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Climate shocks and fertilizer responses: Field-level evidence for rice production in Bangladesh

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Abstract

The fertilizer response of yield has been one of the major indicators of agricultural productivity in both developed and developing countries. Filling the evidence gap remains vital regarding fertilizer response in Asia, particularly in South Asia, given the evolution and emergence of new challenges, including intensifying climate shocks. We aim to partly fill this knowledge gap by investigating the associations between climate shocks and fertilizer response in Bangladeshi rice production. Using three rounds of nationally representative farm household panel data with plot-level information, we assess fertilizer response functions regarding rice yield and how the shapes of these response functions are heterogeneous in relation to anomalies in temperatures, droughts, and rainfall. We find robust evidence that climate anomalies have adverse effects on fertilizer responses, including higher temperatures for the Boro and the Aman irrigated systems and higher temperatures and droughts for the Aman rainfed systems. These findings hold robustly under various fertilizer response function forms, i.e., polynomial function and stochastic Linear Response Plateau. Furthermore, results for stochastic Linear Response Plateau are also consistent for both switching regression type models and Bayesian regression models.

JEL Codes: Q01, Q12, Q01, Q19

Keywords: Rice fertilizer response, climate change, stochastic Linear Response Plateau, maximum likelihood estimation, Bayesian regression, Bangladesh.

1 Background

Agrifood system development remains critical in achieving a broad range of sustainable development goals. Raising agricultural productivity has been considered instrumental in not only reducing hunger but also stimulating economic growth and reducing poverty (McArthur & Mccord 2017; Gollin et al. 2021), improving nutrition and health (Fan et al. 2019), environmental sustainability (Khatri-Chhetri et al. 2023), and resilience (e.g., Wang et al. 2022; Takeshima et al. 2022).

The yield response to fertilizer has been one of the major indicators of agricultural productivity in both developed countries and developing countries. In developing regions of Asia, circumstantial evidence suggests that yield response to fertilizer has risen sufficiently over the last several decades through more fertilizer-responsive varieties (Otsuka & Kalirajan 2006), enabling infrastructure (Rashid et al. 2013), and fertilizer price reduction associated with fertilizer industry development (Ahmed 1995; Kafiluddin & Islam 2008).

Nonetheless, filling the evidence gap remains vital regarding fertilizer response in Asia, particularly in South Asia, given the evolution and emergence of new challenges, including intensifying climate shocks like rising and more volatile temperature regimes and intensifying droughts. Experimental level evidence has long pointed toward the potential susceptibility of fertilizer response to changing climate conditions (e.g., Rötter et al. 1997; Yamoah et al. 1998; Aulakh et al. 2003; Abera et al. 2022). More field-level evidence is needed to strengthen the overall evidence base of the linkage between climate change and fertilizer response.

We aim to partly fill this knowledge gap by investigating the associations between climate shocks and fertilizer response in Bangladeshi rice production. Using three rounds of nationally representative plot-level panel data, we assess various forms of fertilizer response functions regarding rice yield (namely, polynomial functional forms and stochastic Linear Response Plateau) and how the shapes of these response functions are affected by anomalies in temperatures, droughts, and rainfall. As discussed, we find robust evidence that climate anomalies adversely affect fertilizer responses, including higher temperatures for the Boro and the Aman irrigated systems and higher temperatures and droughts for the Aman rainfed system. These findings hold robustly under various fertilizer response function forms, i.e., polynomial function and stochastic Linear Response Plateau.

Bangladesh is an ideal case to assess the climate effects on rice fertilizer response. The country is one of the most land-scarce countries even within Asia (with one of the smallest average land holding sizes of 0.35 ha in 2010 according to the World Census of Agriculture), where yield per inputs use is a critical determinant of productivity. The country's agricultural sector still employs more than 1/3 of all workers whose livelihoods depend on the sustenance of agricultural productivity. Bangladesh is also highly vulnerable to climate change.

This paper contributes to various strands of literature. The paper contributes to the literature on fertilizer sector development in South Asia, including Bangladesh (Rashid et al. 2013; Ahmed et al. 2021 Chapter 5; Kishore et al. 2021) by providing evidence on returns to, and relatedly, demand for chemical fertilizer. The paper further contributes to the literature that studies field-level effects of climate risks on agricultural productivity in South Asia, including Bangladesh (e.g., Banerjee 2010; Sarker et al. 2012; Birthal & Hazrana 2019; Dubey et al. 2020; Li 2023; Amare et al. 2023) by adding insights into fertilizer response as a potential effect pathway. The paper also contributes to the literature on fertilizer response, including those studying stochastic Linear Response Plateau based on switching regression framework (Ackello-Ogutu et al. 1985; Paris 1992; Tembo et al. 2008) and Bayesian regression framework (e.g., Holloway & Paris 2002; McFadden et al. 2018; Ouedraogo & Brorsen 2018; Ng'ombe & Lambert 2021), by integrating climate shocks as a heterogeneity factor in fertilizer responses.

The remainder of this paper is structured as follows. Section 2 discusses the literature on climate change and fertilizer response. Section 3 describes the empirical approaches. Section 4 summarizes data and descriptive statistics. Section 5 discusses the results. Finally, section 6 concludes.

2 Climate shocks, rice production and fertilizer response

Past studies provide indicative evidence that climate conditions affect fertilizer response in rice and other crops.

Rainfall

In developing countries, fertilizer response can be variable depending on various factors, including rainfall (Rötter et al. 1997; Morris et al. 2007). In Ethiopia (Alem et al. 2010), the current year's fertilizer use intensity is positively associated with higher rainfall levels experienced in the previous year. Rainfall variability, on the other hand, impacts fertilizer use decisions negatively, implying that variability raises the risks and uncertainty associated with fertilizer use.

Where fertilizer is broadcast, instead of more careful application (such as Urea Deep Placement), more fertilizer tends to get blown away by wind or washed away by rain (USAID / MARKETS).

At experimental levels, some studies suggest a reduced response to fertilizer under wetter conditions (e.g., Yamoah et al. 1998). On the other hand, Aulakh et al. (2003) argues that greater rainfall may enhance the solubility of fertilizer in the soil, which may increase the nutrient availability for plants.

Temperature

While direct evidence is relatively scarce regarding the effects of temperature on fertilizer response, several studies report the potentially negative effects on rice yields in Asia. In Bangladesh, increasing maximum and minimum temperatures affect rice yields adversely (Sarker et al. 2012). In Sri Lanka, climatic variables have concave, non-monotonic effects upon production, and that output is close to maximized at current climatic values (Ratnasiri et al. 2019). At experimental levels, some studies suggested greater fertilizer response in wheat production under higher temperatures in Ethiopia (Abera et al. 2022).

3 Empirical approach

We estimate the effects of climate shocks on fertilizer response functions in two common empirical frameworks used in the literature; (a) standard polynomial response function, and (b) Linear Response Plateau (LRP) function.

3.1 Standard polynomial response function

We estimate plot-level polynomial regression through pooled cross-section regression with farm household fixed-effects and year fixed effects, separately for each rice production system. Specifically, we estimate

$$y_{ijts} = \alpha_{s0} + \alpha_{xs1}x_{ijts} + \alpha_{xs2}x_{ijts}^2 + \alpha_{xsw1}(x_{ijts} \cdot w_{jts}) + \alpha_{xsw2}(x_{ijts}^2 \cdot w_{jts})$$
$$+ \alpha_{ws}w_{jts} + \alpha_{zs}z_{ijts} + c_{js} + \varepsilon_{ijts} \quad (1)$$
$$\forall s \in \{\text{Boro, Aman irrigated, Aman rainfed}\}$$

in which yield on plot i cultivated by farmer j in year t, types of season/irrigation method s (y_{ijts}) is regressed on nitrogen[2] use per ha (x_{ijts}), its squared term x_{ijts}^2, weather shocks in areas where j is located (w_{jts}), other time-variant exogenous factors z_{ijts}. Equation (1) is estimated separately for each type of rice production system s. Notations α's are estimated parameters and ε_{ijts} is the idiosyncratic error term. c_{js} is the time-invariant farm household fixed-effect. Parameters α_{xsw1} and α_{xsw2} capture the effects of weather shocks on fertilizer responses, which is our primary interests.

Variables z_{ijts} include age of the producer (which affects overall farming experience, use of modern production practices), varietal technologies used (whether the variety used has been formally released, the year of release of the formally released varieties), physical plot characteristics such as distance from home and the maximum flood depth that the plot undergoes within a year, year the plot was acquired (which proxies producer's familiarity with plots), average soil characteristics of the area,[3] whether the plot is under sharecropping system, and the number of the type of equipment used.[4] Variables z_{ijts} also include year dummy variables and their interaction with division dummy variables indicating Bangladesh's 8 divisions, to control for any specific shocks in each year common across all samples within each division.

Potential endogeneity

While the potential endogeneity of x_{ijts} can lead to inconsistent estimates in fertilizer

[2]Our analyses focus on nitrogen as the primary chemical fertilizer nutrients since other nutrients phosphorus (P) and potassium (K) are largely correlated with nitrogen. We also estimated the models including P and K and find that results are generally robust.

[3]This variable is based on the yield reduction potentials of different aspects of soils developed by Fischer et al. (2008) and used by FAO et al. (2012). Specifically, Fischer et al. (2008) classify soil attributes as "no or slight limitation", "moderate limitations", "severe limitations", "very severe limitations", each corresponding to 80-100%, 60-80%, 40-60%, and 20-40% of yield potentials, for 7 soil attributes (nutrient availability, nutrient retention capacity, rooting conditions, oxygen availability to roots, excess salts, toxicity, workability). We assign mid-points of each classification (90%, 70%, 50%, and 30%) to respective class of soil attributes, and took average across all attributes, to proxy soil quality.

[4]Specifically, this variable is the number of the types used among equipment for planting, fertilizer application, pesticide application, weeding, and harvesting.

response, evidence is generally ambiguous in the literature. Many recent field-level fertilizer response studies assume that fertilizer variables are exogenous, especially after controlling for farm fixed-effects or correlated random effects (e.g., Liu & Myers 2009; Sheahan et al. 2013; Burke et al. 2020) due to time-lags between fertilizer application and harvesting period. Furthermore, as the weather shocks become more extreme to unprecedented levels, farmers' prior knowledge of actual fertilizer response function may become less reliable. Farmers may have more limited capacity to adjust fertilizer use in response to expected harvest, thereby potentially mitigating the bias arising from reverse causality (importantly, household-fixed effects control for factors like risk aversion).

We provide supporting evidence of relatively exogeneity by estimating panel instrumental-variables (IV) regression for (1). IVs include price of urea, cluster-neighbor-average value of x_{ijts} (the average value of x_{ijts} of all samples in the villages where i is located, but excluding the value of x_{ijts} of i itself), and their interactions with weather variable w_{jts}. Cluster-neighbor-average variables have also been used as IVs in past studies (e.g., Benjamin 1992; Le 2010; Ji et al. 2012; Min et al. 2017; Dillon et al. 2019; Dolislager et al. 2021). Following Baltagi (2013), we use within-transformed version of these variables as IVs. In the results section, we show that our fertilizer variables are exogenous based on endogeneity tests applied to this IV-regression.

3.2 Linear Response Plateau (LRP) function

As was described above, LRPs have been considered one of the important alternative specifications to characterize the fertilizer response that follows von Liebig law of the minimum[5] (e.g., Spillman 1933; Perrin 1976; Parris 1992). A stylized model of a LRP function is characterized as

$$y_{ijts} = \min\{f(x_{ijts}, w_{jts}, \beta_f), p(w_{jts}, z_{ijts}, \beta_p, c_{ijs})\} + v_{ijts} \quad \forall s \in \{\text{Boro, Aman irrigated, Aman rainfed}\} \tag{2}$$

[5]The "law of the minimum" hypothesizes that crop yield is a proportional function of the scarcest nutrient available to the plant, and thus increasing the availability of nonlimiting nutrients does not affect crop yield (von Liebig 1862).

where y_{ijts} follows the linear response function f determined by x_{ijts}, w_{its} and parameters β_f, up to the plateau level p which depends on w_{jts}, z_{ijts}, parameters β_p and c_{ijs}, and idiosyncratic error term v_{ijts}.

3.2.1 LRP based on Maddala-Nelson switching regression (MNSR) framework with Correlated Random Effects

One of the common empirical frameworks to estimate (2) is the Maddala- Nelson Switching Regression (MNSR) model. Following Paris (1992), under certain assumptions, MNSR model is estimated through maximum likelihood estimation (MLE) based on the following likelihood function:

$$\max_{\beta} \ln L(\beta) = \max_{\beta} \sum_{i=1}^{N} \ln h\big(y_{ijts}, x_{ijts}, w_{jts}, z_{ijts}, c_{js}, \beta_{fs}, \beta_{ps}\big) \tag{3}$$

$$\forall s \in \{\text{Boro, Aman irrigated, Aman rainfed}\}$$

in which $h(\cdot)$ is the unconditional density function,

$$h(\cdot) = \frac{\phi_1}{\sigma_1}\left[1 - \Phi_2\big(\delta_{ijts}\big)\right] + \frac{\phi_2}{\sigma_2}\left[\Phi_2\big(\delta_{ijts}\big)\right] \tag{4}$$

$$\phi_1 = \phi\left[\frac{y_{ijts} - f(\cdot)}{\hat{\sigma}_1}\right], \phi_2 = \phi\left[\frac{y_{ijts} - p(\cdot)}{\hat{\sigma}_2}\right] \tag{5}$$

$$\delta_{ijts} = \frac{f(\cdot) - p(\cdot)}{\hat{\sigma}_2} \tag{6}$$

$$f(\cdot) = \beta_{fs0} + \beta_{fsx}x_{ijts} + \beta_{fsxw}\big(x_{ijts} \cdot w_{its}\big) + \beta_{fsw}w_{jts} + \beta_{fsz}z_{ijts} + \hat{c}_{fsj,CRE} \tag{7}$$

$$p(\cdot) = \beta_{ps0} + \beta_{psw}w_{jts} + \beta_{psz}z_{ijts} + \hat{c}_{psj,CRE} \tag{8}$$

where notations $\beta's$ are estimated parameters, and other symbols refer to the same variables and parameters described above.

The first part of equation (4) consists of the probability that the predicted values from the linear segment of response function f is below the plateau $p(\cdot)$, times the normal density function ϕ_1 and parameter σ_1, based on residuals $y_{ijts} - f(\cdot)$. The second part of equation (4) consists of the probability that the production falls under plateau regime (where the predicted value of yield from $f(\cdot)$ exceeds the plateau), and the normal density function ϕ_2 and parameter σ_2 that maximizes the fit between observed yield y_{ijts} and the plateau. Notation $\Phi_2(\cdot)$ is a cumulative distribution function, corresponding to the probability that observed yield is in plateau regime. We estimated MNSR using '`mlexp`' command in STATA, and initial values of parameters obtained from the linear regressions.

In MLE, directly separating out time-invariant fixed effects c_i can lead to biased estimates due to well-known "incidental parameter problems". We therefore apply a Mundlak (1978)-Chamberlain (1984) Correlated Random Effects (CRE) model, in which average values of time-variant exogenous variables that are assumed correlated with c_{js} (denoted by a vector $\hat{c}_{js,CRE}$) are included as additional control variables, to substitute $\hat{c}_{js}$. Specifically, we included the farm household-level average values of all variables in z_{ijts}.

In the MLE estimation, parameters β_{fs0} and β_{ps} in (7) and (8) cannot be estimated separately but rather estimated jointly as a single coefficient. Similarly, β_{fz} and β_{pz}, $\hat{c}_{fsj,CRE}$ and $\hat{c}_{psj,CRE}$ in (7) and (8) are estimated as single coefficients, respectively. These coefficients are not our primary interests, but rather simply account for other factors to minimize biases in the coefficients of our primary interests (β_{fsx}, β_{fsxw}, β_{fsw} and β_{psw}).

3.2.2 Bayesian estimation of stochastic Linear Response Plateau (LRP)

We also estimate LRP through Bayesian regression approach. The Bayesian approach offers useful robustness checks for our results; in the approach, researcher's prior beliefs on the parameters are updated by posterior information obtained from the data based on Bayes' rules, which is radically different from the process assumed under the MNSR.[6]

Following the exposition by Ng'ombe & Lambert (2021), a Bayesian LRP model is estimated by (notation s is suppressed for simplicity),

$$y_{ijt} = \min\{f(x_{ijt}, w_{jt}, \gamma_f), p(w_{jt}, z_{ijt}, \gamma_p, c_{ij})\} + \varepsilon_{ijt} \tag{9}$$

$$f(\cdot) = \gamma_{f0} + \gamma_{fx}x_{ijt} + \gamma_{fxw}(x_{ijt} \cdot w_{it}) + \gamma_{fw}w_{jt} + \gamma_{fz}z_{it} + \hat{c}_{fi,CRE} \tag{10}$$

[6] While a non-Bayesian framework assumes that structural parameters are nonstochastic and focus on obtaining particular point estimates, a Bayesian framework instead assumes that structural parameters are stochastic, and focuses on obtaining the distributions of possible point estimates.

$$p(\cdot) = \gamma_{p0} + \gamma_{pw} w_{jt} + \gamma_{pz} z_{it} + \hat{c}_{pi,CRE} \tag{11}$$

$$\gamma_f \sim N(\gamma_{f0}, \sigma_{f0}^2), \gamma_p \sim N(\gamma_{p0}, \sigma_{p0}^2), \sigma_\varepsilon^2 \sim N(\gamma_{\varepsilon 0}, \delta_{\varepsilon 0}^2) \tag{12}$$

where γ_f and γ_p are a set of estimated parameters that determine linear response function f and plateau p, respectively. σ_ε^2 is the estimated variance of idiosyncratic error term ε_{ijt}. Parameters γ_{f0}, γ_{p0}, $\gamma_{\varepsilon 0}$ are priors for the respective mean parameters, while σ_{f0}^2, σ_{p0}^2 and $\delta_{\varepsilon 0}^2$ are priors for variance terms.

In our estimation, we used the estimates on parameters and standard errors from MNSR as the prior variables. The estimation is conducted by using statistical software R's package '`brms`' developed by Bürkner (2017).[7]

3.3 Construction of climate variables

Our analyses focus on water-related and temperature-related climate variables for the Boro and the Aman systems. Based on the common production patterns, we define the Boro and the Aman systems to fall under December through May and June through November, respectively.

The water-related climate variables consist of drought index and precipitation, averaged over the entire duration of each production season. Because water-related climate shocks may be less constraining under irrigated conditions (the Boro system and the Aman irrigated system), we only consider drought and rainfall shocks for the Aman rainfed system.

The temperature-related climate variables consist of Growing Degree Days (GDD) and High Nighttime Temperature (HNT), which have been considered increasingly important factors in agricultural production including that of rice (e.g., Peng et al. 2004; Deshênes & Greenstone 2007; Wassmann et al. 2009; Welch et al. 2010; Bheemanahalli et al. 2016; Acharjee et al. 2017; Li 2023).[8] Specifically, in the Bangladesh rice production context, GDD is constructed through the following formula:

[7] More technical details are provided in Ng'ombe & Lambert (2021). We used the Hamiltonian Monte Carlo (HMC) algorithm and its extension, the no-U-turn sampler (NUTS). The HMC and NUTS have been considered in recent literature as more stable and converge faster than other major samplers like Metropolis-Hastings updates and Gibbs sampling (Ng'ombe & Lambert (2021).

[8] Harmful Degree Days (HDD), such as the average daily temperatures exceeding 33 °C (Wassmann et al. 2009; Bheemanahalli et al. 2016) is also an important indicator. We, however, excluded HDD because of relatively few occurrences of HDD in Bangladesh.

$$GDD = \sum_{d}^{D} \{\min[\max(T_{mean,d}, T_{base}), T_h] - T_{base}\} \quad (13)$$

where $T_{mean,d}$ is the average temperature of the day d in respective production season, T_{base} and T_h are the range of temperature for rice production, and D is the number of days within the particular production season. Following the past studies for rice production in Asia including Bangladesh (e.g., Acharjee et al. 2017; Li 2023), we set $T_{base} = 10$ °C. Similarly, we set $T_h = 33$ °C, following studies that indicate increasingly harmful effects on rice production with daily average temperature exceeding 33 °C (Wassmann et al. 2009; Bheemanahalli et al. 2016).

Similarly, HNT is computed as

$$HNT = \sum_{d}^{D} \{\max(T_{min,d} - 20), 0\}, \quad (14)$$

following studies suggesting that nighttime minimum temperature exceeding 20 °C can have negative effects on rice yield (e.g., Peng et al. 2004; Welch et al. 2010).[9]

4 Data and descriptive statistics

The plot-level panel data of rice production are extracted from the Bangladesh Integrated Household Survey (BIHS) collected by the International Food Policy Research Institute (IFPRI) (IFPRI 2019). The BIHS data are 3-round nationally representative panel data of plot-level agricultural production in Bangladesh that cover both the Boro and the Aman systems in 2011, 2014, and 2018. Specifically, out of a total of 24,379 plot-level observations from all 3-rounds, we focus on a total of 15,496 plot-level observations (8,048 for the Boro system, 3,124 for the Aman irrigated system, and 4,324 for the Aman rainfed system) on which rice is produced in either the Boro or the Aman systems in at least 2-rounds so that farm household fixed-effects and year fixed effects can be appropriately controlled.

Climate data

Historical temperature data are extracted from WorldClim data (Fick & Hijmans 2017)

[9] We also tested other thresholds, such as 25 °C instead of 20 °C, following studies including Acharjee et al. (2019). We found that results are generally robust.

and AgERA5 data (AgERA5 daily mean temperatures developed by the European Centre for Medium-Range Weather Forecasts (Dee et al. 2011). WorldClim is monthly high-resolution temperature data available for 1 km by 1 km grids. In contrast, AgERA5 is daily data, but its spatial resolution is only 6.0 arcminutes (11.1 km at the equator). We, therefore, follow Li (2023) to combine these two data to generate daily temperature at 1 km by 1 km grids.

In addition, historical monthly rainfall data are taken from The Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) by Funk et al. (2015). Historical monthly drought indices are extracted from the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010). The SPEI quantifies drought severity in comparable ways across time and space. The SPEI is correlated with water balance, and more negative values indicate greater drought severity. Monthly rainfall and SPEI-index of drought are then used to compute the average values during each of the Boro and the Aman systems.

We then compile proxy variables that represent location-specific weather anomalies, namely historical percentiles following the past studies (e.g., Takeshima et al. 2020).[10] Historical percentile is similar to historical z-scores, an alternative that is also commonly used, but is more robust even when weather patterns are not normally distributed over time.

Fertilizer nutrient data

The BIHS data reports fertilizer quantity in terms of products, rather than nutrients. We therefore convert them into nitrogen equivalent based on the typical nutrient composition used in Bangladesh (Quader 2009), as is shown in Table 1.

Descriptive statistics

Table 2 summarizes the descriptive statistics of our sample. Most sample plots are small, with an average size of 0.11 ~ 0.13 ha. The average yield is 5.7 (ton/ha), 3.0, and 4.1 in each of the Boro, the Aman rainfed, and the Aman irrigated systems. Nitrogen use intensity varies from 51 (kg/ha) for the Aman rainfed to 78 for the Aman irrigated and 93 for the Boro system. Formally released varieties are more commonly used for the Boro than the Aman systems. Hybrid varieties are still relatively rare, accounting for 13% for the Boro and less than 5% for the

[10]As is shown later, we also conducted robustness checks using alternative proxies, such as historical z-score and differences with historical means and found that results are broadly consistent.

Aman system. On average, plots have been cultivated for about 14 years. Plots are typically located about 500 m from home and located in areas where flood depth can reach 1 ~ 2.4 m at its highest within a year, and about 10% of plots are sharecropped. The average number of the types of tools used (including tools for land preparation, planting, chemical application, weeding, and harvesting) is about 0.5 per plot, although they can vary considerably across plots. Most plots have high soil quality.

Table 3 summarizes the average climate patterns in 2011, 2014, and 2018, expressed as percentile relative to the historical distribution. Overall, for the Boro system, 2014 was relatively warmer and drier, while 2018 was somewhat cooler and wetter. For the Aman system, both rainfed and irrigated areas experienced signs of increased temperature volatility (characterized by both increased HDD and reduced HNT), intensifying drought as well as declining rainfall toward 2018.

5 Results

5.1 Standard polynomial function

Table 4 and Table 5 present the results of main parameters of polynomial specification of fertilizer response function (1), for the Boro system, the Aman irrigated system, and the Aman rainfed system, respectively. Weather shock variables are standardized so that non-interacted "Nitrogen" and "Nitrogen squared" variables represent the average conditions across all weather conditions. Variables interacted with weather shock variable capture the effects of one standard deviation (1SD) changes in weather anomalies (absolute deviations from the 50th percentile of historical distribution). In both tables, in addition to the full results, we also show that results are consistent even when excluding all other control variables. In Table 4 and Table 5, average parameters exhibit standard positive but declining fertilizer response of yield, indicated by statistically significantly positive coefficients for "Nitrogen" and negative coefficients for "Nitrogen squared". For illustrative purposes, Figure 1 through Figure 3 visualize results in Table 4 and Table 5 using how average fertilizer response curves change in response to typical weather shocks.[11]

[11]In these figures, we compare the cases with 33 and 67 percentiles of weather conditions relative to historical distributions.

Statistically significant coefficients of interaction variables indicate that weather shocks significantly affect the slopes and curvatures of fertilizer response functions. For the Boro system (Table 4), More abnormal GDD negatively shifts the coefficients for “Nitrogen”, while positively shift the intercept. More abnormal HNT positively shifts the slope, while negatively shifting the coefficient for “Nitrogen squared”.

For the Aman irrigated system, effects of GDD anomaly is generally similar to that for the Boro system; GDD anomaly generally suppresses yield response to nitrogen. More abnormal HNT has similar effects of generally suppressing yield response to nitrogen, although it also reduces the curvature and shifting to relatively more straight response curve.

For the Aman rainfed system (Table 5), generally GDD and HNT anomalies negatively shift the coefficient for “Nitrogen” while positively shifting the weather shocks. More abnormal GDD and HNT, therefore, generally raise rice yield at lower nitrogen level, but suppress yield responses to nitrogen inputs. In contrast, greater drought and lower rainfall shocks positively shift coefficients for “Nitrogen” while negatively shifting coefficients for “Nitrogen squared” and intercept. More abnormal drought and rainfall, therefore, raises yield responses to nitrogen at lower nitrogen use levels, while reducing the response at higher nitrogen use levels. Figure 3 illustrates that, with more abnormal drought and rainfall, yield responses to nitrogen in the Aman rainfed system are greater particularly at lower nitrogen levels, but the overall yield potentials decline.

Exogeneity of fertilizer variables

Table 6 summarizes key test statistics assessing the potential endogeneity of fertilizer variables in equation (1), estimated through aforementioned IV-regressions. Tests statistics suggest that the set of IVs used are sufficient so that the models have sufficient identification power (with the null hypotheses of under-identification broadly rejected), but also not overidentified so that consistency is maintained. Based on the test statistics of the Hausman endogeneity tests, we generally fail to reject the null hypothesis that fertilizer variables are exogenous. The polynomial regression results Table 4 are therefore consistent. The exogeneity of fertilizer variables in polynomial regression also adds more relevance for the results of stochastics LRP which are discussed in subsequent sections, even though directly testing endogeneity in LRP framework is beyond the scope of this study.

5.2 Linear stochastic plateau function

The above results based on standard polynomial regression are also generally consistent when we instead assume fertilizer response to follow a stochastic LRP function. Table 7 and Table 8 show the main results estimated from MNSR (3) through (8) estimated through the Maximum Likelihood regression, and the Bayesian regression through (9). The results in Table 7 and Table 8 indicate that anomalies in various weather parameters from historical norms have statistically significantly adverse effects on the linear fertilizer response. Figure 4 illustrates the corresponding yield response under the normal condition and 1SD deviation in weather anomalies.

Results should be interpreted as the approximation around the average data points of observations shown in descriptive statistics in Table 2, and caution is needed when interpreting the patterns further away from the average data points.

For the Boro system (Table 7), the average linear response of yield (ton/ha) to nitrogen (ton/ha) is approximately 2.5, and estimated average plateau is around 6.2 ton / ha. However, 1SD increases in GDD and HNT anomalies reduce this response by around 1.4 ~ 1.6. Similarly, 1SD increases in GDD anomaly reduce the yield plateau by about 0.04 ~ 0.07 ton / ha.

Similarly, for the Aman irrigated system, while the average linear response is around 3 ~ 3.5, 1SD increases in GDD and HNT anomalies reduce this response by about 2.5 and 2.7 ~ 3.8, respectively, and though they shift up the overall response function by 0.1 ~ 0.4 ton/ha. Furthermore, 1SD increases in GDD and HNT anomalies also reduce yield plateau by about 0.3 ~ 0.4 ton/ha.

For the Aman rainfed system (Table 8), patterns are broadly consistent; 1SD increases in GDD and HNT anomalies reduce linear responses by about 2 ~ 4, relative to the average linear response of about 7, although they also shift up the linear response function by about 0.1 ~ 0.3 ton/ha, and 1SD increases in GDD anomalies also shift up the yield plateau by about 0.4 ton / ha, from the original plateau of about 3.5 ton / ha. 1SD increases in drought and rainfall anomalies have opposite effects; while they increase the linear responses by about 5 and 3, respectively, they shift down the overall linear response function by 0.1 ~ 0.2, and yield plateau by about 0.1 (albeit insignificantly in the maximum likelihood estimation).

Overall, results based on the LRP model generally suggest patterns consistent with polynomial regressions. Greater anomalies in temperatures (mostly warmer temperatures in recent years) reduce marginal yield response to nitrogen. Greater abnormality in drought and rainfall generally increase marginal yield response to nitrogen particularly at lower nitrogen level, but reduce overall yield potentials.

5.3 Robustness checks

Our primary measurements of weather anomalies are based on percentiles with respect to historical distribution of weather variables. We also estimated polynomial regressions using alternative anomaly measurements, namely z-values and d-values (simple deviations from historical averages). Appendix Table 9 and Table 10 summarize the results for the primary variables. These results suggest that our primary results are robust against the use of alternative measures of weather anomalies.

5.4 Other covariates

Our primary interests are on yield responses to nitrogen and effects of weather anomalies. While effects of other covariates are of secondary interests, they are generally intuitive. Formal varieties (for which age of varieties since formal release is recorded) have higher yields, while older varieties tend to have lower yields. Older farmers achieve higher yields in Aman rainfed system, possibly because the Aman rainfed system is more traditional for which older farmers have greater production knowledge (e.g., Nuthall 2009). In the Boro system, in contrast, younger farmers achieve higher yields possibly because the Boro system is more intensive requiring greater use of more modern inputs including intensive irrigation, for which younger farmers may have greater adaptive skills. Interestingly, soil quality has rather ambiguous effects on yields, with higher soil quality index negatively associated with yield in some cases. Such ambiguous effects of soil quality index may rather reflect the unique soil type requirements in rice eco-systems (Moorman & Breemen 1978; Vial et al. 2020), and general yield sensitivity to soil heterogeneity. Sharecropping is associated generally positively with yields. While counterintuitive, this is possibly because sharecropping allows tenants to split production risks with landlords (Singh 1989; Jacoby & Mansuri 2009) and may be actually inducing tenant producers to adopt riskier but yield-enhancing management practices. While using more types of tools is generally associated with higher yields, it may be sometimes negatively associated with yields (particularly in the Boro system) if spending on more tools competes with expenditures on other more productive inputs.

6 Conclusions

The fertilizer response of yield has been one of the major indicators of agricultural productivity in both developed and developing countries. Filling the evidence gap remains vital regarding fertilizer response in Asia, particularly in South Asia, given the evolution and emergence of new challenges, including intensifying climate shocks. We aimed to partly fill this knowledge gap by investigating the associations between climate shocks and fertilizer response in Bangladeshi rice production, using three rounds of nationally representative plot-level panel data.

We find robust evidence that climate anomalies adversely affect fertilizer responses, including higher temperatures for the Boro and the Aman irrigated systems, and higher temperatures and droughts for the Aman rainfed system. These findings commonly hold under various fertilizer response function forms, notably polynomial function and stochastic Linear Response Plateau. Furthermore, stochastic Linear Response Plateau results are consistent for switching regression-type and Bayesian regression models.

The study findings have important policy implications. Investment in public R&D is likely to play a critical role. Investment in public R&D to assess/develop varieties with high/resilient fertilizer response under climate shocks (which may include drought-resistant, heat-tolerant rice varieties) is likely to be required, which is also consistent with the suggestions by other studies advocating the importance of R&D for climate resilience in Bangladesh (Salim et al. 2020). At the same time, R&D should also be promoted to identify climate-smart crop husbandry practices, including alternatives to fertilizer application. For example, in other developing countries, farmers adapted to higher temperatures by diverting investment from productivity-enhancing technologies such as fertilizer to adaptive, loss-reducing, defensive inputs such as pesticides and weeding labor (e.g., Jagnani et al. 2021). Such strategies may be particularly effective if combined with improvement in seasonal climate forecasting system. Where non-rice crops have better fertilizer response potential under the emerging climate regime, further research to support required crop diversification may be encouraged. In South Asia, yield responses to excessive temperatures vary across crops (Birthal 2021), and crop diversification sometimes mitigates the adverse effects of climate anomalies (Birthal & Hazrana 2019). Lastly, continued investigations are needed regarding the relationship between fertilizer response and climate shocks, which is not static but is rather more evolutionary, as the climate shocks are expected to intensify in the near future.

References

Abera W, L Tamene, K Tesfaye, D Jiménez, H Dorado, T Erkossa, J Kihara, JS Ahmed, T Amede & J Ramirez-Villegas. 2022. A data-mining approach for developing site-specific fertilizer response functions across the wheat-growing environments in Ethiopia. *Experimental Agriculture 58*:e9.

Acharjee TK, G van Halsema, F Ludwig & P Hellegers. 2017. Declining trends of water requirements of dry season Boro rice in the north-west Bangladesh. *Agricultural Water Management 180*:148-159.

Acharjee TK, G van Halsema, F Ludwig, P Hellegers & I Supit. 2019. Shifting planting date of Boro rice as a climate change adaptation strategy to reduce water use. *Agricultural Systems 168*:131-143.

Ackello Ogutu C, Q Paris & WA Williams. 1985. Testing a Von Liebig Crop Response Function Against Polynomial Specifications. *American Journal of Agricultural Economics 67*:873-80.

Ahmed R. 1995. Liberalization of agricultural input markets in Bangladesh: process, impact, and lessons. *Agric. Econ. 12*(2):115-128.

Ahmed A, N Islam & MK Mujeri. 2021. *Securing food for all in Bangladesh.* Dhaka, Bangladesh: University Press Limited.

Amale HS, PS Birthal & DS Negi. 2023. Delayed monsoon, irrigation and crop yields. *Agricultural Economics 54*(1):77-94.

Aulakh MS, NS Pasricha & GS Bahl. 2003. Phosphorus fertilizer response in an irrigated soybean–wheat production system on a subtropical, semiarid soil. *Field Crops Research 80*(2):99-109.

Baltagi B. 2013. *Econometric Analysis of Panel Data. 5th ed.* Chichester, UK: Wiley.

Banerjee L. 2010. Effects of Flood on Agricultural Productivity in Bangladesh. *Oxford Development Studies 38*(3):339-356.

Benjamin D. 1992. Household composition, labor markets and labor demand: Testing for separation in agricultural household models. *Econometrica 60*, 287-322.

Bheemanahalli R, R Sathishraj, J Tack, LL Nalley, R Muthurajan & KSV Jagadish. 2016. Temperature thresholds for spikelet sterility and associated warming impacts for sub-tropical rice. *Agricultural and Forest Meteorology 221*:122-130.

Berck P & G Helfand. 1990. Reconciling the Von Liebig and Differentiable Crop Production

Functions. *American Journal of Agricultural Economics 72*:985-96.

Birthal PS, J Hazrana, DS Negi & SC Bhan. 2021. Climate change and land-use in Indian agriculture. *Land Use Policy 109*:105652.

Birthal PS & J Hazrana. 2019. Crop diversification and resilience of agriculture to climatic shocks: Evidence from India. *Agricultural Systems 173*:345-354.

Burke WJ, SS Snapp & TS Jayne. 2020. An in-depth examination of maize yield response to fertilizer in Central Malawi reveals low profits and too many weeds. *Agricultural Economics 51*(6):923-940.

Bürkner PC. 2017. *Advanced Bayesian multilevel modeling with the R package brms*. arXiv preprint arXiv:1705.11123.

Dee DP, SM Uppala, AJ Simmons, P Berrisford, P Poli, S Kobayashi & U Andrae. 2011. The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society 137*(656):553-97.

Deshênes O & M Greenstone. 2007. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review 97*(1):354-385.

Dillon B, P Brummund & G Mwabu. 2019. Asymmetric non-separation and rural labor markets. *Journal of Development Economics 139*:78-96.

Dolislager M, T Reardon, A Arslan, L Fox, S Liverpool-Tasie, C Sauer & DL Tschirley. 2021. Youth and adult agrifood system employment in developing regions: Rural (peri-urban to hinterland) vs. urban. *Journal of Development Studies 57*(4):571-93.

Dubey R, H Pathak, B Chakrabarti, S Singh, DK Gupta & RC Harit. 2020. Impact of terminal heat stress on wheat yield in India and options for adaptation. *Agricultural Systems 181*:102826.

Fan S, S Yosef & R Pandya-Lorch. 2019. *Agriculture for improved nutrition: Seizing the momentum*. IFPRI.

FAO (Food and Agriculture Organization) et al. 2012. *Harmonized World Soil Database (version 1.2).”* Rome: FAO; Laxenburg, Austria: IIASA.

Fick SE & RJ Hijmans. 2017. WorldClim 2: New 1km spatial resolution climate surfaces for global land areas. *International Journal of Climatology 37*(12):4302-4315.

Gollin D, CW Hansen & A Wingender. 2021. Two Blades of Grass: The Impact of the Green

Revolution. *Journal of Political Economy 129*(8):2344-2384.

Holloway G & Q Paris. 2002. Production efficiency in the von Liebig model. *American Journal of Agricultural Economics 84*(5):1271-1278.

IFPRI. 2019. *Bangladesh Integrated Household Survey (BIHS) 2011, 2015, 2018-2019*. IFPRI. Washington DC. https://doi.org/10.7910/DVN/NXKLZJ.

Jacoby HG & G Mansuri. 2009. Incentives, supervision, and sharecropper productivity. *Journal of Development Economics 88*(2), 232-241.

Jagnani M, CB Barrett, Y Liu & L You. 2021. Within-season producer response to warmer temperatures: Defensive investments by Kenyan farmers. *Economic Journal 131*(633):392-419.

Ji Y, X Yu & F Zhong. 2012. Machinery investment decision and off-farm employment in rural China. *China Economic Review 23*(1):71-80.

Khatri-Chhetri A, TB Sapkota, S Maharjan, NC Konath & P Shirsath. 2023. Agricultural emissions reduction potential by improving technical efficiency in crop production. *Agricultural Systems 207*, 103620.

Kafiluddin A & MS Islam. 2008. *Fertilizer Distribution, Subsidy, Marketing, Promotion and Agronomic Use efficiency Scenario in Bangladesh.* Mimeo.

Kishore A, M Alvi & TJ Krupnik. 2021. Development of balanced nutrient management innovations in South Asia: perspectives from Bangladesh, India, Nepal, and Sri Lanka. *Global Food Security 28*, 100464.

Le KT. 2010. Separation hypothesis tests in the agricultural household model. *American Journal of Agricultural Economics 92*(5):1420-31.

Li M. 2023. Adaptation to expected and unexpected weather fluctuations: Evidence from Bangladeshi smallholder farmers. *World Development 161*:106066.

von Liebig J. 1862. *Die Chemie in ihrer Anwendung auf Agricultur and Physiologie*. 7e Aufl., vol. II, Braunschweig: F. Vieweg und Sohn.

Liu Y & R Myers. 2009. Model selection in stochastic frontier analysis with an application to maize production in Kenya. *Journal of Productivity Analysis 31*, 33-46.

Maddala GS & FD Nelson. 1974. Maximum Likelihood Methods of Markets in Disequilibrium. *Econometrica 42*:1013-30.

McArthur JW & GC McCord. 2017. Fertilizing growth: Agricultural inputs and their effects in economic development. *Journal of Development Economics 127*:133-152.

McFadden BR, BW Brorsen & WR Raun. 2018. Nitrogen fertilizer recommendations based on plant sensing and Bayesian updating. *Precision Agriculture 19*:79-92.

Min S, J Huang & H Waibel. 2017. Rubber specialization vs crop diversification: the roles of perceived risks. *China Agricultural Economic Review 9*(2):188-210.

Moormann FR & N van Breemen. 1978. *Rice, soil, water, land.* IRRI. Los Baños, Laguna, Philippines.

Ng'ombe JN & DM Lambert. 2021. Using Hamiltonian Monte Carlo via Stan to estimate crop input response functions with stochastic plateaus. *Journal of Agriculture and Food Research 6*:100226.

Nuthall P. 2009. Modelling the origins of managerial ability in agricultural production. *Australian Journal of Agricultural and Resource Economics 53*(3):413-436.

Ouedraogo F & BW Brorsen. 2018. Hierarchical Bayesian estimation of a stochastic plateau response function: Determining optimal levels of nitrogen fertilization. *Canadian Journal of Agricultural Economics 66*(1):87-102.

Otsuka K & K Kalirajan. 2006. Rice green revolution in Asia and its transferrability to Africa: An introduction. *The Developing Economies 44*(2), 107-122.

Paris Q. 1992. The Von Liebig Hypothesis. *American Journal of Agricultural Economics 74*:1019-28.

Peng S, J Huang, JE Sheehy, RC Laza, RM Visperas, X Zhong, GS Centeno, GS Khush & KG Cassman. 2004. Rice yields decline with higher night temperature from global warming. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(27):9971-9975.

Perrin RK. 1976. The Value of Information and the Value of Theoretical Models in Crop Response Research. *American Journal of Agricultural Economics 58*:54-61.

Quader AA. 2009. strategy for developing the fertilizer sector in Bangladesh for sustainable agriculture. *Chemical Engineering Research Bulletin 13*(2):39-46.

Rahman, Niaz Md Farhat et al. 2023. 50 years of rice breeding in Bangladesh: genetic yield trends. *Theoretical and Applied Genetics 136*(1):18.

Ratnasiri S, R Walisinghe, N Rohde & R Guest. 2019. The effects of climatic variation on rice production in Sri Lanka. *Applied Economics 51*(43):4700-10.

Rötter R, H Van Keulen & MJW Jansen. 1997. Variations in yield response to fertilizer application in the tropics: I. Quantifying risks and opportunities for smallholders based on crop growth simulation. *Agricultural Systems 53*(1):41-68.

Salim R, K Hassan & S Rahman. 2020. Impact of R&D expenditures, rainfall and temperature variations in agricultural productivity: Empirical evidence from Bangladesh. *Applied Economics 52*(27):2977-90.

Sarker MAR, K Alam & J Gow. 2012. Exploring the relationship between climate change and rice yield in Bangladesh: An analysis of time series data. *Agricultural Systems 112*:11-16.

Sheahan M, R Black & T Jayne. 2013. Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. *Food Policy 41*:39-52.

Singh I. 1989. Reverse Tenancy in Punjab Agriculture: Impact of Technological Change. *Economic and Political Weekly 24*(25):A86-A92.

Spillman WJ. 1933. *Use of the Exponential Yield Curve in Fertilizer Experiments.* United States Department of Agriculture Technical Bulletin 348, Washington, DC.

Takeshima H, B Balana, J Smart, HO Edeh, MA Oyeyemi & KS Andam. 2022. Subnational public expenditures, short-term household-level welfare and economic flexibility: Evidence from Nigeria. *Agricultural Economics 53*(5):739-755.

Tembo G, BW Brorsen, FM Epplin & E Tostão. 2008. Crop input response functions with stochastic plateaus. *American Journal of Agricultural Economics 90*(2):424-434.

Vial LK, A Molesworth & RD Lefroy. 2020. Balancing rice and non-rice crops: Managing the risks from soil constraints in Mainland Southeast Asian rice systems. *Field Crops Research 246*, 107677.

Wang R, RM Rejesus, JB Tack, JV Balagtas & AD Nelson. 2022. Quantifying the yield sensitivity of modern rice varieties to warming temperatures: Evidence from the Philippines. *American Journal of Agricultural Economics 104*(1):318-339.

Wassmann R, SVK Jagadish, K Sumfleth, H Pathak, G Howell, A Ismail, R Serraj, E Redona, RK Singh & S Heuer. 2009. Regional vulnerability of climate change impacts on Asian rice production and scope for adaptation. *Advances in Agronomy 102*:91-133.

Welch JR. 2010. Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences 107*(33):14562-67.

Yamoah CF, MD Clegg & CA Francis. 1998. Rotation effect on sorghum response to nitrogen fertilizer under different rainfall and temperature environments. *Agriculture, ecosystems & environment 68*(3):233-243.

Table 1. Nutrient composition of typical chemical fertilizer used in Bangladesh

Type of fertilizer	Nitrogen	Phosphate	Potassium
Urea	45-46%		
TSP / SSP (99% almost all TSP)		TSP - 44-48%	
DAP / MAP	18%	46%	
MP			60-62%
Ammonia	21%		
NPK – very small quantity	15%	15%	15%

Source: Quader (2009).

Table 2. Descriptive statistics (among panel plot samples with at least 2 rounds of data)

Variables	Unit	Boro (irrigated) (N = 8,048)	Aman rainfed (N = 4,324)	Aman irrigated (N = 3,124)
		Mean (std.dev)	Mean (std.dev)	Mean (std.dev)
Paddy production	ton	0.680 (0.793)	0.360 (0.397)	0.433 (0.506)
Paddy plot size	ha	0.126 (0.161)	0.126 (0.128)	0.109 (0.123)
Paddy yield	ton / ha	5.697 (1.644)	2.995 (1.560)	4.057 (1.507)
Chemical fertilizer (Nitrogen)	ton / ha	0.093 (0.071)	0.051 (0.046)	0.078 (0.059)
Age of varieties since release	yes = 1	0.698 (0.459)	0.438 (0.496)	0.345 (0.475)
Age of varieties since release	years	14.042 (9.832)	10.192 (13.475)	6.799 (11.161)
Hybrid variety	yes = 1	0.130 (0.336)	0.014 (0.118)	0.048 (0.214)
Years cultivating plots	years	14.223 (11.561)	13.839 (11.559)	14.070 (11.034)
Distance to the plot from home	km	0.574 (0.852)	0.458 (0.583)	0.558 (0.690)
Plot flood depth (annual maximum)	meter	2.368 (2.957)	1.577 (1.554)	0.989 (1.475)
Sharecropping	yes = 1	0.126 (0.332)	0.134 (0.341)	0.079 (0.270)
Number of tools used	count	0.493 (0.559)	0.382 (0.512)	0.607 (0.583)
Soil quality index[a]	Ratio to potential	0.859 (0.034)	0.850 (0.034)	0.863 (0.020)
Age of producers	year	48.680 (11.972)	49.496 (11.873)	47.328 (11.966)
Year (2011)	yes = 1	0.331 (0.469)	0.328 (0.468)	0.325 (0.467)
Year (2014)	yes = 1	0.375 (0.484)	0.385 (0.487)	0.366 (0.482)
Year (2018)	yes = 1	0.294 (0.455)	0.287 (0.453)	0.309 (0.462)

Source: Authors.

[a]Soil quality index is the average across 7 quality traits; nutrient availability, nutrient retention capacity, rooting conditions, oxygen availability to roots, excess salts, toxicity, and workability that affect field management, extracted from FAO et al. (2012).

Table 3. Climate conditions in 2011, 2014 and 2018 (historical percentiles)

	Unit	2011	2014	2018
Boro system				
GDD	Historical percentile	53 (7)	43 (7)	24 (5)
HNT	Historical percentile	61 (16)	77 (13)	13 (6)
Aman irrigated system				
GDD	Historical percentile	62 (8)	29 (13)	34 (12)
HNT	Historical percentile	61 (14)	25 (11)	25 (14)
Aman rainfed system				
GDD	Historical percentile	68 (11)	22 (13)	30 (17)
HNT	Historical percentile	75 (15)	25 (13)	28 (16)
Drought index	Historical percentile	66 (13)	87 (6)	98 (3)
Rainfall	Historical percentile	52 (21)	37 (21)	12 (12)

Source: Authors.

Note: For irrigated systems (Boro, and Aman irrigated systems), we only focus on temperature related shocks.

Table 4. Rice yield response to nitrogen and weather shocks (polynomial specification) – irrigated system

Variables	Boro				Aman irrigated			
	Weather variables				Weather variables			
	GDD		HNT		GDD		HNT	
Nitrogen	2.608***	2.642***	2.303***	2.341***	7.380***	7.765***	8.196***	8.513***
	(0.474)	(0.475)	(0.449)	(0.448)	(1.660)	(1.621)	(1.469)	(1.521)
Nitrogen squared	–2.320	–2.358	–2.321**	–2.369***	–17.547***	–19.832***	–20.646***	–22.644***
	(1.554)	(1.544)	(0.805)	(0.788)	(6.116)	(6.318)	(6.107)	(6.313)
Nitrogen * Weather shock	–1.372**	–1.357**	1.565**	1.628**	–4.145***	–4.490***	–6.029***	–6.191***
	(0.639)	(0.635)	(0.675)	(0.671)	(1.337)	(1.369)	(1.227)	(1.248)
Nitrogen squared *	–1.026	–1.115	–5.203**	–5.433**	7.568	9.111	18.609***	18.993***
Weather shock	(2.786)	(2.767)	(2.392)	(2.356)	(5.602)	(5.764)	(5.247)	(5.280)
Weather shock	0.172***	0.163***	–0.081*	–0.076*	0.196**	0.204**	0.168**	0.164**
	(0.048)	(0.048)	(0.045)	(0.046)	(0.082)	(0.084)	(0.077)	(0.079)
Age of varieties since		0.197***		0.185***		0.004		0.013
release (yes)		(0.064)		(0.063)		(0.054)		(0.054)
Age of varieties since		–0.094*		–0.074		0.001		–0.002
release		(0.056)		(0.056)		(0.056)		(0.055)
Age of respondents		–0.088**		–0.089**		–0.016		–0.006
		(0.036)		(0.037)		(0.073)		(0.073)
Distance to the plot from		0.024		0.023		–0.012		–0.015
home		(0.021)		(0.021)		(0.032)		(0.032)
Years cultivating plots		–0.004		–0.003		–0.042		–0.042
		(0.027)		(0.027)		(0.040)		(0.039)
Soil quality index		–0.105		–0.119		–0.175*		–0.229**
		(0.137)		(0.136)		(0.098)		(0.097)
Plot flood depth (annual		0.006		0.002		–0.004		0.006
maximum)		(0.023)		(0.023)		(0.038)		(0.039)
Sharecropping		0.024		0.023		0.053*		0.059*
		(0.023)		(0.023)		(0.032)		(0.032)
Number of tools used		–0.023		–0.027		0.100**		0.095**
		(0.026)		(0.026)		(0.039)		(0.040)
Hybrid dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies * division	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	5.247***	5.190***	5.328***	5.264***	3.155***	3.280***	3.201***	3.344***
	(0.052)	(0.058)	(0.043)	(0.052)	(0.101)	(0.119)	(0.083)	(0.102)
No. of obs.	8,048	8,048	8,048	8,048	3,124	3,124	3,124	3,124

R-square	.499	.501	.498	.500	.540	.542	.542	.545
p-value (H_0: model insignificant)	.000	.000	.000	.000	.000	.000	.000	.000

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

Note: GDD = Growing Degree Days; HDD = Harmful Degree Days; HNT = High Nighttime Temperature.
Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 5. Rice yield response to nitrogen and weather shocks (polynomial specification) – Aman rainfed system

Variables	Weather variables							
	GDD		HNT		Drought		Rainfall	
Nitrogen	6.667***	5.927***	7.858***	7.027***	8.159 ***	7.413***	7.963***	7.015***
	(1.056)	(1.060)	(1.215)	(1.229)	(1.028)	(1.029)	(1.192)	(1.191)
Nitrogen squared	–12.214**	–10.615*	–18.812**	–16.894**	–13.803***	–12.851***	–19.238***	–16.651***
	(5.651)	(5.663)	(7.342)	(7.531)	(4.722)	(4.616)	(5.885)	(5.804)
Nitrogen * Weather shock	–3.688***	–3.227***	–4.180***	–3.594***	10.958***	9.704***	5.122***	4.470***
	(1.264)	(1.251)	(1.075)	(1.085)	(1.369)	(1.351)	(1.241)	(1.265)
Nitrogen squared * Weather	12.845	11.238	6.964	5.269	–46.074***	–39.046***	–24.737***	–21.551***
shock	(8.461)	(8.448)	(7.662)	(7.855)	(8.914)	(8.612)	(7.396)	(7.611)
Weather shock	0.414***	0.381***	0.234***	0.188***	–0.306***	–0.285***	–0.134***	–0.109**
	(0.058)	(0.059)	(0.056)	(0.056)	(0.048)	(0.048)	(0.048)	(0.048)
Age of varieties since release		0.032		0.056		0.047		0.054
(yes)		(0.053)		(0.053)		(0.053)		(0.053)
Age of varieties since release		–0.088*		–0.105**		–0.097*		–0.106**
		(0.050)		(0.051)		(0.051)		(0.050)
Age of respondents		0.126*		0.129*		0.096		0.115*
		(0.066)		(0.065)		(0.065)		(0.064)
Distance to the plot from		0.001		0.003		-0.001		-0.002
home		(0.031)		(0.031)		(0.031)		(0.031)
Years cultivating plots		0.015		0.015		0.010		0.014
		(0.036)		(0.036)		(0.036)		(0.036)
Soil quality index		1.848**		1.655**		2.091***		1.957***
		(0.660)		(0.820)		(0.807)		(0.642)
Plot flood depth (annual		0.033		0.026		0.023		0.029
maximum)		(0.043)		(0.043)		(0.043)		(0.043)
Sharecropping		0.072***		0.060**		0.061**		0.058**
		(0.028)		(0.028)		(0.028)		(0.028)
Number of tools used		0.180***		0.184***		0.167***		0.193***
		(0.030)		(0.030)		(0.031)		(0.030)
Hybrid dummy		Yes		Yes		Yes		Yes
Year dummies		Yes		Yes		Yes		Yes
Year dummies * division		Yes		Yes		Yes		Yes
Household fixed effects		Yes		Yes		Yes		Yes
Intercept	2.181***	2.445***	2.389***	2.664***	2.389***	2.619***	2.535***	2.787***
	(0.067)	(0.076)	(0.072)	(0.079)	(0.056)	(0.064)	(0.046)	(0.056)
No. of obs.	4,324	4,324	4,324	4,324	4,324	4,324	4,324	4,324
R-square	.517	.525	.515	.523	.523	.529	.513	.521

p-value (H_0: model insignificant)	.000	.000	.000	.000	.000	.000	.000	.000

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

Note: GDD = Growing Degree Days; HDD = Harmful Degree Days; HNT = High Nighttime Temperature.
Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 6. Endogeneity tests of nitrogen variable

Categories	Weather variables			
	GDD	**HNT**	**Drought**	**Rainfall**
Boro				
p-value (H_0: underidentified)	.042	.034		
p-value (H_0: not over-identified)	.237	.821		
p-value (H_0: exogenous)	.366	.585		
Aman irrigated				
p-value (H_0: underidentified)	.036	.086		
p-value (H_0: not over-identified)	.818	.214		
p-value (H_0: exogenous)	.189	.137		
Aman rainfed				
p-value (H_0: underidentified)	.084	.063	.018	.069
p-value (H_0: not over-identified)	.882	.536	.233	.325
p-value (H_0: exogenous)	.184	.121	.138	.238

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

Note: GDD = Growing Degree Days; HNT = High Nighttime Temperature

Identification statistics are based on Generalized Method of Moments regressions which are efficient in the presence of unknown heteroskedasticity in error terms.

Table 7. Linear Response Plateau estimations – irrigated system

Variables	Boro				Aman irrigated			
	GDD		HNT		GDD		HNT	
	MNSR	Bayesian	MNSR	Bayesian	MNSR	Bayesian	MNSR	Bayesian
Nitrogen	2.585***	2.458***	2.328***	2.412***	2.928***	3.129***	3.658***	3.443***
	(0.446)	(0.288)	(0.426)	(0.292)	(0.626)	(0.476)	(0.955)	(0.489)
Nitrogen * Weather shock	–1.609***	–1.414***	–1.440***	–1.561***	–2.635***	–2.514***	–3.811***	–2.733***
	(0.461)	(0.283)	(0.425)	(0.284)	(0.599)	(0.434)	(0.853)	(0.398)
Weather shock	0.118**	0.139***	0.151***	0.205***	0.083	0.152***	0.424***	0.078*
	(0.060)	(0.039)	(0.058)	(0.038)	(0.073)	(0.050)	(0.095)	(0.049)
Plateau	6.204***	6.206***	6.209***	6.211***	4.662***	4.612***	4.431***	4.663***
	(0.045)	(0.044)	(0.041)	(0.040)	(0.031)	(0.030)	(0.064)	(0.030)
Plateau * Weather shock	–0.069**	–0.038*	0.024	0.016	–0.390***	–0.344***	–0.327***	–0.330***
	(0.031)	(0.020)	(0.022)	(0.023)	(0.037)	(0.039)	(0.065)	(0.035)
Age of varieties since	–0.268***	–0.268***	–0.212***	–0.218***	0.072	0.073*	0.007	0.085**
release (yes)	(0.080)	(0.044)	(0.078)	(0.045)	(0.066)	(0.042)	(0.071)	(0.041)
Age of varieties since	0.070	–0.062	0.034	0.023	–0.119*	–0.068*	0.048	–0.053
release	(0.074)	(0.041)	(0.074)	(0.040)	(0.061)	(0.040)	(0.073)	(0.039)
Age of respondents	–0.060	–0.058	–0.093	–0.087**	–0.055	–0.079	–0.107	–0.062
	(0.059)	(0.035)	(0.058)	(0.036)	(0.073)	(0.048)	(0.078)	(0.048)
Distance to the plot from	0.039	0.034	0.041	0.038*	0.023	0.016	–0.056	0.009
home	(0.029)	(0.019)	(0.029)	(0.020)	(0.039)	(0.024)	(0.040)	(0.027)
Years cultivating plots	–0.025	–0.010	–0.041	-0.023	–0.031	–0.045	0.009	–0.045
	(0.038)	(0.024)	(0.037)	(0.024)	(0.045)	(0.034)	(0.053)	(0.031)
Soil quality index	–0.639**	–0.598***	–0.696**	–0.653***	–0.012	–0.027	–0.160	–0.039
	(0.321)	(0.203)	(0.301)	(0.170)	(0.108)	(0.070)	(0.142)	(0.063)
Plot flood depth (annual	0.021	0.023	0.004	0.001	–0.027	–0.023	–0.021	–0.031
maximum)	(0.032)	(0.021)	(0.032)	(0.021)	(0.047)	(0.029)	(0.051)	(0.029)
Sharecropping	0.020	0.026	0.011	0.018	0.026	0.028	0.140***	0.026
	(0.030)	(0.020)	(0.029)	(0.018)	(0.036)	(0.026)	(0.059)	(0.026)
Number of tools used	–0.039	–0.045*	–0.063*	–0.066***	0.043	0.025	0.112**	0.049
	(0.034)	(0.023)	(0.033)	(0.021)	(0.046)	(0.032)	(0.057)	(0.035)
CRE terms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	4.656***	4.653	4.689***	4.680	3.193***	3.189	3.156***	3.190
	(0.077)	(0.074)	(0.071)	(0.066)	(0.086)	(0.085)	(0.113)	(0.080)
σ_u	0.946	0.941	0.913	0.910	0.643	0.639	1.076	0.640
	(0.035)	(0.036)	(0.034)	(0.037)	(0.028)	(0.030)	(0.038)	(0.029)
σ_s	0.946	0.943	0.913	0.912	0.643	0.641	1.076	0.641
	(0.035)	(0.037)	(0.034)	(0.034)	(0.028)	(0.029)	(0.038)	(0.027)
σ_ε	1.731	1.599	1.736	1.673	1.474	1.361	1.532	1.365

	(0.021)	(0.012)	(0.021)	(0.011)	(0.026)	(0.015)	(0.057)	(0.015)
No. of obs.	8,048	8,048	8,048	8,048	3,124	3,124	3,124	3,124
Log-likelihood	–14,868		–14,872		–5,170		–5,251	

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

Note: GDD = Growing Degree Days; HNT = High Nighttime Temperature. MNSR = Maddala- Nelson Switching Regression. Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 8. Linear Response Plateau estimations – Aman rainfed system

Variables	GDD		HNT		Drought		Rainfall	
	MNSR	Bayesian	MNSR	Bayesian	MNSR	Bayesian	MNSR	Bayesian
Nitrogen	6.588***	6.430***	7.699***	6.594***	8.130***	7.463***	7.076***	7.290***
	(0.986)	(0.728)	(1.091)	(0.820)	(1.108)	(0.665)	(1.122)	(0.773)
Nitrogen * Weather shock	–3.870***	–2.198***	–3.990***	–3.484***	5.263***	4.906***	2.970***	2.857***
	(0.829)	(0.606)	(0.928)	(0.676)	(0.911)	(0.592)	(0.922)	(0.591)
Weather shock	0.282***	0.243***	0.133*	0.134***	–0.187***	–0.143***	–0.102*	–0.202***
	(0.065)	(0.052)	(0.076)	(0.049)	(0.061)	(0.050)	(0.062)	(0.043)
Plateau	3.532***	3.520***	3.401***	3.398***	3.416***	3.415***	3.414***	3.402***
	(0.089)	(0.090)	(0.085)	(0.089)	(0.097)	(0.087)	(0.079)	(0.073)
Plateau * Weather shock	0.336***	0.447***	–0.071	–0.012	–0.053	–0.174***	–0.066	–0.093**
	(0.083)	(0.057)	(0.068)	(0.047)	(0.072)	(0.064)	(0.059)	(0.043)
Age of varieties since release	–0.003	0.052	0.055	0.098**	0.030	0.054	0.040	0.098**
(yes)	(0.071)	(0.046)	(0.078)	(0.049)	(0.076)	(0.046)	(0.076)	(0.046)
Age of varieties since release	–0.007	0.033	–0.035	0.012	–0.016	–0.035	–0.032	0.023
	(0.068)	(0.046)	(0.075)	(0.056)	(0.074)	(0.050)	(0.073)	(0.050)
Age of respondents	0.145**	0.101**	0.154*	0.126**	0.111	0.083*	0.165**	0.131***
	(0.074)	(0.042)	(0.089)	(0.055)	(0.085)	(0.047)	(0.078)	(0.053)
Distance to the plot from	–0.004	–0.012	–0.015	–0.021	-0.022	–0.021	-0.023	–0.029
home	(0.038)	(0.025)	(0.040)	(0.024)	(0.040)	(0.026)	(0.040)	(0.027)
Years cultivating plots	0.037	0.031	0.030	0.022	0.024	0.009	0.024	0.026
	(0.047)	(0.034)	(0.051)	(0.033)	(0.050)	(0.030)	(0.049)	(0.034)
Soil quality index	–0.088**	–0.088***	–0.054	–0.047*	–0.054	0.196***	–0.054	–0.046**
	(0.034)	(0.023)	(0.035)	(0.027)	(0.035)	(0.032)	(0.035)	(0.023)
Plot flood depth (annual	0.080	0.042	0.067	0.030	0.069	0.033	0.061	0.024
maximum)	(0.058)	(0.033)	(0.063)	(0.036)	(0.063)	(0.038)	(0.060)	(0.036)
Sharecropping	0.032	0.054**	0.047	0.055**	0.055	0.067**	0.046	0.056**
	(0.044)	(0.026)	(0.045)	(0.028)	(0.046)	(0.027)	(0.046)	(0.027)
Number of tools used	0.330***	0.235***	0.272***	0.203***	0.272***	0.175***	0.321***	0.225***
	(0.051)	(0.029)	(0.058)	(0.032)	(0.059)	(0.029)	(0.058)	(0.032)
CRE terms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	2.242***	2.245***	2.141***	2.138	2.148***	2.153	2.223***	2.223***
	(0.071)	(0.070)	(0.082)	(0.078)	(0.081)	(0.074)	(0.083)	(0.081)
σ_u	1.799	1.795	1.761	1.758	1.779	1.778	1.791	1.785
	(0.038)	(0.041)	(0.042)	(0.044)	(0.040)	(0.040)	(0.039)	(0.041)
σ_s	1.799	1.797	1.761	1.757	1.779	1.777	1.791	1.785
	(0.038)	(0.039)	(0.042)	(0.040)	(0.040)	(0.039)	(0.039)	(0.042)
σ_ε	1.086	1.363	1.133	1.397	1.106	1.393	1.108	1.382
	(0.031)	(0.014)	(0.040)	(0.014)	(0.042)	(0.014)	(0.036)	(0.014)

No. of obs.	4,324	4,324	4,324	4,324	4,324	4,324	4,324	4,324
Log-likelihood	–7,642		–7,671		–7,664		–7,680	

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

Note: GDD = Growing Degree Days; HNT = High Nighttime Temperature. MNSR = Maddala- Nelson Switching Regression. Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 9. Rice yield response to nitrogen and weather shocks (polynomial specification) using alternative weather shock measurements – irrigated system

Variables	Boro				Aman irrigated			
	GDD		HNT		GDD		HNT	
	z-value	d-value	z-value	d-value	z-value	d-value	z-value	d-value
Nitrogen	2.918***	2.954***	2.477***	1.670***	7.586***	7.014***	8.075***	8.112***
	(0.455)	(0.447)	(0.522)	(0.399)	(1.672)	(1.700)	(1.465)	(1.516)
Nitrogen squared	–2.313*	–2.564**	–3.138**	–0.536	–19.412***	–17.692***	–21.435***	–21.778***
	(1.313)	(1.114)	(1.270)	(0.769)	(6.287)	(6.363)	(6.113)	(6.289)
Nitrogen * Weather shock	–2.021***	–1.657**	1.338**	1.802***	–4.170***	–3.500**	–5.843***	–5.946***
	(0.667)	(0.708)	(0.632)	(0.658)	(1.426)	(1.450)	(1.086)	(1.254)
Nitrogen squared *	–0.492	–2.021	–4.574**	–5.910**	7.951	6.022	18.493***	17.804***
Weather shock	(2.671)	(2.803)	(2.271)	(2.251)	(5.909)	(6.008)	(4.974)	(5.266)
Weather shock	0.232***	0.220***	–0.045	–0.089*	0.147*	0.095	0.171**	0.182**
	(0.063)	(0.064)	(0.044)	(0.051)	(0.082)	(0.096)	(0.069)	(0.079)

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

Note: d-value is the simple difference from historical means.

Table 10. Rice yield response to nitrogen and weather shocks (polynomial specification) using alternative weather shock measurements – Aman rainfed system

Variables	GDD		HNT		Drought		Rainfall	
	z-value	d-value	z-value	d-value	z-value	d-value	z-value	d-value
Nitrogen	5.708***	6.169***	6.590***	6.721 ***	10.092 ***	9.889***	7.288***	6.830***
	(1.143)	(1.191)	(1.215)	(1.366)	(1.173)	(1.092)	(1.335)	(1.174)
Nitrogen squared	–9.313	–10.557	–13.079*	–12.425	–26.561***	–25.117***	–18.462***	–15.937***
	(6.555)	(6.769)	(7.535)	(8.485)	(5.491)	(4.914)	(6.936)	(5.702)
Nitrogen * Weather shock	–2.180**	–2.379**	–4.515***	–4.109***	12.726***	13.551***	4.484***	4.239***
	(1.113)	(1.132)	(1.252)	(1.235)	(1.510)	(1.467)	(1.405)	(1.149)
Nitrogen squared * Weather	8.720	9.218	13.005	12.946	–54.034***	–59.338***	–18.107**	–17.672***
shock	(7.555)	(7.620)	(9.212)	(8.875)	(9.005)	(8.737)	(8.673)	(5.647)
Weather shock	0.224***	0.262***	0.221***	0.106*	–0.254***	–0.151**	–0.090*	–0.094**
	(0.052)	(0.055)	(0.059)	(0.056)	(0.068)	(0.069)	(0.052)	(0.048)

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

Note: d-value is the simple difference from historical means.

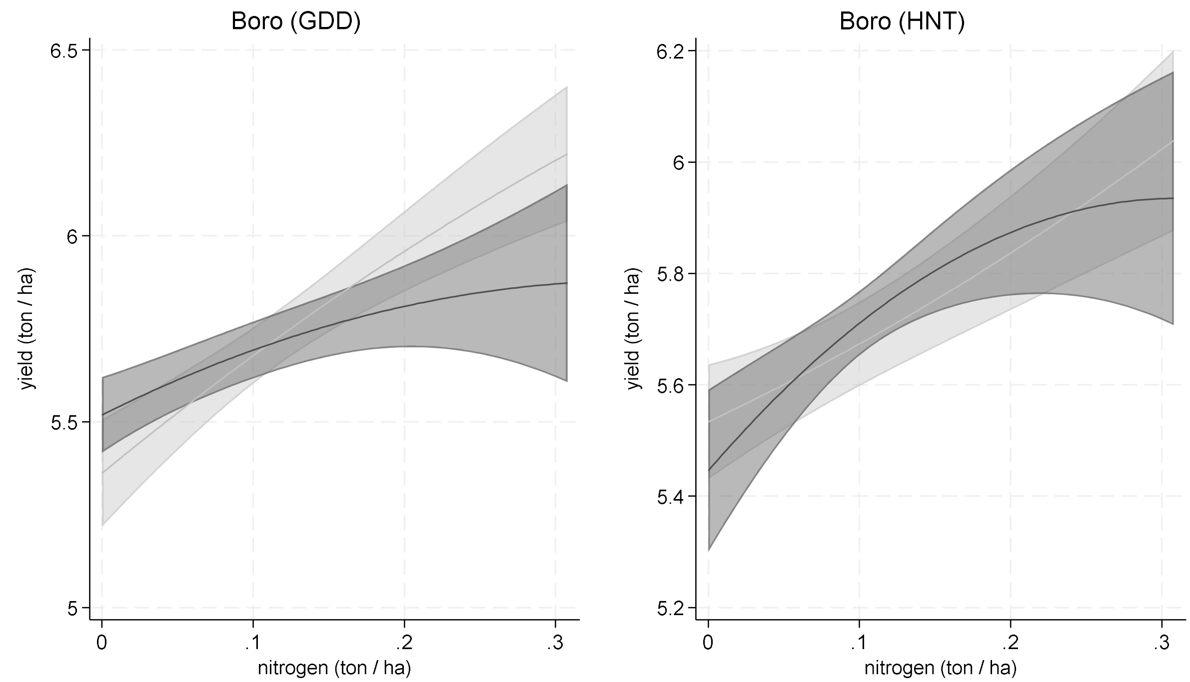


Figure 1. Illustration of fertilizer response under different weather conditions (Boro)

Source: Authors. GDD = growing degree days; HNT = high nighttime temperature.

Dark gray – 67 percentile of weather condition relative to historical distribution

Light gray – 33 percentile of weather condition relative to historical distribution

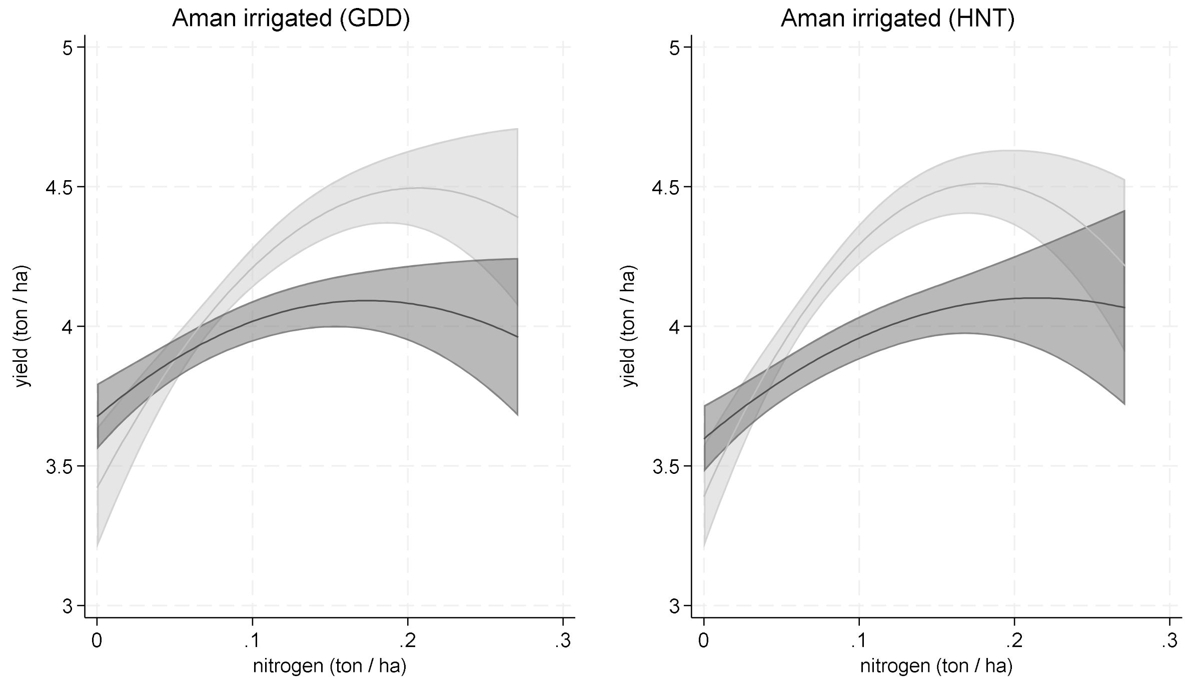


Figure 2. Illustration of estimated fertilizer response under different weather conditions (Aman irrigated)

Source: Authors. GDD = growing degree days; HNT = high nighttime temperature.

Dark gray – 67 percentile of weather condition relative to historical distribution

Light gray – 33 percentile of weather condition relative to historical distribution

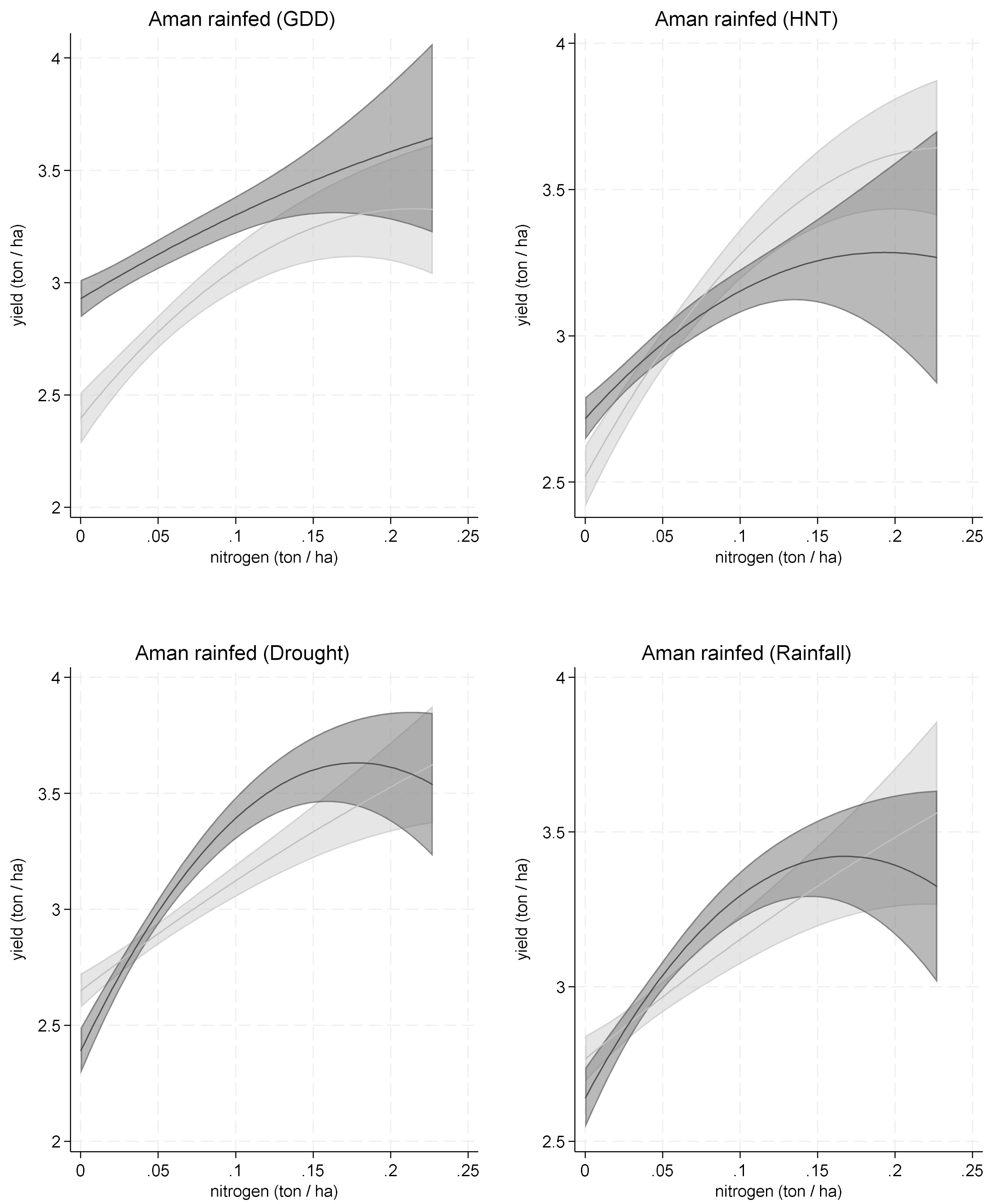
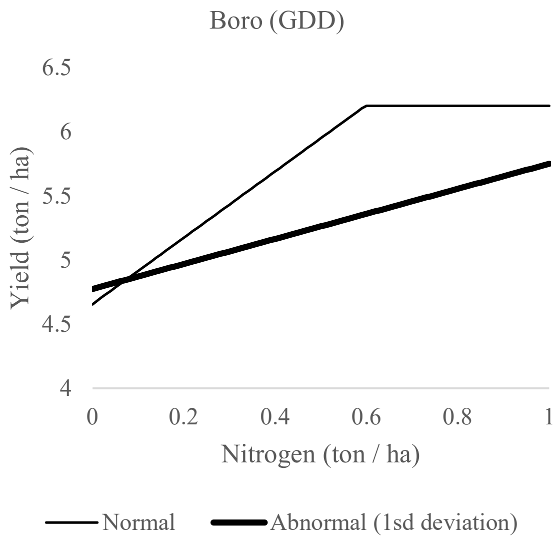


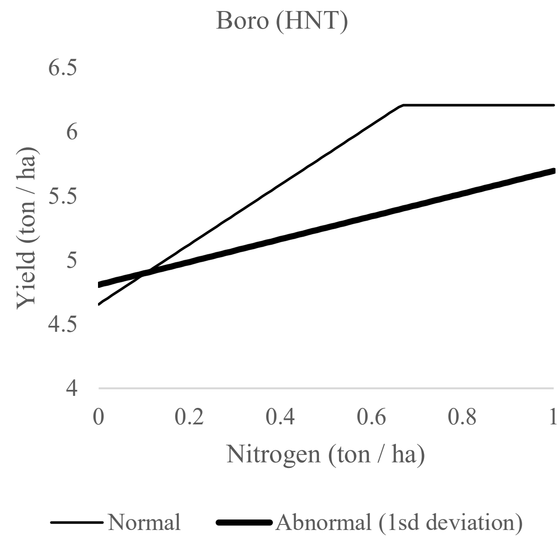
Figure 3. Illustration of estimated fertilizer response under different weather conditions (Aman rainfed)

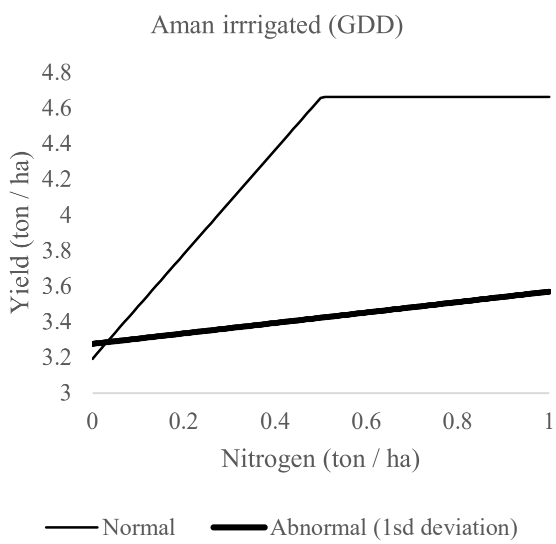
Source: Authors. GDD = growing degree days; HNT = high nighttime temperature.

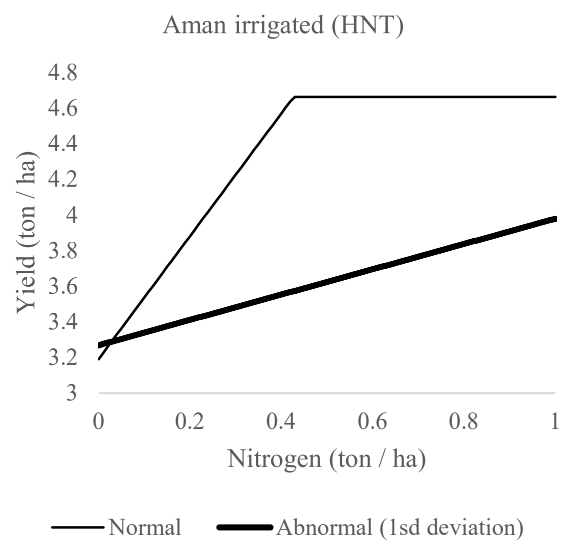
Dark gray – 67 percentile of weather condition relative to historical distribution

Light gray – 33 percentile of weather condition relative to historical distribution


Boro (GDD)
6.5
6
5.5
5
4.5
4
0
0.2
0.4
0.6
0.8
1
Yield (ton / ha)
Nitrogen (ton / ha)
Normal
Abnormal (1sd deviation)


Boro (HNT)
6.5
6
5.5
5
4.5
4
0
0.2
0.4
0.6
0.8
1
Yield (ton / ha)
Nitrogen (ton / ha)
Normal
Abnormal (1sd deviation)


Aman irrrigated (GDD)
4.8
4.6
4.4
4.2
4
3.8
3.6
3.4
3.2
3
0
0.2
0.4
0.6
0.8
1
Yield (ton / ha)
Nitrogen (ton / ha)
Normal
Abnormal (1sd deviation)


Aman irrigated (HNT)
4.8
4.6
4.4
4.2
4
3.8
3.6
3.4
3.2
3
0
0.2
0.4
0.6
0.8
1
Yield (ton / ha)
Nitrogen (ton / ha)
Normal
Abnormal (1sd deviation)

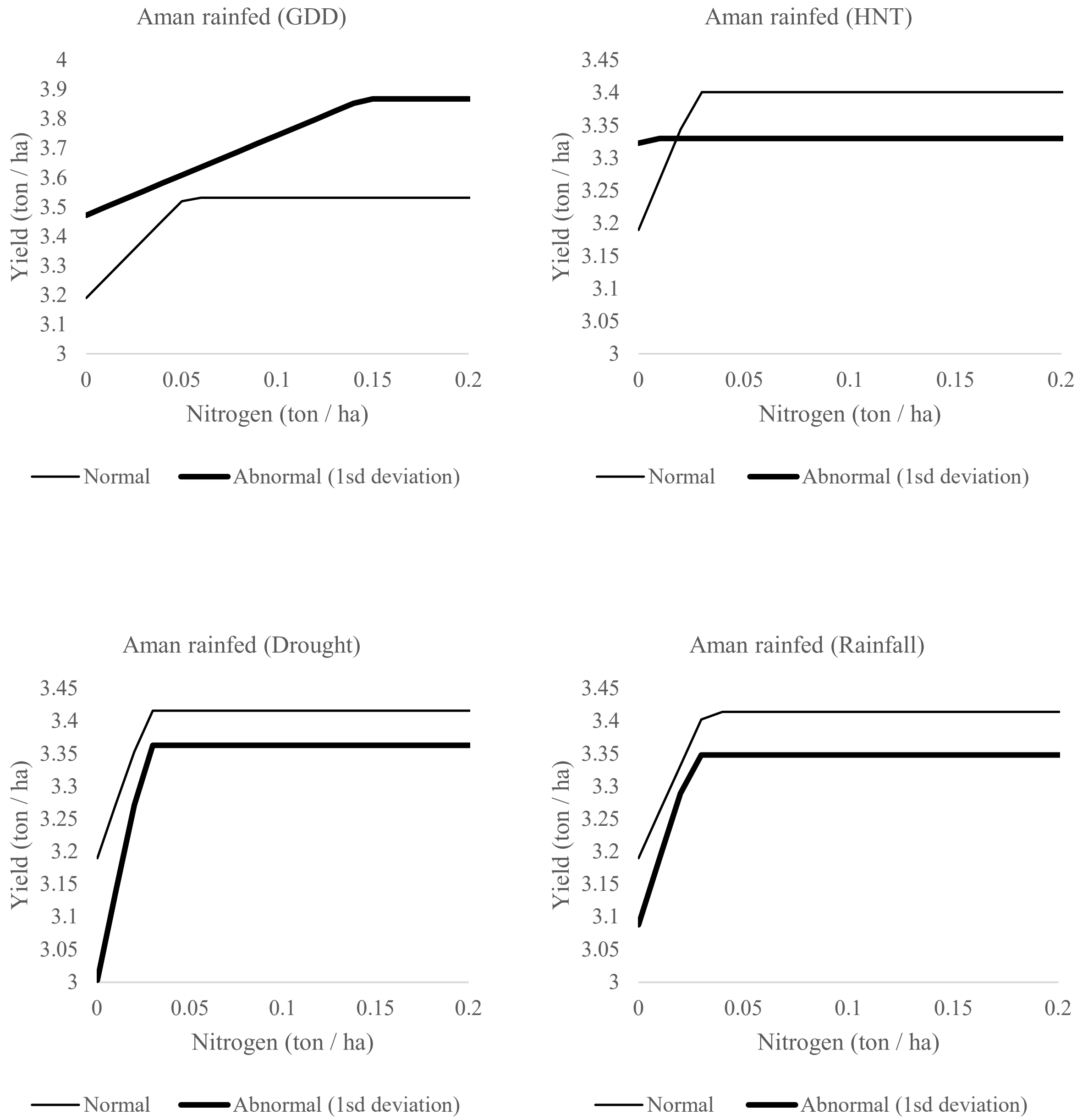


Figure 4. Linear Response Plateau under different weather shocks

Source: Authors.