stress compared to other crops (Chen, et al., 2023, Deng, et al., 2017, Yu, et al., 2012)， with breeding efforts historically focusing on cold tolerance over heat adaptation (Deng, et al., 2017).

As shown in Columns (1) and (2) in Panel C of Table 3, wheat shows positive but statistically insignificant associations between extreme heat exposure and climate-related breeding innovation, highlighting key biological and institutional constraints. First, wheat's complex allohexaploid genome (Consortium, et al., 2018) poses greater technical challenges for rapid varietal improvement compared to rice and maize. Second, unlike hybrid maize and rice systems, wheat cultivation is dominated by farmer-saved seed practice, with growers often reusing seed across planting cycles rather than purchasing commercial seeds. This substantially lowers market demand for new wheat varieties. Our market data indicate wheat seed replacement rates average only 8.18%, compared to 12.48% for maize and 15.27% for rice. Consequently, private firms face weaker incentives to invest in climate-resilient wheat breeding.

These crop-specific patterns in seed firms' responses to extreme heat exposure highlight how biological, agronomic, and institutional factors influence climate adaptation through breeding innovation, suggesting the need for crop-specific strategies rather than a one-size-fits-all approach.

6.3 Mechanism analysis

We examine the mechanisms through which extreme heat exposure induces climate-resilient breeding innovation among seed firms, identifying three key pathways: 1) market signals, captured through seed adoption rates as an indicator for farmer demand; 2) biophysical stressors, measured by pest and disease prevalence, and 3) government policy priorities, proxied using web-scraper data from official government communication.

6.3.1 Market Signals: Farmer Demand Channel

Farmer demand for climate-resilient seeds is a key driver of breeding innovation at the firm level. We use land shares of adopted climate-resilient varieties as revealed demand indicators. As shown in Table 4 (Panel A), extreme heat exposure is statistically associated with increased adoption of HDT ($\beta=0.0148$, $p<0.05$), PDR ($\beta=0.0528$, $p<0.05$), and stacked traits ($\beta=0.0092$, $p<0.10$). The rising demand for climate-related seeds likely incentivizes firms to expand their

R&D efforts on developing more climate-related traits, contributing to the innovation patterns observed in our baseline results.

Notably, demand responses exhibit distinct crop-specific patterns. For maize (Panel B), extreme heat significantly boosts adoption of all trait categories: HDT ($\beta=0.0145$, $p<0.05$), PDR ($\beta=0.0480$, $p<0.05$), and stacked traits ($\beta=0.0107$, $p<0.05$). In contrast, for rice and wheat (Panels C and D), extreme heat is linked with higher adoption of PDR varieties ($\beta=0.0637$, $p<0.1$ and $\beta=0.2018$, $p<0.05$, respectively), but shows no statistically significant associations with HDT or stacked traits. These results align with the crop-specific responses observed in firms' breeding innovation. This disconnect between demand and innovation in wheat PDR varieties may stem from market concentration dynamics. Adoption data show that farmers tend to consolidate around a few established PDR varieties rather than adopt newer innovations—the top ten wheat varieties account for 52.49% of total adoption area compared to 30.02% for maize. This concentration likely reduces the marginal returns to new variety development, dampening firms' incentives to innovate despite the demand signals.

<Table 4 about here>

6.3.2 Biophysical shocks: crop pest and disease prevalence

Extreme heat exposure may stimulate seed breeding innovation through its impact on pest and disease prevalence. To formally test this biophysical mechanism, we employ a two-stage analytical framework. In the first stage, we estimate the effect of extreme heat exposure on pest and disease prevalence using county-level data:

$$\ln CPD_{i,t}^{k} = \partial_0 + \partial_1 CountyExposure_{i,t}^{k} + \partial_2 X_{i,p,t} + \gamma_i + \mu_t + \lambda_{n,t} + \varepsilon_{i,t} \tag{5}$$

Where $CountyExposure_{i,t}^{k}$ represents the level of extreme heat exposure for crop k in county i and year t, and $CPD_{i,t}^{k}$ denotes the prevalence rates of crop pests and diseases in county i and year t, calculated as the weighted ratio of the affected area to total cultivated area in related province, with weights based on the share of crop k plating area.

As Table 5 shows, extreme heat exposure is significantly associated with increased prevalence of increased pest and disease for all three crops, at the 1% significance level, with particularly stronger effects on maize (β = 0.0279) compared to rice (β = 0.0021) and wheat (β = 0.0016). These results are consistent with findings from Wang, et al. (2022) and provide empirical support for the first step of our proposed mechanism.

<Table 5 about here>

In the second stage, we investigate how biophysical shocks influence breeding innovation. Table 6 presents regression results that include both extreme heat exposure and pest/disease prevalence. We find that pest and disease exposure is positively and statistically associated with the number of PDR varieties across all three crops at the 10% level. Once pest and disease exposure is controlled for, the previously significant effects of extreme heat exposure on PDR varieties become statistically insignificant, suggesting that biophysical stress mediates much of the observed relationship.

We also find that, for corn, extreme heat exposure remains positively and significantly associated with the numbers of HDT and stacked varieties even after controlling for pest and disease exposure. In contrast, the statistical significance of extreme heat exposure disappears for rice and wheat once biophysical stressors are included. These findings suggest that while biotic stress is a key pathway driving PDR innovation, abiotic stress, particularly in maize, continues to stimulate HDT and stacked trait development.

<Table 6 about here>

6.3.3 Policy Priority measured by official government communication

We explore the third potential pathway through government policy priorities, proxied by official government communications on climate-related agricultural issues. We conduct the following TWFE estimation:

$$\begin{aligned}\ln CPD_{i,t}^{k} = {} & \partial_0 + \partial_1 FirmExposure_{i,t}^{k} \\ & + \partial_2 GA_{i,p,t} \\ & + \partial_2 FirmExposure_{i,t}^{k} \times GA_{i,p,t} \\ & + \partial_2 X_{i,p,t} + \gamma_i + \mu_t + \lambda_{n,t} + \varepsilon_{i,t}\end{aligned} \quad (6)$$

where $GA_{i,p,t}$ represents the firm-level weighted average of the provincial government priority proxy for crop k in year t, using the same spatial weighting scheme as extreme heat exposure. We distinguish those official government communications addressing either climate-related issues or crop pest/disease-related issues.

As shown in Table 7, we find that climate-related government communication significantly amplifies the effect of extreme heat exposure on HDT variety innovation (β=0.016, p<0.01). Similarly, government communications focused on crop pests and diseases enhance the impact of extreme heat on PDR innovation (β=0.1868, p<0.10), with a much larger effect size. For stacked-trait varieties, climate-related government communications reinforce the positive effects of extreme heat, whereas pest- and disease-related communications dampen this relationship, suggesting potential trade-offs in breeding priorities when addressing multiple stressors simultaneously.

<Table 7 about here>

6.4 Heterogeneity analysis

6.4.1 Differentiated Effects across Inventor Types

Given the differing incentive mechanisms in the state and private sectors, we delve deeper into the varied impacts that distinct types of inventors' experience. As shown in Table 8, private firms demonstrate significantly stronger responsiveness to extreme heat exposure by developing more climate-resilient seeds, including HDT (β=0.0317, $p<0.01$), PDR (β=0.1036, $p<0.05$), and stacked varieties (β=0.0315, $p<0.01$). However, such associations are not statistically significant for SOEs. These findings are consistent with Long and Wang (2025) and Moscona and Sastry (2023), highlighting the important role of the private sector in driving climate adaptation through market-oriented and profit-driven innovation. Furthermore, as shown in Table 8, private firms show particularly strong innovation responses in maize (β=0.214, $p<0.01$), reflecting the crop's high commercial value and its reliance on hybrid seeds, which ensures recurring demand. For rice and wheat, private sector responses are statistically insignificant.

<Table 8 about here>

6.4.2 Differentiated Effects across Innovation Models

We examine differential responses to extreme heat exposure across three innovation models based on the types of applicants involved in seed variety registration: 1) independent innovation (single-firm applicants); 2) inter-firm collaboration (joint applications by multiple firms), and 3) public-private partnerships (co-applications between firms and research institutions). These models represent different pathways of knowledge creation and transfer, each with unique implications for climate adaptation.

As shown in Table 10, the independent innovation model is the strongest responsiveness to extreme heat exposure, with statistically significant and positive associations between extreme heat exposure and the number of PDT, PDR, and stacked varieties, all significant at the 5% level. In contrast, we find no statistically significant associations for the inter-firm collaborative or public-private partnership models.

Across crop types, we find a similar pattern, where the independent innovation model drives significant increases in all three trait categories at the 10% significance level, while public-private partnerships are statistically associated with PDR innovation at the 10% level. For rice, extreme heat exposure is statistically associated with increases in PDR and stacked-trait varieties at the 10% level within the independent innovation model, but no such associations are found for the two collaborative models. Wheat, consistent with earlier findings, shows no significant response across any innovation model.

These findings highlight the central role of firm-level R&D capacity in driving climate-resilient seed innovation in China. Competitive dynamics may constrain inter-firm collaboration, limiting horizontal knowledge sharing and transfer necessary for effective collective innovation. Although the contribution of private-public partnerships remains marginal in practice, constrained by institutional and structural barriers, such partnerships have the potential to enhance climate resilience, as demonstrated in HICs, where formal innovation consortia and robust intellectual property regimes facilitate collaboration (Long and Wang, 2025, Moscona and Sastry, 2023). Strengthening intellectual property protections and incentivizing formalized innovation networks could unlock substantial efficiency gains and improve the sector's adaptive capacity under climate stress.

6.5 Mitigation Effects of Climate-Resilient Varieties

Building on our findings that extreme heat exposure stimulates climate-resilient breeding innovation, we examine whether these newly developed varieties effectively mitigate climate-induced yield losses. We develop a novel county-level analytical framework to quantify mitigation effects.

We first construct a county-level innovation exposure based on the weighted average of provincial-level innovation exposure, using the weights reflecting each county's share of the total crop planting area. Formally, the city-level innovation exposure is given below:

$$\begin{aligned} InovationExposure_{c,t}^{k,j} &= \frac{Area_{c,t}^{k}}{\sum_{c\in p} Area_{c,t}^{k}} \times InnovationExposure_{p,t}^{k,j} \\ &= \frac{Area_{c,t}^{k}}{\sum_{c\in p} Area_{c,t}^{k}} \times \frac{\sum_{i} InnovationAdoptionArea_{i,p,t}^{k,j}}{\sum_{i} InnovationAdoptionArea_{i,p,t}^{k\ j}} \end{aligned} \tag{7}$$

where $Area_{c,t}^{k}$ represents the planting area of crop k in county c and year t, and $nnovationExposure_{p,t}^{k,j}$ represents the adoption area of variety type j (e.g., HDT, PDR) in province p and year t.

We estimate the mitigation effects of climate-resilient varieties through the county-level mode, formulated below:

$$\begin{aligned} lnYields_{c,t}^{k} = {} & \partial_0 + \partial_1 CountyExposure_{c,t}^{z} \\ & + \partial_2 InnovationExposure_{c,t}^{k,j} \\ & + \partial_3 CountyExposure_{c,t}^{z} \times InnovationExposure_{c,t}^{k,j} \\ & + \partial_4 X_{c,t} + \gamma_c + \mu_t + \varepsilon_{i,t} \end{aligned} \tag{8}$$

Where $Yields_{c,t}^{k}$ represents crop k's yield per unit of planting area in county c and year t.

$CountyExposure_{c,t}^{z}$ represents the climate stress z (e.g. extreme heat exposure and cpd exposure) in county c and year t. This dual approach allows us to separately identify two key pathways in mitigating climate-related yield losses: 1) the extent to which HDT varieties reduce yield losses from extreme heat, and 2) the extent to which PDR varieties reduce pest and disease pressure, as established in earlier analysis. Our spatial weighting scheme, based on county-level crop area shares, ensures that innovation exposure reflects actual adoption patterns rather than variety availability alone. By capturing localized adaptation outcomes and distinguishing between abiotic and biotic stress pathways, this framework offers comprehensive evidence on the yield benefits of climate-induced innovation.

As shown in Table 12, we find significant crop-specific yield losses from extreme heat exposure, with the greatest loss for rice ($\beta=-0.0041$, $p<0.01$), followed by maize ($\beta=-0.0012$, $p<0.05$), while wheat shows no statistically significant association between extreme heat exposure and yield. Pest and disease pressure has even more severe yield losses, reducing yield 3.26% ($p<0.01$) for wheat, 3.82% ($p<0.05$) for rice, and 1.90% ($p<0.05$) for maize. The results provide strong empirical support for the theoretical predictions of Ma, et al. (2025) regarding climate-amplified pest damages and the corresponding yield losses.

As shown in Table 12, the coefficients of the interaction terms between extreme heat exposure and HDT or PDR innovation reflect the mitigation effects of innovation on climate-related yield losses. We find that HDT varieties significantly mitigate climate-related yield losses for all three crops: 0.0014 ($p<0.01$) for rice, 0.00135 ($p<0.01$) for maize, and 0.0019 ($p<0.01$) for wheat. On the other hand, PDR varieties significantly mitigate climate-related yield losses for rice (0.0113, $p<0.01$) and maize (0.0049, $p<0.1$) for maize, but not for wheat. These results are consistent with earlier work by Liu, et al. (2010) and Liu, et al. (2013). These mitigation effects are economically significant: our production-weighted estimates suggest these varietal improvements preserved approximately 5,059.43 tons of annual major grain output (i.e. 1,066.73 ton of corn and 3,992.70 ton of rice) during our study period.

Wheat stands out for its limited adaptive gains. Despite substantial pest/disease-related yield losses ($\beta=-0.0326$, $p<0.01$), current PDR varieties show no statistically significant mitigation effects. This disconnect may suggest either technological challenges in wheat breeding or a misalignment between commercialized traits and on-the-ground stress conditions. These findings highlight a critical gap in the adaptive capacity of wheat and the need for targeted public investment to address market failures in crops with low private R&D incentives.

<Table 12 about here>

7. Conclusion

This study provides the first comprehensive analysis of how seed firms in an LMIC respond to extreme heat through breeding innovation, drawing on multi-source data on extreme heat, seed variety registrations, adoption rates, and cropping systems. In particular, we construct two novel firm-level, crop-specific exposure measures: one capturing extreme heat exposure—more accurately reflecting the incentives for climate adaptation in the seed industry--and another capturing pest and disease exposure, which allows us to investigate additional pathways through which extreme heat exposure may adversely impact crop yield, in turn, stimulate breeding innovation.

We find that extreme heat exposure measured by an additional HDD is associated with an increase of HDT varieties by 2.6% and PDR varieties by 9%. Private firms are more effective in breeding innovation to respond to climate stress than SOEs, and the independent innovation model is more effective than inter-firm collaboration and private-public partnership collaboration models. These effects are driven by three key pathways: (1) shifts in farmer demand toward climate-resilient seed varieties, (2) intensified pest/disease prevalence amplified by extreme heat, and (3) government policy priorities proxied by official communications of climate- and pest/disease-related issues. We also find that the adoption of these improved seed varieties helps save approximately 5,059.43 tons of annual grain production. However, the benefits vary significantly across crops--maize and rice show strong adaptive gains, while wheat lags behind, constrained by both biological and institutional constraints.

The findings offer important policy implications. While market-driven innovation has proven effective for commercial crops, strategic crops like wheat require complementary public research investments. Policies should support both private and public sectors, while also strengthening collaboration between the two. Future research in the following directions is merited, including the optimal mix of policy instruments across different crop systems, and the broader welfare impacts of climate-induced breeding innovation.

We acknowledge two key limitations. First, our analysis focuses on extreme heat exposure, while other climate factors, such as drought, flooding, and shifting seasonalities, may also influence breeding priorities. Second, we use official government communications of crop climate- and pest/disease-related issues as a proxy to measure government policy priorities. Future research incorporating more direct and accurate measures of government policy priorities is needed. Despite these limitations, this study provides new empirical evidence that the seed industry in an LMIC is responsive to extreme heat, offering critical insights for global strategies aimed at strengthening agricultural adaptation and resilience.

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Table 1.
Summary statistics of key variables.

Variable	Description	Obs	Mean	SD
Panel A Extreme Heat Exposure				
Firm-Specific EH Exposure	Firm-level exposure to heat above 30℃ (general threshold)	3822	3.1648	1.1310
Corn-Specific EH Exposure	Maize-specific firm-level exposure to heat above 34℃	2197	0.1528	1.3694
Wheat-Specific EH Exposure	Wheat-specific firm-level exposure to heat above 24℃	1383	3.4105	0.9367
Rice-Specific EH Exposure	Rice-specific firm-level exposure to heat above 30℃	446	5.4727	0.3391
Panel B New crop seed breeding varieties				
Major Grain Crops seed breeding innovation	the logarithm of new HDT varieties of Major Grain Crops	3822	0.0152	0.1094
	the logarithm of new PDR varieties of Major Grain Crops	3822	0.3449	0.5878
	the logarithm of new HDT and HDR varieties of Major Grain Crops	3822	0.0143	0.1063
Corn seed breeding innovation	the logarithm of new HDT varieties of Corn	3822	0.0066	0.0706
	the logarithm of new PDR varieties of Corn	3822	0.2061	0.4559
	the logarithm of new HDT and HDR varieties of Corn	3822	0.0057	0.0656
Rice seed breeding innovation	the logarithm of new HDT varieties of Rice	3822	0.0076	0.0794
	the logarithm of new PDR varieties of Rice	3822	0.1492	0.4241
	the logarithm of new HDT and HDR varieties of Rice	3822	0.0076	0.0794
Wheat seed breeding innovation	the logarithm of new HDT varieties of Wheat	3822	0.0010	0.0286
	the logarithm of new PDR varieties of Wheat	3822	0.0172	0.1461
	the logarithm of new HDT and HDR varieties of Wheat	3822	0.0010	0.0286
Panel C Pests and Disease Prevalence and Agricultural Production				
County-level CPD exposure	Corn-specific CPD exposure (5-Year Lagged Average)	28793	0.4013	0.4192

	Rice-specific CPD exposure (5-Year Lagged Average)	24231	0.2983	0.4776
	Wheat-specific CPD exposure (5-Year Lagged Average)	27126	0.4676	0.5382
Firm-specific CPD exposure	Total Major grain crops CPD exposure (4-Year Lagged Peak)	3118	62.7629	34.0161
	Corn-specific CPD exposure (4-Year Lagged Peak)	1797	96.4619	33.2881
	Rice-specific CPD exposure (4-Year Lagged Peak)	1173	12.0125	12.3083
	Wheat-specific CPD exposure (4-Year Lagged Peak)	372	127.9136	41.9464
County-level Crop production	the logarithm of crop yield (t/ha)	29698	1.5962	0.3699
	the logarithm of rice yield (t/ha)	16680	1.9141	0.3022
	the logarithm of wheat yield (t/ha)	23796	1.1878	0.5307
County-level Crop planting area	Corn planting area (kha)	32765	8.8244	9.0852
	Rice planting area (kha)	27281	12.0281	13.8264
	Wheat planting area (kha)	31024	8.1356	11.2586
Panel D Government attention (GA) index				
Firm-specific GA to Climate Change	Weighted provincial GA to climate change	3822	0.3723	0.5267
Firm-specific GA to CPD	Weighted provincial GA to CPD	3822	0.0962	0.2432

Table 2
Firm-level breeding innovation in response to extreme heat exposure

	Number of Seed Varieties of Major Crops (Corn, Rice, and Wheat)			
	HDT	PDR	HDT and PDR	Non-climate
	(1)	(2)	(3)	(4)
Extreme heat	0.0260***	0.0900**	0.0261***	0.0170
	(0.010)	(0.041)	(0.009)	(0.034)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
No. of OBSs	3,822	3,822	3,822	3,822
R^2	0.258	0.534	0.255	0.526

Notes: This table presents the effects of extreme heat exposure on the number of new crop varieties using the two-way fixed effects model specified in Eq. (4). The dependent variable in columns (1)–(4) is the logarithm of the number of new heat- or drought-resistant(HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties and non-climate varieties respectively. The non-climate varieties are defined as those that are either HDT varieties or PDR varieties. The independent variable is extreme heat exposure, which is measured as local 30-year averages of annual degree days in growing season (i.e., March to October) weighted by the annual share of a firm's seed varieties across provincial level cropping land. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3
Firm-level breeding innovation by crops in response to extreme heat exposure

	Number of Seed Varieties of Corn		
	HDT	PDR	HDT and PDR
	(1)	(2)	(3)
Panel A: Number of Seed Varieties of Corn			
Corn-specific Extreme heat (34℃)	0.0185**	0.0713**	0.0185**
	(0.008)	(0.032)	(0.008)
No. of OBSs	2,187	2,187	2,187
Panel B: Number of Seed Varieties of Rice			
	(4)	(5)	(6)
Rice-specific Extreme heat (31℃)	0.0186	0.1614**	0.0186
	(0.016)	(0.071)	(0.016)
No. of OBSs	1,379	1,379	1,379
Panel C: Number of Seed Varieties of Wheat			
	(7)	(8)	(9)
Wheat-specific Extreme heat (24℃)	0.0445	0.0285	0.0445
	(0.048)	(0.217)	(0.048)
No. of OBSs	440	440	440

Notes: This table presents the effects of extreme heat exposure on the number of new varieties across major crops using the two-way fixed effects model specified in Eq. (4). Panel A presents the impact of extreme heat exposure on the development of new maize varieties, Panel B displays the results for rice, and Panel C illustrates the findings for wheat. The dependent variable in columns (1)-(3) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties of corn respectively. The dependent variables in columns (4) - (9) are similar for rice and wheat. The independent variable is crop-specific extreme heat exposure, which is measured as local 30-year averages of annual degree days above crop-specific temperature threshold in growing season, weighted by the crop-specific annual share of a firm's seed varieties across provincial level cropping land. Control variables, year fixed effects, and firm fixed effects are controlled in our analysis. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4
Adoption: total land share allocated for different types of crop varieties

	HDT	PDR	HDT and PDR
Panel A: Total land share allocated for Seed Varieties of Major Crops			
	(1)	(2)	(3)
Extreme heat	0.0148**	0.0528**	0.0092*
	(0.006)	(0.026)	(0.005)
No. of OBSs.	3,822	3,822	3,822
Panel B: Total land share allocated for Seed Varieties of Corn			
	(4)	(5)	(6)
Corn-specific Extreme heat (34℃)	0.0145**	0.0480**	0.0107**
	(0.006)	(0.023)	(0.005)
No. of OBSs	2,187	2,187	2,187
Panel C: Total land share allocated for Seed Varieties of Rice			
	(7)	(8)	(9)
Rice-specific Extreme heat (31℃)	0.0008	0.0637*	0.0009
	(0.003)	(0.035)	(0.003)
No. of OBSs	1,379	1,379	1,379
Panel D: Total land share allocated for Seed Varieties of Wheat			
	(10)	(11)	(12)
Wheat-specific Extreme heat (24℃)	0.0077	0.2018**	0.0066
	(0.020)	(0.082)	(0.019)
No. of OBSs	440	440	440

Notes: This table presents the effects of extreme heat exposure on farmers' seed demand using the two-way fixed effects model specified in Eq. (4). Panel A shows the results for major crops, Panel B for corn, Panel C for rice, and Panel D for wheat. The dependent variable in columns (1)–(3) is the logarithm of total land share share allocated for HDT, PDR, and stacked varieties of major crops, respectively. The dependent variable in columns (4)–(12) is similar. Control variables, year fixed effects, and firm fixed effects are controlled in our analysis. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 5

The effect of extreme heat exposure on the incidence of diseases and pests

	lncropcpd (1)	lncorncpd (2)	lnricecpd (3)	lnwheatcpd (4)
Extreme heat (30℃)	0.0030***			
	(0.000)			
Corn-specific Extreme heat (34℃)		0.0279***		
		(0.003)		
Rice-specific Extreme heat (31℃)			0.0021***	
			(0.000)	
Wheat-specific Extreme heat (24℃)				0.0016***
				(0.000)
Control variables	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
County FE	Yes	Yes	Yes	
No. of OBSs.	35,981	32,681	27,180	30,957
R2	0.926	0.852	0.878	0.818

Notes: This table presents the effect of extreme heat exposure on the incidence of diseases and pests across crops using the two-way fixed effects model specified in Eq. (5). The dependent variable in columns (1)–(4) is the logarithm of incidence of pests and diseases of major crops (corn, rice, and wheat), corn, rice, and wheat in county respectively. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 6

The effects of extreme heat and CPD exposure on new seed varieties of crops

	HDT	PDR	HDT and PDR
Panel A: Number of Seed Varieties of Major Crops			
	(1)	(2)	(3)
CPD exposure	-0.0000	0.0020*	0.0000
	(0.000)	(0.001)	(0.000)
Extreme heat (30℃)	0.0313**	0.0635	0.0312**
	(0.013)	(0.049)	(0.013)
No. of OBSs.	2,996	2,996	2,996
Panel B: Number of Seed Varieties of Corn			
	(4)	(5)	(6)
Corn-specific cpd exposure	0.0001	0.0015*	0.0000
	(0.000)	(0.001)	(0.000)
Corn-specific Extreme heat (34℃)	0.0213**	0.0299	0.0207**
	(0.010)	(0.036)	(0.010)
No. of OBSs	1,678	1,678	1,678
Panel C: Number of Seed Varieties of Rice			
	(7)	(8)	(9)
Rice-specific cpd exposure	-0.0002	0.0057*	-0.0002
	(0.001)	(0.003)	(0.001)
Rice-specific Extreme heat (31℃)	0.0424	0.1293	0.0424
	(0.029)	(0.107)	(0.029)
No. of OBSs	1,084	1,084	1,084
Panel D: Number of Seed Varieties of Wheat			
	(10)	(11)	(12)
Wheat-specific cpd exposure	-0.0002	0.0026*	-0.0002
	(0.000)	(0.001)	(0.000)
Wheat-specific Extreme heat (24℃)	0.0091	-0.1663	0.0091
	(0.009)	(0.197)	(0.009)
No. of OBSs	340	340	340

Notes: This table presents the effects of extreme heat exposure and CPD exposure on new seed varieties of crops using the two-way fixed effects model specified in Eq. (4). Panel A shows the results for major crops, Panel B for corn, Panel C for rice, and Panel D for wheat. The independent variable is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties of major crops respectively. The core dependent is cpd exposure and extreme heat exposure. The cpd exposure is the weighted provincial incidence of pests and disease (weight strategy same as extreme heat exposure). In our analysis, we employed a 4-year lag and selected the maximum pest exposure over this period as the representative measure. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 7
The effect of government awareness on seed breeding innovation

	HDT	PDR	HDT and PDR
Panel A: Number of Seed Varieties of Major Crops			
	(1)	(2)	(3)
Extreme heat	0.0386**	0.0862	0.0385**
	(0.017)	(0.067)	(0.017)
GA of CC	-0.0431***	-0.0768	-0.0364***
	(0.015)	(0.116)	(0.014)
Extreme heat × GA of CC	0.0160***	0.0229	0.0141***
	(0.005)	(0.033)	(0.005)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
No. of OBSs	1,765	1,765	1,765
Panel B: Number of Seed Varieties of Major Crops			
	(4)	(5)	(6)
Extreme heat	0.0427**	0.0842	0.0423**
	(0.018)	(0.067)	(0.017)
GA of CPD	0.1064*	-0.6373	0.1080*
	(0.064)	(0.412)	(0.064)
Extreme heat × GA of CPD	-0.0264	0.1868*	-0.0271*
	(0.016)	(0.112)	(0.016)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
No. of OBSs	1,765	1,765	1,765

Notes: This table presents the interaction effect of extreme heat exposure and government awareness on seed breeding innovation using the two-way fixed effects model specified in Eq. (6). Panel A presents the interaction effects of extreme heat exposure and government awareness of climate change on seed breeding innovation, while Panel B focuses on the interaction between extreme heat exposure and government awareness of crop pests and diseases. The government awareness is measured by the weighted the logarithm of the number of news articles published on official government websites that include both the name of the province and climate-related or crop pest- and disease-related keywords respectively (weighting strategy same as extreme heat exposure). In the analysis we lagged them by three years. Robust standard errors in parentheses are clustered at the firm level. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 8

The heterogeneous effects of extreme heat exposure on new seed varieties of major crops across ownership

	Number of Seed Varieties of Major Crops					
	by state-owned firms			by private firms		
	HDT	PDR	Stacked	HDT	PDR	Stacked
	(1)	(2)	(3)	(4)	(5)	(6)
Extreme heat (30℃)	0.0034	0.0148	0.0054	0.0317***	0.1036**	0.0315***
	(0.007)	(0.047)	(0.006)	(0.012)	(0.050)	(0.012)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of OBSs	1,009	1,009	1,009	2,813	2,813	2,813
R2	0.116	0.474	0.100	0.278	0.521	0.272

Notes: This table presents the heterogeneous effects of extreme heat exposure on new seed varieties of major crops across ownership using the two-way fixed effects model specified in Eq. (4). The independent variable of column (1)-(3) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties developed by state-owned firms respectively. The independent variable of column (4)-(6) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties developed by private firms respectively. The dependent is extreme heat exposure. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 9.
The heterogeneous effects of extreme heat exposure on new seed varieties of corn, rice, and wheat across ownership

	by state-owned firms			by private firms		
	HDT	PDR	Stacked	HDT	PDR	Stacked
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Number of Seed Varieties of Corn						
Corn-specific Extreme heat (34℃)	0.0036	0.0342	0.0067	0.0223**	0.0839**	0.0223**
	(0.007)	(0.045)	(0.006)	(0.010)	(0.039)	(0.010)
No. of OBSs	407	407	407	1,780	1,780	1,780
R^2	0.149	0.456	0.135	0.248	0.510	0.222
Panel B: Number of Seed Varieties of Rice						
	(7)	(8)	(9)	(10)	(11)	(12)
Rice-specific Extreme heat (30℃)	/	-0.0564	/	0.0214	0.1571	0.0214
	/	(0.081)	/	(0.027)	(0.104)	(0.027)
No. of OBSs	/	467	/	912	912	912
R^2	/	0.488	/	0.315	0.536	0.315
Panel C: Number of Seed Varieties of Wheat						
	(13)	(14)	(15)	(16)	(17)	(18)
Wheat-specific Extreme heat (30℃)	0.0489	0.0069	0.0489	-0.0091	-0.1539	-0.0091
	(0.065)	(0.074)	(0.065)	(0.020)	(0.747)	(0.020)
No. of OBSs	157	157	157	283	283	283
R^2	0.180	0.239	0.180	0.259	0.326	0.259

Notes: This table presents the heterogeneous effects of extreme heat exposure on new seed varieties of corn, rice, and wheat across ownership using the two-way fixed effects model specified in Eq. (4). Panel A shows the result for corn, Panel B for rice, and Panel C for wheat. The independent variable of column (1)-(3) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties of corn developed by state-owned firms respectively. The independent variable of column (4)-(6) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties of corn developed by private firms respectively. The dependent variable in columns (7) - (18) is similar for rice and wheat. The dependent is extreme heat exposure. Columns 7 and 8 are omitted because the number of valid samples is 0. Control variables, year fixed effects, and firm fixed effects are controlled in our analysis. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 10

The heterogeneous effects of extreme heat exposure on new seed varieties of major crops across innovation type

	Number of Seed Varieties of Major Crops								
	independent innovation			inter-firm collaborative innovation			public-private collaborative innovation		
	HDT	PDR	Stacked	HDT	PDR	Stacked	HDT	PDR	Stacked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Extreme heat (30℃)	0.0232**	0.0857**	0.0534**	0.0007	-0.0149	-0.0004	0.0034	0.0156	0.0077
	(0.009)	(0.038)	(0.027)	(0.001)	(0.010)	(0.003)	(0.003)	(0.016)	(0.011)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of OBSs	3,822	3,822	3,822	3,822	3,822	3,822	3,822	3,822	3,822
R2	0.237	0.487	0.379	0.145	0.271	0.250	0.244	0.492	0.403

Notes: This table presents the heterogeneous effects of extreme heat exposure on new seed varieties of major crops across innovation type using the two-way fixed effects model specified in Eq. (4). The independent variable of column (1)-(3) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties developed by independent innovation respectively. The independent variable of column (4)-(6) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties developed by inter-firm collaborative innovation respectively. The independent variable of column (4)-(6) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties developed by public-private collaborative innovation respectively. The dependent is extreme heat exposure. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 11

The heterogeneous effects of extreme heat exposure on new seed varieties of corn, rice, and wheat across innovation type

	independent innovation			inter-firm collaborative innovation			public-private collaborative innovation		
	HDT	PDR	Stacked	HDT	PDR	Stacked	HDT	PDR	Stacked
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Number of Seed Varieties of Corn									
Corn-specific Extreme heat (34℃)	0.0180**	0.0706**	0.0179**	/	-0.0098	/	0.0008	0.0203**	0.0008
	(0.008)	(0.030)	(0.008)	/	(0.007)	/	(0.001)	(0.009)	(0.001)
No. of OBSs	2,187	2,187	2,187	/	2,187	/	2,187	2,187	2,187
R2	0.241	0.515	0.220	/	0.319	/	0.105	0.389	0.105
Panel B: Number of Rice Varieties									
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Rice-specific Extreme heat (30℃)	0.0053	0.1026*	0.0892*	0.0041	-0.0154	-0.0119	0.0100	0.0674	0.0636
	(0.011)	(0.055)	(0.046)	(0.004)	(0.019)	(0.011)	(0.011)	(0.057)	(0.048)
No. of OBSs	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379	1,379
R2	0.261	0.465	0.395	0.150	0.268	0.254	0.260	0.491	0.390
Panel C: Number of Wheat Varieties									
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
Wheat-specific Extreme heat (30℃)	0.0445	0.0575	0.0445	/	0.0069	/	/	-0.0574	/
	(0.048)	(0.209)	(0.048)	/	(0.009)	/	/	(0.087)	/
No. of OBSs	440	440	440	/	440	/	/	440	/
R2	0.203	0.330	0.203	/	0.182	/	/	0.293	/

Notes: This table presents the heterogeneous effects of extreme heat exposure on new seed varieties of corn, rice, and wheat across innovation type using the two-way fixed effects model specified in Eq. (4). Panel A shows the result for corn, Panel B for rice, and Panel C for wheat. The independent variable of column (1)-(3) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties of corn developed by independent innovation respectively. The independent variable of column (4)-(6) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties of corn developed by inter-firm collaborative innovation respectively. The independent variable of column (7)-(9) is the logarithm of the number of new heat- or drought-resistant (HDT) varieties, new pest- or disease-resistant (PDR) varieties, new HDT and PDR varieties of corn developed by public-private collaborative innovation respectively. The dependent variables in columns (9) - (18) are similar for rice and wheat. The dependent is extreme heat exposure. Columns (4), (6), (22), (24), (25) and (27) are omitted due to zero valid samples. Control variables, year fixed effects, and firm fixed effects are controlled in our analysis. Robust standard errors in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Table 12

The mitigation of seed breeding innovation on the climate damage of crop yield

	Wheat yield	Rice yield	Corn yield
	(1)	(2)	(3)
Panel A			
County-level EH Exposure	-0.0007	-0.0041***	-0.0012**
	(0.001)	(0.000)	(0.000)
County-level EH Exposure × Wheat HDT innovation	0.0014***		
	(0.000)		
County-level EH Exposure × Rice HDT innovation		0.0135***	
		(0.004)	
County-level EH Exposure × Corn HDT innovation			0.0019*
			(0.001)
Year FE	YES	YES	YES
County FE	YES	YES	YES
Obs.	23,618	16,526	29,525
R^2	0.870	0.729	0.728
Panel B			
	(4)	(5)	(6)
County-Level Wheat CPD incidence	-0.0326***		
	(0.011)		
County-level Wheat CPD incidence × PDR innovation exposure	0.0035		
	(0.003)		
County-Level Rice CPD incidence		-0.0382**	
		(0.017)	
County-level Rice CPD incidence × PDR innovation exposure		0.0113***	
		(0.003)	
County-Level Corn CPD incidence			-0.0190**
			(0.009)
County-level Corn CPD incidence × PDR innovation exposure			0.0049*
			(0.003)
Year FE	YES	YES	YES
County FE	YES	YES	YES
Obs.	19,078	7,286	23,904

R^2	0.8897	0.8345	0.7688

Notes: This table presents the mitigation of seed breeding innovation on the climate damage of crop yield using the two-way fixed model specified in Eq. (8). Panel A shows the mitigation effect of HDT innovation on crop yield damage caused by extreme heat exposure, and panel B shows the mitigation effect of PDR innovation on crop yield damage caused by pest and disease exposure. The independent variables in columns (1) to (6) are the yield per unit area of wheat, rice and corn in counties. The HDT and PDR innovation exposure are at the county level, which is obtained by weighting provincial innovation exposure by planting area share. The unit of observation is a county-year. Robust standard errors are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Figure 1 The number and proportion of annual new seed varieties of major crops developed by seed firms from 2000-2015

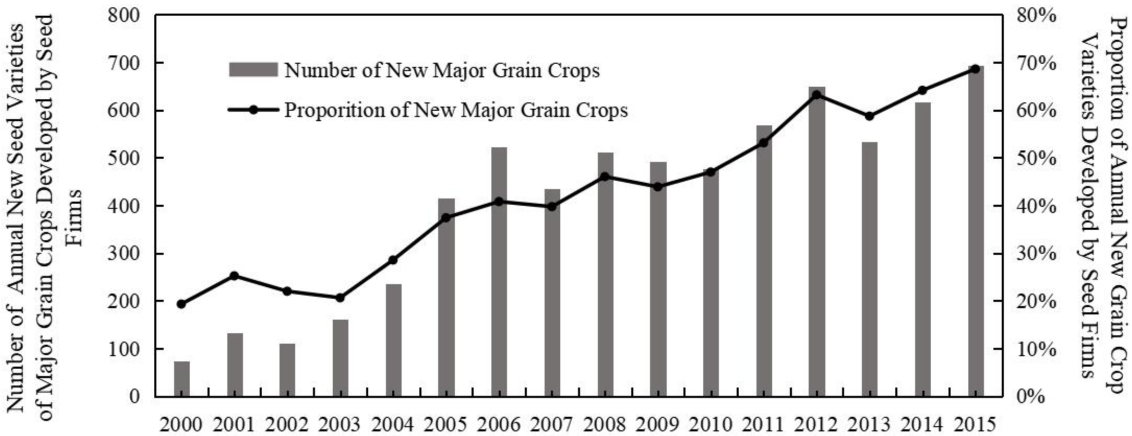
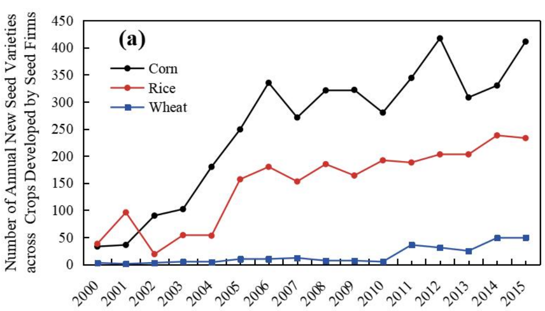


Figure 2 The number and proportion of annual new seed varieties across crops developed by seed firms from 2000-2015



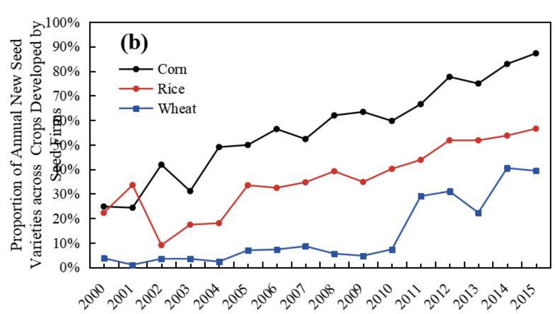


Figure 3 The number and proportion of HDT and PDR varieties developed by seed firms from 2000-2015