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Center for Agricultural and Rural Development
Iowa State University
Ames, Iowa 50011-1070
www.card.iastate.edu

Eseul Choi Lee is PhD Student, Department of Economics, Iowa State University, Ames, Iowa 50011. E-mail: eschoi@iastate.edu.

Guilherme DePaula is Assistant Professor, Department of Economics, Iowa State University, Ames, Iowa 50011. E-mail: gdepaula@iastate.edu

Peter Kyveryga is Analytics Agronomist, John Deere, Johnston, Iowa 50131. E-mail: kyverygapeter@johndeere.com.

Suzanne Fey is Analyst, Iowa Soybean Association, Ankeny, Iowa 50023. E-mail: sfey@iasoybeans.com.

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For questions or comments about the contents of this paper, please contact Guilherme DePaula, gdepaula@iastate.edu.

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Adapting Nitrogen Management to Climate Change: Evidence from On-farm Field Experiments in Iowa

Eseul Choi * Guilherme DePaula† Peter Kyveryga‡ Suzanne Fey§

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Abstract

Climate change will likely increase the intensity of rainfall and therefore the probability of nitrogen leaching in agriculture. The more nitrogen leached through soils, the less nitrogen available for plant growth and the higher the likelihood of polluted water streams. We combine the effect of excessive rainfall on crop productivity and on water pollution in a simple economic model for nitrogen management and then estimate the model using experimental data from the Iowa Soybean Association. We find that the productivity effect is three times higher than the pollution effect. An increase in excessive rainfall induced by climate change would increase both water pollution and the cost of controlling nitrogen pollution because nitrogen becomes more productive. There is potential for adaptation as the probability of N leaching under excessive rainfall increases from 32% to 77% depending on the farmer's choice of crop rotation and the timing and form of N fertilization.

Keywords: Nitrogen, Water Pollution, On-farm Experiments, Corn, Iowa.

JEL Codes: Q15, Q52, Q53, C93

*Department of Economics, Iowa State University. eschoi@iastate.edu.

†Department of Economics and Center for Agricultural and Rural Development (CARD), Iowa State University. gdepaula@iastate.edu.

‡Iowa Soybean Association and John Deere. kyverygapeter@johndeere.com.

§Iowa Soybean Association. SFey@iasoybeans.com

1 Introduction

Excessive rainfall intensifies nitrogen (N) leaching in agriculture reducing crop yields and polluting water streams. The more N leached through soils the less N available for plant growth. We refer to the yield loss induced by inadequate N fertilization as the yield penalty. Farmers "insure" against yield penalty by overapplying N. [1] Also, the more N leached, the higher the chance that the N will reach water streams and impact human health, ecological habitats, and recreational activities. The effect of excessive rainfall is thus two-fold: an increase in the yield penalty and an increase in the probability of water pollution. In this article, we combine this double effect into a simple framework to assess the efficient level of N under excessive rainfall. We show how the relative magnitude of these two effects determine the efficient level of N, and we use on-farm experimental data from the Iowa Soybean Association (ISA) to estimate the yield penalty and the pollution effects. We find that the yield penalty effect is three times higher than the pollution effect. The counterintuitive implication of this result is that an increase in excessive rainfall induced by climate change would increase both water pollution and the cost of managing pollution. The intuition for this result is that N, the fertilizer as well as the pollutant, becomes more productive under excessive rainfall and so it becomes more efficient to use more N fertilizer. However, we also find that some combinations of management practices could help farmers avoid this double impact of excessive rainfall.

To estimate the effect of excessive rainfall on yield penalty and on water pollution, we need to overcome three empirical challenges: (a) the endogeneity of N fertilization; (b) the measurement of excessive rainfall; and, (c) the measurement of the probability of leaching that damages the environment. To address these three challenges, we use a set of ISA on-farm field experiments conducted over nine years across the state of Iowa. First, the farmer chooses the N fertilization rate based on a variety of factors that affect yield, such as soil and climate characteristics, the farmer's experience and financial resources, and production technology. As a result, production function estimates based on observational data will tend to overestimate the N effect to the extent that more N fertilizers are applied on higher quality land. ISA uses on-farm field experiments to randomize N application across farms, soil and climate characteristics, and management practices. We use two ISA experiments in our empirical analysis, the first of which covers 36 fields and 586 strips from 2017 to 2021 with five N rates randomized at the strip level. The second experiment covers 107 fields and 2,305 strips from 2007 to 2010 with two N rates also randomized at the strip level. We use the experimental variation in N rates to estimate an unbiased production function.

The second empirical challenge is the measurement of a low-frequency event such as excessive rainfall. Ideally, we would randomize excessive rainfall across farms, but with the exception of small, localized experiments, it is impractical to randomize extreme weather.

[1] Babcock (1992) shows how weather uncertainty can explain N overapplication in crop production.

Instead, we use the variability in early-season excessive rainfall across time and space in the ISA experiments to estimate the effects of excessive rainfall. Our preferred measure of excessive weather is a binary variable identifying early-season rainfall above the 80^{th} percentile of the historical distribution. We show that the experimental data is balanced across wet and dry weather, and we control for observed climate and soil characteristics and unobserved field characteristics using field fixed-effects in our regressions.

The third empirical challenge is the measure of potential environmental damage from N leaching. It is difficult to link N leached in one corn field to a pollution measure in a water stream in a large region. However, agronomists have completed small-scale experiments to measure water pollution and have established a robust relationship between N content in the soil and the plant stalk at the end of the season and N pollution in water streams (Balkcom et al. 2003; Anderson and Kyveryga 2016; Lawlor et al. 2008). In their second experiment with 107 fields, ISA conducted cornstalk nitrate tests (CSNT) at the end of the season. We use the measures of N concentration at the cornstalk to determine N deficiency and to estimate the probability of N leaching following the agronomic literature. We test the robustness of our estimates with an analysis of the Guided Stalk Nitrate Survey (GSS), which also contains CSNT for 3,917 fields tested from 2006 to 2014.

We have three main empirical results. First, N becomes significantly more productive with excessive rainfall. An increase in N application from 150 lbs/acre to 175 lbs/acre increases corn yield by 3% under normal weather conditions, 6% under excessive rainfall above the 80^{th} percentile, and 9% under excessive weather above the 90^{th} percentile. This increase in the marginal product of N is partially a result of N losses and the increase in the yield penalty. We find that the yield penalty doubles with excessive rainfall. Under normal weather, the yield penalty is approximately 0.9, implying that a 25 lbs/acre error in the N rate would reduce yield by 0.6%. With excessive rainfall, the yield loss doubles to 1.2%. Errors in N application are more costly with excessive rainfall, and it is therefore efficient for both a farmer and a social planner to increase N application as an insurance against productivity losses.

The effect of excessive rainfall on N leaching is large but it is only one-third of the magnitude of the effect of excessive rainfall on the yield penalty. The risk of N leaching increases by 41% and 59% with excessive rainfall above the 80^{th} and the 90^{th} percentile, respectively. We estimate that the marginal damage (MD)—the economic cost of one additional unit of N application—increases under excessive rainfall from 0.09 to 0.13 \$ per lb of N as the probability of leaching increases. This estimate for the MD assumes a social cost of N (SCN) of 0.20 \$ per lb of N. A higher SCN, which would include the impact on coastal eutrophication, would result in an increase in the MD of N leaching of 2.78 \$ per lb of N under excessive rainfall, or about six times the average cost of the N fertilizer. Normally, such a large increase in environmental damages would lead to a reduction in the efficient level of N application. However, this would only occur if the effect of excessive rainfall on N productivity remained constant. In fact, we find that the productivity effect is three times larger than the environmental effect, implying that excessive rainfall would simultaneously increase environmental damages and the efficient level of N fertilization.

Finally, we estimate the effect of excessive rainfall across farm management practices to identify potential adaptation strategies. ISA experimental data and the GSS survey cover different N forms, timings of N application, and crop rotations. We look at two types of crop rotation—corn after soybeans (C-S) and corn after corn (C-C); three N forms—anhydrous ammonia (AA), urea ammonium nitrate (UAN), and manure; and, three timings of N application—fall, spring, and side-dressing (SD). We find that the practices most resilient to the effects of excessive rainfall are C-S rotation, SD or split N application, and the use of UAN. Excessive rainfall affects these practices least; however, they are not necessarily the most environmentally friendly. For example, UAN causes the highest enviromental MD under any weather conditions because it has a higher nitrate content, which is more prone to leaching. However, the probability of AA leaching increases significantly with excessive rainfall, more so than for UAN. We then further examine combinations of management practices. We find that the combination of fall application of manure N with C-C rotation has the highest increase in the probability of leaching under excessive rainfall—77%. By contrast, the probability of leaching increases by 33% with the combination of SD N application with C-S rotation.

We test the robustness of our empirical results using alternative definitions of excessive rainfall, regression specifications, and datasets and experiments. We test field-specific and field-agnostic definitions of excessive rainfall as well as different absolute and relative thresholds with datasets covering different time periods. We find a consistent and significant excessive rainfall effect in recent decades and a smaller effect in the historical data. We test specifications with multiple control variables for soil and farm characteristics as well as different combinations of fixed effects. We highlight the importance of field and block fixed effects to control for variation in the effectiveness of N absorption by the plant across fields, even when N application is randomized in on-farm experiments. We also test our empirical model using historical experiments from ISA and a variety of subsamples from survey data. We confirm the significant effect of excessive rainfall on the yield penalty and the probability of leaching.

This article contributes to the literature on weather effects on crop production, to the analysis of agricultural non-point source pollution, and to a small but growing literature on the resiliency of N management practices. First, our analysis contributes to establishing the causal effect of excessive rainfall on corn yield response function by utilizing experimental data. Although there has been progress in estimating the yield response function to determine the optimal N rate, the current literature does not directly estimate the effect of weather on the efficient level of N fertilization. Instead, past studies focus on a stochastic production function to study uncertainty in the supply of N for crop growth and to explain overapplication of N as a risk-insuring behavior (Babcock, 1992). Despite the advances in related empirical research using experimental data (Tembo et al., 2008; Boyer et al., 2013), the stochastic production function framework offers limited guidance for N management under a variety of weather conditions. [2] Our analysis departs from the previous literature by explicitly showing how the yield response function varies with rainfall anomalies, and by providing the optimal N application rate by normal and excessively wet conditions.

More recently, researchers have made significant progress studying the effects of weather on crop yields (Deschênes and Greenstone, 2007; Ray et al., 2015; Wing et al., 2021)); however, most studies focus on the effects of temperature (Schlenker and Roberts, 2006) or water stress (Lobell et al., 2014). Few studies examine the effect of excessive rainfall. Li et al. (2019) uses U.S. county-level data to study the effect of rainfall anomaly on crop yields and finds that a moderate rainfall anomaly tends to increase yields but extremely excessive rainfall can be detrimental to corn yields. A limitation of these types of analyses is the potential endogeneity of rainfall anomalies. Although an occurrence of excessive rainfall is random, farmers adapt by adjusting management practices such as N fertilization, timing of N application, N form, and crop rotation as the likelihood of excessive rainfall increases. For example, farmers may adapt by splitting N application using SD or simply by changing the level of N fertilizer based on previously realized weather conditions. Furthermore, such adaptations vary at the farm and field level. Our analysis addresses this potential endogeneity by utilizing individual field-level experimental data, as the experiment design with random N application rates does not allow for adaptive N application based on weather conditions in the previous or current growing season.

This article also presents new evidence on the effects of excessive rainfall and N fertilization on potential N leaching into water streams. Although the impact of N leaching on water quality is well-established in the literature (Almaraz et al., 2018; Bylund et al., 2017; Rabotyagov et al., 2014),[3] identifying the causal relationship between N application and water pollution using aggregated data is difficult because of the large heterogeneity in the link between N concentrations in watersheds and upstream non-point pollution sources (Hendricks et al., 2014; Skidmore et al., 2023; Metaxoglou and Smith, 2022). For example, Paudel and Crago (2021) matches county-level fertilizer use with a nutrient concentration in the watershed using 55 years of data for the entire United States and estimates a positive relationship between fertilization and water pollution. However aggregating data at the county level over heterogeneous fields could lead to insignificant precipitation effects on nitrate con-

[2]See Dhakal and Lange (2021) for a comprehensive review of the literature on crop yield response functions.

[3]Specifically, N leaching may cause eutrophication and contamination of drinking water, creating potential health risks to humans and damages to ecological systems. See the Environmental Protection Agency (EPA) website for detailed information about the environmental damages of N leaching: https://www.epa.gov/nutrientpollution/effects.

centration in water streams due to the potential of offsetting effects (Jaynes et al. 2001; Randall and Goss 2008; Li et al. 2022; Liu et al. (2022)). To overcome this challenge, we use individual field-level N loss measures developed by agronomists, the late-season CSNT, and provide new evidence for the effects of N management practices and excessive rainfall on the probability of N leaching. [4]

Lastly, our analysis contributes to the assessment of weather-resilient N management strategies. Policymakers in the United States have been promoting N management practices in agriculture to address environmental damages (Ribaudo et al., 2011). Previous studies use agronomic simulation models to examine the effect of alternative N management practices on crop yields and N leaching (De Laporte et al., 2021; Mérel et al., 2014). More recent economics studies use an approach similar to ours, which considers the social costs of N fertilization. For example, Gourevitch et al. (2018) estimate the social cost of N based on the impacts of N on air and water pollution, and then calculate the socially optimal nitrogen application rate at the county level in Minnesota. Our analysis differs by also accounting for the impact of excessive rainfall on the effectiveness of farming practices using the concept of weather resilience. We consider the double effect of abnormal weather on N productivity and on the potential for N leaching and propose a simple framework to evaluate N management practices when farmers face large weather uncertainty.

The article is organized as follows. Section 2 summarizes the agronomic background for excessive rainfall and N leaching. Section 3 builds a simple model for efficient N management under excessive rainfall. Section 4 describes the ISA experiments and provides descriptive statistics. Section 5 reports our empirical results. Section 6 simulates our model to assess the changes in the efficient level of N management under excessive rainfall. Section 7 summarizes our robustness analysis. Section 8 concludes and provides implications of our results and the next steps for the analysis.

2 Excessive Rainfall and Nitrogen Leaching

2.1 Excessive Rainfall Trend in Iowa

Climate change will likely increase average annual precipitation and the intensity of local rainfall in North America (Christensen et al. (2007), Prein et al. (2017a), 2017b). In the northern part of the continent, the increase in average annual precipitation may reach 20%. Figure 1 shows the early-season precipitation anomalies for Iowa from 1900 to 2020 (NOAA (2022)). The early season, which comprises May, June, and July, is important because of its influence on N leaching from agriculture. A precipitation anomaly is defined as a deviation from the historical average of 318 mm (1901–2000).

[4] Alternatively, agronomists uses individual field-level nutrient runoff data measured by the edge-of-field monitoring (Daniels et al., 2018).

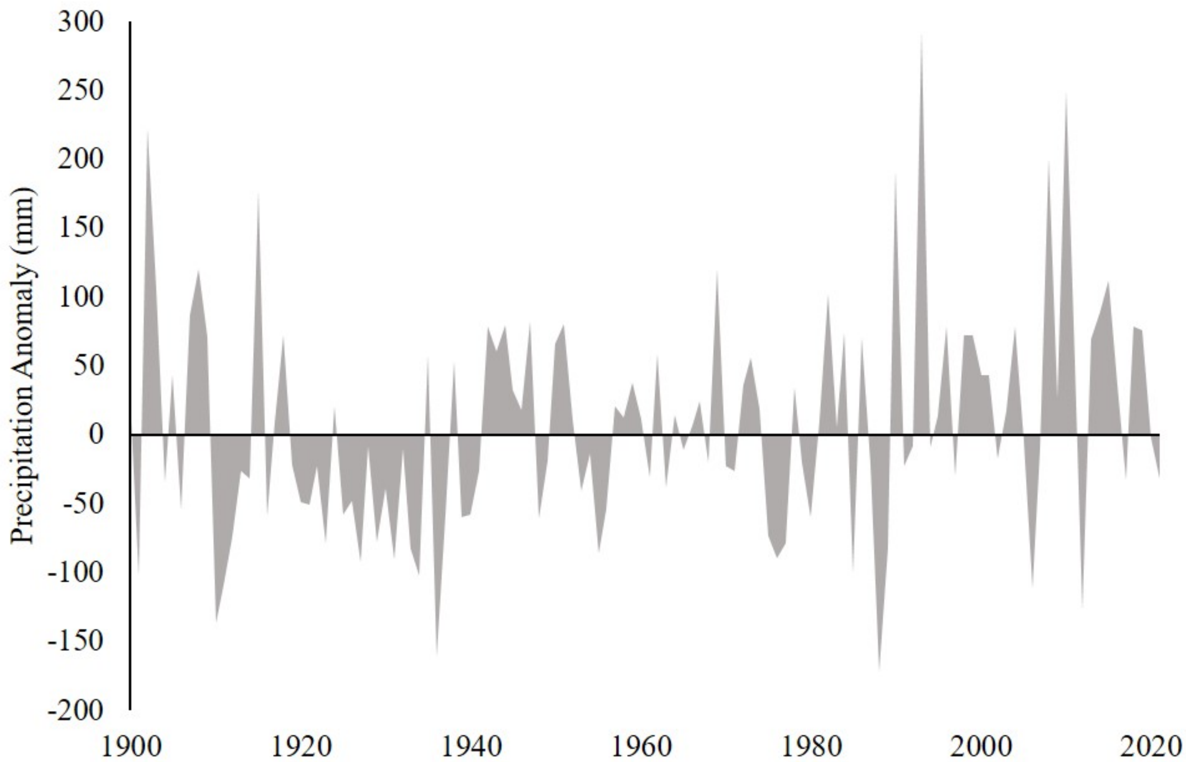


Figure 1: Early-season precipitation anomalies in Iowa.

Note: An early-season precipitation anomaly is a deviation from the 318 mm 100-year average (1901–2020) precipitation for the months of May, June, and July. Source: National Oceanic and Atmospheric Administration (NOAA (2022).

Figure 1 illustrates two trends. The first trend is an increase in average precipitation as reflected in the higher frequency of positive anomalies after 1990. Average precipitation U.S. Midwest increased by by 9% since 1991 relative to the 1901–1960 average (Walsh et al. (2014)). The second trend is an increase in the variance and magnitude of excessive precipitation. The two largest anomalies happened in 1993 and 2010 and were 3-sigma precipitation events (i.e., events categorized as three standard deviations from the mean). The precipitation event in 1993 totaled 610 mm, almost twice the average, while that in 2020 reached 567 mm. Before 1990, the probability of a year with excessive rainfall above one standard deviation from the average was just 10%. Since 1990, the probability of a 1-sigma precipitation anomaly has increased to 25%. Furthermore, this large variability in precipitation at the state level likely underestimates the variability faced by farmers at the field level.

2.2 Nitrogen Cycle in Corn Production and Water Pollution

Figure 2 shows a simplified version of the N cycle in corn production and illustrates the relationship among N fertilization, rainfall, and the residual nitrate concentration in cornstalks at the end of the season. There are two sources of N: N from the soil (Ns) and N fertilizers (Nf). Farmers typically use ammonium nitrate, urea, or manure for N fertilization in corn production. The timing of N application may vary. Normally, farmers apply N in the late fall after the soil temperature drops below 50 °F, the spring before the planting season, or the early summer using SD application. [5] Soil N is derived from the mineralization of soil organic matter or nitrification, a biological process of the oxidation of ammonia to nitrite. The amount of N in the soil varies under different management practices such as the choice of crop rotation.

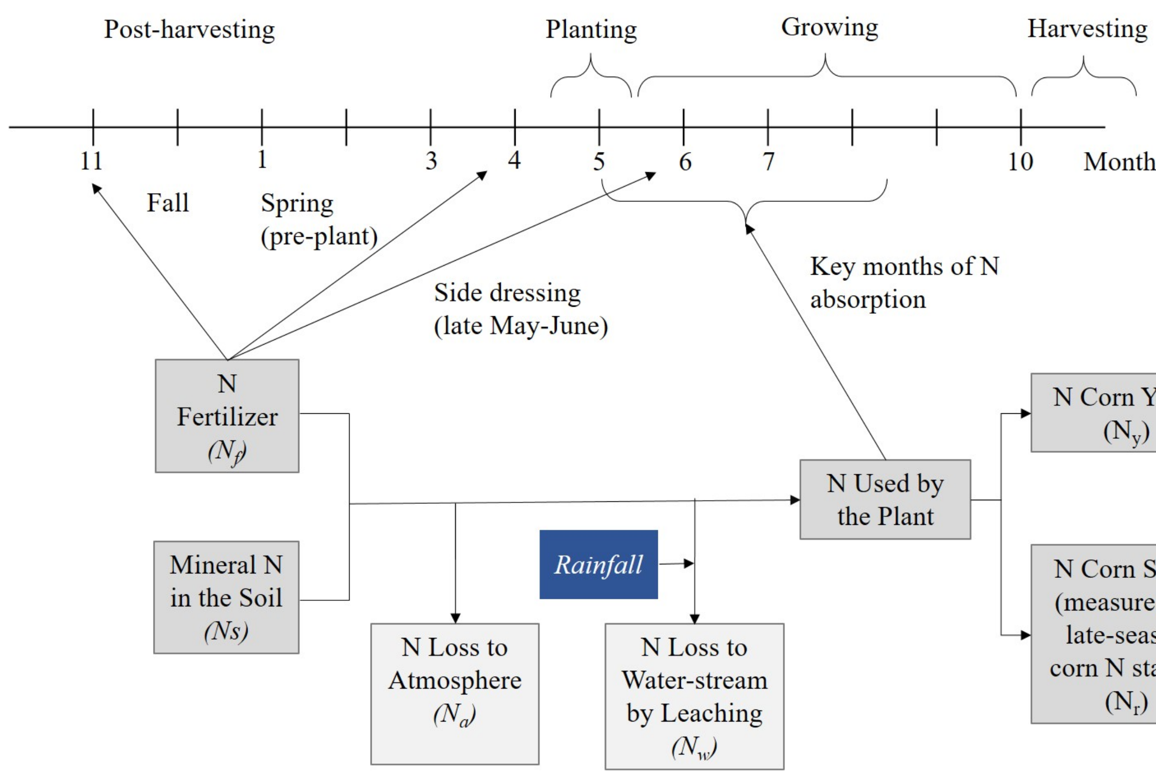


Figure 2: Simplified nitrogen cycle in corn production.

A proportion of the N supplied by the soil and N fertilizers are used by the plant to produce the corn kernels, N_y, and proportions are lost into the atmosphere, N_a, and into water streams, N_w. If the supply of N is above the N used by the plant and lost into the environment, there will be residual N in the cornstalk, N_r. The amount of N leached into water is the difference between the two sources of N and its other uses:

$$N_w = N_s + N_f - N_y - N_a - N_r \tag{1}$$

2.3 Excessive Rainfall and Residual Nitrogen

Excessive rainfall promotes leaching and the denitrification of nitrate N in the soil (Jaynes et al. 2001; Randall and Goss 2008; Li et al. 2022). Nitrate is a negatively charged ion that is repelled from negatively charged soil clay particles and can freely move with water in the soil solution. Soil moisture is important for the movement of nitrate ions to plant roots for absorption. However, a higher soil moisture after excessive rainfall can cause preferential or excessive water flow through the soil profile and leach a significant amount of nitrate below the plant rooting zone. Nitrate leaching can reach 70 lbs of N per acre because of the extensive tile drainage systems installed to remove excessive water in production fields.

[5] The SD application is the process of N fertilization between rows of corn during the early stages of plant growth.

Agronomists find that N loads from tile drainage systems strongly correlate with the tile water discharge, which is directly impacted by the amount of rainfall (Lawlor et al. 2008).

Agronomists can assess the probability of N leaching at the end of the crop season using measures of residual N such as the N content in the soil and in cornstalks. A 12-year survey of farmers' fields in Iowa shows that early-season rainfall increased nitrate concentration in rivers and subsequently decreased nitrate supply to the corn crop, measured using the late-spring soil nitrate and late-season CSNTs (Balkcom et al. 2003). A low concentration of N in the cornstalk after the growing season suggests an inadequate supply of N for the plant. This deficiency could result from the underapplication of N fertilizers and excess losses of N into the environment. In normal rainfall conditions, the concentration of N in the cornstalk at the end of the season should be in the optimal range (250–2,000 ppm) considering that farmers in Iowa are advised to apply near or above optimal N fertilizer rates (Sawyer and Mallarino 2018). [6] An optimal late-season cornstalk N concentration indicates that the N from the soil and fertilizers has supplied the plant's needs.

In excessive rainfall conditions, more N will be lost through leaching, leading to a lower residual cornstalk concentration at the end of the season. Agronomists test this negative relationship among cornstalk N concentrations, N losses, and water pollution using field surveys in Iowa (Anderson and Kyveryga 2016; Balkcom et al. 2003). They find low nitrate (NO3 N) loads in rivers (below 50 mgd^1) with optimal or higher cornstalk concentrations, but high nitrate loads in rivers (100–350 mgd^1) with deficient cornstalk N concentrations. We use the relationship between cornstalk N concentration and water pollution to estimate a damage function.

3 Theory: Efficient N Use under Excessive Rainfall

In this section, we propose a simple framework for assessing the impact of excessive rainfall on N use in crop production. The novelty of the proposed framework is the combination in one simple model of the effect of excessive rainfall on both the marginal productivity of N application and the probability of leaching. We solve the nitrogen optimization problems of the farmer and social planner when there is a probability of excessive rainfall (p). The main result is a simple expression for the level of inefficient N use, namely, the difference between the private and social optimal levels of N fertilization. We use this result to assess potential adaptation and mitigation strategies for N application under excessive rainfall. The three

[6] Iowa farmers previously estimated the N fertilizer needs for their corn crops using a "yield goal formula." The premise was that fertilizer needs are proportional to corn yields. Specifically, fertilizer rates were calculated by multiplying historical corn productivity by average N fertilizer use efficiency (e.g., 1.0–1.2 lbs of N for each bushel of corn yield) minus N credits from animal manure or previous soybean or alfalfa crops (Morris et al. 2018). While this yield goal formula is simple for farmers to use, it ignores N losses and the effect of corn and fertilizer prices on the optimal N rate. During the past decade, university extension agronomists across the Midwest have started promoting a more advanced system of N recommendations called the "maximum return to nitrogen" (see http://cnrc.agron.iastate.edu/). This new system uses the results of small-plot N response trials to estimate the economically optimal N rates at the regional, state, or sub-state level considering the mode of crop rotation and prices (Sawyer and Nafziger 2005).

key components of our framework are a production function, a damage function, and the representation of extreme rainfall.

Production Function. The production function is a quadratic function that links corn yield and N use. We rearrange the quadratic function in the form of a target input model commonly used in the development economics literature to model uncertainty in input use (Foster and Rosenzweig 1995). The corn yield (Y) is the sum of the maximum potential yield ($\hat{Y}$) and a loss function that penalizes the under- or overapplication of N:

$$Y = \hat{Y} - a(\hat{N} - N)^2 \tag{2}$$

The optimal level of N application ($\hat{N}$) that produces the maximum yield ($\hat{Y}$) is unknown and likely varies with soil type, climate, and management practices. We assume that the farmer knows the mean value of $\hat{N}$ based on guidance from extension agents and input manufactures as well as the farmer's own experience. The positive parameter a is a yield penalty, which we assume varies with the soil and weather conditions. A higher yield penalty means that errors in N application lead to higher yield losses.

Damage Function. We use a simple threshold damage function for the environmental impact of N leaching. The key assumption is the existence of a threshold level of N application above which there is a significant probability of damaging leaching. Under this threshold level, the plant can absorb much of the N during its growth process and no residual N becomes available to cause significant leaching. [7] The expected damage (E[D]) is the probability of damaging leaching (Π) multiplied by the excess amount of N multiplied by SCN:

$$E[D] = \Pi(N - \hat{N})SCN. \tag{3}$$

The damage function in equation (3) is defined only when there is excess N and the probability of damaging leaching. Π captures the likelihood of the excessive application of N. Once the nitrate reaches the damaging level, SCN is the economic damage of an additional unit of N. [8]

Excessive Rainfall. The final component of our conceptual framework is modeling excessive rainfall. We define two rainfall states: normal rainfall (R for the regular state) with probability $1 - p$ and extreme rainfall (W for the wet state) with probability p. We allow the parameters of the production and damage functions to differ by state. The regular rainfall state is thus characterized by one set of parameters ($\hat{Y}_R$, $\hat{N}_R$, a_R, Π_R)), whereas the wet state's parameters are another set ($\hat{Y}_W$, $\hat{N}_W$, a_W, Π_W). We solve the optimal N rates

[7]The production functions can be extended by adding other inputs and the damage function can be extended by modeling damage as a nonlinear function of N application. We leave these extensions to future work. In this article, we instead focus on adding excessive rainfall into the damage and production functions.

[8]In our empirical analysis, we use the SCN estimates from the extensive literature on nitrate pollution.

of the farmer and social planner as a function of the probability of extreme rainfall and the parameters for each state of production.

3.1 The Farmer's Nitrogen Optimization Problem

The farmer will choose the optimal N application rate (N^*) to maximize their profits considering the two possible states of production (normal and wet). For simplicity, we normalize the price of corn to 1 and assume that the cost of N is 0 in our theoretical framework. We use different combinations of output and input prices in our simulations.

The farmer's optimization problem is:

$$\underset{N}{Max}\ (1-p)[\hat{Y}_R - a_R(\hat{N}_R - N)^2] + p[\hat{Y}_W - a_W(\hat{N}_W - N)^2].$$

The farmer's optimal N application rate is:

$$N^* = \frac{(1-p)\hat{N}_R + \alpha p \hat{N}_W}{1 + (\alpha - 1)p} \tag{4}$$

where the parameter α captures the relative magnitude of the yield penalty under abnormal and normal rainfall.

Definition 1: Yield Penalty Growth Factor *(*α*).* α is the ratio of the yield penalty in the wet and normal states, $\alpha = \frac{a_W}{a_R}$. It captures the change in the yield penalty as a result of excessive rainfall. As the yield penalty captures the curvature of the production function, an α above 1 implies an increase in the marginal product of N.

If only the normal rainfall state existed ($p = 0$), the farmer's optimal N application rate would be $\hat{N}$. Given the uncertainty about the rainfall state, the optimal rate is a weighted average between the yield-maximizing N rates in the two rainfall states. The optimal N rate N^* is above $\hat{N}_R$ as long as $\hat{N}_W$ is above $\hat{N}_R$. For example, if the farmer believes that it is optimal to apply more N in seasons with excessive rainfall to protect their yield, $\hat{N}_W > \hat{N}_R$. In this case, N use tends to increase as uncertainty about the rainfall state rises (Babcock 1992).

3.2 The Social Planner's Nitrogen Optimization Problem

The social planner chooses the optimal N application rate to maximize a social welfare function that includes profits and environmental benefits. When the rainfall state is uncertain, the social planner maximizes the expected profit, net of the environmental damage.

The social planner's optimization problem is:

$$\underset{N}{Max}\,(1-p)[\hat{Y}_R-a_R(\hat{N}_R-N)^2-\Pi_R(N-\hat{N}_R)\widetilde{SCN}]+p[\hat{Y}_W-a_W(\hat{N}_W-N)^2-\Pi_W(N-\hat{N}_W)\widetilde{SCN}].$$

The social planner's optimal N rate is:

$$N^{**} = N^* - \frac{[(1-p)\Pi_R + p\Pi_W]}{2a_R(1+(\alpha-1)p)}\widetilde{SCN}$$

The social planner's optimal N rate is always below the farmer's optimal rate because of the expected environmental damage from N use. To simplify the equations, we normalize the corn price to 1 and express the SCN relative to the price of corn, $\widetilde{SCN} = SCN/P^{corn}$. β is the relative magnitude of the probability of leaching under wet conditions.

Definition 2: Probability of Leaching Growth Factor *(β)*. β is the ratio of the probability of the leaching penalty in the wet and normal states, $\beta = \frac{\Pi_W}{\Pi_R}$. It captures the change in the probability of leaching as a result of excessive rainfall.

We can rearrange the social planner's optimal N solution to derive an equation for the difference between the optimal N rates of the farmer and social planner $(N^* - N^{**})$, Δ. Δ captures the inefficient amount of N application when the rainfall state is uncertain:

$$\Delta = N^* - N^{**} = [\frac{1+(\beta-1)p}{1+(\alpha-1)p}]\frac{\Pi_R}{2a_R}\widetilde{SCN} \tag{5}$$

Equation (5), the main theoretical result from our analysis, provides a simple framework for assessing the different drivers of inefficient N application. If the probability of extreme rainfall were zero ($p = 0$), the difference between the optimal rates of the social planner and farmer would be $\Delta = \frac{\Pi_R}{2a_R}\widetilde{SCN}$, namely, the expected MD adjusted by the yield penalty. In the general case, with the presence of the two rainfall states, the difference between optimal N rates of the farmer and social planner depends on the probability of extreme rainfall as well as on the extent to which the yield penalty and probability of leaching change in the extreme rainfall state. We summarize our analysis of the drivers and potential mitigating factors of inefficient N fertilization in the following four theoretical implications.

Implication 1. *Extreme rainfall increases the expected environmental damage from N fertilization.* Implication 1 is a direct result from the damage function in equation (3) under the assumption that the probability of leaching increases with extreme rainfall, $\beta > 1$.

Implication 2. *The effect of extreme rainfall on efficient N use depends on the relative change in the yield penalty and probability of leaching, $\beta - \alpha$.* The derivative of Δ with respect to the probability of extreme rainfall is $\frac{\partial\Delta}{\partial p} = (\beta-\alpha)\frac{(\Pi_R/2a_R)\widetilde{SCN}}{(1+\alpha p)^2}$. An increase in the frequency of extreme rainfall leads to higher inefficiency in N use if $\beta > \alpha$. A larger increase in the probability of leaching, larger β, increases the expected environmental damage and overapplication of N ($N^* > N^{**}$).

Implication 3. *Extreme rainfall may increase the cost of controlling N pollution.* If $\alpha > \beta > 1$, the expected damage increases with extreme rainfall, whereas the inefficiency in N use decreases. The explanation is that a larger increase in the yield penalty raises the cost of reducing N application. Farmers would then have an incentive to "insure" against yield losses by overapplying N.

Implication 4. *There are two channels for controlling N pollution under extreme rainfall: reducing the likelihood of leaching (reducing β) and reducing the yield penalty (reducing α).* One example of a beta-reducing strategy is the adoption of cover crops to prevent nitrate leaching. Examples of alpha-reducing strategies are the adoption of seed technologies more resistant to changes in rainfall and the optimization of the timing and form of N fertilization. The choice of the optimal mitigation strategy should consider the relative costs and benefits of all strategies.

4 Field Experiments in Iowa

We use experimental data from two ISA experiments to estimate the parameters α and β. We estimate a production function using ISA's five-rate on-farm strip experiments to calculate α. To calculate β, we estimate an N deficiency probability function using on-farm trials with late-season CSNTs. We describe these two experiments in the next two subsections.

4.1 Five-rate On-farm Experiments

The ISA ran on-farm strip trial experiments to study the effect of N fertilization on corn yields in 36 fields across Iowa from 2017 to 2021 (ISA, 2021). Figure 3 shows the locations of the experiments. All the fields are located in private farms that of ISA members. While most of the fields were chosen randomly, ISA agronomists contacted participants in previous experiments to conduct N trials in some cases. The experimental areas adopted similar crop management practices (same corn hybrid seed, tillage, weed management, disease control, and pest management) except for the N fertilizer treatments.

ISA applied five levels of N (80, 110, 140, 170, and 200 lbs N/acre) for most of the experiments with C-S and five levels of N (110, 140, 170, 200, and 230 lbs N/acre) for the experiments with C-C. The experimental unit was a field-long strip, ranging from 800 to 1,300 feet. The width of the strip, 30 to 90 feet, was chosen to match the farmers' fertilization equipment. Each experiment had three to five replications or blocks to capture within-field variability. A block or replication is defined as a group of five strips in sequence. Figure 3 shows the experimental design. Each color represents a different N rate. The field in figure

3 has 15 strips grouped into three blocks.

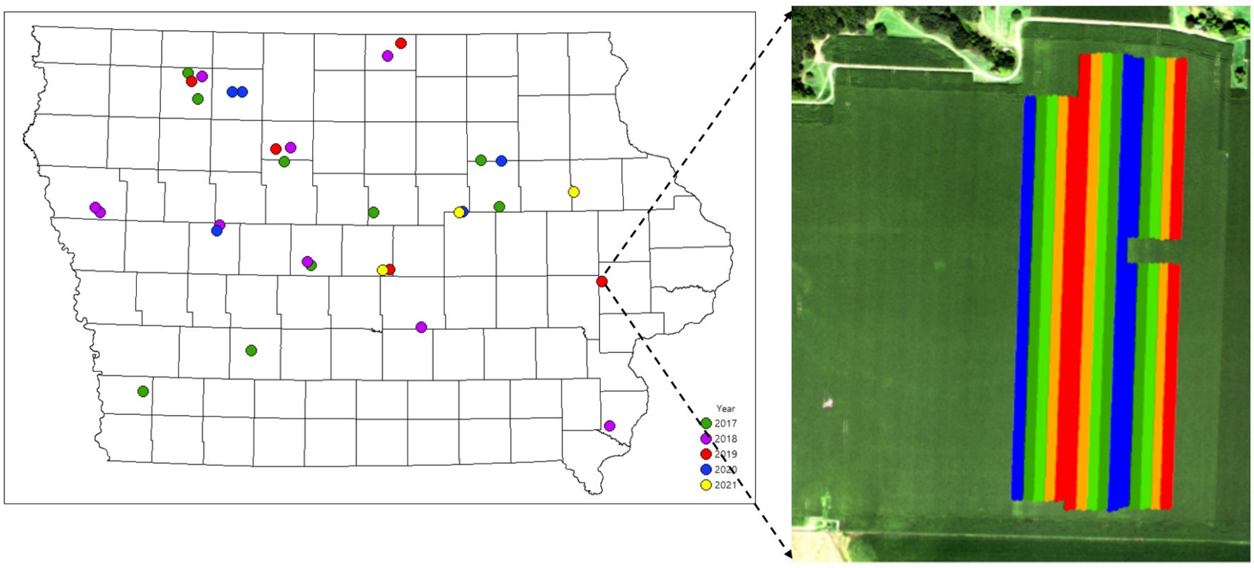


Figure 3: Experiment design: Five-rate on-farm strip trials.

Note: The left-hand side is a map of Iowa with the location of each of the 36 fields used in the Iowa Soybean Association's five-rate on-farm strip trials. The colors represent years: green is 2017, purple is 2018, red is 2019, blue is 2020, and yellow is 2021. The right-hand side shows the experiment design for one field. The experimental unit is a field-long strip in which each color represents a different nitrogen rate. The field in figure 3 has 15 strips grouped into three blocks.

The dataset for the five-rate experiments has 36 fields, 126 blocks, and 586 strips. The ISA measured corn yields using combine harvesters equipped with yield monitoring and positional navigation systems. Each strip had one yield observation measured in bu/acre at the standard 13.5% corn moisture level. Kyveryga et al. (2018) describes the protocols developed by ISA to run the experiments. The farmers also reported their standard N rate, the crop rotation used, and the timing and form of N fertilization. ISA integrated the experimental data with information on the soil characteristics (organic matter, soil drainage quality, and corn suitability rating – CSR) and weather data (precipitation and the number of growing degree days). The data on soil characteristics were sourced from the Soil Survey Geographic Database (SSURGO) (NRCS-USDA, 2022) and the weather data were gathered from NASA Daymet (Thornton et al., 2022) and Iowa Environmental Mesonet (Herzmann et al., 2004).

4.2 Two-rate On-farm Experiments with Cornstalk Nitrate Tests

The second ISA experiment was a two-rate on-farm strip trial with CSNTs. The experimental unit was a field-long strip, as in the five-rate experiment. However, in the two-rate experiment, each block contained two strips: a control strip with the farmer's normal N rate and a treatment strip either with the normal rate minus 50 lbs N/acre or the normal rate plus 50 lbs N/acre. [9] The strips were randomly assigned to the treatment or control groups. As before, the experimental design controlled for management practices such as seed type,

[9]The rates of the control and normal treatments depend on the farmer's information on expected weather and weather-related risk, previous crops, soil characteristics, application form and timing, input prices, and expected output price.

tillage, weed management, disease control, and pest management.

Figure 4 shows the locations of the fields and experimental design for one field. ISA conducted the two-rate experiments in 107 fields in Iowa from 2007 to 2010 [10]. The right-hand side of figure 4 shows the strips in different tones of green and boxes indicating the locations of the CSNTs. The final dataset has 1,915 observations and also includes information about the soil characteristics, weather, and the timing and form of N application.

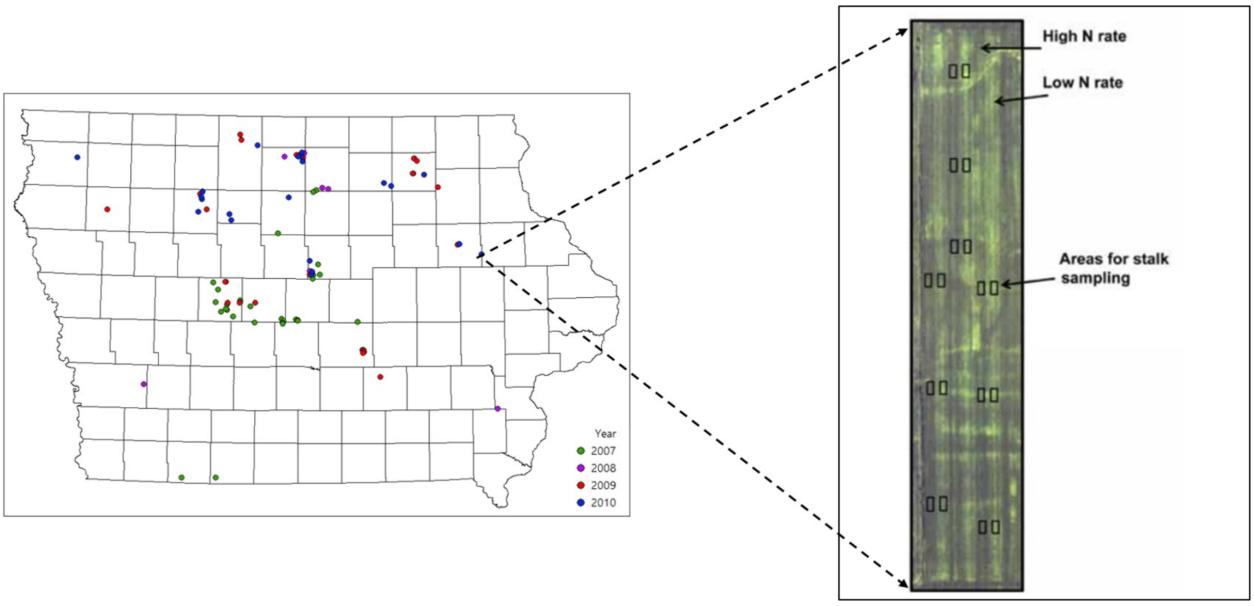


Figure 4: Experiment design: Two-rate trials with cornstalk nitrate tests.

Note: The left-hand side shows the location of each of the 107 fields used in the Iowa Soybean Association's two-rate on-farm trials with cornstalk nitrate tests. The colors in the map represent years: green is 2007, purple is 2008, red is 2009, and blue is 2010. The left-hand side shows the experiment design for one field. The experimental unit is a field-long strip and the different gradients of green represent control and treatment strips. The field in figure 3 has three blocks with three strips per block.

The advantage of the two-rate experiment is the measurement of nitrate concentration in the cornstalk at the end of the season. We use the cornstalk N concentration to model the probability of N deficiency. The CSNT is an indicator of the plant N sufficiency—the final balance between N supply and demand for the plant. When tested, plants that fell into a low stalk nitrate category had a lower supply of N from both fertilizers and the soil, whereas plants that fell into the excessive category likely had a higher supply of N. Hence, the oversupply of N to the plant did not produce a yield response but did create residual N in the stalk.

ISA used the CSNT in each trial in the early fall before the harvest to estimate the corn N status (demand for N relative to supply). ISA selected six or nine sampling areas for the CSNT for each block of the control and treatment strips in a field. The small boxes in figure 5 show the sampled locations. In each sampling area, six-inch stalk segments were cut from 10 plants. The stalk nitrate concentration values were classified as low for below 250 ppm (N demand is above supply and plants likely respond to additional N applications), optimal for 250–2,000 ppm (N demand equals supply), and excessive for above 2,000 ppm (N supply

[10] The experiment spans from 2006 to 2014, but the CSNT was implemented only during the period from 2007 to 2010. For the estimation of the production function we use the entire period from 2006 to 2014.

is above demand). Each field had 12 or 18 samples of stalk nitrate.

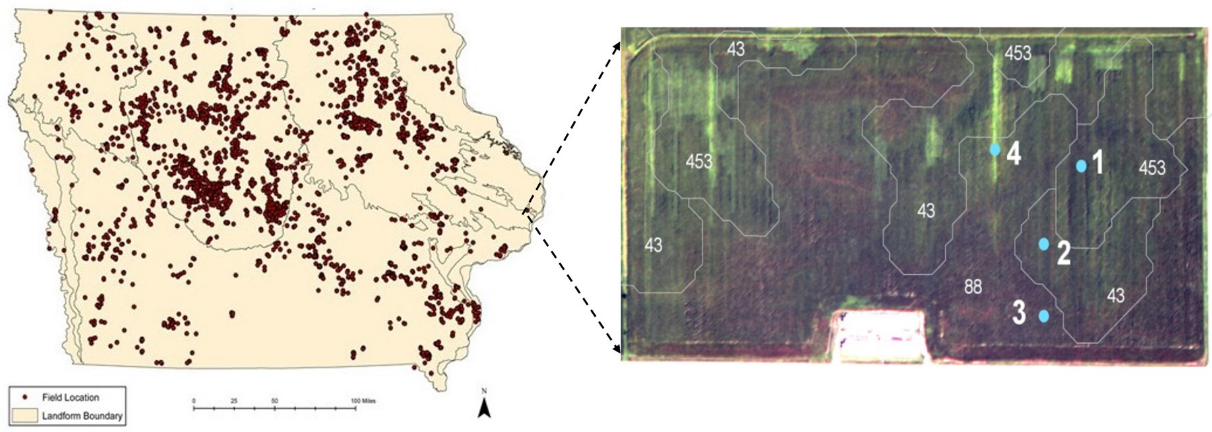


Figure 5: Guided stalk nitrate survey.

Note: The left-hand side shows a map of Iowa with the location of each of the fields that were surveyed in the Guided Stalk Nitrate Survey (683 fields in 2006 and 824 in 2007). The right-hand side shows the sampling locations for the cornstalk nitrate tests in one field. The sampling locations are identified with numbers. In each field, three sampling areas were selected in three predominant soil types to represent the average corn nitrate status (locations 1, 2, and 3). Sample 4 was selected as target deficiency area for this field.

Finally, we use a complementary survey of CSNTs in Iowa to investigate the effect of N management practices on N deficiency and the probability of environmental damage, namely, the GSS. The GSS, which was run by ISA, used CSNTs to examine 3,917 fields from 2006 to 2016 (Laurent et al. 2023). Figure 5 shows the locations of the fields tested and sampling areas in one field. In each field, three sampling areas with three predominant soil types were selected to represent the average corn nitrate status. The sampling locations are numbered in figure 5. The survey dataset had 13,715 observations. The advantage of GSS is its broader coverage of management practices—farmers provided information about field management (previous crop and tillage) and N management (fertilizer and manure form, rate, timing, and placement). However, N rates were not randomized in GSS.

4.3 Excessive Rainfall Variation

Table 1 reports the summary statistics of the two ISA experiments by rainfall percentile. The early-season rainfall variable captures the total precipitation for May, June, and July. The fields in our sample show significant spatial and temporal variation in rainfall. The 25-year average early-season rainfall is approximately 375 mm and the 25-year standard deviation is about 120 mm. We define our preferred measure of excessive rainfall at the field level using the 80th percentile of early-season precipitation for the 25-year period from 1995 to 2020. We also test alternative measures of excessive rainfall using the 65^{th} and 90^{th} percentiles as well as the absolute threshold measures. As the randomization of excessive rainfall across on-farm trials covering a large region such as Iowa is impractical, we instead exploit the spatial and temporal variation in excessive rainfall in the two ISA experiments to estimate the production and damage functions. The five-rate and two-rate experiments have five fields and 79 strips and 40 fields and 720 samples with excessive rainfall, respectively.

In both experiments, the rainfall in wet fields is more than 1 standard deviation above the normal rainfall level. In dry fields, the rainfall is more than 1 standard deviation below the normal rainfall level. These results confirm that the occurrence of wet and dry weather is an abnormality in these fields.

Table 1 also shows the sample balance across the rainfall percentiles. The sample is balanced for farm characteristics and outcomes but not for N application practices and years. The CSR and corn yields are similar in wet and normal fields. The yields in wet fields are slightly lower (higher) in the five-rate (two-rate) experiment. Furthermore, the crop rotation is predominantly soybean/corn across the rainfall percentiles. The percentage of N application during the fall in wet fields is higher than that in normal fields. UAN is the preferred form of N in the five-rate experiment and AA is the most used N form in the two-rate experiment. In our empirical analysis and simulations, we use the data from the two ISA experiments and the larger GSS survey dataset to estimate separate models by the timing and form of N application. The heterogeneity in the production and damage functions by timing and form is itself insightful about possible mitigation strategies for N leaching. We also use this heterogeneity analysis to assess whether the imbalanced sample affects our main results.

The randomization of N rates differs in the two experiments. In the five-rate experiment, ISA used five arbitrary N rates across the fields; and, by contrast, in the two-rate experiment, ISA added and subtracted 50 lbs from the farmer's N rate. The experimental N rate is well balanced in the five-rate experiment across the rainfall percentiles. However, in the two-rate experiment, the average N rate is 190 lbs/acre in wet fields and 156 lbs/acre in normal fields. This difference is due to the farmer's higher N rate in wet fields in the two-rate experiment. Interestingly, the farmer's rate in the five-rate experiment is lower in wet fields, suggesting that no systematic overapplication of N in areas with higher rainfall occurs. We use the five-rate experimental dataset to estimate the production function and the two-rate experimental dataset to estimate the damage function. Moreover, we use field fixed-effects to control for unobserved field characteristics that may be correlated with the farmer's N rate to mitigate the potential for endogeneity in this rate in the two-rate experiment.

Table 1: Summary Statistics by Rainfall Percentile

	Five-rate experiment			Two-rate experiment		
	Normal	Dry	Wet	Normal	Dry	Wet
Precipitation (mm)	370	241	476	337	264	570
	(8)	(12)	(0)	(9)	(22)	(5)
25-year avg. precipitation	378	384	368	375	374	359
	(4)	(9)	(0)	(3)	(11)	(2)
25-year std. precipitation	118	123	110	134	121	124
	(2)	(4)	(0)	(3)	(7)	(1)
Threshold p80 precipitation	456	454	422	454	451	439
	(8)	(13)	(0)	(6)	(19)	(3)
Yield (bu/acre)	204	207	185	182	188	190
	(21)	(18)	(21)	(17)	(16)	(13)
N rate - experiment (lb/acre)	145	151	147	156	150	191
	(42)	(42)	(40)	(28)	(25)	(30)
N rate - farmer (lb/acre)	183	163	168	153	151	173
	(37)	(28)	(13)	(8)	(20)	(5)
Corn suitability rating	74	84	79	78	82	80
	(5)	(5)	(1)	(4)	(7)	(3)
CSNT N concentration (ppm)				732	1,096	735
				(931)	(1,055)	(792)
Stalk with N deficiency (%)				0.56	0.47	0.65
Soybean-corn rotation (%)	69	66	80	74	65	69
Timing of N application (%)						
Fall	5	19	41	55	71	78
Spring	48	41	25	38	29	5
Side-dressing	41	27	0	7	0	18
Form of N application (%)						
Urea ammonium nitrate	55	38	25	14	25	18
Anhydrous ammonia	39	49	15	51	66	38
Manure				35	9	45
Experiment year (%)						
2007				54	100	0
2008				0	0	43
2009				45	0	3
2010				2	0	55
2017	21	47	0			
2018	32	6	66			
2019	22	0	19			
2020	25	25	15			
2021	0	22	0			
Number of fields	17	14	5	67	23	40
Number of strips / samples	268	239	79	1,195	390	720

Note: Table 1 presents summary statistics by rainfall percentile: dry (<p20), normal (p20 - p80), and wet (>p80). CSNT=cornstalk nitrate test. Standard deviations are in parenthesis.

5 Empirical Results

5.1 Production function

We estimate a quadratic production function to recover the parameters of the target input model (Equation 2):

$$Y_s = \theta_0 + \theta_1 N_s + \theta_2 N_s^2 + \theta_3 I(wet)_s + \theta_4 I(wet)_s \cdot N_s + \theta_5 I(wet)_s \cdot N_s^2 + \lambda X + \delta_{fb} + e_s \quad (6)$$

where Y_s is the observed corn yield; N_s is the experimental N rate in strip s; and, I(wet) is a dummy variable equal to 1 if we observe excessive rainfall. The parameters of interest are the yield penalty under normal weather, $-\theta_2$, the yield penalty under excessive rainfall, $-\theta_2 - \theta_5$, and alpha, $\frac{\theta_2+\theta_5}{\theta_2}$. X is a set of control variables and includes a dummy variable for dry weather, defined as precipitation under the 20th percentile, and its interaction with the N rate. The reference weather category is normal weather, between the 20th and the 80th percentile. δ_{fb} are the field and block fixed-effects. There are 36 fields and 126 blocks in our sample. The field fixed-effects capture unique field attributes such as farm characteristics and common production inputs and management practices. The block fixed-effects capture sub-field soil and climate features. We estimate the production function in equation 6 using the ISA five-rate experimental data.

We find that N becomes significantly more productive with excessive rainfall. Table 2 shows our results for the production function. Columns 1–3 report results for excessive rainfall, defined as early-season precipitation above the 65^{th} percentile (column 1), the 80^{th} percentile (column 2), and the 90^{th} percentile (column 3). [11] The unit of measurement for N rate in our sample is 25 lbs and the marginal product of N under normal weather is 16.34–1.80N (column 2). [12] Increasing the N rate from 150 lbs/acre to 175 lbs/acre increases corn yield by 5.5 bu/acre in normal weather, which is approximately a 3% increase in yield. A similar increase in the N rate with excessive rainfall would increase corn yield by 10 bu/acre (approximately 6%). The marginal product of N with excessive rainfall is 36.31–4.37N (column 2). In the more extreme case of excessive rainfall, defined as early-season rainfall above the 90^{th} percentile (column 3), a similar increase of N application increases corn yield by 15 bu/acre or 9%. [13] These results suggest a strong complementarity between N and excessive early season rainfall.

[11] We compute all percentiles of rainfall at the field level. We report additional results for alternative definitions of excessive rainfall in the robustness section.

[12] With a quadratic production function, the marginal product of N is $\theta_1 + 2\theta_2 N_s$ under normal weather, and $(\theta_1 + \theta_4) + 2(\theta_2 + \theta_5)N_s$ under excessive rainfall.

[13] The average corn yield in the United States for the 2020/2021 and 2021/2022 seasons was 171.4 and

Table 2: Corn Production Function with Excessive Rainfall

	Dependent variable is corn yield (bu/acre)		
	(1)	(2)	(3)
N rate	13.34***	16.34***	17.47***
	(3.373)	(2.986)	(2.846)
N rate squared	-0.766**	-0.902***	-0.948***
	(0.301)	(0.260)	(0.244)
N rate x I(wet p65)	15.55***		
	(5.501)		
N rate squared x I(wet p65)	-0.888*		
	(0.465)		
N rate x I(wet p80)		19.97***	
		(7.421)	
N rate squared x I(wet p80)		-1.285**	
		(0.603)	
N rate x I(wet p90)			33.54***
			(6.538)
N rate squared x I(wet p90)			-2.207***
			(0.501)
N rate x I(dry)	3.723	0.721	-0.403
	(4.702)	(4.432)	(4.339)
N rate squared x I(dry)	-0.176	-0.0413	0.0046
	(0.406)	(0.376)	(0.365)
Constant	172.4***	172.4***	172.4***
	(9.327)	(9.327)	(9.327)
Fixed effects	Field-block	Field-block	Field-block
Yield penalty:			
Normal weather (a_R)	0.766**	0.902***	0.948***
	(0.301)	(0.260)	(0.244)
Wet weather (a_W)	1.654***	2.187***	3.155***
	(0.354)	(0.544)	(0.438)
α (wet/normal: a_W/a_R)	2.158**	2.425***	3.329***
	(0.966)	(0.924)	(0.972)
Observations (strips)	586	586	586
R^2	0.957	0.954	0.954

Note: Table 2 shows the results for a fixed-effects production function of corn using the experimental data with five rates. There are 36 fields and 126 blocks in our sample. The unit of the nitrogen rate variable is 25 lbs. The variables I(wet) and I(dry) are dummy variables equal to 1 if the weather was wet or normal. The regressions also include an interaction between a dummy for rotation and nitrogen rate. All standard errors are clustered at the block level. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

The yield penalty also doubles with excessive rainfall. We report estimates for the yield penalty by the rainfall state and estimates for α in aable 2. The yield penalty under normal weather is approximately 0.9, implying that a 25 lbs/acre error in N application would reduce corn yield by close to 1 bu/acre, or 0.6%. The yield penalty increases to 2.19 with excessive rainfall (column 2) while yield becomes more sensitive to the N rate. The same 25 lbs/acre error in N use would result in a yield loss of about 1.2% with excessive rainfall. Furthermore, in the case of extreme rainfall, the yield penalty more than triples to 3.155 (column 3) and a 25 lbs/acre error would reduce yield by approximately 1.85%. [14] A larger yield penalty with excessive rainfall is consistent with overapplication of N. Farmers anticipating heavier rains may "insure" against potential yield loss by applying additional N upfront. A higher yield penalty means that errors in N application rates are more costly with extreme rainfall. However, excessive rainfall also affects potential environmental damages caused by N fertilization. We estimate this effect in the following subsection.

5.2 Damage function

Ideally, we would link N leaching in a water stream to the original corn field and then estimate the environmental damage for each field. Unfortunately, such detailed linkage is rarely available outside small experiments. However, agronomists use such experiments to establish relationships between water pollution and field N applications. For example, agronomists show that the level of residual N in the soil or at the corn stalk at the end of the season negatively correlates to the amount of N leached into water streams. Specifically, when the N concentration in the cornstalks at the end of the season is lower than 2 gN/kg (N deficiency), the annual mean $NO_3 - N$ load in rivers increases significantly. We use the relationship between N deficiency in cornstalk and mean N load in rivers to estimate a damage function for N fertilization.

We can express the probability of N leaching into water as the probability of deficient N at the end of the season, small N_r, after we control for the effect of the other components within the N balance. Most importantly, the amount of N fertilizer applied will affect both leached N and residual N. We use ISA experimental dataset with randomized N application to control for N fertilization. Our regression model replicates an ideal experiment where we "fix" the amount of N fertilization, control for the effects of weather and soil characteristics, and allow only for variation in rainfall abnormality. We assume that, once we control for other potential N sources and uses, the conditional probability of N deficiency is a good

177 bushels per acre respectively (WASDE, 2022).

[14] Graphically, the yield penalty captures the curvature of the production function. The production function is thus much flatter in the normal rainfall case than in the excessive or extreme rainfall cases.

approximation for the probability of N leaching into water streams:

$$Pr(N_w > 0|N_f, Z) \approx Pr(N_r < \underline{N_r}|N_f, Z) = \Lambda(\lambda_0 + \lambda_1 N_f + \lambda_2 I(wet) + \lambda Z) \tag{7}$$

where $\underline{N_r}$ is the threshold defined by agronomists for N deficiency; 2 gN/kg, λ is a logistic probability model for the probability of N deficiency; and, Z is a set of weather and soil attributes that includes the number of degree days during the growing season, mean precipitation, the standard deviation of precipitation, soil drainage, soil suitability for corn production, and a dummy variable for dry weather (rainfall < p20). These attributes correlate with plant growth and N losses. The parameter of interest is λ_2, which is the effect of excessive rainfall on the probability of N deficiency. We use our estimates for λ_2 to compute β, the ratio of the probability of leaching under normal and excessive rainfall. [15]

We find that excessive rainfall significantly increases the N deficiency in cornstalks, indicating a large effect on the probability of N leaching. Table 3 shows our estimates for a logit model for N deficiency, where columns 1, 2, and 3 report estimates for three definitions of excessive rainfall: (a) above the 65^{th} percentile (column 1); (b) above the 80^{th} percentile (column 2); and, (c) and above the 90^th percentile (column 3). The effect of excessive rainfall is significant and increases with the severity of extreme rainfall. The predicted probability of N deficiency with normal rainfall is 0.45 and increases to 0.63 and 0.64 with rainfall above the 65^{th} and 80^{th} percentiles, respectively (columns 1 and 2). With excessive rainfall at the 90^{th} percentile, the probability of deficiency reaches 0.73. All predicted probabilities are estimated at the mean value of each explanatory variable.

The effect of each control variable is consistent with the N balance equation and an increase in the N rate reduces N deficiency. Higher soil suitability to corn production increases N deficiency, likely because more productive soils have higher yield potential and therefore higher N demand for plant growth. The effects of soil drainage, mean precipitation, number of degree days, and soil organic matter on N deficiency are not statistically significant. The effect of rainfall variability is positive and large, consistent with the agronomic arguments for the relationship between rainfall and N leaching. We also estimate logit models with county and landform fixed-effects and arrive at similar results.

Finally, we compute β, the relative increase in the risk of N deficiency and leaching with excessive rainfall or the risk ratio in probability models. The risk of N deficiency increases by 41% and 59% with excessive rainfall (columns 1 and 3), which suggests a significant increase

[15] More generally we could define $Pr(N_w > 0|N_f, Z) = KPr(N_r < \underline{N_r}|N_f, Z)$ but for the estimation of $beta$ only the relative measure of the probability under wet and normal rainfall conditions matters. The constant K would not affect the relative probability

Table 3: Probability of Nitrogen Deficiency with Excessive Rainfall

	Logit model for N stalk deficiency		
	(1)	(2)	(3)
I(wet p65)	0.839***		
	(0.309)		
I(wet p80)		0.871***	
		(0.307)	
I(wet p90)			1.292***
			(0.355)
N rate	-0.0111***	-0.0111***	-0.0117***
	(0.00248)	(0.00246)	(0.00262)
Corn suitability rating (CSR)	0.0264*	0.0266*	0.0309**
	(0.0147)	(0.0146)	(0.0150)
Drainage	-0.226	-0.256	-0.234
	(0.302)	(0.300)	(0.299)
Average precipitation	-0.00690	-0.00683	-0.0106
	(0.0116)	(0.0116)	(0.0110)
Standard deviation precipitation	0.0328**	0.0329**	0.0340**
	(0.0151)	(0.0151)	(0.0155)
I(dry)	-0.0499	-0.0443	-0.0835
	(0.490)	(0.490)	(0.475)
July GDD	0.000384	0.000406	4.76e-07
	(0.000739)	(0.000743)	(0.000560)
Organic matter	-0.0891	0.0899	0.0829
	(0.0629)	(0.0621)	(0.0633)
Constant	-2.777	-2.861	-1.305
	(3.153)	(3.137)	(2.974)
Predicted probability of N deficiency:			
Normal weather (Π_R)	0.45	0.45	0.46
	(0.04)	(0.04)	(0.03)
Wet weather (Π_W)	0.63	0.64	0.73
	(0.05)	(0.05)	(0.06)
β (wet/normal: Π_W/Π_R)	1.41	1.43	1.59
	(0.17)	(0.17)	(0.16)
Observations (samples)	1,845	1,845	1,845
Chi^2	32.99	33.17	33.38

Note: Table 3 shows the results for a logistic regression for the probability of nitrogen deficiency in cornstalks at the end of the season. The nitrogen content at the stalk is considered deficient if under 250 ppm. The model is estimated using the two-rate experimental dataset from ISA. The nitrogen rate is randomized in the experiment and the unit of the nitrogen rate variable is 25 lbs. The variables I(wet) and I(dry) are dummy variables equal to 1 if the weather was wet or normal. The logistic regressions also include a dummy variable for dry weather, the number of growing degree days, and the soil organic matter. *, **, and *** denotes significance at 10%, 5%, and 1% level, respectively.

in environmental damages (Implication 1). The effect of excessive rainfall on efficient N management depends on the relative size of α and β (Implication 2). The increase in yield penalty is larger than the increase in the probability of deficiency. The difference, $\alpha - \beta$, is 0.75 for rainfall above the 80^{th} percentile and 1.73 with rainfall above the 90^{th} percentile. These results imply an increase in the cost of environmental protection (Implication 3) and suggests that alpha-reducing strategies may be more effective in adapting N management to abnormal rainfall (Implication 4).

5.3 Alpha-beta Framework

Figure 6 summarizes our findings, with blue circles representing our estimates for α and β using the full sample and alternative definitions of excessive rainfall. α and β estimates close to 1 imply that excessive rainfall will not lead to additional leaching or an increase in the yield penalty.

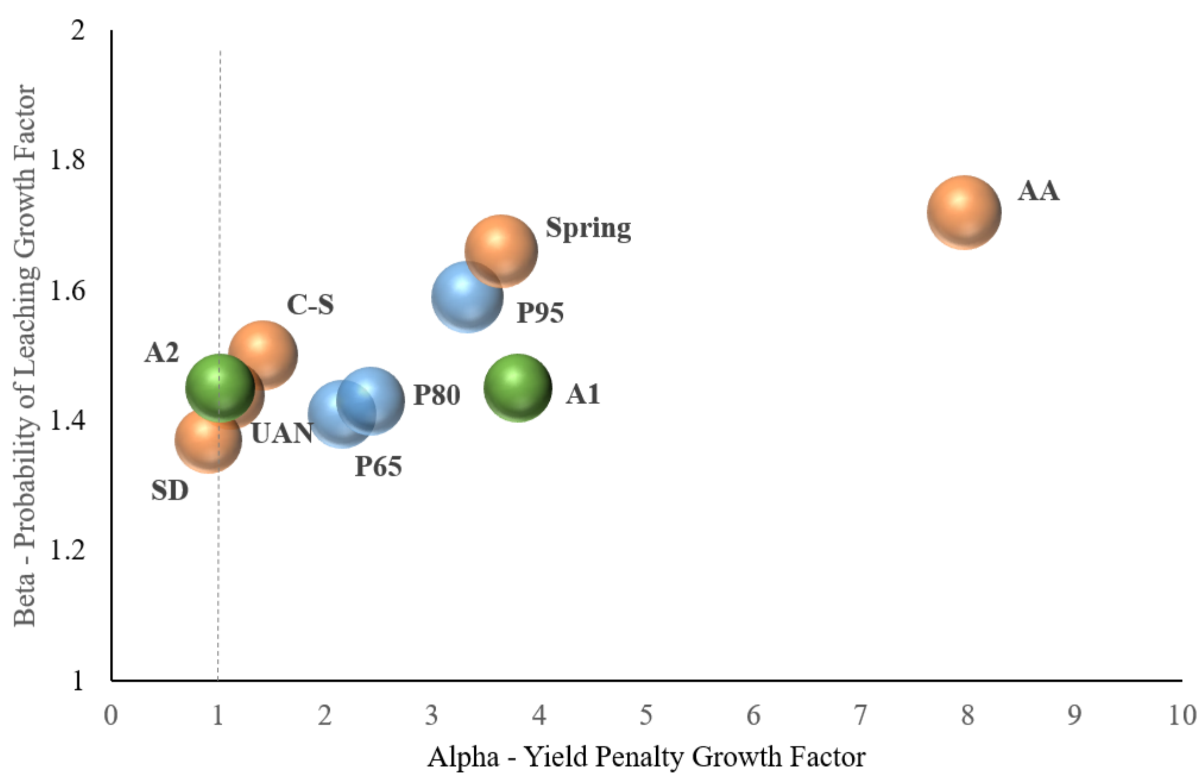


Figure 6: Summary of findings using alpha-beta framework.

Note: figure 6 shows our estimates for the parameters α and β for different subsamples of the experimental data. The blue circles are the estimates for the full sample for three definitions of excessive rainfall based on percentiles of early-season rainfall ($65^{th}, 80^{th}, and 90^{th}$ percentiles). The orange circles are the estimates of α and β for subsamples with different management practices: **AA** – anhydrous ammonia; **UAN** – urea ammonium nitrate; **C-S** – corn-soybean rotation; **Spring** – spring N application; **SD** – side-dressing application. The green circles are the estimates for split N application: **A1** – first nitrogen application; **A2** – second nitrogen application. The size of the circles are proportional to the magnitude of the parameter β.

Our estimates using excessive rainfall, defined as the 65^{th} and 80^{th} percentiles (P65 and P80 on the graph), are similar. Excessive rainfall will increase the probability of leaching by 40% and the yield penalty by 150%. In general, we find that the effect of excessive rainfall tends to be much higher on the yield penalty than on the probability of leaching. If we define excessive rainfall using the 95^{th} percentile of early-season rainfall, our estimates for α and β increase. In this case, excessive rainfall increases the probability of leaching by 60% and the yield penalty by 250%. Such a large increase in the yield penalty would raise the optimal level of N application. In the next two subsections, we use the alpha-beta framework to assess the heterogeneous effect of excessive rainfall for alternative management and adaptive practices.

5.4 Management Practices: Rotation, Form, and Timing

We examine heterogeneity in the effect of excessive rainfall on α and β for alternative management practices to identify potential adaptive practices. We examine the heterogeneity of the α and β parameters for two types of crop rotation—C-S and C-C; three N forms—AA, UAN, and manure; and, three timings of N application—fall, spring, and SD. Table 4 shows our α and β estimates for each management practice. We use the same model specification as in the previous section and the 80^{th} percentile definition of excessive rainfall. We use the five-rate experimental data to estimate the production function and the GSS survey dataset to estimate the damage function for subsamples by management practice. Figure 6 plots our α and β estimates by management practice.

We find that α and β vary with management practice. Panel 1 of table 4 shows our estimates by crop rotation. Our estimate for alpha for C-C is not statistically significant as most farms in our sample use the more common C-S rotation. We find that β for the C-C rotation is higher than for C-S, implying a higher probability of leaching under excessive rainfall. One possible explanation is the higher N application rate on the C-C rotation. There is usually a large amount of residue in the soil after corn production, which tends to immobilize N in the soil and reduce N supply to the plant. As a result, farmers predominantly apply more N for C-C production, which may result in more leaching.

The effect of excessive rainfall on α and β varies significantly by N form (see panel 2 of table 4 for estimates). AA has a significantly larger alpha than UAN although standard errors are largely due to small subsample sizes. AA also has the highest estimate for β, followed by UAN and manure. Our estimates for β are much more precise as we use the larger GSS dataset. We also report in table 4 the expected MD of N leaching for each management practice using equation 3, along with an SCN estimate of \$0.20/lb N. As expected, UAN has the highest MD in both weather states because it has 25% of its N content as nitrate, which tends to be more prone to leaching. However, we find that AA has the largest change in the yield penalty and in the probability of leaching with excessive rainfall. The

Table 4: Results by Management Practice

	Production		Damage		Expected Damage ($/lb)	
	α	Obs.	β	Obs.	Normal Weather	Wet Weather
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1. Crop rotation:						
Corn-soybean (C-S)	1.42	420	1.5	8259	0.08	0.11
	(0.4)		(0.06)		(0)	(0)
Corn-corn (C-C)	-2.86	166	2	3792	0.05	0.11
	(1.87)		(0.12)		(0)	(0)
Panel 2. Form of N application:						
Anhydrous ammonia	7.97	269	1.72	6065	0.06	0.1
	(8)		(0.08)		(0)	(0)
Urea ammonium nitrate	1.11	305	1.44	3905	0.08	0.12
	(0.48)		(0.07)		(0)	(0)
Manure	-14.37	532	1.6	2309	0.07	0.1
	(124.5)		(0.13)		(0)	(0.01)
Panel 3. Timing of N application						
Fall	-1.56	87	1.68	5139	0.07	0.11
	(0.86)		(0.08)		(0)	(0)
Spring	3.64	246	1.66	5459	0.07	0.11
	(0.99)		(0.08)		(0)	(0)
Side-dressing	0.91	241	1.37	1634	0.08	0.11
	(0.37)		(0.11)		(0)	(0.01)

We calculate the β and marginal damage ($/lb) from the averaged predicted probabilities using the GSS data. The results shown in panels 2 and 3 are based on the production function estimates using the five-rate experimental data. The only exception is for the manure subsample, which is based on the two-rate experimental data after dropping outliers in terms of nitrogen rate at 5% and yields at 1% before 2011. In these models we use the control variables of corn suitability rating, organic matter, average precipitation, standard deviation precipitation, drainage, and year fixed-effects for the manure subsample. Complete results are reported in Tables 11 and 12 in the appendix.

expected MD under wet weather conditions is similar for all three forms. Manure differs from other N forms for its high uncertainty in production. Our alpha estimate for manure is not statistically different from zero and has a very high standard error even using a larger subsample. Since manure has a large uncertainty in N content, farmers tend to apply a higher N rate with manure than for other N forms. Furthermore, the consecutive application of manure over several years increases the uncertainty of mineral N already in the soil (nitrate and ammonium), which then can increase soil mineralization and reduce demand for N application. Finally, manure is commonly applied in the fall before the colder weather slows down manure decomposition and ammonium nitrification, leading to high variability in yield response to manure application.

Finally, panel 3 in table 4 shows our estimation for alternative timing of N application. We also find that α and β differ by timing—SD has the lowest estimates for both α and β, which suggests that it is more resilient to excessive rainfall. Our alpha estimate for SD is 0.91, implying no change in the yield penalty, while our β estimate is 1.37, the lowest of all management practices. SD application is a different practice because the farmer has more information about the status of the crop, the soil, and the growing season weather at the time of application (late-May to mid-June). Our β estimates for fall and spring applications are higher, indicating a greater probability of leaching with excessive rainfall. In this case, the excessive rainfall impact occurs after N application, thus increasing the risk of N loss by leaching and denitrification. Also, our alpha estimate for spring is over three times higher than for SD, suggesting there is a large gain from learning about the weather before N application.

5.5 Adaptive Practice: Split N Application

Farmers may adapt to excessive rainfall by splitting N application throughout the season. For example, a farmer may apply less N in the fall or early spring and then apply additional N in late-May or early-June after learning about weather and crop conditions. This adaptive strategy potentially reduces the leaching and yield losses, and saves on N expenses. We exploit a unique feature of the two-rate experimental design to assess the split N application strategy. In the two-rate experiment, the farmers in the treatment group apply N twice during the season. The first N application, N_1, is done in the fall or early spring, while the second application of 50 lbs, N_2, happens in late May or early June. In the two-rate experiment design, N_1 is the farmer's normal N rate, whereas N_2 is zero for the control group (single N application) and 50 lbs for the treatment group (split N application). [16]

We estimate the production function in equation 6 with two N rates, N_1 and N_2, and their interactions with the excess rainfall variable. Our parameters of interest are the interaction variables $N_2\, rate \times I(wetp80)$ and $N_2\, rate\ squared \times I(wetp80)$, and we estimate separate α parameters for first and second N applications. We control for field and farm characteristics using measures for CSR, organic matter (OM), a dummy variable for poor soil drainage, and landform fixed-effects. Given the smaller sample sizes, we do not use field-block fixed-effects. We focus our analysis on subsamples with the largest number of fields: full sample; fall application with C-C rotation; fall application with C-S rotation; and, spring application with C-S rotation. We also estimate the damage function separately for subsamples with single and split application, which enables us to compare the predicted probability of leaching under the two practices.

We find evidence that the second N application has a smaller impact on both the yield penalty and on the probability of leaching. Table 5 reports our estimates for the production and damage functions with split N application. [17] We do not have sufficient variation in the interaction of N and excessive rainfall for the subsamples of fall with C-C rotation and spring

[16]The two-rate experiment records the primary timing and primary N form applied in each field. Although it is common for farmers to use several N forms in multiple applications, in the two-rate experiment farmers mostly use SD for the second N application.

[17]See appendix table ?? for complete regression results.

with S-C rotation. However, the effect of the second N application is statistically significant with the most common practice of applying first in the fall with the S-C rotation. The α estimates for the second application, 1.02, is a fraction of the estimate for the estimate for the first application, 3.80 (column 3). This result confirms the adaptive value of the split N application. When the farmer applies N only once, the yield penalty under excessive rainfall increases sharply, therefore justifying overapplication as insurance. However, the second application is not sensitive to excessive rainfall. [18]

The predicted probability of leaching tends to be lower under split N application but is not statistically different than single applications in our samples. For the full sample, excessive rainfall increases the probability of leaching by 56% and 34% under single and split applications, respectively. The difference is larger with fall application and S-C rotation—47% under single application and 14% with split application. We would expect a significantly smaller effect on leaching with split application, yet our analysis of this adaptive practice deviates from an ideal experiment in two ways. First, farmers would ideally use less N in the first application and make adjustments in the second application. However, in the two-rate experiment design, farmers applied their normal N rate in the first application. Thus, we should not expect a significant reduction in β with the split application. In fact, we should expect an increase because farmers add 50 lbs of N in the second application. Finally, farmers commonly use UAN—which has a higher propensity to leach—as the N form in the second application. The similar estimates under single and split applications are thus an encouraging sign that the second N application has a small effect on the likelihood of leaching. Figure 6 shows that SD and split N application (A1) are among the most resilient management practices under excessive rainfall with relatively small estimates for both α and β.

6 Simulation: Efficient N Use under Excessive Rainfall

To ascertain the efficient level of N use under excessive rainfall, we simulate the efficient level of N fertilization under normal and wet weather conditions. At the efficient level of N, N^{**}, the marginal benefit and the marginal SCN use are equal (see figure 7 for the simulation). The marginal benefit is the farmer's marginal net revenue and represents the farmer's economic gain for adding one more pound of N. We define farmer net revenue as

[18] In the case of spring with S-C rotation, the marginal product of the second N application is significant and the shape of the production function changes from normal to wet weather. This result implies a shortage of N, likely due to leaching, and therefore applying more N increases yields. By contrast, we find no change in the shape of the production function from normal to wet weather when the first N application happens in the fall (table 5 columns 2 and 3). The insignificant effect of the second N application is likely the result of an over application of N in the fall. Farmers commonly apply high N rates in the fall anticipating N losses as there is a larger uncertainty about the weather with the earliest N application. Furthermore, the most common N form applied in the fall is manure, which also has the largest uncertainty in yield returns.

Table 5: Results by Adaptive Practice

	Dependent variable: corn yield (bu/acre)			
	(1) **Full**	(2) **Fall-Corn**	(3) **Fall-Soybean**	(4) **Spring-Soybean**
N_1 rate	19.270***	188.199***	3.77	101.779*
	(6.22)	(45.04)	(7.53)	(58.93)
N_1 rate squared	-1.552***	-11.674***	-0.328	-10.188
	(0.44)	(2.73)	(0.49)	(6.48)
N_2 rate	36.378***		24.334***	133.868**
	(7.57)		(7.24)	(66.84)
N_2 rate squared	-15.334***	2.624***	-9.604***	-65.301**
	(3.62)	(0.41)	(3.50)	(32.63)
N_1 rate x I(wet p80)	-15.642	-368.530***	17.034	-162.701*
	(15.29)	(45.09)	(14.33)	(84.29)
N_1 rate squared x I(wet p80)	1.518	24.197***	-0.92	16.617*
	(1.12)	(2.82)	(1.01)	(8.58)
N_2 rate x I(wet p80)	-31.218**	16.394		-184.036***
	(13.03)	(19.38)		(65.31)
N_2 rate squared x I(wet p80)	15.448**	-7.864	-0.189	88.315***
	(6.21)	(9.09)	(0.79)	(31.71)
Observations (strips)	1161	204	661	197
R^2	0.346	0.844	0.402	0.792
Yield penalty α (wet/normal: a_W/a_R):				
α_1	0.02	-1.07	3.80	-0.63
	(0.65)	(0.28)	(6.12)	(0.71)
α_2	-0.01	-2.00	1.02	-0.35
	(0.41)	(3.46)	(0.08)	(0.23)
Predicted probability of N deficiency β (wet/normal: Π_W/Π_R):				
β_{single}	1.56	1.18	1.47	1.42
	(0.16)	(0.34)	(0.20)	(0.26)
Observations (corn stalk)	886	140	473	162
β_{split}	1.34	1.45	1.14	0.31
	(0.28)	(0.28)	(0.35)	(0.03)
Observations (corn stalk)	716	114	440	99

Note: table 5 reports results for the estimation of the production and damage function for split N application. We control for the potential effect of outliers. The two-rate experiment is prone for outliers because the addition of 50 lbs of N may lead to unrealistically high N rates. Also, the small sample sizes further increase the model's sensitivity to outliers. We removed outlier observations with a DfBeta greater than $\frac{2}{\sqrt{n}}$. We control for field and farm characteristics using measures for corn suitability rating, organic matter, a dummy variable for poor soil drainage and landform fixed-effects, shown in Table 10 in Appendix. Given the smaller sample sizes, we do not use field-block fixed-effects, and we focus our analysis on the subamples with the largest number of fields: full sample; fall application with C-C rotation; fall application with C-S rotation; and, spring application with C-S rotation.

corn price times yield minus N cost and calculate the marginal benefit of N using historical prices for corn ($4/bu) and N fertilizer ($0.4/lb) (Mcconnell et al. 2022) and our estimates for the production function (table 2). The marginal benefit function is the downward line in figure 7 and has a negative slope equal to $-2ap$, where a is the yield penalty and p is the probability of excessive rainfall. The slope is larger under wet weather conditions because the yield penalty increases with excessive early-season rainfall (figure 7b). The bands around the marginal benefit line are confidence bands representing the 95% confidence interval. The private optimal N rate, N^*, is determined at the intersection between the marginal benefit function and the zero-axis, where marginal net revenue equals zero.

The marginal SCN application is the expected economic damage of adding one pound of N to corn production, which is the probability of N leaching times the SCN (see equation 3). We assume that the marginal SCN is constant at the farm level, as the relative contribution of one farm to water pollution is small. We use our estimates for the probability of N deficiency (see table 3) to approximate the probability of leaching under normal and wet weather. As there is large uncertainty in the calculation of the SCN, we use a range of values following the literature referred to by the Environmental Protection Agency (EPA, 2015). [19] For the lower bound, we use Compton et al. (2011) estimate for the economic impact of N fertilization on drinking water—the treatment costs in drinking water wells—for a total of $0.09/lb N. For the medium level SCN, we add the negative impact of N fertilization to waterfront property values, $0.2/lb N, taken from Sobota et al. (2015) and Dodds et al. (2009). For the upper bound, we adopt Birch et al. (2011) estimate of $4.35/lb N for the economic impact of a coastal eutrophication on the recreational use of an estuary. The horizontal dashed lines in figure 7 show the low, medium, and high values for the SCN. The MD of N is higher under wet weather because the probability of leaching increases with excessive rainfall.

Table 6 reports the simulation results for low, medium, and high values of the SCN. For these simulations, we use our estimates for α and β using the full sample for the five-rate experiment and excessive rainfall, defined as the 80^{th} percentile of historical precipitation (p80) (table 2 column 2). The yield penalty more than doubles, $\alpha = 2.43$, and the probability of leaching increases by 43% with excessive rainfall. Both parameters are statistically different from zero. As $\alpha > \beta > 1$, excessive rainfall will lead to higher damages (Implication 1) and a higher cost of pollution management (Implication 3). The cause for this double impact is the large increase in the yield penalty. Errors in N application are more costly with excessive

[19] The document and accompanying spreadsheet is publicly available at https://www.epa.gov/nutrient-policy-data/research-and-reports-nutrient-pollution. The SCN measures are reported in 2020 US dollars based on the CPI inflation index from the U.S. Bureau of Labor Statistics at https://data.bls.gov/pdq/SurveyOutputServlet. Also, we convert the weight metric from kilograms to pounds.

rainfall, and the farmer and the social planner will increase N application during excessive rainfall.

Table 6: Efficient N Rates with Low, Medium, and High Social Cost of Nitrogen

			Normal weather			Wet weather		
	α	β	N^*	N^{**}	MD	N^*	N^{**}	MD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low SCN	2.43	1.43	191.9	188.5	0.04	193.3	191.3	0.06
(0.09 \$/lb N)	(0.92)	(0.17)	(16.8)	(15.94)	(0)	(12.2)	(11.8)	(0)
Medium SCN	2.43	1.43	191.9	184.0	0.09	193.3	188.7	0.13
(0.20 \$/lb N)	(0.92)	(0.17)	(16.8)	(14.85)	(0.01)	(12.2)	(11.3)	(0.01)
High SCN	2.43	1.43	191.9	22.41	1.96	193.3	93.9	2.78
(4.35 \$/lb N)	(0.92)	(0.17)	(16.8)	(38.17)	(0.17)	(12.2)	(18.2)	(0.22)

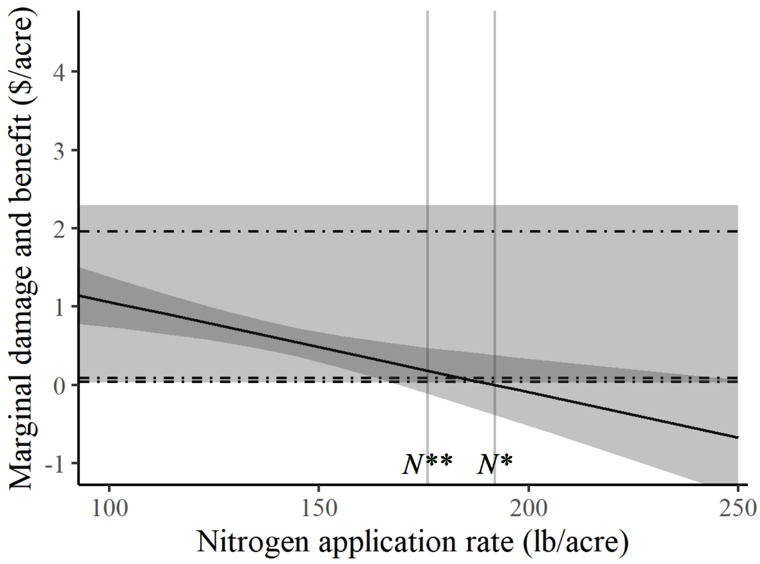
Note: Table 6 reports the simulation results for low, medium, and high values of the social cost of nitrogen (SCN). N^* is the private optimal level of N application measured in lbs/acre. N^{**} is the socially optimal level of N application measured in lbs/acre. MD is the marginal damage of nitrogen application measured in \$/lb N. α and β are the growth factors for the yield penalty and the probability of leaching. For these simulations, we use our estimates for α and β using the full samples for the five-rate and two-rate experiments. We define excessive rainfall as the 80^{th} percentile of historical precipitation (p80) (table 2 column 2).

Under normal weather conditions, we estimate the optimal private N rate at 192 lbs/acre, close to the guidance for N fertilization in Iowa.[20] The private rate N^* does not vary with the SCN as the farmer optimization problem does not consider the cost of pollution. The social planner rate varies with the SCN, ranging from 188.5 lbs/acre with low SCN to 22.4 lbs/acre with high SCN. The difference between the private and socially optimal rates, Δ, is not statistically different from zero with low SCN but increases with the SCN and becomes very large, almost 170 lbs/acre, and statistically different with high SCN. The MD of N application also increases with the SCN. With low SCN, the MD is 0.04 \$/lb N or about 10% of the cost of N fertilizer. The MD is almost twice the fertilizer cost at the medium SCN and increases to \$1.96/lb N, or five times the fertilizer cost.

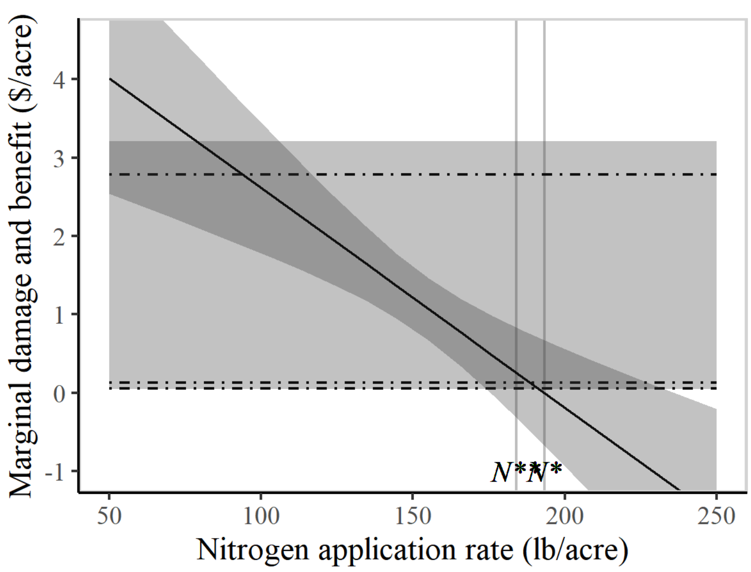
Under wet weather conditions, the optimal private N rate is slightly higher than in normal weather. The farmer considers the higher yield penalty when optimizing N fertilization and "insures" against yield losses. The social planner rate is also higher but increases faster with the SCN. Figure 7b shows how the steeper marginal benefit function in wet weather intersects the MD function at a higher N rate. Under wet weather, N is more productive at lower rates because of the higher yield penalty. The marginal product of N for the target-input model production function is $2a(\hat{N} - N)$. The marginal product increases with the yield penalty and the difference between the target rate and N. The effect of the higher yield penalty is clearer with the high SCN. The social planner's optimal N rate doubles from 55

[20]For example, universities in the corn belt collaboratively contribute to the provision of the optimal nitrogen application rate calculator, which can be found at http://cnrc.agron.iastate.edu/.

lbs/acre under normal weather to 113 lbs/acre under wet weather. In this case, the private N rate is closer to the efficient rate (Implication 2).



A - Normal weather



B - Wet weather (p80)

Figure 7: Optimal nitrogen rates by early-season rainfall.

Note: Figure 7 shows the private and socially optimal nitrogen rates for normal and wet early-season weather conditions. Wet weather is defined as excessive rainfall above the 80^{th} percentile. The optimal nitrogen rate is determined at the intersection of the marginal damage and marginal benefit functions. The horizontal dashed lines are the marginal damage functions for the lower bound, upper bound, and the mean social cost of nitrogen. The marginal benefit function is defined as the net revenue for an additional unit of nitrogen and has the 95^{th} confidence interval band.

The striking difference between N management in normal and wet weather is the increase in both the damages and the efficient level of N rates. The MD under wet weather is 42% higher and reaches \$2.78/lb N with high SCN, seven times the fertilizer cost. With such high damages, the social planner would apply less N. However, the socially optimal N rate, N^{**}, doubles in wet weather. This counter-intuitive result reflects the high growth rate in the yield penalty with excessive rainfall. The yield penalty increase of 143% is over three times higher than the increase in MD. It would be too costly for the social planner to reduce

Table 7: Parameter Values Used in the Simulation

Parameter	Value (2020 US$)
Corn price	4 ($/bu)
Nitrogen fertilizer price	0.4 ($/lb)
Social cost of nitrogen	0.09 (low) $\sim$ 0.20 (mid) $\sim$ 4.35 (high) ($/lb)
Probability of nitrogen loss (p80)	0.45 (normal) and 0.64 (wet)
Probability of nitrogen loss (p90)	0.46 (normal) and 0.73 (wet)
Range of nitrogen rate	50–250 lbs

Note: The corn price is the historical corn price (Mcconnell et al., 2022). The social costs of nitrogen application include drinking water treatment costs and economic impacts to waterfront property and recreational use (Birch et al., 2011; Compton et al., 2011; Sobota et al., 2015; Dodds et al., 2009). The probability of nitrogen loss is calculated from the logistic regression results in table 3.

the optimal N rate further. A potential solution for mitigating the damages under excessive rainfall would be to adopt management practices that reduce the increase in the yield penalty (reduce β) or reduce the damage in wet weather (reduce α). Our simulation results suggest that reductions in β may be particularly beneficial given the large change in yield penalties.

7 Robustness Analysis

We test the robustness of our main results considering alternative model specifications, definitions of excessive rainfall, and datasets. We find a consistent effect of excessive rainfall on the productivity of N application and on the probability of leaching under multiple management practice combinations. We highlight the importance of controlling for field and block characteristics in the empirical analysis of N management.

7.1 Alternative Models

The advantage of the experimental data is the randomization of N application across fields. However, the randomization of N application in on-farm field experiments does not necessarily imply a randomization of the effectiveness of N fertilization because other factors, such as soil characteristics, may influence how much N is taken by the plant and how much is lost. To examine the effect of field quality, we test alternative empirical models with different controls for field characteristics using the five-rate experimental data. We find robust results once we control for unobserved field characteristics using field and block fixed-effects.

Table 13 (Appendix C) presents results. In column 1, we report results for a specification with no controls. The model in column 2 has control variables for CSR, a dummy for poor drainage, soil organic matter, and N form and timing, as well as the mean and standard deviation of precipitation over the past 25 years. In column 3, we add year fixed-effects, which controls for annual variation in rainfall. Table 17 shows full estimation results for columns 2 and 3. The interaction variables are not statistically significant in the first three models (columns 1 to 3), but once we control for year variation, the sign of the interaction variable becomes positive, as expected.

The regression models in columns 4 and 5 control for both year and block fixed-effects. The results with and without year effects differ because of spatial correlations between field characteristics and climate. With year fixed-effects, the model relies only on within-year variation. Once we control for field or block fixed-effects, the estimates of the interaction variables become economically and statistically significant. Note that the block is a sub-area within a field. Although the estimates of the two models with fixed-effects are consistent, block fixed-effects give us more precise estimates by controlling for within-field differences. Furthermore, α changes significantly from less than or close to 1 to greater than 2 as we better control for field characteristics. The estimates for α without the fixed effects in columns 1, 2, and 3 are misleading regarding the effect of excessive rainfall. However, the estimates reported in columns 4 and 5 confirm the significant yield penalty resulting from abnormally wet weather.

7.2 Alternative Definitions of Excessive Rainfall

We test the robustness of our results against alternative definitions of excessive rainfall considering field-specific and field-agnostic definitions of abnormal weather. The field-specific definitions are based on alternative local thresholds, whereas the field-agnostic definition is based on an absolute threshold of precipitation across all fields. We use two indicators to define the thresholds of abnormally dry and wet weather: (a) 0.8 and 1.2 times the mean precipitation and (b) one standard deviation from the mean. Table 14 presents the threshold precipitation values (in mm) for each alternative definition and data set. We add another experimental dataset from ISA with seven N application rates to test the robustness. This seven-rate experiment was completed from 1987 to 1991. We find that rainfall thresholds are robust across alternative definitions and data sets, with the exception of the seven-rate dataset, which shows significantly lower thresholds for both dry and wet weather. The distribution of precipitation has moved rightward since the timeframe for the seven-rate ISA experiment. Given that the absolute thresholds of all data except the seven-rate data are similar, we also create a common absolute threshold for the five-rate, two-rate, and GSS datasets by considering the 20^{th} and 80^{th} percentiles of one empirical distribution of precipitations from 1981–2020. The resulting dry and wet thresholds are 274.13 mm and 454.03 mm, respectively.

Table 15 presents the results of our robustness analysis. We use the same models and dataset as in our main results (see table 2) but with different definitions of abnormal rainfall. The results show evidence for a significant effect of excessive rainfall on the productivity of N fertilization. We find large estimates for α across the different definitions of excessive rainfall, although the precision of the estimates varies across models. Our estimates also vary across definitions of excessive rainfall because of the differences in the thresholds of wet weather (see table 14). For instance, the threshold of wet weather for the definition of *Mean +-1SD* is about 40 mm higher, resulting in the highest estimate for α, 4.66, indicating a larger yield loss. In the case of the *absolute percentile* definition, the smaller effect of excessive rainfall reflects the local management practices or field characteristics that provide adaptive capacity against extreme weather. For example, even high levels of precipitation may not be considered severe if the climate is naturally wetter in some regions and if the field and the farmer are better equipped to handle heavy rainfall. Hence, in our main analysis, we focus on the relative measures of severe wet weather.

7.3 Alternative Experiments and Subsamples

We test the robustness of the effects of excessive rainfall in the production and damage functions using different experimental data and subsamples. Panel 1 of table 16 shows our estimates for α using our baseline models and the seven-rate experimental dataset from Kyveryga et al. (2007). All estimates for α are significant despite the small sample sizes but not statistically different from one. The results suggest that corn production was less sensitive to excessive rainfall 30 years ago when the seven-rate experiment was completed. However, as noted in the previous section, the thresholds for excessive rainfall were lower between 1987–1991, indicating a lower frequency of excessive rainfall. Also, corn production has expanded in the last 30 years with higher use of mechanized fertilization, which could lead to larger use of N in areas with wetter weather. Farmers that rely on historical statistics for N use under excessive rainfall would likely incur large yield losses as α is higher based on the most recent experiments.

Finally, we test how the combination of multiple management practices affect our results, focusing on the most prevalent combination of practices with a significant number of observations in the larger GSS survey dataset. Unfortunately, we do not have sufficient data to estimate α for combinations of practices, and so our analysis focuses on β estimates. Table 16 shows our estimates for β for 10 combinations of practices and figure 8 shows an ordered bar chart for the change in the probability of leaching under excessive rainfall for each combination of practices. Again, we find economically and statistically significant estimates for β across all combinations. However, we also find heterogeneity in our estimates for β. The combined practice of fall application with manure N and C-C rotation has the largest increase in the probability of leaching with excessive rainfall, approximately 77%. In general, C-S rotation has a lower β consistent with our previous estimates. In fact, even the more resilient SD application has a high estimate for β when combined with C-C rotation. The combination of practices with the lowest increase in the probability of leaching is SD application with C-S rotation (32%), less than half the effect of the fall-manure-C-C combination. In terms of expected damages, combinations with manure N have consistently high values. Also, combinations with UAN tend to have high expected damages under wet weather, as expected.

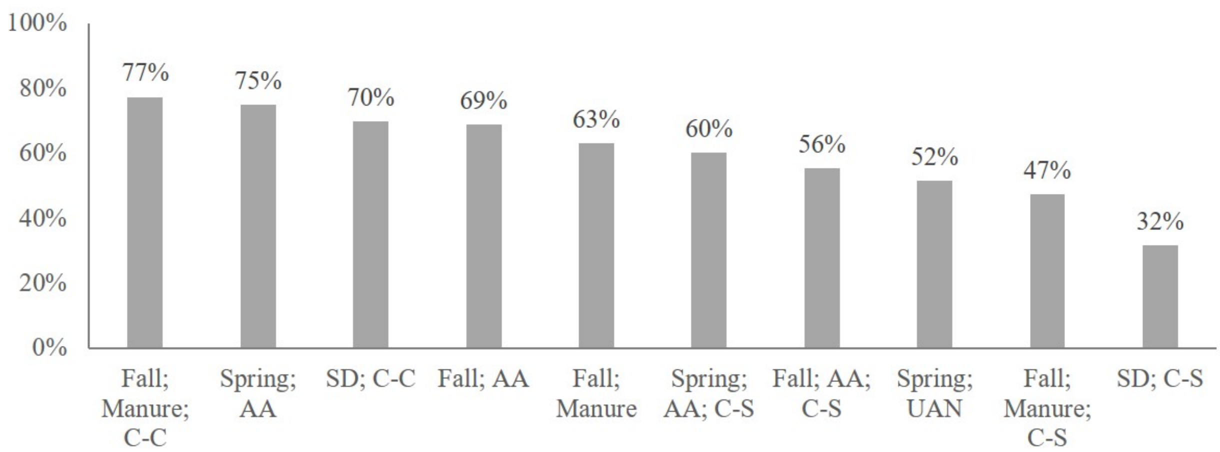


Figure 8: Probability of leaching by combination of management practices.

Note: Figure 8 shows our estimates for beta—the change in the probability of leaching with excessive rainfall—for combinations of management practices. The management practices are: **Fall; AA** - fall application with anhydrous ammonia nitrogen; **Fall; Manure** - fall application with manure nitrogen; **Spring; AA** - spring application with anhydrous ammonia nitrogen; **SD; C-S** - side-dressing with corn after soybeans rotation; **SD; C-C** - side-dressing with corn after corn application; **AA; C-S; Fall** - fall application with anhydrous ammonia nitrogen and corn after soybeans rotation; **AA; C-S; Spring** - spring application with anhydrous ammonia nitrogen and corn after soybeans rotation; **Manure; C-S; Fall** - fall application with manure nitrogen and corn after soybeans rotation; and **Manure; C-C; Fall** - fall application with manure nitrogen and corn after corn rotation.

8 Conclusion

We build an economic model for efficient N management under excessive rainfall and estimate the model parameters using ISA experimental data for the state of Iowa. Our results have implications for N guidance and N leaching adaptation. During the past decade, university extension agronomists across the Midwest have started promoting a more advanced system of N recommendations called "maximum return to nitrogen". [21] This new system uses the results of small-plot N response trials to estimate the economically optimal N rates at the regional, state, or sub-state level considering the mode of crop rotation and prices. Despite recent improvements, it is impractical to have one general state or sub-state N recommendation given the large spatial and temporal variability in optimal N rates across fields. Also, the "maximum return to nitrogen" does not account for the effect of rainfall

[21] See http://cnrc.agron.iastate.edu/ for detailed information about maximum return to nitrogen.

or the timing and form of N fertilization. We show that under excessive rainfall, efficient N fertilization depends on the rate of change of two parameters—the yield penalty and the probability of leaching—and both parameters vary with management practices. We provide initial estimates for efficient N use but more research is needed to refine N guidance further under excessive rainfall across a larger set of management practice combinations. The alpha-beta framework proposed in this article can help guide the design of more on-farm field experiments to improve N guidance further for farmers.

Our analysis is also informative for climate adaptation in agriculture. Climate change will likely increase the frequency of excessive rainfall through an increase in the concentration of atmospheric water vapor. We find that water pollution through leaching will increase and pollution management will become more costly because N becomes more productive. These results further highlight the value of adaptation. We assess the relative resilience of management practices to excessive rainfall and we find a large variation in resiliency but also large uncertainty. For example, we find that fall application of manure with C-C rotation is very sensitive to excessive rainfall and can lead to significant additional leaching. However, we also find it challenging to estimate a production function for manure given the uncertainty in N content with the N form. Thus, the next step in this analysis is to refine the on-farm experiment design further to study the most common management practices, as these may also lead to the highest environmental damages under excessive rainfall. This analysis can be informative to policymakers designing incentive for farmers to adopt more sustainable management practices and production technologies.

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Appendix A. Data Description

We use three experimental data sets and one survey data set, along with two sources of weather data. Figure 9 presents the total precipitation levels from May to July and the experiment sites during experimental periods. Table 8 summarizes all data sets and 9 describes variables used in the analyses.

We create an indicator variable for the abnormal state of the weather. We use a local empirical distribution of precipitation to classify current precipitation by quantiles into abnormally wet, normal, or abnormally dry. We obtain historical daily precipitation data from NASA Daymet,[22] which is 1km x 1km gridded high-resolution data recorded since 1980. We use the centroid coordinates of each field to extract daily weather variables. Since the period of Daymet does not cover the seven-rate data, we obtain additional daily precipitation from the Iowa Environmental Mesonet and match the city name with the precipitation of the nearest station as there is no coordinate information in the Mesonet dataset. [23]

We aggregate the daily rainfall information into total precipitation from May to July, which is a critical period for plant growth and nitrate intake. We then use the past 25 years of observations to build the local empirical distribution for each field and year. If the current precipitation is above the 80^{th} percentile or below the 20^{th} percentile of this distribution, we classify it as abnormally wet weather or abnormally dry weather, respectively. This approach is consistent with definitions of extreme weather using the local 90^{th} percentile as a threshold. However, too extreme weather tends to destroy the crop output regardless of management practices, limiting our ability to study the adaptive effect of the management. We therefore use the 80^{th} percentile threshold as our baseline criterion for the wet weather anomaly. We also provide results for alternative thresholds.

Lastly, we also report section scatter plots for the five-rate and two-rate experimental datasets used in our main analysis. In figure 10, the colors of dots represent different fields. In figure 12, the dark and light blue dots indicate the single and split applications. In the case of a split application, the total application rates of N are used. A grey horizontal line refers to 250 ppm, which is the threshold of N deficiency in the corn stalk residual.

[22]Data is available publicly at https://daymet.ornl.gov/getdata.
[23]The Iowa Environmental Mesonet data is publicly available at https://mesonet.agron.iastate.edu.

Table 8: Description of Data Sets

Abbreviation	Type (structure)	Description	Variables	Period	Fields	Obs. (units)
seven-rate	Experiment (Field)	For each field, 7 levels of N rate were examined from 0 to about 302.7lb.	N rate, yield; rotation, city	1987-1991	54	364 (strips)
five-rate	Experiment (Field-block)	For each field, 5 levels of N rate are examined with 3-5 replications.	N rate, yield; rotation, form, timing, drainage, soil characteristics, coordinates	2017-2021	36	586 (strips)
two-rate-yield	Experiment (Field-block)	For each field, two levels of N rate are examined at most 22 replications. Three types of experiments are conducted: (1) farmer's chosen rate (manure) vs + chemical 50lb, (2) farmer's chosen rate (chemical) vs + 50lb, and (3) farmer's chosen rate (chemical) vs -50lb.	N rate, yield; rotation, form, timing, drainage, soil characteristics, planting date, landform, coordinates, GDD of April-July	2006-2014	169	1837 (strips)
two-rate-CSNT	Experiment + CSNT (Field)	For each field, 9-18 corn stalk samples labeled by treatment regardless of block are tested.	N rate, nitrate level in corn stalk residual; rotation, form, timing, drainage, soil characteristics, CSR, landform, coordinates, GDD of April-July	2007-2010	130	2297 (samples)
GSS	Survey + CSNT (Field)	For each field, 3-4 corn stalk samples are tested.	N rate, nitrate level in corn stalk residual; rotation, form, timing, drainage, soil characteristics, CSR, HEL, landform, coordinates, GDD of April-July	2006-2016	3917	13715 (samples)
Weather	Public data	(1) NASA Daymet: 1km x 1km gridded high-resolution data matched with data by coordinates	Daily precipitation	1980-2021		
		(2) Iowa Environmental Mesonet matched with 7R data by the nearest station	Daily precipitation	1950-2021		
SSURGO	Public data	Soil Survey Geographic Database matched with data by coordinates	CSR, drainage, organic matter, landform			

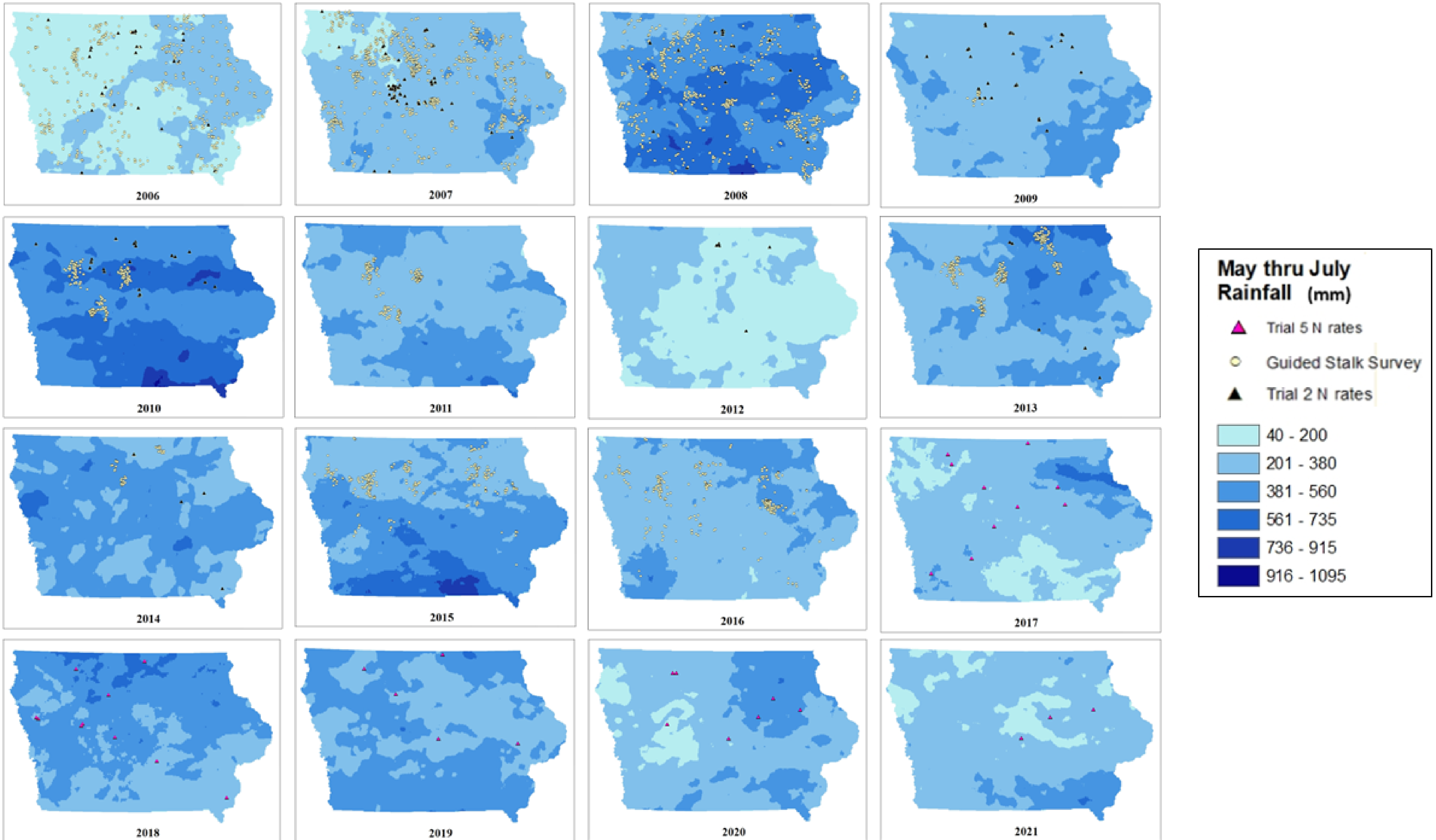

Figure 9: Precipitation and experiment sites, 2006–2021.

Table 9: Description of Variables

Variable	Description	Unit	Data source
Corn yield	Harvested corn yields	bu/acre	ISA. 2021,Kyveryga et al. 2013, 2007
N stalk deficiency	Dummy variable equal to 1 if the end-of-season nitrate level in corn stalk is less than 250 ppm		Kyveryga et al. 2013; Laurent et al. 2023
N rate	Application rates of nitrogen fertilizer	lbs/acre	ISA. 2021, Kyveryga et al. 2013; Laurent et al. 2023; Kyveryga et al. 2007
N1 rate	Application rates of nitrogen fertilizer that farmer chose if the additional fertilizer was randomly treated; otherwise, total application rate	lbs/acre	Kyveryga et al. 2013
N2 rate	Application rates of nitrogen fertilizer added randomly by an experimental design; zero if not treated	lbs/acre	Kyveryga et al. 2013
I(dry)	Dummy variable equal to 1 if the current precipitation is less than 20 percentile of a field-specific empirical distribution of precipitation from May to July (Section 7.2 uses alternative definitions of wet weather.)		Thornton et al. 2022, Herzmann et al. 2004
I(wet p80)	Dummy variable equal to 1 if the current precipitation is greater than or equal to 80 percentile of a field-specific empirical distribution of precipitation from May to July Similarly, I(wet p65) and I(wet p90) are generated based on 65th and 90th percentiles. (Section 7.2 uses alternative definitions of wet weather.)		Thornton et al. 2022, Herzmann et al. 2004
Average precipitation	Mean of a field-specific empirical distribution of precipitation from May to July of past 25 years	mm	Thornton et al. 2022, Herzmann et al. 2004
Standard deviation precipitation	Standard deviation of a field-specific empirical distribution of precipitation from May to July of past 25 years	mm	Thornton et al. 2022, Herzmann et al. 2004
July GDD	Growing degree days until the end of July	GDD	Herzmann et al. 2004
Corn suitability rating (CSR)	Corn Suitability Rating indicates soil productivity from 0 to 100 based on soil type, slope, and weather.		NRCS-USDA. 2022
Drainage	Dummy variable equal to 1 if drainage is poor like tile drainage		NRCS-USDA. 2022
Organic matter	Proportion of soil that contains living and dead organic matter like plant residues	%	NRCS-USDA. 2022
Land-form	Categorical variable which groups Iowan land by geomophology, including Des Moines, Northwest Iowa Plains, Southern Iowa Drift Plain, Iowan Surface		NRCS-USDA, 2022

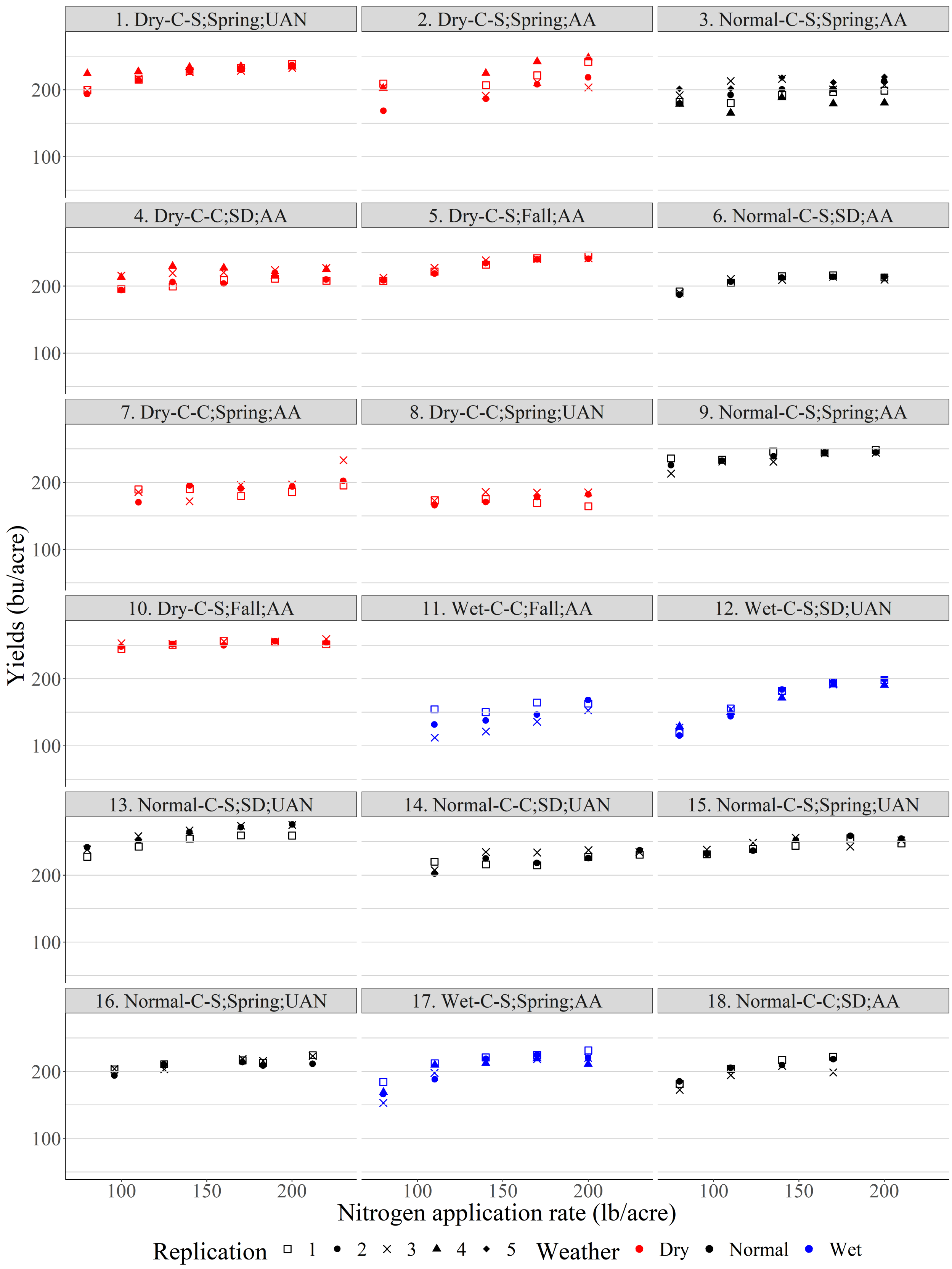

Figure 10: The relationship between corn yields and nitrogen application rates in the five-rate data

Note: Figure 10 presents a scatter plot of corn yields and nitrogen application rates by field. The heading in each box indicates the growing season weather and the nitrogen management combinations. The dots are colored by weather abnormality condition during the growing season and their shapes refer to the experimental replication within the field.

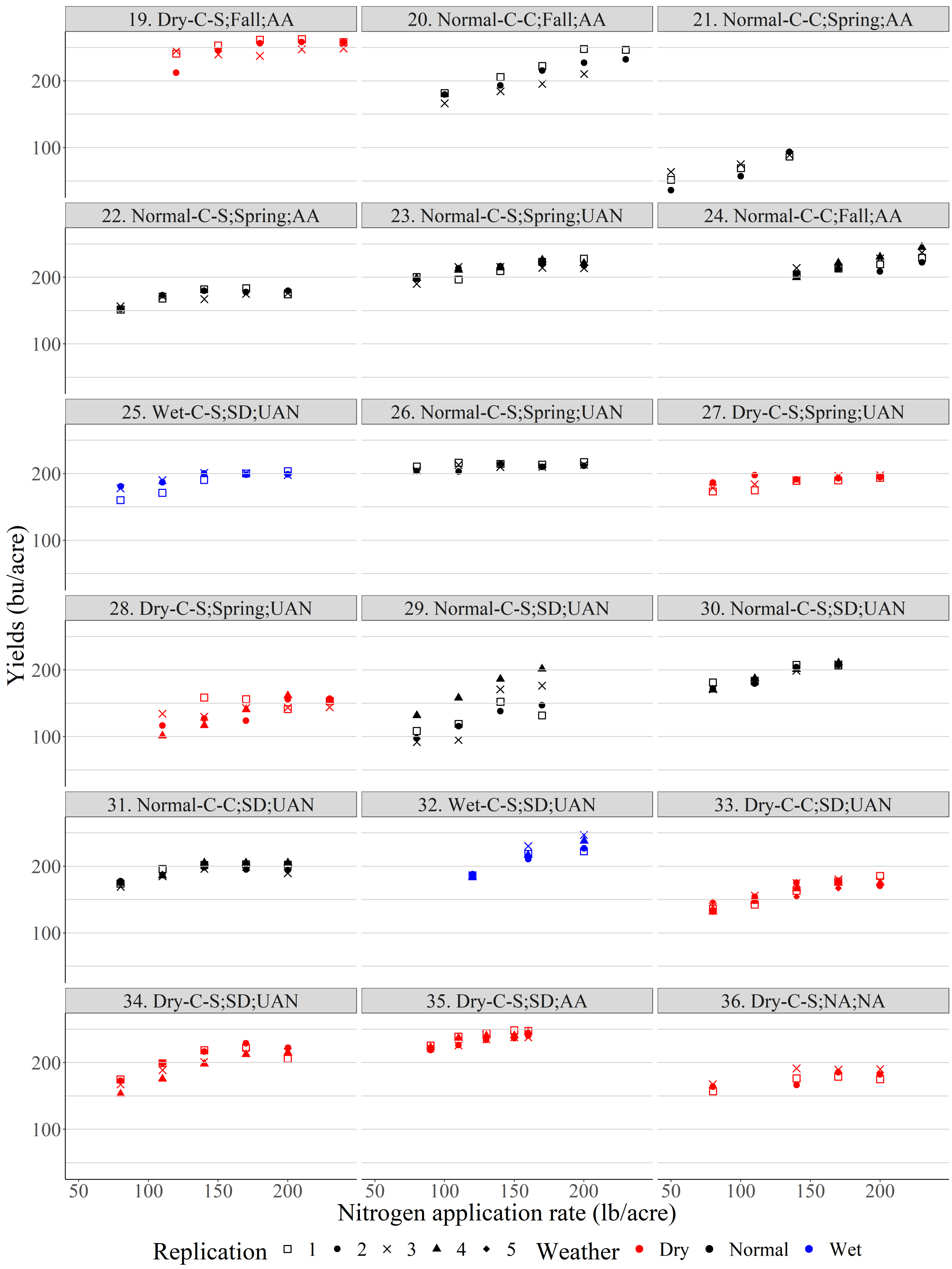

Figure 11: (b) The relationship between corn yields and nitrogen application rates in the five-rate data.

Note: Figure 11 presents a scatter plot of corn yields and nitrogen application rates by field. The heading in each box indicates the growing season weather and the nitrogen management combinations. The dots are colored by weather abnormality condition during the growing season and their shapes refer to the experimental replication within the field.

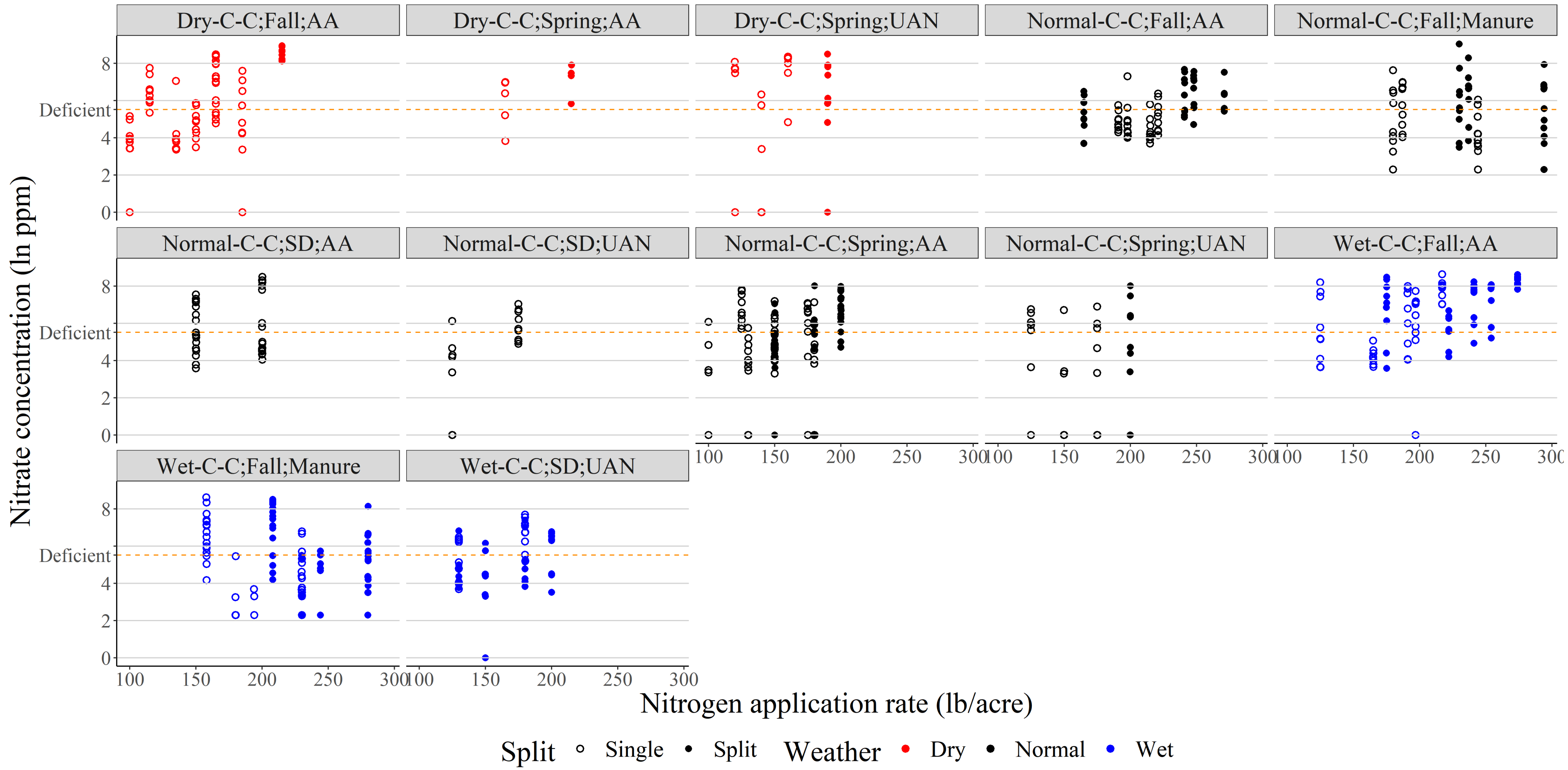

Figure 12: The Relationship between Nitrate Concentration and N Application Rates in the two-rate-CSNT data: Corn-Corn RotationThe relationship between nitrate concentration and nitrogen application rates in the two-rate Cornstalk Nitrate Test data: Corn-corn rotation.

Note: Figure 12 presents a scatter plot of nitrate concentration and nitrogen application rates for each weather and management combination. The shape of each dot indicates whether nitrogen was applied in a single or split application, while the color corresponds to the weather condition. The y-axis represents the natural logarithm of nitrate concentration, with lines indicating the deficiency level labeled as ln(250).

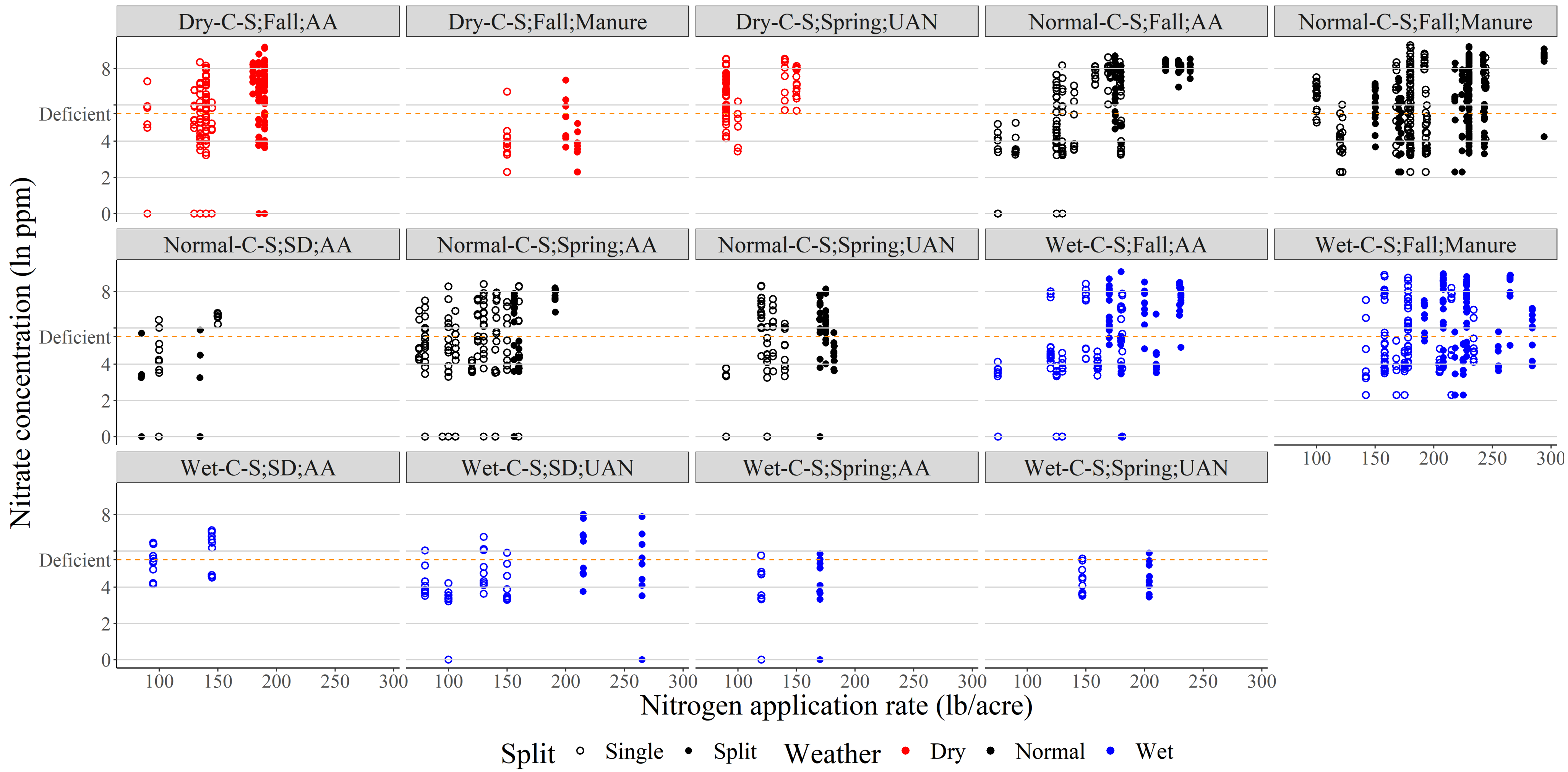

Figure 13: The relationship between nitrate concentration and nitrogen application rates in two-rate Cornstalk Nitrate Test data: Corn-soybean rotation.

Note: Figure 13 presents a scatter plot of nitrate concentration and nitrogen application rates for each weather and management combination. The shape of each dot indicates whether nitrogen was applied in a single or split application, while the color corresponds to the weather condition. The y-axis represents the natural logarithm of nitrate concentration, with lines indicating the deficiency level labeled as ln(250).

Appendix B - Management Practices in Section 5

Table 10: Estimation Results for Production Function with Split Application (Table 5)

	Dependent variable: corn yield (bu/acre)			
	(1)	(2)	(3)	(4)
	Full	**Fall-Corn**	**Fall-Soybean**	**Spring-Soybean**
N_1 rate	19.270***	188.199***	3.770	101.779*
	(6.219)	(45.042)	(7.528)	(58.931)
N_1 rate squared	-1.552***	-11.674***	-0.328	-10.188
	(0.439)	(2.729)	(0.488)	(6.480)
N_2 rate	36.378***		24.334***	133.868**
	(7.565)		(7.242)	(66.838)
N_2 rate squared	-15.334***	2.624***	-9.604***	-65.301**
	(3.619)	(0.413)	(3.501)	(32.627)
N_1 rate × I(wet p80)	-15.642	-368.530***	17.034	-162.701*
	(15.290)	(45.088)	(14.328)	(84.292)
N_1 rate squared × I(wet p80)	1.518	24.197***	-0.920	16.617*
	(1.116)	(2.818)	(1.009)	(8.583)
N_2 rate × I(wet p80)	-31.218**	16.394		-184.036***
	(13.030)	(19.384)		(65.311)
N_2 rate squared × I(wet p80)	15.448**	-7.864	-0.189	88.315***
	(6.211)	(9.087)	(0.793)	(31.709)
N_1 rate × I(dry)	-3.965	-162.580***	-13.816	-83.918
	(8.000)	(47.955)	(14.956)	(61.069)
N_1 rate squared × I(dry)	0.331	10.044***	1.843	8.767
	(0.637)	(2.904)	(1.446)	(6.657)
N_2 rate × I(dry)	-17.051*		-4.545	
	(9.773)		(9.801)	
N_2 rate squared × I(dry)	8.249*	-4.060***	1.239	
	(4.462)	(1.089)	(4.550)	
I(dry)	12.653	650.056***	20.956	196.428
	(25.521)	(193.305)	(40.277)	(134.017)
I(wet p80)	34.775	1369.330***	-66.985	406.536*
	(50.349)	(176.696)	(48.812)	(209.505)
Corn suitability rating (CSR)	0.236***	0.124*	-0.018	1.186***
	(0.073)	(0.072)	(0.061)	(0.384)
Organic matter	0.691***	0.275***	0.473	4.952*
	(0.197)	(0.069)	(0.660)	(2.678)
Average precipitation	-0.196**	-0.561***	-0.145	0.412
	(0.096)	(0.114)	(0.103)	(0.445)
Standard deviation precipitation	0.397***	-0.339	0.320***	0.499**
	(0.096)	(0.241)	(0.104)	(0.220)
Drainage	-5.630***	-5.351**	3.369	-26.402***
	(1.808)	(2.113)	(2.561)	(6.773)
Constant	132.345***	-318.230	188.714***	-385.957**
	(35.968)	(194.923)	(39.679)	(167.190)
Landform FE	Yes	Yes	Yes	Yes
Observations (strips)	1161	204	661	197

Table 10: Estimation Results for Production Function with Split Application (Table 5)

	Dependent variable: corn yield (bu/acre)			
	(1)	(2)	(3)	(4)
	Full	**Fall-Corn**	**Fall-Soybean**	**Spring-Soybean**
R^2	0.346	0.844	0.402	0.792
Std.Errors	Field	Field	Field	Field

Note: Table 10 shows the results for the linear model of the production function using the two-rate experimental dataset from the Iowa Soybean Association. The N_1 rate represents the farmer's selected rate, while the N_2 rate indicates the additional application rate, randomly assigned as zero for the control group and 50 lbs for the treatment group. The unit of the nitrogen rate variable is 25 lbs, and the variable I(wet) is a dummy variable equal to 1 if the weather was wet. Standard errors are clustered at the field level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Production Function Estimation Results Used for Analysis in Table 4

	Soybean	Corn	AA	UAN	Manure	Fall	Spring	SD
Constant	135.288***	135.421***	170.913***	80.759***	433.240***	105.883***	189.245***	80.759***
	(11.161)	(17.231)	(11.933)	(29.452)	(149.555)	(18.115)	(15.236)	(29.649)
N rate	24.092***	13.932***	10.227***	24.211***	3.839	23.479***	16.241***	29.472***
	(3.544)	(3.213)	(3.528)	(4.501)	(12.933)	(4.866)	(2.910)	(4.322)
N rate squared	-1.673***	-0.532**	-0.352	-1.596***	-0.093	-0.979***	-1.079***	-1.964***
	(0.283)	(0.268)	(0.335)	(0.353)	(0.804)	(0.337)	(0.249)	(0.354)
N rate x I(wet p80)	14.443*	-24.580***	31.985***	8.259	-19.516	-34.126***	38.202***	2.999
	(7.563)	(7.278)	(10.796)	(9.890)	(23.641)	(8.284)	(7.560)	(9.863)
N rate squared x I(wet p80)	-0.699	2.054***	-2.458**	-0.182	1.435	2.501***	-2.852***	0.186
	(0.609)	(0.691)	(0.950)	(0.744)	(1.543)	(0.736)	(0.627)	(0.748)
N rate x I(dry)	-7.722	4.762	1.905	-2.360	14.522	-6.898	-9.663	2.288
	(5.037)	(8.129)	(5.391)	(7.127)	(17.402)	(6.026)	(6.164)	(6.128)
N rate squared x I(dry)	0.796*	-0.559	-0.244	0.321	-0.892	0.019	0.987*	-0.164
	(0.409)	(0.679)	(0.471)	(0.591)	(1.101)	(0.426)	(0.522)	(0.501)
Corn suitability rating (CSR)					0.006			
					(0.100)			
Organic matter					0.257			
					(0.296)			
Average precipitation					-1.196***			
					(0.457)			
Standard deviation precipitation					1.417***			
					(0.425)			
Drainage					2.259			
					(5.007)			
Num.Obs.	420	166	269	305	532	87	246	241
R2	0.949	0.967	0.965	0.946	0.473	0.976	0.969	0.950
Std.Errors	Block	Block	Block	Block	Field	Block	Block	Block
FE (Field$\times$block)	Yes	Yes	Yes	Yes	No (Y$\times$L)	Yes	Yes	Yes

Note: Table 11 provides the production function estimates that are used in the analysis in Table 4. The nitrogen rate is scaled by a factor of 1/25. The model employed field-by-block fixed -ffects using the five-rate experimental data, except for the Manure subsample. As there are no observations of manure in the five-rate experimental data, we use the two-rate experimental data before 2011 after excluding outliers at 5% for N rate and 1% for yields. For the manure subsample, we use fixed-effects of year-by-landform and control variables of CSR, organic matter, average precipitation, standard deviation precipitation, and drainage. Standard errors are clustered at the field level for the manure subsample and at the block level for other subsamples.

*, **, and *** denotes significant level at 10%, 5%, and 1% respectively.

Table 12: Damage Function Estimation Results Used for Analysis in Table 4

	Logit model for N stalk defficiency							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	C-S	C-C	AA	UAN	Manure	Fall	Spring	SD
I(wet p80)	0.795***	1.188***	0.958***	0.800***	0.845***	0.956***	0.946***	0.667***
	(0.0755)	(0.111)	(0.0892)	(0.106)	(0.157)	(0.0970)	(0.0931)	(0.169)
I(dry)	0.00155	0.654***	-0.250**	0.287**	0.473***	0.0626	0.344***	-0.256
	(0.0871)	(0.144)	(0.116)	(0.128)	(0.159)	(0.114)	(0.112)	(0.223)
N rate	-0.00740***	-0.00612***	-0.0112***	-0.00922***	-0.00342***	-0.00565***	-0.0102***	-0.0129***
	(0.000976)	(0.00125)	(0.00123)	(0.00142)	(0.00122)	(0.00103)	(0.00125)	(0.00215)
Corn suitability rating (CSR)	-0.00532***	-0.000569	-0.00315	-0.00390	0.00124	-0.000171	-0.00354	-0.00715*
	(0.00192)	(0.00313)	(0.00232)	(0.00267)	(0.00446)	(0.00257)	(0.00237)	(0.00414)
Organic matter	0.0195	-0.0411*	-0.00768	0.00535	-0.0218	-0.0592**	0.0172	0.00509
	(0.0177)	(0.0229)	(0.0260)	(0.0275)	(0.0409)	(0.0278)	(0.0198)	(0.0265)
Average precipitation	-0.00210	0.00206	0.000849	0.000815	0.00589	0.000869	0.00225	-0.00115
	(0.00190)	(0.00304)	(0.00224)	(0.00279)	(0.00450)	(0.00265)	(0.00221)	(0.00437)
Standard deviation precipitation	0.00989***	0.00867**	0.00321	0.0223***	0.00740	-0.000271	0.0159***	0.0144**
	(0.00257)	(0.00410)	(0.00293)	(0.00397)	(0.00595)	(0.00333)	(0.00317)	(0.00647)
Drainage	-0.188***	-0.421***	-0.438***	-0.172*	-0.216	-0.506***	-0.225***	-0.0927
	(0.0661)	(0.100)	(0.0870)	(0.0989)	(0.155)	(0.0986)	(0.0791)	(0.126)
Constant	1.187	-0.386	1.866**	-1.181	-2.482	1.688	-1.023	1.204
	(0.742)	(1.121)	(0.925)	(1.049)	(1.608)	(1.034)	(0.851)	(1.666)
FE (landform)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,259	3,792	6,065	3,905	2,309	5,139	5,459	1,634
R2	0.0502	0.0819	0.0720	0.0679	0.0348	0.0522	0.0760	0.0803
Std.Errors	Field	Field	Field	Field	Field	Field	Field	Field

Note: Table 12 presents the damage function estimates used to obtain β in Table 4. For each subsample, we estimate the logit model using the GSS data. The nitrogen rate is scaled to 25 lbs. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Appendix C - Robustness Tests

Table 13: Estimates with Alternative Model Specifications

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	95.06**	170.72**	100.36	160.33***	159.63***
	(44.61)	(83.75)	(78.77)	(12.34)	(9.33)
N rate	29.23**	29.04***	25.29***	15.78***	16.34***
	(12.81)	(8.93)	(6.47)	(4.54)	(2.99)
N rate squared	-1.67*	-1.80***	-1.53***	-0.85**	-0.90***
	(0.93)	(0.68)	(0.52)	(0.40)	(0.26)
N rate x I(wet)	-1.53	-2.59	4.44	20.53*	19.97***
	(20.82)	(20.61)	(18.97)	(11.09)	(7.42)
N rate squared x I(wet)	0.18	0.42	-0.09	-1.34	-1.28**
	(1.57)	(1.56)	(1.43)	(0.90)	(0.60)
N rate x I(dry)	-11.10	-10.15	-12.85	1.26	0.72
	(14.86)	(10.00)	(9.59)	(6.15)	(4.43)
N rate squared x I(dry)	0.54	0.62	0.90	-0.09	-0.04
	(1.16)	(0.79)	(0.76)	(0.52)	(0.38)
α	0.89	0.77	1.1	2.6	2.4
SE	(0.91)	(0.83)	(0.94)	(1.55)	(0.92)
Num.Obs.	586	574	574	586	586
R2	0.189	0.309	0.383	0.925	0.954
Std.Errors	Field	Field	Field	Field	Block
FE	No	No	Year	Field x Year	Block x Year
Controls	No	Yes	Yes	No	No

Note: Table 13 shows the corn production function estimation results employing different control variables with the five-rate experimental data. The unit of the nitrogen rate variable is 25 lbs, and the variables I(wet) and I(dry) are dummy variables equal to 1 if the weather is wet or dry, respectively. The control variables for column (2) include corn suitability rating, a dummy for poor drainage, soil organic matter, N form, N timing, and mean and standard deviation of historic precipitation. Table 17 in the appendix shows the complete results for columns (2) and (3).

*, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 14: Thresholds (mm) for Excessive Rainfall by Alternative Datasets

	Five-rate	Two-rate (yield)	Two-rate (CSNT)	GSS	Seven-rate
A. Local percentile (mm)					
p20	296.4	278.8	277.1	278.8	231.1
	(25.3)	(24.9)	(23.5)	(29.8)	(13)
p65	396.7	402.3	401.9	397.1	354
	(30.5)	(16.7)	(18.2)	(20.6)	(24.2)
p80	450.2	444.2	445.3	448.2	391
	(39.8)	(24.6)	(22.4)	(33.1)	(27.3)
p90	531.6	514.7	511.5	516	434.2
	(50.8)	(42.9)	(37.4)	(50)	(30.1)
B. Local mean +- 20% (mm)					
0.8 mean	303	295.2	294.9	294.7	253.4
	(22.1)	(12.8)	(12.7)	(17.1)	(12.1)
1.2 mean	454.6	442.7	442.3	442.1	380.1
	(33.2)	(19.2)	(19.1)	(25.6)	(18.1)
C. Local mean +- 1 SD (mm)					
mean-1SD	261.2	244.5	241.4	243.2	221.1
	(21.9)	(14.2)	(11.7)	(20.3)	(14)
mean+1SD	496.4	493.4	495.9	493.6	412.5
	(37.1)	(27.2)	(27.3)	(31.5)	(21.4)
D. Absolute percentile (mm)					
p20	274.1	286.9	269.5	277.6	273.1
p80	454	455.7	453.4	449.3	456.1
N.fields	36	169	130	3,917	54
N.obs	586	1,837	2,297	13,715	364
Period	2017-2021	2006-2014	2007-2010	2006-2016	1987-1991

Note: Table 14 presents alternative definitions of abnormal weather. CNST=cornstalk nitrate test. GSS=Guided Stalk Nitrate Survey. The first three panels report the mean and standard deviation of each field's threshold precipitation levels for each data set. We define the thresholds using three alternative methodologies: (panel A) the percentile of the local empirical distribution of precipitation; (panel B) 0.8 and 1.2 times the historical mean precipitation; and (panel C) one standard deviation from the historical mean precipitation. In the last panel (panel D), the absolute percentiles are obtained from a single empirical distribution of precipitation that includes all fields. The unit measure for precipitation is *mm*.

Table 15: Production Function Estimates with Alternative Definitions of Excessive Rainfall

	Model 1 Mean +- 20%	Model 2 Mean +- 1SD	Model 3 Absolute percentile
Constant	68.799***	164.062***	165.035***
	(8.818)	(7.219)	(8.145)
N rate	15.080***	15.160***	17.497***
	(3.036)	(2.607)	(3.073)
N rate squared	-0.786***	-0.761***	-1.007***
	(0.259)	(0.224)	(0.257)
N rate x I(wet)	20.246***	37.563***	12.418*
	(7.719)	(5.276)	(6.737)
N rate squared x I(wet)	-1.226*	-2.782***	-0.491
	(0.669)	(0.451)	(0.566)
N rate x I(dry)	2.020	2.605	-1.893
	(4.352)	(3.938)	(4.207)
N rate squared x I(dry)	-0.171	-0.266	0.145
	(0.368)	(0.337)	(0.353)
R2	0.956	0.956	0.958
Std.Errors	Block	Block	Block
FE (Field x block)	Yes	Yes	Yes
α	2.6	4.7**	1.5
	(1.15)	(1.46)	(0.63)
Num.Obs.	586	586	586
Dry (%)	43.34	26.11	34.81
Normal (%)	45.05	67.06	51.19
Wet (%)	11.60	6.83	13.99

Note: Table 15 shows the results for a fixed-effect production function of corn estimated using the five-rate experimental data as in table 2, but with alternative definitions of abnormal weather. The unit of the nitrogen rate variable is 25 lbs, and the variables I(wet) and I(dry) are dummy variables equal to 1 if the weather was wet or dry, respectively. The regressions also include an interaction between a dummy for rotation and nitrogen rate. All standard errors are clustered at the block level. The last panel of the table reports the percentage of observations that fall into each weather category, as defined by the alternative definitions of abnormal weather. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 16: Results for Alternative Experiments and Combinations of Management Practices

	Production		Damage		Expected Marginal Damage	
	alpha	Obs.	beta	Obs.	Normal Weather	Wet Weather
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1. 7-rate Experimental Data:						
Full	0.86	364				
	(0.17)					
Corn-soybean (C-S)	0.62	182				
	(0.18)					
Corn-corn (C-C)	1.04	182				
	(0.23)					
Panel 2. GSS Survey Data:						
Fall; AA			1.687	3112	0.136	0.23
			(0.107)		(0.007)	(0.009)
Fall; Manure			1.63	2020	0.135	0.22
			(0.135)		(0.007)	(0.013)
Spring; AA			1.75	2562	0.107	0.186
			(0.149)		(0.005)	(0.012)
Spring; UAN			1.516	2618	0.167	0.253
			(0.084)		(0.007)	(0.009)
SD; C-S			1.316	1085	0.193	0.255
			(0.115)		(0.011)	(0.014)
SD; C-C			1.698	508	0.115	0.194
			(0.309)		(0.015)	(0.021)
AA; C-S; Fall			1.555	2359	0.146	0.227
			(0.113)		(0.007)	(0.011)
AA; C-S; Spring			1.602	1662	0.122	0.196
			(0.161)		(0.007)	(0.015)
Manure; C-S; Fall			1.473	1260	0.148	0.218
			(0.161)		(0.009)	(0.017)
Manure; C-C; Fall			1.773	727	0.118	0.209
			(0.248)		(0.011)	(0.02)

Note: Table 16 reports estimates for α from the seven-rate experimental data and estimates of β for 10 combinations of practices using the large Guided Stalk Nitrate survey dataset. The estimates for α are obtained using the field fixed-effect model for the production function estimation. All models for β include controls for excessive dry weather, nitrogen rate, corn suitability rating, mean and variance of precipitation, drainage, and landform fixed-effects. Standard errors for β estimates are clustered at the field level. AA=anhydrous ammonia. UAN=urea ammonium nitrate. SD=side-dressing.

Table 17: Complete Estimation Results of Table 13

	Model 1	Model 2	Model 3	Model 4	Model 5
N rate	29.227**	29.043***	25.285***	15.785***	16.342***
	(12.809)	(8.933)	(6.473)	(4.545)	(2.986)
N rate squared	-1.670*	-1.800***	-1.533***	-0.848**	-0.902***
	(0.930)	(0.678)	(0.519)	(0.400)	(0.260)
N rate x I(wet p80)	-1.529	-2.593	4.442	20.527*	19.970***
	(20.821)	(20.608)	(18.973)	(11.094)	(7.421)
N rate squared x I(wet p80)	0.177	0.420	-0.090	-1.339	-1.285**
	(1.574)	(1.557)	(1.434)	(0.904)	(0.603)
N rate x I(dry)	-11.100	-10.152	-12.846	1.264	0.721
	(14.858)	(10.000)	(9.588)	(6.149)	(4.432)
N rate squared x I(dry)	0.541	0.623	0.897	-0.091	-0.041
	(1.159)	(0.793)	(0.763)	(0.515)	(0.376)
Corn suitability rating (CSR)		0.672	1.040**		
		(0.495)	(0.435)		
Organic matter		2.664	-0.737		
		(6.154)	(4.428)		
Drainage		-0.461	14.523		
		(13.895)	(10.065)		
Form (UAN)		-14.319	17.972		
		(11.932)	(14.115)		
Timing (SD)		0.055	-13.471		
		(17.395)	(15.587)		
Timing (Spring)		-2.201	-10.353		
		(16.989)	(13.956)		
Year (2018)			-6.555		
			(13.936)		
Year (2019)			-39.450**		
			(15.285)		
Year (2020)			-64.953***		
			(20.495)		
Year (2021)			-12.366		
			(17.178)		
Constant	95.065**	170.717**	100.362	160.333***	159.634***
	(44.605)	(83.754)	(78.769)	(12.342)	(9.332)
FE	No	No	Year	Field x Year	Block x Year
Num.Obs.	586	574	574	586	586
R2	0.189	0.309	0.506	0.925	0.954
Std.Errors	Field	Field	Field	Field	Block

Table 17 shows the complete estimation results of columns (2) and (3) of Table 13 while other columns are same as Table 13's. One unit of nitrogen rate is scaled to 25 lbs. The default groups of form and timing are AA and fall. The baseline year is 2017. Note that since each field appeared only in one year, the field or block fixed effects perform equivalently to field-by-year or block-by-year effects.

*, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 18: Production Function Estimation Results for α in Table 16

	Full	Soybean	Corn
N rate	0.524***	0.403***	0.644***
	(0.056)	(0.054)	(0.077)
N rate squared	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
N rate x I(wet p80)	-0.058	-0.123*	0.007
	(0.090)	(0.074)	(0.115)
N rate squared x I(wet p80)	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)
N rate x I(dry)	-0.191*	-0.115	-0.268*
	(0.098)	(0.124)	(0.140)
N rate squared x I(dry)	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
I(wet p80)	10.801		
	(7.410)		
I(dry)	20.935***	55.256***	41.708***
	(7.482)	(8.864)	(10.317)
Constant	91.738***	91.385***	86.604***
	(4.807)	(3.904)	(6.090)
Num.Obs.	364	182	182
R2	0.906	0.939	0.921
Std.Errors	Field	Field	Field
FE	Field	Field	Field

Table 18 presents the production function estimation results using the seven-rate experimental data used to obtain α in Panel 1 of Table 16. The unit of nitrogen rate is scaled to 25 lbs. As each field was recorded only in one year, field fixed-effects controls for field-by-year effects.

*, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 19: Damage Function Estimation Results for β in Table 16

	Logit model for N stalk defficiency									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fall; AA	Fall; Manure	Spring; AA	Spring; UAN	SD; C-S	SD; C-C	AA; C-S; Fall	AA; C-S; Spring	Manure; C-S; Fall	Manure; C-C; Fall
I(wet p80)	0.989***	0.898***	0.913***	0.922***	0.654***	0.904***	0.839***	0.807***	0.727***	1.006***
	(0.122)	(0.167)	(0.147)	(0.129)	(0.210)	(0.313)	(0.142)	(0.182)	(0.222)	(0.270)
I(dry)	-0.402**	0.471***	-0.160	0.542***	-0.425*	0.429	-0.464***	-0.383*	0.366*	0.603**
	(0.161)	(0.169)	(0.187)	(0.150)	(0.251)	(0.506)	(0.173)	(0.219)	(0.216)	(0.279)
N rate	-0.0106***	-0.00365***	-0.0130***	-0.00806***	-0.0124***	-0.00852**	-0.00746***	-0.0122***	-0.00290	-0.00230
	(0.00175)	(0.00135)	(0.00203)	(0.00170)	(0.00294)	(0.00388)	(0.00242)	(0.00296)	(0.00200)	(0.00245)
CSR	-6.26e-05	-0.000949	-0.00633*	-0.00362	-0.00772	-0.0131	-0.000747	-0.00938**	-0.00528	0.00458
	(0.00319)	(0.00487)	(0.00360)	(0.00329)	(0.00523)	(0.00831)	(0.00359)	(0.00411)	(0.00603)	(0.00864)
Organic matter	-0.0507	-0.0643	0.00386	0.0118	0.0948*	-0.0427*	-0.0169	0.0198	-0.0307	-0.122
	(0.0376)	(0.0461)	(0.0276)	(0.0419)	(0.0554)	(0.0236)	(0.0488)	(0.0234)	(0.0708)	(0.0758)
Average precipitation	0.000857	0.00316	0.00417	0.00398	-0.00172	0.000602	0.00167	-0.000553	-0.000862	0.00594
	(0.00342)	(0.00489)	(0.00323)	(0.00347)	(0.00558)	(0.00878)	(0.00376)	(0.00433)	(0.00603)	(0.00981)
SD precipitation	-0.00323	0.0103*	0.00516	0.0281***	0.0170**	0.0131	-0.00217	0.00578	0.0134*	0.00473
	(0.00405)	(0.00626)	(0.00455)	(0.00488)	(0.00815)	(0.0120)	(0.00452)	(0.00586)	(0.00775)	(0.0120)
Drainage	-0.596***	-0.386**	-0.326***	-0.274**	0.253	-0.479**	-0.472***	-0.344***	-0.183	-0.730**
	(0.125)	(0.172)	(0.117)	(0.139)	(0.188)	(0.223)	(0.150)	(0.128)	(0.248)	(0.284)
Constant	3.072**	-0.967	0.303	-3.146**	0.0198	1.104	1.773	2.194	-0.176	-1.139
	(1.381)	(1.751)	(1.357)	(1.272)	(2.172)	(3.151)	(1.548)	(1.701)	(2.226)	(3.374)
FE (landform)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,112	2,020	2,562	2,618	1,085	508	2,359	1,662	1,260	727
R2	0.0741	0.0411	0.0678	0.0847	0.0738	0.0835	0.0568	0.0638	0.0327	0.0596
Std.Errors	Field	Field	Field	Field	Field	Field	Field	Field	Field	Field

Table 19 shows the damage function estimation results for β in Panel 2 of table 16. We use the GSS data to estimate a logit model for each subsample. The unit of nitrogen rate is scaled to 25 lbs. CSR and SD are abbreviations of corn suitability rating and standard deviation. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.