Learning About a Warming World:
Attention and Adaptation in Agriculture

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Abstract

Global warming threatens the livelihoods of 600 million low-income agricultural workers. I study how farmers learn about the environment and the consequences for climate change adaptation. Rice farmers in Bangladesh must form beliefs about local soil salinity, a climate danger exacerbated by rising sea levels that can be mitigated by planting salinity-tolerant seeds. Comparing beliefs about salt levels to agronomic readings, I find that on average farmers hold correct environmental perceptions, but this masks substantial errors across individuals. I explain this pattern using a conceptual framework of belief formation featuring an identification problem: farmers must learn about multiple unobserved environmental threats from ambiguous signals. As a result, farmers endogenously process data in support of their priors, e.g., someone worried about high salinity will interpret low yield as a sign of too much salt. Climate change amplifies this process by systematically altering the environmental risks farmers consider most threatening. I test and confirm the framework’s predictions using a pair of natural experiments that capture two changes emblematic of global warming: salient shocks that capture attention (e.g., tidal flooding) and subtle shifts that go unnoticed (e.g., groundwater contamination through rising sea-levels). Despite equal effects on true salt levels, I find asymmetric impacts on beliefs as subtle groundwater intrusion causes no change in perceptions while saltwater floods spur significant overestimation. Analyses of rainfall and flooding perceptions exhibit similar patterns to those of soil salinity. In large-scale field experiments, I document major economic consequences of environmental beliefs: correcting misperceptions significantly alters farmers’ demand for salinity-tolerant seeds with substantial impacts on profits. I use this experimental variation to estimate and validate a structural model of seed choice that allows me to simulate counterfactual policies and underscores the influence of environmental beliefs.

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1 Introduction

The environmental change stemming from global warming poses an existential threat, especially to the 600 million smallholder farmers whose livelihoods directly depend on the climate. To mitigate these dangers, individuals must adapt to the evolving world around them. Optimal decision-making requires farmers to form accurate beliefs about the environmental conditions they face, a potentially difficult task amid the subtle shifts (e.g., rising sea levels) and salient shocks (e.g., flooding) characteristic of the warming planet.

How do farmers learn about and subsequently adapt to climate change? I examine this belief formation process and its economic impacts in the context of soil salinity, flooding, and monsoon intensity, three of the most important dimensions of global warming impacting the world’s poor. Although these factors play a key role in agricultural choices, farmers have little access to direct measurement of local climate conditions such as flood risk or soil salinity, creating scope for inefficient behavior if farmers misperceive their environment. My study takes place in Bangladesh, ground zero for the harmful consequences of climate change. In this paper, I describe new data on environmental beliefs and true conditions, build a simple conceptual framework of learning amid global warming, use several quasi-natural experiments to test the theory’s key predictions, present results from large-scale field experiments that quantify the economic impacts of environmental beliefs, and estimate a structural model of adaptation decisions to conduct policy counterfactuals.

I first assess the accuracy of climate beliefs by collecting information on farmers’ perceptions and the ground truth. In a large-scale panel survey with nearly 2,300 rice farmers across 250 villages, I use a visual method to precisely elicit probabilistic beliefs in this low-numeracy population. Focusing on the case of soil salinity, I measure farmers’ expectations about the salt content of their own plots. This belief directly enters into high-stakes decision-making as farmers choose whether or not to plant salinity-tolerant varieties, which grow better than alternative seeds in high salt conditions but relatively worse in low ones. To capture the ground truth in the absence of existing salinity data, I use agronomic sensors to test soil conditions on farmers’ own plots during repeated readings over the agricultural season.

Despite a lack of access to measurement technology, average soil salinity beliefs across

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1 Salt-affected soils threaten agricultural productivity on 30% of irrigated land worldwide (Hopmans et al., 2021). One in four people face significant flood risk, 89% of whom live in low- or middle-income countries (Rentschler et al., 2022). The South Asian monsoon provides water to nearly a quarter of humanity.
farmers exhibit remarkable accuracy when comparing perceptions to the direct soil readings from farmers’ own plots.\(^2\) This overall relationship masks significant heterogeneity across farmers, however, with the vast majority of variation in farmers’ perceptions left unexplained by the ground truth. As evidence that this dispersion reflects more than noise, I show that gaps between soil salinity beliefs and the agronomic readings strongly predict farmers’ decisions to plant salinity-tolerant seeds. Farmers with more land, more experience, and viewed as more skilled by their neighbors hold more accurate beliefs, suggesting that learning frictions might play a key role.

I document similar patterns of beliefs with respect to flooding and monsoon intensity. To overcome biased coverage in existing flood data, I develop an approach to detect local inundation at a daily level anywhere in the world by combining methods from machine learning and geophysics in the analysis of satellite data.\(^3\) For rainfall, I use remote sensing data combined with weather models to estimate the intensity of precipitation during the monsoon season in each village. Similarly to the case of soil salinity, I find significant heterogeneity in beliefs that predicts important economic behavior, including demand for a flood insurance contract.

To explain this equilibrium distribution of environmental misperceptions, I use a simple conceptual framework of belief formation amid climate change. Guided by the results of narrative qualitative interviews and open-ended questions with my main sample, the framework features farmers who infer environmental conditions by observing the output of their harvest and physical characteristics of their crops. Different potential factors impacting yield manifest themselves in the same way, creating an identification problem (Acemoglu et al., 2016). A farmer observing low yield, for example, cannot distinguish between high soil salinity and insufficient fertilizer as the root cause. As a result, I show that Bayesian farmers with arbitrarily small differences in initial beliefs will nevertheless fail to converge to agreement about their local environment if they initially disagree on which environmental threat is more likely. This gap occurs because farmers’ (potentially incorrect) ranking of priors exhibit persistence in this underidentified setting. Initial expectations about which environmental features matter

\(^2\) In a regression of beliefs on the truth, I cannot reject that the coefficient on the agronomic readings equals 1 and the intercept term equals 0.

\(^3\) I describe this method in full in Patel (2023), where I also analyze the economic consequences of flooding and how households adapt to inundation events. To briefly summarize the measurement approach, I estimate surface water at a 90-meter resolution using radar-based satellites that can detect water with incredible accuracy—notably by “seeing” through clouds to avoid the biases plaguing traditional satellite photos. The infrequency of these satellites’ orbits severely restricts their ability to reliably detect all but the longest-lasting floods. To fill in the gaps between satellite passes, I train a supervised machine learning algorithm to predict this gold-standard measure using a battery of other remote sensing data available at a daily frequency. The method effectively extends the coverage of advanced sensors and enables me to estimate two-decades worth of daily flooding at a high spatial resolution.
ter most shape the interpretation of signals, so new data reinforces prior beliefs, similarly to the literature on misspecified learning (Heidhues et al., 2021). For example, a farmer who initially expects soil salinity to be high will (rationally) interpret a bad harvest as evidence of too much salt, even if another factor might actually be the culprit.

How does global warming shape this belief formation process? I focus on how farmers learn from two classes of signals characteristic of climate change: salient shocks and subtle shifts in the environment. In the case of soil salinity, experiencing a flood with saline water (perhaps due to a tidal surge, for instance) constitutes a salient shock by drawing farmers’ attention to the salt that has just been deposited onto the plot’s surface. By contrast, rising sea levels that cause the intrusion of ocean water into a farmer’s irrigation source subtly shifts soil salinity.

Experiencing a salient event instead of a subtle one can generate persistent gaps in learning. I show how this same prediction can emerge under three scenarios: a purely Bayesian model with no behavioral friction, a Bayesian learner with imperfect information, and a farmer facing attention costs. The most appropriate setting will depend on the specific context. In the first Bayesian benchmark, if the informational content of the two types of events differentially changes farmers’ beliefs going into the next period, then farmers will endogenously interpret new data in different ways. This can sustain the initial disagreement perpetually because farmers have shifted their expectations about the relative danger of different environmental risks, which shapes how they process new information in this under-identified setting. Second, even when the underlying informational content of salient shocks and subtle shifts are the same, if farmers fail to notice the subtle changes in their environment, their beliefs will still differentially change, again leading to a gap in priors entering the next harvest. Third, I show that even in the case where the core informational content is the same and farmers notice both the salient shock and the subtle shift such that their posterior beliefs are identical, learning differences can still emerge in equilibrium if the salient shock changes which environmental threats come to mind upon seeing new data. The relevant mechanism depends on the environmental context, e.g., farmers might always notice any

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4 Although I use the terms salient shocks and subtle shifts, conceptually, both are “shocks” in the sense of being unexpected deviations to the climate. The distinction between these two aspects of climate change has been discussed in a psychology literature discussing learning and the adaptation process (Gilbert, 2006; Johnson and Levin, 2009; Gifford, 2011). More broadly, economists have documented that behavior responds more to drastic shifts than to gradual change and the difficulties of learning from infrequent hazards (Davis, 2004; Greenstone and Gallagher, 2008; Da et al., 2014; Wagner, 2022; Heft-Neal et al., 2023).

5 This distinction captures a key way in which my framework differs from other limited attention models (e.g., Hanna et al. (2014)). Contrary to previous work, I assume farmers always incorporate all available data into their learning process—in this case, all observable features of their crops and land. In my set-up, limited attention instead restricts the potential ways in which farmers interpret this information by operating through the set of hypotheses considered as opposed to the data processed.
time it rains when forming monsoon beliefs but not an incremental increase in groundwater salinity when learning about their soil. Regardless of the channel, however, I show that in all cases, experiencing a salient shock instead of a subtle shift can have permanent impacts on beliefs by altering how farmers interpret new data, endogenously changing the diagnosticity of harvest signals with respect to different environmental threats.

I test these theoretical predictions using two quasi-random natural experiments that separately identify the causal impact of salient shocks and subtle shifts in soil salinity. The large geographic scope of my surveys—spanning approximately 15 percent of the land area of Bangladesh—provides substantial variation in underlying climate to provide the statistical power for these analyses. First, I examine flooding with salty water as an example of a salient shock. These floods deposit salt directly onto plots. Underscoring the attention-grabbing nature of these environmental events, farmers mention them more than any other factor when recalling the determinants of their soil’s salinity. Second, I use salinity intrusion into irrigation water as an illustration of a subtle shift. As sea levels rise, salty water from the ocean can contaminate the water used by farmers to irrigate their rice plants, increasing soil salinity. This process—much of which occurs underground—can easily go overlooked.

I use two distinct identification strategies to estimate the consequences of these environmental events. First, I use a difference-in-differences design to isolate the causal impact of experiencing a flood with more instead of less saline water—the salient environmental shock. I hold constant any other general impacts of floods (unrelated to the saltiness of the water) and the propensity to experience a salty flood by conditioning on a machine-learning generated measure of flood risk and the salt content of local river systems I calculate from data collected at river stations scattered throughout the country. Second, I use a triple difference-in-differences framework to capture idiosyncratic variation in salinity intrusion into irrigation water—the subtle environmental shift. I compare villages with differentially higher exposure to quasi-random deviations in sea-level rise and ocean salinity modulated by the village’s distance to the coast, using satellite data to measure ocean height and salt levels.

Consistent with the conceptual framework’s predictions, I find asymmetric impacts of these two types of climate signals on beliefs. Although both saltier floods and contaminated irrigation water cause equivalent increases in true soil salinity as measured by the direct agronomic sensors, only saltier floods—the salient shocks—move farmers’ perceptions of their soil’s salt content, whereas salinity intrusion in irrigation—the subtle shift—has no impact on beliefs. The increase in salinity beliefs following a salty flood far exceeds the true impact on soil conditions, ultimately generating overestimation of salt levels. In line with the model’s key mechanisms, farmers also alter their interpretation of data on crops and yield depending on the nature of their past environmental experiences. Using a lab-in-
the-field exercise to test farmers’ ability to diagnose rice issues, I find that experiencing a salty flood raises farmers’ skill specifically with respect to correctly identifying symptoms distinct of salinity. Overestimation nevertheless occurs because salty floods also increase the likelihood that farmers use generic plant characteristics (e.g., plant death) to learn about salinity. Groundwater intrusion, by contrast, increases the chance that farmers attribute salinity-specific plant features to non-salinity explanations.

These environmental misperceptions have economic costs if they distort important decisions, such as adaptation to climate change. To estimate the causal impact of environmental beliefs on technology adoption, I conduct large-scale field experiments among the same sample of farmers in Bangladesh and find that beliefs have large impacts on agricultural production decisions and profits. I first measure demand for the soil salinity information I gathered from agronomic readings on farmers’ plots, using the Becker-DeGroot-Marschak (BDM) method to preserve incentive compatibility. More than 80% of farmers have a positive willingness-to-pay for these data. Embedding an experiment into this elicitation, I randomly provide some farmers with data on soil readings. This information has large impacts on farmers predictions of future soil salinity conditions, especially among those who held more inaccurate beliefs initially. The treatment effects persist in a follow-up phone survey six months later. To evaluate the consequences for technology adoption, I elicit willingness-to-pay for a salinity-tolerant seed variety, again using BDM. Using treatment assignment as an instrument, I find that 1 s.d. higher soil salinity beliefs causes a 41% increase in demand for salinity-tolerant seeds.

In a separate experiment, I show that the decision to adapt this climate adaptation technology on the margin has high economic stakes. Farmers must match their seed choice to the appropriate environmental conditions: salinity-tolerant varieties grow better than alternatives in high salt conditions but relatively worse in low ones. Prior to planting, I randomly offer some farmers a small amount of these salinity-tolerant seeds for free. This offer causes a significant increase in the share of land planted with a salinity-tolerant variety, especially among farmers who initially overestimated salinity conditions. I return to farmers after harvest and find that farmers who overestimated salt levels and therefore planted more salinity-tolerant seeds in inappropriate (low salinity) soil experience a large reduction in agricultural profits, underscoring the risk of mismatching adaptation and environmental conditions. These results extend beyond soil salinity: in an additional information experiment providing farmers with information about flood risk, I again find strong evidence that environmental beliefs impact economic decision-making, this time as measured by demand for a flood insurance contract.

Finally, I quantify the role of misperceptions about the local environment in climate
change adaptation by using these randomized experiments to discipline a structural model of seed choice. Given the non-linear relationship between technology adoption and beliefs, the reduced form results alone do not reflect the overall effect of expectations on adaptation. I estimate a mixed multinomial logit model with random coefficients to allow for correlation of choices across different seeds (McFadden, 1974; Train, 2009). I estimate the parameters among the treatment group from the seed experiment and then validate the predictions in the control group.\textsuperscript{6} The model fit performs extremely well in this out-of-sample test: regressing true seed choices on the predicted choice probabilities yields a coefficient indistinguishable from 1. Using this structure, I simulate the adoption of salinity tolerant seeds under alternative environmental beliefs. Conditional on the truth, moving from the 10\textsuperscript{th} percentile of salinity beliefs (significant underestimation of salt levels) to the 90\textsuperscript{th} percentile (overestimation of salinity) increases take-up of salinity-tolerant seeds by 81%.

Overall, these results suggest that policymakers can increase appropriate adaptation to climate change by targeting information to places based off their previous exposure to salient shocks versus subtle shifts. The cost of collecting high-quality local data presents one potential practical challenge. For instance, gathering salinity readings from farmers’ own plots may be infeasible at scale. Motivated by this concern, I embed an additional arm into my information experiment that provided farmers solely with geographically aggregated data on salinity without any information specific to their own plots. Nevertheless, I find that farmers have a high demand for this aggregate data and that the treatment effects on behavior are even larger than those from providing the information specifically about farmers’ own land. Collecting and distributing environmental data at scale presents a promising policy for improving adaptation to climate change.

\textbf{Related literature} This study builds on three strands of literature. First, I contribute to the rich set of papers examining adaptation to climate change and environmental threats.\textsuperscript{7} My approach follows an impressive set of papers combining experiments with structural estimation including Todd and Wolpin (2006); Kremer et al. (2011); Duflo et al. (2012), and Attanasio et al. (2012). See Todd and Wolpin (2023) for a review. See, among others, Bardhan (1983), Nordhaus (1991), Fafchamps (1993), Rosenzweig andBinswanger (1993), Mendelsohn et al. (1994), Nordhaus (1994), Kahn (2005), Agrawal (2008), Deschênes and Greenstone (2011), Acemoglu and et al. (2012), Boustan et al. (2012), Gallagher (2014), Hornbeck and Naidu (2014), Hsiang and Jina (2014), Anman and Schlenker (2015), Currie et al. (2015), Desmet and Rossi-Hansberg (2015), Bakkenes and Mendelsohn (2016), Barreca et al. (2016), Burke et al. (2016), Burke and Emerick (2016), Auffhammer (2018), Kahn and Zhao (2018) Kocornik-Mina et al. (2020), Conte et al. (2021), Biardeau et al. (2020), Giuliano and Nunn (2021), Kahn (2021), Peri and Robert-Nicoud (2021), Shapiro (2021), Baylis and Boomhower (2022), Carleton et al. (2022), Cicala et al. (2022), Gandhi et al. (2022), Greenstone et al. (2022), Moscona (2022), Nath (2022), Ostriker and Russo (2022), Acemoglu et al. (2023), Harstad (2023), Bilal and Rossi-Hansberg (2023), Jedwab et al. (2023), Hornbeck (2023), Moscona and Sastry (2023), and Grosset et al. (2023).
A growing body of work has considered these issues specifically in low- and middle-income countries, where both the climate dangers and relevant margins of adaptation differ considerably from richer settings. Much of the research on developing countries has focused on rainfall and temperature, perhaps due to the relative accessibility of data. I focus on floods, monsoon intensity, and especially soil salinity, a major yet understudied environmental threat endangering agricultural households across the globe. Existing work has examined a host of important frictions to individual investment in adaptation, including credit constraints (Lane, 2022), information asymmetries (Beaman et al., 2014; Mahadevan et al., 2023), financial market imperfections (Karlan et al., 2014), supply-side frictions (Emerick et al., 2016), and market structures (Bhandari et al., 2022). I build on this research by studying the role of environmental beliefs, a distinct potential barrier to coping with climate change. I provide some of the first direct measurements of decision-relevant environmental beliefs using frontier methods in the elicitation of subjective expectations and directly link them to farmers’ choices. I show that these environmental beliefs have large consequences for climate change adaptation even amid the host of other frictions documented in the literature, with important implications for policy. For example, my results suggest increasing

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10 The papers considering the economics of salinity intrusion (all of which happen to focus in Bangladesh) include Chen and Mueller (2018) on the migration consequences, Chen et al. (2022) on the effects on nighttime lights, and Guimbeau et al. (2023) on the health impacts.

11 Most direct measurement of climate beliefs has taken place in rich countries, and often on more general aspects of the environment as opposed to those expectations that directly impact decision-making of the surveyed individual (Baldauf et al., 2020; Decehleprêtre et al., 2022). The other papers examining the consequences of local environmental beliefs include Kala (2019), which inferred farmers beliefs about the monsoon onset using a revealed preference argument about their planting behavior, Bakkesen and Barrage (2022), which elicited flood risk beliefs in Rhode Island, and Zappalà (2023), which studied farmers' perceptions about past droughts.

12 To my knowledge, one of the only other papers eliciting local, decision-relevant environmental beliefs in a manner that can be precisely compared to true conditions is Gine et al. (2015), in which the authors document predictors of farmers’ beliefs about monsoon onset in India, measuring expectations using similar techniques to the ones I use here. See Delavande (2023) for a broader discussion of eliciting beliefs in low-numeracy populations.
the measurement of soil salinity and disseminating those results could generate substantial economic gains.

Second, I add to the literate on the economics of beliefs. Despite the important role environmental perceptions in particular play in the economic decisions of smallholder farmers, we have extremely little evidence on how individuals form these expectations and learn from the signals around them (Kala, 2019). I am able to make progress on this question by combining precise belief measurement across a large geographic area with quasi-random natural experiments in past climate shocks. In doing so, I build on a growing set of papers studying the role of past experiences in shaping beliefs. In my conceptual framework, past experiences shape how Bayesian farmers interpret signals because they operate in a data-scarce environment, giving priors outsized influence on the interpretation of new data (Acemoglu et al., 2016; Gentzkow et al., 2023). In an extension with limited attention, I show that even when farmers learn from and observe the exact same data, if the nature of past signals changes which environmental explanations most easily come to mind, learning gaps can nevertheless occur. This mechanism is distinct from the set of inattention models in which agents’ priors shape from which features they learn (Hanna et al., 2014; Schwartzstein, 2014; Gagnon-Bartsch et al., 2021; Bordalo et al., 2023). Instead, I show how the nature of past climate exposure can cause farmers to react differently even when they are attending to the exact same set of new signals. My focus on the differential impacts of salient shocks and subtle shifts relates to a growing literature on inference from seemingly uninformative attributes.

The core features of my conceptual framework—many hypotheses, limited information, and heterogeneous experiences—apply to many economic settings beyond the agricultural decision-making process I examine. For example, stock brokers learning about the fundamentals of a firm by observing the stock price face a very similar problem. By focusing on the salient shocks and subtle shifts characteristic of climate change, however, I speak directly to how individuals learn about the warming world, which has implications for mitigation and adaptation policies more broadly.

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14 See, for instance, Mullainathan (2002), Malmendier and Nagel (2016), Enke et al. (2020), Malmendier (2021), Graeber et al. (2022), Fudenberg et al. (2022), and Bordalo et al. (2023).
15 In concurrent work, Kapons and Kelly (2023) examine the role of prior beliefs in the field settings in biasing inference.
16 For example, see Busse et al. (2015), BenYishay and Mobarak (2019), Hartzmark et al. (2021), Bordalo et al. (2022a), Conlon et al. (2022), and Alatas et al. (2023).
Finally, I build on a long literature on the adoption of new techniques and products in developing countries. This important body of work has documented many significant determinants of the decision to invest in new technology—particularly in agricultural settings—such as social learning (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Beaman et al., 2021), comparative advantage (Suri, 2011), factor market failures (Jones et al., 2022), limited attention (Hanna et al., 2014), and present bias (Duflo et al., 2011). I test whether beliefs about the local environment play a role in shaping farmers’ choices above and beyond these other factors. The results of my experiments and structural estimation show these beliefs can explain a large share of variation in technology adoption.

2 How Accurate Are Environmental Beliefs?

This section reviews the different decision-relevant climate characteristics I examine in this paper, presents the data on the environment and farmers’ perceptions that I use to answer these questions, and compares expectations to the truth to test for evidence of learning frictions.

2.1 Environmental Context

I study the dimensions of soil salinity, flooding, and monsoon rainfall due to their first-order importance in the economic lives of the Bangladeshi poor, as well as hundreds of millions of households across the globe. My primary focus is the amount of salt in the soil, a growing problem in both senses of the phrase. First, the salinity content of the soil can substantially impact plant health, particularly for rice—the most common and important crop in Bangladesh. Farmers widely recognize this critical component of the agricultural

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18 A growing set of papers has explored the value of information in environmental contexts, including Fishback et al. (2011), Rosenzweig and Udry (2013), Rosenzweig and Udry (2014), Weinberger et al. (2018), Barwick et al. (2019), Rosenzweig and Udry (2019), Burlig et al. (2022), Fabregas et al. (2019), Molina and Rudik (2022), Leevers (2023), Fairweather et al. (2023), Krutti et al. (2023), Rudder and Viviano (2023), and Shrader et al. (2023).

19 Extending far beyond rice production in Bangladesh, soil salinity poses one of the greatest threats to food security worldwide. Across most crops, soil featuring a share of soluble salts in the root zone exceeding a plant’s tolerance can significantly inhibit growth. Salt-affected soils occur globally—with an estimated impacted area of over a billion hectares (Hopmans et al., 2021). From Sudan to Peru, Vietnam to Pakistan, salinity’s negative impacts especially jeopardize the livelihoods of agricultural households in low- and middle-
production function, with 98.24% of respondents in my sample reporting that a lot of salt in the soil harms crops. Second, climate scientists forecast significant increases in soil salinity under global warming through a combination of environmental forces including rising sea levels, increased evaporation, droughts, and floods (Mukhopadhyay et al., 2021). Projections in Bangladesh suggest soil salinity alone could reduce output by 15 percent in some areas by 2050 (Clarke et al., 2015; Dasgupta et al., 2015, 2018).

Farmers can adapt to this threat by altering their fertilizer, irrigation method, seed variety, or crop choice, or by shifting away from agriculture altogether. Salinity-tolerant seeds in particular offer a promising avenue for adaptation and are widely encouraged by the government in saline-prone areas. To understand the trade-offs associated with this seed choice, I consider two complementary pieces of evidence: farmers’ own perceptions of the returns to these seeds, and objective agronomic assessments of their performance. I first elicit farmers’ beliefs about the returns to switching their seed to a salinity-tolerant one (or vice versa if they are already planting a salt-resistant seed), and scale this by their expectation about their total harvest. Appendix Figure A.1 plots the relationship between the perceived marginal return to salinity-tolerant seeds against farmers’ beliefs about soil salinity on their plots (described further below). The results show a strong positive relationship that emerges above the government recommended threshold for adopting these resistant varieties, consistent with farmers understanding the value of this technology. To supplement these subjective assessments, I next build a new database of rice varieties by collating information on its resistance and tolerance to various environmental threats, typical plant height, yield, and year of release from various official sources. Appendix Table D.1 presents simple bi-variate regressions illustrating how other seed dimensions vary with salinity-tolerance. Consistent with common understanding, the data show salinity-tolerant seeds perform worse than other varieties in ideal, non-salty conditions. The adoption decision therefore requires matching the technology to the appropriate conditions: in soil with high salinity, farmers achieve higher yields with salinity-tolerant rice but would be better off with a different seed choice amid

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20 According to the Soil Resources Development Institute, the amount of salinity-affected land already increased more than 25 percent between 1973 and 2009 to reach 1.05 million hectares.

21 I use a visual belief elicitation to elicit these expectations in a quantitative manner (Delavande et al., 2011). See Appendix Section C.2 for details.

22 First, I use records from the website of the Digital Herbarium of Crop Plants from the Department of Crop Botany at Bangabandhu Sheikh Mujibur Rahman Agricultural University, which itself aggregates information from the seed developers. I supplement this data with additional information on the growth duration of each seed from the Food and Agriculture Organization on Bangladesh. For the remaining seeds without information from either of these sources, I execute online searches for each variety, conduct phone surveys with four seed dealers across the Khulna division, and use information directly elicited from farmers in my survey. For further details, see Appendix Section D.1.
low salt levels.

Identifying salinity levels on their own plots presents a substantial challenge for this population who lack access to accurate measurement technology. Table A.2 presents the indicators farmers report looking for to assess salt levels in their own soil, based off of responses to an open-ended question in the survey. Almost no farmer has ever used an electrical conductivity sensor or relied on a government agricultural officer who might have access to more accurate salinity information. Farmers most heavily rely on literally seeing the salt on the surface of the soil—which often represents an extreme form of salt inundation and cannot be seen once plots have been flooded—or on salient visual characteristics of the plant—such as ultimate height or characteristics of the leaves. Using plant characteristics can present a challenging inference problem when a host of other factors can also impact how plants look. To examine the extent of this challenge, I measure farmers ability to diagnose high levels of salt in the soil by showing a random selection of five images of rice plants damaged by salinity, disease, or pests, and asking them what may have caused the issues. When shown photos of rice grown in too much salt, 59.93 percent of farmers fail to report salinity as a potential explanation for any of the images, and 32.34 percent misidentify salinity as the cause of photos of plants suffering from pests or disease.

Consistent with the difficulty of directly measuring soil salinity, many farmers hold incorrect beliefs about the underlying environmental process behind soil salinity and effective adaptation. Although 83.63 percent correctly reported that soil salinity changes over the course of the calendar year, just 31.20 percent correctly name the months when it is highest.23 Along the same vein, spraying sugar water across plots has emerged as a popular adaptation method, with 24.62 percent of farmers reporting that spraying sugar water helps to combat salinity and 10.93 percent having taken that measure in the past. Yet from an agronomic perspective, this method does nothing to improve the soil while costing farmers both time and money from paying for the sugar.

In addition to soil salinity, I also examine floods and monsoon intensity. As the world’s most common natural disaster, flooding can have catastrophic impacts on both agricultural production—by damaging crops and fields—and general well-being, destroying homes or entire villages. Climate scientists forecast that under even conservative projections of global warming, much of the world will experience both higher frequency and severity of flooding, particularly in developing countries where floods already cause the most harm (Kahn, 2005; Brunner et al., 2021; IPCC, 2022). In Bangladesh, flooding can arise from excess rains,

23 Relatedly, 34.40 percent correctly identified a month when salinity is typically lowest, and only 22.07 correctly answered both questions. See Appendix Section C.2 for further details on the construction of these variables.
the breaching of riverbanks, tidal surges, and cyclones. Farmers can adapt to flood risk by adjusting their agricultural input choices (i.e. by changing what crop they harvest or planting flood-tolerant seed varieties), changing their occupations, or migrating. The amount of rainfall during the monsoon season impacts a host of important decisions about agricultural production. Global warming has amplified the variability of the South Asian monsoon and increased the likelihood of extreme rainfall events (Mohan and Rajeevan, 2017).

2.2 Measuring True Environmental Conditions

The scarcity of existing information on the local environment presents a significant challenge to farmers, government officials, and researchers. I overcome this obstacle by collecting and constructing new data on climate conditions. 24

Because very little soil salinity data exists in Bangladesh, I primarily rely on salinity measurements I collected directly from farmers’ plots. I equipped enumerators with handheld electrical conductivity (EC) meters which I used to measure salinity twice during the 2022-2023 season on a randomly selected plot for each farmer in my main sample. 25 I take the first reading around the time of the baseline survey, prior to the planting of Boro season rice, and the second reading during the spring, prior to harvest. I convert these measurements taken at specific points in time during the calendar year into an average seasonal exposure to salinity based on a simple linear model I estimate from historical government soil samples collected monthly from nearby soil sites. The 2022-23 soil salinity season ultimately exhibited quite unusual patterns relative to historical norms, as shown in Appendix Figure A.8. The fall salinity readings indicate salt levels fairly typical of this area, with 82.58% of farmers’ plots in my sample expected to experience salinity above the government-recommended threshold for adopting salinity-tolerant seeds. The salinity measured in February and March 2023 was significantly lower than previous springs, and after incorporating these additional measurements into the model, the resulting overall salinity was abnormally low for the season, with just 4.61% of farmers’ plots ultimately above that same threshold. I verified these trends in the soil sample data I obtained from the government and confirmed the overall accuracy

24 In the case of flooding and monsoon intensity, I calculate exposure for each of Bangladesh’s 5,158 unions, the fourth administrative level with an average size of 22 square kilometers. This helps to minimize measurement error inherent in much of the environmental data that might arise by instead linking to a finer geographic level—such as a given farmers’ own plot—while retaining the high spatial resolution necessary to capture meaningful variation across space. In the survey and field experiment, I sample one village within each union, and thus use the two terms interchangeably when discussing those results.

25 I randomly selected plots, weighting by the area of the plot. The median number of plots is 2. When eliciting size, I asked about the five largest plots (which only binds for a very small minority of farmers): the median plot size is 24 decimals, where one decimal equals 1/100th of an acre.
of the handheld sensors I used through laboratory tests.\textsuperscript{26}

To overcome biased underreporting of flooding in existing datasets, I combine methods from machine learning and geophysics in the analysis of remote sensing data to detect flood exposure every day for the past two decades.\textsuperscript{27} The oldest, most frequently orbiting satellites carry optical sensors that take daily photos of the earth as they pass over, notably used by economists to measure economic growth based on changes in night-time luminosity (Henderson et al., 2012). In the context of flooding, these photographs feature an important drawback: they cannot see through clouds. Given the non-random correlation between precipitation and flooding, this missing data presents a serious problem when trying to accurately measure surface water across time and space.\textsuperscript{28} More recently developed radar-based sensors take a different approach by emitting pulses of microwave radiation at the earth. While these instruments maintain high accuracy regardless of atmospheric conditions, they are only available for recent years at less frequent intervals. Relying solely on these data would miss many floods that happen to occur in between satellite passes. I use methods from machine learning to get the best of both worlds: the accuracy of radar-based sensors with the temporal coverage of optical ones. Using a combination of online news articles, river height measurements, and government reports, I show my remote sensing measure passes a variety of validation checks. For further details on the limitations of existing flood datasets, the methodology I use to create this new measure of flooding, and the validation of this method, see Patel (2023).

I measure local rainfall using the Global Precipitation Measurement v6 (Huffman, 2019), which combines remote sensing data with precipitation gauge analyses in a model to estimate high-frequency, high-resolution rainfall.\textsuperscript{29} I first calculate average precipitation within each union every 30 minutes for the past 20 years. My primary rainfall measure then aggregates these data to the annual level to capture the number of rainy days during the monsoon.

\textsuperscript{26} For details on these tests and further details on this data collection, see Appendix Section B.2.
\textsuperscript{27} Click here for an online guide to my flood detection methodology.
\textsuperscript{28} In fact, the Global Flood Database (Tellman et al., 2021)—one of the most systematic attempts to create a panel dataset of flooding using satellite data—only successfully maps 913 of 3,054 flood events globally from the DFO dataset using this optical data.
\textsuperscript{29} Like many developing countries, the quality of local rainfall data in Bangladesh suffers from the sparsity of weather stations. For example, Bangladesh Meteorological Department (BMD) provided data from just 35 gauge stations across the entire country to estimate the Huffman (2019) algorithm. Consequently, the estimates from the gridded precipitation data used in this paper more heavily rely on remote sensing data and modeling. Recent research comparing the validity of the gridded product to on-the-ground rainfall measures typically find a strong correlation, with particularly high accuracy for detecting the existence of rainfall as opposed to the quantity (Islam, 2018; Khairul et al., 2018; Montes et al., 2021). These findings reinforce my use of this data to measure days of rainfall during the monsoon instead of quantity directly, yet the estimates likely still feature significant measurement error. To partially address this potential bias, I calculate the sum of squared distances between the centroid of each union and the three closest BMD stations from that list of 35 (Hoque et al., 2011) and control for this weather-station remoteness measure in all relevant analyses.
season, which I define as May 15th through October 15th to align the Bengali calendar.  

### 2.3 Measuring Farmers’ Beliefs about Environmental Conditions

To capture farmers’ perceptions of the local climate, I conducted surveys with 2,279 farmers who serve as the primary decision-makers on their plots across 250 villages spanning the Khulna division of Bangladesh. The widespread geographic coverage of sampled villages throughout this area—which stretches more than 8,600 miles—allows me to capture significant spatial heterogeneity in climate conditions. I first interviewed households at the beginning of the Boro rice growing season and conducted an endline survey after harvest. My primary measures consist of farmers’ past, present, and future perceptions of flooding, rainfall, and soil salinity. To elicit quantitative beliefs in this low numeracy population, I use a visual elicitation method in which enumerators instruct farmers to place buttons on images in accordance with their perceived likelihood of each pictures scenario, a method which the vast majority of farmers understood well. I use this approach to measure perceptions of soil salinity on farmers’ own plots, the likelihood of experiencing flooding of different durations, and the intensity of rainfall during the monsoon season.

Eliciting comparable soil salinity beliefs to the agronomic measures presents a challenge because no one naturally thinks in deciSiemens per meter (dS/m), the units of the electrical conductivity sensors. I overcome this using an image of rice plants taken from the experiment to mirror the belief elicitation question which asks respondents to classify rainy days as those for which it rains for at least one hour with normal sized drops, I define a rainy day as one with at least .5 mm of rain, which follows the threshold for slight rain as defined by the U.S. Geological Survey.

For further details on sampling, see Appendix Section C.1. Appendix Table A.1 presents basic demographic information about this sample. Appendix Figure C.2 presents a timeline of data collection. The sample restrictions pose a potential threat to the interpretation of results. By limiting respondents to Boro season rice farmers still living in each village, I could be selecting for those farmers who—due to their beliefs—have not adapted by switching to a different economic activity or permanently migrating away. Two factors help to address this concern. First, those who have yet to adapt along these dimensions constitute the policy-relevant population. Second, an extremely low share of farmers in the sample report any likelihood of these extensive margin adaptation measures. For instance, 96.05 percent of respondents say no when asked, “If the amount of salt in your soil became very high, would you consider stopping planting rice in the Boro season?”

See Appendix Section C for details on this survey including links to the full questionnaires for the baseline and endline surveys, both in English and Bangla. Farmers answered a series of comprehension questions to gauge understanding of the belief elicitation method: across both the baseline and the endline, 63.67 percent of respondents answered these questions perfectly, and just 3.82 percent of respondents answered all three comprehension questions incorrectly. Just 11.63 percent reported that they found the example belief elicitation to be either “a lot” or “very” confusing. I pre-specified conducting cuts of the data by how well respondents answer these practice questions, their education, and their socio-economic status. This belief elicitation approach has been widely used to measure beliefs in similar settings (Delavande et al., 2011; Gine et al., 2015; Delavande, 2023).

I elicited beliefs about soil salt content during the baseline survey for the 2022-23 season and during the endline survey for the 2023-24 season. For flooding and rainfall, I randomized at the individual level whether respondents answered those belief questions in the baseline or the endline surveys.
in Grattan et al. (2002) in which researchers grew a standard rice seed in different growing conditions, randomly changing the salt content of the soil across treatment arm. The image shows seven plants from different arms at the end of the growing season, where the healthiest, tallest plants correspond to the lowest salt levels, and the least healthy plants grew in the highest soil salinity. I explain this image in detail to farmers, ensure their understanding that the photos capture different salinity levels, and then ask them to predict through the allocation of 10 buttons across the images which of the pictures they expect to look most like a plant grown by these researchers who used a not saline-tolerant seed on their plot, replicating all aspects of the farmer’s soil such as the water, fertilizers, and weather over the course of the season.44 Because I know the salinity conditions used in the original experiment to grow the rice plants in each picture, I can back out from farmers’ answers their expected salinity in dS/m.

I designed this question to address several potential concerns in the elicitation of soil salinity beliefs. First, salinity evolves over the course of the season due to many factors, including the types of fertilizer used by farmers, the amount of rain (that can potentially wash away salts from the surface), and the irrigation water. As a result, I made sure farmers understood that these factors should be taken into consideration when making their prediction. Of course, one potential risk with this approach is that other factors can also impact the height of the rice plant separately from salinity, e.g., a certain pest or disease. Since I do not want to capture predictions about these other risks, I explicitly say to farmers, “We are asking this question because we are trying to understand how much salt you think is in your soil.” Piloting indicated that farmers clearly understood this question to be specifically about salinity, and answered accordingly. Second, I highlight that farmers should assume they are growing a seed that is not salinity tolerant to match the experiment of Grattan et al. (2002), a key step given that nearly half of farmers at baseline expect to plant a salinity-tolerant seed. Interactions across inputs pose a threat to the elicitation if, for instance, farmers irrigate their land with different water sources depending on their seed choice because I am asking them to hold those other factors constant. Reassuringly, however, I ask farmers directly in the endline, and the vast majority report that they do not change any of their other agricultural input decisions based on their seed choice. Third, one might worry that farmers simply predict what they expect their own plants to look like or what they recall from last year instead of thinking through the salinity prediction in particular. To address this, I explicitly ask farmers prior to the main salinity question about the picture that best describes their last harvest and their expectation about their harvest this coming

44 Appendix Section C.2 provides further details on the belief elicitation for soil salinity, rainfall, and for flooding and on the construction of these key variables.
season. Appendix Figure A.5 presents the full distribution of the mean salinity belief that farmers report in dS/m units. As a benchmark, the government recommends switching to a salinity-tolerant seed for values above 4.0 ds/m. In my sample, 43.86 percent believe the salt content on their soil will exceed this threshold over the course of the 2022-23 season.

Although flooding and monsoon intensity do not feature the same unit issues as soil salinity, other challenges emerge in eliciting beliefs about these environmental threats. In particular, these two dimensions may be more vulnerable to level effects from the belief measurement than soil salinity. For floods, I ask farmers to place buttons in accordance with how likely it is they will experience a flood lasting a given length of time (where zero days is one of the options). The fact that I restrict farmers to 10 buttons through which they can express their beliefs can be binding for the low-probability events of rare floods. In other words, I effectively prevent respondents from expressing expectations of likelihoods lower than 10 percentage points. This may explain in part the high rates at which farmers expect floods to occur: on average, respondents predict experiencing 2.33 days of inundation in the next year, and 3.72 days in the next five years. As a complementary belief elicitation method that is less susceptible to this probability weighting concern, I ask farmers, “How many years do you think it would take for a [Horizon] long flood to happen in this village?” where [Horizon] matches the same inundation durations as the other question. Appendix Figure A.3 presents the results from the alternative question, showing that on average, farmers expect flash floods every 6.93 years and even month-long inundation events every 24.63 years. Additionally, my definition of flooding based on the satellite data requires taking a stance on the percentage point increase in surface water to classify a binary flood definition. I take a data-driven approach using survey data with farmers to calibrate a threshold of 20 percentage points. This mechanically implies my measure underestimates true flooding because there will be some small floods below this threshold that I omit. In the case of monsoon intensity, I ask farmers to recount how many days it rained on average for a given two week period during the monsoon season, where I explicitly define the monsoon season as a fixed time period over the calendar year. Because I give conservative bounds for this period to ensure that I capture the relevant monsoon days in all years, even small misperceptions in this period (e.g., excluding one week on either end) can have meaningful

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35 I define a “flood” to respondents as unexpected and unwanted water that enters their land or house and covers the ground, consistent with the type of surface water I am able to detect using the satellite instruments. Additionally, I instruct them to consider a flood as having happened to them if the inundation covers at least half of one of their plots or the water touches their home.

36 These means mask important information about both the distribution of beliefs across farmers and farmers’ perceptions of the distribution of flood risk. Appendix Figure A.2 plots the cumulative distribution function of flooding beliefs over a one-year and five-year horizon, and shows that a significant share of farmers perceive no flood risk as measured by this elicitation.
impacts on the hazard rate of rain. Finally, in both flooding and rainfall, bin effects could play a particularly important role. Due to these reasons, I primarily focus on comparative statics as opposed to level results with respect to these beliefs.

2.4 Assessing Belief Accuracy and Testing for Learning Frictions

Linking the beliefs and environmental data together, I can compare how farmers’ expectations compare to the ground truth and examine the extent to which these patterns suggest frictions in the learning process. On average, farmers exhibit remarkably accurate beliefs about the salt content of their soil. Figure 1 plots a binned scatter plot in blue comparing farmers’ beliefs to the truth. The dashed gray line denotes the 45-degree line. The dots generally fall along the gray line. Consistent with this graphical evidence, Table 1 presents bi-variate regressions of beliefs against true salinity levels as measured via the agronomic sensors. At the 10 percent level, I fail to reject that the slope of this relationship equals 1 and the intercept equals 0, again consistent with accuracy on average. This holds both for the pre-specified sample of those who passed the belief comprehension checks in column (1) and including those who did not in column (2).

This average accuracy masks significant heterogeneity, however. As one way to see this, consider the explanatory power of the regression model. With simply a linear term of the truth and a constant, the agronomic truth can explain less than four percent of the total variance in beliefs. Even using a flexible function of the truth interacting the linear slope with 20 ventiles, the explanatory power of the model still only ever reaches just over six percent.

Some of this unexplained gap between soil salinity beliefs and the truth likely stems from measurement error—but not all. I conduct several empirical tests illustrating that the residual belief error captures a meaningful economic object. Appendix Table A.4 shows results from specifications altering the scope of classical measurement error are inconsistent with noise alone explaining the results. Table 2 and the corresponding plots in Figure 3 show that errors in farmers’ beliefs explains their actual planting behavior with respect to

37 First, column (1) of Appendix Table A.4 shows that classical measurement error alone cannot explain the gap between measured salinity beliefs and the truth by regressing farmers’ answer to a separate, binary question about whether they think the plot’s soil is salty on continuous belief captured via the visual elicitation method. The results show a strong, positive relationship (p-value < .01). Measurement error would have to be correlated across these two very different questions in order to explain this relationship. Second, restricting the sample to those who understood the belief elicitation method better (as measured by their self-reported understanding) in column (2), the explanatory power of the model in fact decreases by more than 50 percent, inconsistent with a story in which measurement error in beliefs drives the errors. Third, error in the agronomic measure of salinity is unlikely to explain the results: regressing individuals’ beliefs on the village leave-out mean, I find essentially no change in the explanatory power of the model.
salinity-tolerant seed choice above and beyond the true salinity content of their land. Farmers who overestimate the salt content of their soil by a larger amount also plant salinity-tolerant seeds on a larger share of their land ($p-$value < .01). This provides evidence that the gaps between beliefs and the true soil conditions capture more than just noise. Next, I examine the individual-level predictors of belief accuracy in Table 3. I focus on four dimensions that we expect might capture skill or farmer’s ability to learn: the amount of land they farm, their age, whether their neighbors’ view them as knowledgeable farmers, and whether their peers follow their agricultural advice. Across all of these dimensions, I find that accuracy is higher among farmers with more data (i.e., more land or experience) and viewed as better farmers. These facts are inconsistent with measurement error explaining the gap between beliefs and the truth and additionally suggest an important scope for learning frictions.

Second, I examine the spatial component of errors. Figure 4 HERE

These results raise an important puzzle: given the strong incentives farmers have to learn the truth, why do mistaken environmental beliefs persist in equilibrium? To shed light on that question, I next turn to a simple conceptual framework of farmer learning.

3 Learning About the Environment

This section presents a simple conceptual framework to illustrate how farmers learn about the environmental inputs into the agricultural production function amid the signals characteristic of global warming.\(^{38}\) The key assumptions I make stem directly from the quantitative findings from my surveys, the farmers’ responses to the open-ended survey questions, and the narrative qualitative interviews I conducted on a separate sample. I include quotations and references to these statistics in footnotes throughout this section.\(^{39}\)

3.1 Set-Up

A farmer grows rice in two periods $t \in \{1, 2\}$. Output in period $t$ is given by the binary indicator $y_t \in \{0, 1\}$, where $y_t = 0$ denotes low harvest, and $y_t = 1$ denotes high harvest. Harvest is subject to a random productivity shock $\xi$ that can be either negative ($\xi = -1$), positive ($\xi = 1$), or neutral ($\xi = 0$). I assume productivity shocks are distributed symmetrically with mean zero such that the positive and negative shocks occur with equal, positive probability denoted by $\rho > 0$ and that neutral shocks occur with positive probability

\(^{38}\) For a formal treatment of all results in this section, please see Appendix Section E.

\(^{39}\) See Appendix Section F.1 for details on the narrative interviewing approach I used and coding procedure for these qualitative data. For additional quotations supporting these assumptions, see Appendix Section F.2.
such that $\rho < .5$. In the first period, farmers make no decisions about inputs and plant the standard seed. In the second period, salinity tolerant seeds are introduced, and farmers decide whether to plant salinity tolerant seed or plant the standard seed. This decision is given by the binary indicator $d_t \in \{0, 1\}$. Planting a standard seed is given by $d_t = 0$, where $d_1 = 0$ by default because salinity tolerant seeds are not available in the first period. In the second period, farmers may plant a salinity tolerant seed, denoted by $d_2 = 1$. Seed choice costs $c(d_t)$, where I normalize such that planting a non-salinity tolerant seed is free $c(d_t = 0) = 0$. I assume planting a salinity tolerant seed costs $c(d_t = 1) > 0$, where $c(d_t = 1)$ is positive yet small to capture the notion that salinity tolerant seeds perform relatively better in high salt environments yet relatively worse than standard seeds amid low salinity.

Two independent and unchanging environmental conditions denoted by the set $\{S, B\}$ can impact harvest, where $S$ is the soil salinity and $B$ is blast, an important fungus threatening rice.\footnote{The same intuition applies in the case of a large number of inputs. I focus on the case of unchanging environmental states: introducing the potential for unobservable shifts in the climate makes the farmers’ problem even more challenging.} I use lower case letters to denote the true, binary environmental states in these respective domains, given by $s \in \{0, 1\}$, where $s = 0$ denotes low salt levels and $s = 1$ denotes high salt levels, and by $b \in \{0, 1\}$, where $b = 0$ denotes no blast and $b = 1$ denotes the presence of blast.\footnote{I focus on learning about soil salinity from agricultural production in this set-up, yet the basic building blocks of this conceptual framework also apply to learning about rainfall and flooding—the other two key climate beliefs I examine in this paper. Appendix Section E.2 discusses extensions to these settings.}

I assume the agricultural production function follows a particular, simple functional form given by Equation 1. The maximization and minimization expressions ensure the binary support of output $y_t \in \{0, 1\}$. Planting salinity tolerant seeds $d_t = 1$ mitigates the damage from soil with high salt content ($s = 1$).

$$y_t(s, b, d_t) = \max (\min (1 - (s - d_t)^2 - b + \xi, 1), 0)$$

(1)

I assume farmers cannot directly observe the environmental states.\footnote{As one farmer said during the endline survey, “We do not have the equipment to test the salinity of the land. Understanding the amount of soil salinity depends on our assumptions.” Appendix Table A.2 illustrates this difficulty by showing the rarity of farmers using salinity sensors or consulting with government officials to learn about salt on their soil.} As a result, farmers are uncertain about how their decision $d_2$ impacts their output $y_2$ entering the second period. This uncertainty is captured by their prior over the states of soil salinity and blast. I use $\hat{s}_t$ and lower case letters to denote beliefs in the environmental domains $S$ and $B$, such that $\hat{s}_t$ denotes a farmer’s belief entering period $t$ about the probability that true salinity levels are high $\hat{s}_t = P(s = 1)$, and $\hat{b}_t$ denotes a farmer’s belief in period $t$ about the probability that
blast is present \( \hat{b}_t = P(b = 1) \). Other than potential misperceptions about the environmental conditions, I assume farmers are correctly specified in their understanding of the production function in Equation 1.

I assume that farmers use Bayes’ rule to learn about these unobserved environmental conditions by updating using the harvest in period 1.\(^{43}\) Note that a key feature of the production function is that farmers face an identification problem: low yield is consistent with both high soil salinity and blast, and high yield is consistent with low salinity and the absence of blast. In other words, I have assumed that poor harvest performance could reflect multiple potential issues in the agricultural production function, and these underlying threats manifest themselves in identical ways.\(^{44}\) Given initial non-degenerate priors about the likelihood of high salinity \( s_1 \), Equation 2 gives the posterior at time \( t \) about the likelihood of high salinity levels, with the symmetric expression for blast beliefs \( \hat{b}_2 \).

\[
\hat{s}_2 = P(s = 1 | \hat{s}_1, y_1)
\]

(2)

Risk-neutral farmers choose seeds to maximize output in period 2 given their beliefs, as shown in Equation 3. To isolate the key mechanism of this framework, I have assumed that farmers stop growing after the second period, implying that farmers are myopic, maximizing only the current period’s output without regard towards the potential learning benefits of experimentation.

\[
U = \max_{d_2} E \left[ y_2(\hat{s}_2, \hat{b}_2, d_2) - c(d_2) \right]
\]

(3)

Finally, I define the default hypothesis as the environmental threat that a farmer perceives to be the most likely to occur, as shown in Definition 1.\(^{45}\)

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\(^{43}\) Appendix Table A.2 shows this is the most commonly used way farmers learn about soil salinity, for instance. As one farmer explained, “We understand the amount of salt in the land by calculating the crop. If the crop is good, it means that the salt content in the land is low.” Additionally, some farmers also use physical characteristics of the plants or the land, though this is less common and less universally applicable. For instance, one farmer pointed out that, “Salinity is easily recognized when the soil is dry and whitish in color. But I can not understand the salinity level if there is water in the land.” Appendix Figure A.14 shows a photograph I took of this type of visible surface salt. This type of signal only appears at extremely high salt levels and is only visible—as this farmer points out—when the land is dry. This makes it impossible, for instance, to assess salinity using this indicator during the growing season because farmers keep their plots perpetually submerged with irrigation water, a particular issue given that salinity increases dramatically over the course of the season, and so is in fact lowest prior to irrigation when surface salts might be possibly viewed.

\(^{44}\) As one farmer said when discussing crops being destroyed, “I don’t know if it’s because of the salinity or something else.”

\(^{45}\) I assume no ties \( (\hat{s}_t \neq \hat{b}_t) \): that is, farmers never hold exactly the same belief about the likelihood of both environmental threats.
Definition 1 An environmental factor \( E \in \{S, B\} \) is the default hypothesis in period \( t \) when the corresponding belief \( \widehat{c}_t = \max(\widehat{s}_t, \widehat{b}_t) \).

3.2 Implications for Learning

In this conceptual framework, beliefs exhibit path dependence: environmental threats that are perceived to be more likely remain relatively more likely after new data is observed. Remark 1 formalizes this statement, and Appendix Section E provides a formal treatment of this result.

Remark 1 If two farmers \( i \) and \( j \) have different default hypotheses \( (\max(\widehat{s}_i, \widehat{b}_i) \neq \max(\widehat{s}_j, \widehat{b}_j)) \), then even if their priors are arbitrarily close \( (|s_i^1 - s_j^1| < \varepsilon) \) and \( (|b_i^1 - b_j^1| < \varepsilon) \), after observing identical data \( (y_i^1 = y_j^1) \), their posterior beliefs will exhibit the same difference in default hypotheses \( (\max(\widehat{s}_2^i, \widehat{b}_2^i) \neq \max(\widehat{s}_2^j, \widehat{b}_2^j)) \).

Because low (high) yield is consistent with both high (low) salinity and (no) blast, the same signal can be interpreted in different ways while still being consistent with the data and correctly specified model. Farmers endogenously process the same raw data differently in accordance with their default hypothesis: low yield is seen as evidence that the environmental threat they initially deemed more likely is indeed true, while high yield is interpreted just the opposite. Note that this divergence does not come from a misspecified mental model or a behavioral friction. Instead, this reflects the Bayesian response and the fact that a farmer’s priors affect how they interpret the ambiguous signal of harvest. In fact, Appendix Section E shows that this effect scales with the degree of “defaultness”: that is, when the gap in priors \( (|s_i^1 - b_j^1|) \) is larger, this skew in interpretation of new data is exacerbated.

Figure 5 provides a graphical illustration of this path dependence in beliefs separately for the cases of high and low yields. Figures 5b and 5a plot the changes in beliefs for a given prior for high and low yield, respectively, and Figures 5c and 5d scale these changes to account for the mechanical limitations to magnitudes given the support of possible beliefs. All graphs exhibit a striking divergence around the 45\(^\circ\)-line—the boundary along which default hypotheses switch. One way of interpreting Remark 1 is that two farmers on either side of that line will remain on separate sides, even after observing the exact same data.

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46 This finding echoes a related result in Chen et al. (2023) in which by virtue of overestimating one technology, farmers endogenously adjust their beliefs about another to justify their observed outcome, leading to underestimation of the second.

47 More general results on the failure of asymptotic agreement in under-identified settings can be found in Acemoglu et al. (2016).
3.3 Extensions

I now discuss various extensions of this conceptual framework that relax some of the main assumptions.

Uncertainty About the Agricultural Production Function  Thus far, I have assumed that farmers perfectly observe how features of the environment impact yield. In practice, farmers learn about both the levels and the marginal costs of climate conditions. One immediate consequence of relaxing perfect information about the agricultural production function is the exacerbation of the identification problem. Farmers who observe a bad harvest now cannot distinguish between (a) low salinity and high salt damages, (b) high salinity and low salt damages, (c) low blast and high blast damage, (d) high salinity and low salt damages.\footnote{This occurs even abstracting away from bottom-coding issues given the impossibility of negative harvest. Non-linearity of this type in the production function (as featured in Equation 1) further exacerbates this issue as because farmers then cannot distinguish between high salinity and high or low salt damages.}

Recent work on convergence in misspecified learning by Heidhues et al. (2021) and Chen et al. (2023) illustrates that even after abstracting away from this identification issue, an incorrect mental model of the agricultural production function can persist in equilibrium as long as farmers can find beliefs that justify the observed output.

Experimentation  A key aspect of this set-up has been the lack of experimentation. In practice, farmers in fact trade off between benefits today and learning for tomorrow (Foster and Rosenzweig, 1995). Indeed, the empirical results that farmers with more land and more experience hold more accurate beliefs suggests an important role for experimentation to overcome this identification problem. Challenges can nevertheless occur that reduce the efficacy of experimentation in leading to correct beliefs. First, I have assumed that farmers are correctly specified about every other aspect of the production function, including notably the ways in which environmental conditions impact yield and the distribution of idiosyncratic production shocks. In reality, these primitives are also unknown to farmers, and uncertainty over those dimensions will exacerbate the identification challenges. Second, when experimentation is costly (due to a subsistence constraint or fixed cost in technology investment, for instance), then farmers may choose not to experiment despite knowing that their beliefs may be wrong because given their priors, the expected benefit of learning may be small.

Social Learning  The conceptual framework also omits another important feature of this setting: social learning. In many ways, one’s neighbors act as a form of experimentation
as discussed above, particularly given the high spatial covariance of environmental threats. One factor that may inhibit the role of social learning to correct beliefs is the nature of errors in this setting. I have thus far been agnostic as to the origins of priors, but as I show below, past environmental experiences play a key role in shaping farmers’ initial beliefs. Because environmental experiences also exhibit high spatial covariance, the neighbors one might turn to for advice likely hold a similar set of biased beliefs.

**Higher Dimensional Signals** I have focused on the simple case in which farmers only observe yield which can either be high or low. In practice, farmers can observe a much richer set of data, such as the color of leaves or a continuous measure of yield. This will help farmers learn when they correctly know that certain physical characteristic is linked with a particular threat, and therefore the cumulative distribution functions of the two environmental beliefs are in fact disjoint, thereby alleviating the identification problem. I find evidence that farmers often do not have knowledge of, for example, the particular leaf patterns emblematic of blast. Without this type of external information, higher dimensional signals do not alleviate the learning challenges in this conceptual framework.

**Learning in the Long-Run** This set-up has focused on the two-period case. What happens to beliefs in the long run? Under the assumption that farmers have full information about the distribution of idiosyncratic production shocks, farmers in this set-up will be able to distinguish between a world in which both environmental threats are present and only one, yet in the one threat case, they are not guaranteed to ever be able to learn which threat is prevalent. In the case where farmers are also uncertain about the distribution of shocks, then even the case of both threats will be fully consistent with the data when in reality only one threat is relevant, or vice versa.

### 3.4 The Formation of Priors

This conceptual framework has illustrated the power of priors in this setting. How do farmers form their initial beliefs about the environment? Many potential sources of information could influence which factors farmers deem important *ex ante*, ranging from wisdom passed along from their peers to guidance provided by agricultural extension workers.

I study how the nature of past environmental shocks shapes the priors held by farmers and thereby the ways in which they interpret signals about their yield. Under the upheaval of changes to the climate under global warming, understanding how farmers learn from shifts in the environment holds particular policy relevance. I therefore focus on two types of signals characteristic of climate change: salient shocks and subtle shifts. Almost all
environmental threats impacted by global warming feature these two classes of changes. For dimensions like rainfall, temperature, and pollution, I consider a daily or seasonal extreme as a salient shock, while secular trends in the distribution—while nevertheless important and observable—I classify as subtle shifts. For natural disaster risk, marginal increases in determinants of the hazard (e.g., riverbank erosion or sea-level rise in the case of flooding) constitute subtle shifts, while an occurrence of the natural disaster (e.g., a flood itself) counts as a salient shock. Appendix Table A.5 provides examples of salient shocks and subtle shifts across a host of different environmental dimensions.

How might salient shocks and subtle shifts vary? I discuss three channels through which experiencing one event rather than the other can lead to persistent learning differences. The relevant mechanism will depend on the context and assumptions made about the types of data to which farmers attend, as I discuss further below. In all cases, however, the main empirical predictions remain the same.

First, remaining in the purely Bayesian world with no restrictions on farmers’ attention, a salient shock may result in different equilibrium beliefs than a subtle one if the statistical content of the signal varies. For example, imagine that experiencing a flood (a salient shock) indicates a significantly higher future flood risk than an incremental increase in river height (a subtle shift) because of what the occurrence of a flood indicates about the data generating process. In this case, a Bayesian farmer who happens to experience a flood as a salient shock will rationally enter the next period with a higher prior belief about future flood risk than one who experienced a subtle shift. This gap in initial beliefs can be amplified by precisely the same mechanism as discussed above in which farmers endogenously alter how they interpret new data in line with their priors. The model predicts that whichever signal suggests higher posterior environmental risk will cause farmers to overestimate that risk by more.\footnote{Consistent with the empirical evidence I find in the setting of soil salinity, I focus on the case where salient shocks lead to overestimation, and thus I assume it is the salient shock that suggests higher environmental risk.}

Whether or not the true statistical content of the signal varies across these two events is a difficult question to answer and of course highly context specific. It is not obvious in this example, for instance, that experiencing a flood (a salient shock) should indeed increase beliefs about future flood risk more than an incremental increase in river height (a subtle shift).

I now focus on the case where both the salient shock and subtle shifts carry the same statistical content but nevertheless lead to learning gaps. To capture this, I introduce limited attention in two ways. First, I consider a case where due to the subtlety of incremental change, that class of shifts can be simply difficult for farmers to notice. In that world, because farmers fail to attend to this information, they do not update their priors about
environmental risk in the same way as they do after experiencing a salient shock, even though both events inherently have the same information about the underlying data generating process. This causes farmers to enter the next period with different initial beliefs, a gap which can be exacerbated by the same mechanisms in this underidentified setting as before. This assumption about failing to notice subtle shifts may be more plausible in some settings than others. On the one hand, incremental increases in the salinity of irrigation water may be too small to be detected by tasting the water, which means that even if farmers use all the tools available to them in an attempt to notice such a change, they may fail to detect such subtle shifts. On the other, farmers might always notice if it's raining, and so even if the number of days of rain does change from year to year, they will always have attended to this data.

Even in cases when the subtle shifts and salient shocks feature the same statistical information and farmers attend to both, differences in the nature of the stimulus can still generate learning gaps amid a different form of limited attention. Specifically, instead of only attending to some environmental data, I instead assume that limited attention restricts the set of potential hypotheses that farmers consider when interpreting a new signal. As discussed in (Hanna et al., 2014), farmers face a high-dimensional space of factors potentially impacting agricultural production, and keeping track of all of these inputs can be challenging in of itself, let alone conducting Bayesian inference across so many dimensions. Salient shocks attract attention automatically and involuntarily, or “bottom up” (Bordalo et al., 2022a).

In doing so, they change which the set of hypotheses that come to mind by making some environmental culprits more salient. This system 1 thinking occurs near-instantaneously: upon seeing new data, farmers apply Bayes’ rule to update their beliefs only among the factors that come to mind. By neglecting those potential explanations that are less available (Tversky and Kahneman, 1973), farmers effectively put more weight on those factors for which they experienced a salient shock.

The key empirical prediction distinguishing these two limited attention frameworks and

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50 Psychologists have noted the evolutionary origins of this cognitive mechanism, which features clear survival benefits. The psychology literature on climate change has particularly noted the challenges this instinct poses when applied to the mitigation of and adaptation to environmental harm (Gilbert, 2006; Johnson and Levin, 2009; Gifford, 2011).

51 Differently from other models of limited attention and belief formation, in my set-up, farmers always attend to all data from which they might learn. Limited attention acts on how farmers interpret these signals and which features are associated with a given hypothesis by limiting the number of hypotheses farmers entertain. In the language of Tversky’s (1977) similarity framework, my model makes the similarity function linking signals and hypotheses endogenous to attention. Previous work, by contrast, treats the link between data and hypotheses as exogenously determined, and instead operationalizes limited attention through agents attending to some signals more than others (Schwartzstein, 2014; Hanna et al., 2014; Gagnon-Bartsch et al., 2021; Bordalo et al., 2022b).

52 This result echoes the empirical findings in Enke (2020).
the Bayesian benchmark stems from how salient shocks differentially impact posterior beliefs as compared to subtle shifts, conditional on their true statistical content being equivalent. Without attention costs, this ancillary feature of the salient shock is irrelevant for farmers beliefs and ultimate decisions. By contrast, amid limited attention that causes farmers to either fail to notice the subtle shift entirely or make it less likely that environmental explanation comes to mind, learning gaps can persist.

4 Learning from Salient Shocks and Subtle Shifts

To test the key predictions of this conceptual framework in the domain of soil salinity, I study two quasi-random natural experiments to capture salient shocks and subtle shifts in the environment.

4.1 Empirical Strategies

Salient Shocks: Saline Floods In my framework, a salient shock alters the environment in a manner that captures farmers’ attention. Under this definition, I can take a data-driven approach to identifying the ideal treatment to answer this question. I ask all of the farmers in my sample to recount any event that has affected the salinity of the soil on the plot about which I measure beliefs and from which I take agronomic readings. At the time of the baseline survey, 17.60% of framers reported ever experiencing at least one event. Flooding is the modal answer, constituting 38.53% of 436 total events. Farmers report salinity increasing in 91.67% of these cases, and specifically mention flooding with salty water 73.21% of the time.

Based on this overwhelming dominance of saline floods among recollected salinity events, I focus on identifying the causal impact of these climate occurrences to test for the role of salient shocks in the model. I adopt a difference-in-differences specification to capture quasi-random variation in the incidence of saline floods, as shown in Equation 4, where \( v(i) \) denotes that the variable is defined at the village level. This main coefficient of interest \( \beta_1 \) captures the differential impact of experiencing a flood with more salty water, holding constant underlying flood risk, local water saltiness, and any other broader impacts of experiencing a flood. I cluster standard errors at the village level, the level of treatment. The quasi-random determinants of flooding and water saltiness allow me to interpret \( \beta_1 \) as the causal impact of happening to actually experience this salient shock. Conditional on the same underlying flood risk, otherwise identical places may or may not experience a flood due to idiosyncratic variation in factors like rainfall and tidal surges. Similarly, the salt content
of water fluctuates randomly due to factors like cloud cover changing the evaporation rate. Water salinity also evolves over the calendar year, and as such the precise timing of a flood can dramatically shape the salt content of the floodwaters. Appendix Figures B.8 and B.11 visualize this variation in salinity in Bangladesh’s rivers and in the ocean off the coast.

$$Y_i = \alpha + \beta_1 \text{Floods}_{v(i)} \times \text{Water Saltiness}_{v(i)} + \beta_2 \text{Flood}_{v(i)} + \beta_3 \text{Water Saltiness}_{v(i)} + \psi \text{Flood Risk}_{v(i)} + \varepsilon_i$$

(4)

To measure past exposure to flooding, I use the same data as before in which I combine methods from machine learning and geophysics to estimate local floods, described further in Patel (2023). I use a supervised machine learning model trained on underlying geographic factors to derive my measure of flood risk, as discussed further in Appendix Section B.1, and control for fixed effects of quintiles of this variable. To capture the saltiness of water, I combine two sources. First, I use remote sensing data from satellites that detects fluctuations in ocean salinity from space. Second, I use data I obtain from the Bangladesh Water Development Board from river stations scattered across the country at which the government directly collects water salinity measurements. Together, these data allow me to measure the saltiness of local water. For ease of interpretation, I convert water salinity into standard deviation units.

**Subtle Shifts: Rising Sea Levels** I cannot use farmers’ own assessments to measure subtle shifts as almost by definition, they will not recall or easily identify these events. Instead, I rely on the scientific literature on soil salinity and climate change, which specifically points to rising sea levels and the associated impact on irrigation water as a driving force behind increasing salinity (Mukhopadhyay et al., 2021). As global warming increases sea levels along the Bangladeshi coast, the water farmers use to grow rice can become saltier, either through underground contamination of groundwater (as illustrated in Appendix Figure A.13), or through river systems themselves becoming saltier upstream.

To isolate the causal impact of subtle shifts, I estimate a triple-differences design. For the first difference, I calculate deviations in ocean water salinity from the village-by-calendar-month mean, thereby comparing villages with relatively higher or lower exposure to local water saltiness compared to their historical average. Second, I calculate deviations in ocean sea level elevation from the village-by-calendar-month mean, thereby comparing villages exposed to higher vs. lower sea level rise relative to their historical average. Finally, I compare villages closer vs. farther from the coast, under the intuition that rising sea levels

\[53 \text{ See Appendix Section B.3 for details on these data.} \]
will infiltrate irrigation water more the closer the village lies to the ocean. This yields the estimating specification shown in Equation 5. I cluster standard errors at the village level, the level of treatment.

\[
Y_i = \alpha + \beta_1 \text{Closer} \times \text{Saltier} \times \text{Higher} + \beta_2 \text{Closer} \times \text{Saltier} + \beta_3 \text{Closer} \times \text{Higher} + \beta_4 \text{Saltier} \times \text{Higher} + \beta_5 \text{Closer} + \beta_6 \text{Saltier} + \beta_7 \text{Higher} + \varepsilon_i \quad (5)
\]

The coefficient of interest \(\beta_1\) captures the degree to which villages closer to the coast happen to be exposed to higher sea levels when the ocean is saltier have differential outcomes. The quasi-random nature of ocean salinity (which can be influenced by factors like cloud cover and evaporation) and sea level rise give a causal interpretation to this regression. I use data from satellites to capture ocean salinity and sea level elevation; see Appendix Section 2.2 for details on these data and variable constructions. For ease of interpretation, I convert all units into standard deviations.

### 4.2 Differential Impacts of Salient Shocks and Subtle Shifts

As a first step in the analysis of these natural experiments, I examine the impact of experiencing a salient shock and subtle shift on the true soil salinity conditions as measured by the agronomic sensors. Columns (1) and (2) of Table 4 present the results of this analysis, reporting the main interaction terms from each difference-in-differences specification (the primary coefficients of interest).\(^{54}\) Coincidentally, it happens to be the case in this context that experiencing a 1 s.d. saltier flood has equivalent impacts on true soil salinity as does experiencing a 1 s.d. increase in ocean elevation interacted with a 1 s.d. saltier ocean among villages 1 s.d. closer to the coast. The salient shock increases measured salinity on farmers’ plots by .153 dS/m while the subtle shift increases it by .113 dS/m, and these effects are not statistically different from one another.

In contrast to the comparable impacts on true salinity, I find markedly asymmetric impacts on farmers’ beliefs. Columns (3) and (4) of Table 4 present the two main interaction terms from the difference-in-differences specifications and shows that only salient shocks increase beliefs, while subtle shocks have no detectable effects. Furthermore, salient shocks increase beliefs by more than the corresponding impact on true salinity, leading to overestimation.

The model predicts that this asymmetry occurs through the differential interpretation of

\(^{54}\)Appendix Tables A.6 and A.7 present coefficients for the full difference-in-differences specifications for the outcome of true soil salinity. Appendix Tables A.8 and A.9 does the same for the outcome of farmers’ beliefs.
signals in this underidentified environment. I directly test for this mechanism by combining other survey questions and a lab-in-the-field elicitation with this natural experiment. First, I simply ask farmers in the endline survey about the signs that they use to learn about salinity on their soil. Table 5 shows that consistent with the theory, farmers experiencing a salient shock disproportionately interpret more “generic” signals as indications of high salinity, particularly as compared to those having experienced a subtle shift. This is consistent with the identification problem: after a salty flood, farmers expect salinity to be a likely environmental threat, and as a result, they interpret even generic indicators of crop health like plant death and stunted height as indications that consistent with their prior belief, salinity is high. Farmers experiencing a subtle shift show no similar pattern.

By the same underlying channel, farmers experiencing salinity intrusion into their irrigation water via a rising sea level shock are more likely to attribute physical indicators of salinity to other causes. After the question referenced above in which I ask farmers to list all features of the crop that might indicate salinity, I ask farmers to list any other environmental causes that could generate the same symptoms. Despite reporting fewer symptoms overall, especially among generic indicators of plant health (as indicated by the results in Table 5), I find that farmers who experienced a subtle shift list significantly more other environmental explanations that could disguise themselves as soil salinity.

Finally, I examine the dynamic consequences of these climate experiences on learning using a lab-in-the-field exercise in which I show farmers images of unhealthy rice crops and ask them to list any potential explanations that might cause the plant to exhibit those symptoms. This was the first question after the consent forms, so farmers were not primed to think about salinity or any other environmental explanation. I ask this question both in the baseline and endline, and I include images for which the true explanation is salinity and not. I then estimate an expanded difference-in-differences specification interacting the natural experiments described above with indicators for the endline survey and the picture actually being caused by salinity. This captures the differential impact of having experienced a salty flood on improvements in accuracy about diagnosing salinity issues over the course of the 2022-23 season (and the corresponding effect for subtle shifts). Table 6 shows that farmers who experienced the salty flood become disproportionately more accurate at diagnosing salinity issues in particular, highlighting that past experience can have persistent impacts on learning itself as opposed to simply level effects. These specifications include farmer fixed effects and picture fixed effects.
5 Consequences of Beliefs for Climate Adaptation

How do these patterns of beliefs shape decision-making? This section presents the results from large-scale field experiments to measure the economic consequences of environmental beliefs.\footnote{For a discussion of the ethical considerations around all of the experiments in this project, see Appendix Section G.}

5.1 The Causal Impact of Beliefs on Technology Adoption

I estimate the causal effect of environmental beliefs on farmers’ adoption of climate technology using an information experiment centered around the salinity data I collect from farmers’ plots. The script introduced this information to farmers by explaining that the salt levels would be provided using both numbers and pictures and also in relative terms to the government’s official recommendation regarding the soil salinity level above which farmers should adopt saline-tolerant seeds. I embed this randomization into a Becker-DeGroot-Marschak elicitation of farmers’ willingness-to-pay (WTP) for information about the amount of salinity on their soil.\footnote{I pre-registered this experiment \url{here}. All randomization occurred within strata, which I define based on the intersection of village with direction of soil salinity belief error, determined based off of farmers’ baseline beliefs.} To measure demand using this approach, beginning with a low price, I ask farmers if they would be willing to purchase the item for that price.\footnote{During piloting, it became clear that norms against accepting gifts for free distorted the results of the BDM when beginning at 0 BDT. To circumvent this issue, I begin the price list at a small positive value, and only ask about 0 BDT if the respondent says no to that initial price.} If they say yes, I increase the price and ask again, repeating until the respondent says no. I then randomly select a price, and if the respondent was willing to purchase the good for that amount, the transaction takes place. Following Dizon-Ross and Jayachandran (2022), I elicit WTP for a plate as a benchmark good to include as a control.

In the case of soil salinity information, Farmers faced a price randomly drawn price from a bi-modal distribution with nearly all of the mass split evenly between 0 and 500 BDT, while prices in between were drawn with probability .0001 each to preserve incentive compatibility. Prior to the price list elicitation, most farmers viewed this information as useful: 69.42 percent of farmers said it would be extremely or very helpful, while just 1.98 percent said it would not be helpful at all. Farmers’ demand reflects these attitudes: the median farmer offered up to 30 BDT for the information, with an average value of 41.74 BDT, and 84% of farmers had a positive willingness-to-pay. Within this information experiment, I also randomize the type of information: some farmers were only offered average salinity levels for their upazila, while others were in addition offered data on their own plots. I delay
discussion of this aspect of the experiment until the conclusion, but note the distinction for now to explain the specification for estimating treatment effects.

As a first-stage, this information does shift farmers’ perceptions about the amount of salt in their soil next year. I test for this effect by estimating equation 6, where Prior denotes farmer i’s prediction about the 2022-23 soil salinity level on their plot, OwnTruth signifies the true salinity as measured by the EC-meters, UpaTruth denotes the average of these salinity readings across all participating farmers in i’s upazila, OwnTreatment_i indicates whether farmer i received information about OwnTruth, and UpaTreatment_i does the same for UpaTruth. Table 10 presents the results from these regressions, showing large F-statistics regardless of whether I restrict the sample to those who pass the belief elicitation comprehension checks or not. Consistent with soil salinity ultimately being quite low during the 2022-23 season, most farmers in the treatment group updated downwards, expecting lower salt levels in the future.

\[ Y_i = \alpha + Prior_i + \beta_1 OwnTreatment_i + \beta_2 OwnTreatment_i \times OwnTruth_i + \beta_3 OwnTreatment_i \times UpaTruth_i + \beta_4 UpaTreatment_i + \beta_5 UpaTreatment_i \times UpaTruth_i + \varepsilon \]  
(6)

Using treatment as an instrument, I can measure how demand for salinity tolerant seed varieties varies with beliefs. I show that randomly providing farmers with information about salinity content on their soils as measured by the EC-meters (using the same visual as the belief elicitation to convey the information) shifts both their incentivized willingness-to-pay for a salinity-tolerant seed variety and their expectations about agricultural behavior moving forward. In this context, the information typically shifted farmers’ beliefs downward, with a resulting decrease in the seed willingness-to-pay and a decline perceived likelihood of planting a saline tolerant seed next season, as shown in Table 11.

5.2 Salinity-Tolerant Seed Experiment

How much does adaptation to salinity through seed choice impact farmers’ ultimate economic well-being? To answer that question, I conduct a separate experiment, randomly varying the marginal cost of planting saline-tolerant seeds during the baseline survey. Sim-

58 The endline survey exhibited an extremely low attrition rate of 1.14 percent. Farmers receiving a saline-tolerant seed BDM price of 0 during the baseline were slightly more likely to not be found in the endline (0.77 percentage points), an effect which is marginally statistically significant (p-value=0.08) but amounts to a difference of just 9 farmers, too small to meaningfully impact any results.
ilar to the soil salinity information above, I embed this randomization into the price drawn during the Becker-DeGroot-Marschak elicitation of farmers’ WTP for a saline-tolerant variety.\textsuperscript{59} I draw the seed price from a distribution of prices that equals 0 BDT with probability .49905, 200 BDT with probability .49905, and each price in between with probability .0001 to preserve incentive compatibility. Let $Free_i$ denote an indicator for whether farmer $i$ was randomly assigned a price of 0. To estimate the impact of adoption of the saline-tolerant seed variety $\text{Tolerant}_i$ on agricultural output $Y_i$, I estimate the regression specification in equation 7, instrumenting for adoption of seed 67 using $Free_i$. Following the pre-specified heterogeneity, my primary specification excludes the 31.07 percent of households who had already purchased their seeds for the season at the time of the interview.

$$Y_i = \alpha + \beta Tolerant_i + \epsilon_i$$

I “reversed” the experimental design in this format (randomizing seeds in the baseline and information in the endline) in order to minimize the rounds of data collection necessary. In order to interpret the impact on harvest as a potential consequence of information, I must assume that the set of compliers is comparable across the two experiments: that is, that the marginal seed user induced via the information treatment is not differentially selected from the marginal seed user induced via the lower BDM price. In fact, an even weaker assumption still allows me to take an intent-on-the-treated interpretation: if shifting beliefs about salinity is equivalent to changing the marginal cost of purchasing saline-tolerant seeds, then I can link these two experiments together to draw conclusions about the impact of information on profits.

I first find that 85.9 percent of farmers have a positive WTP for these seeds, and 38.7 percent have a WTP greater than the market price.\textsuperscript{60} Randomly assigning half of farmers a price of zero, I find that being assigned a price of 0 during the BDM procedure increases the likelihood of planting a salinity-tolerant seed by 13.87 percentage points, or 32 percent of the control group mean of 42 percentage points. In both the reduced form and instrumental variables framework, I find evidence that the treatment (and subsequent increase in salinity tolerant planting) reduced agricultural profits, consistent with soil salinity being especially low during the 2022-23 season. Together, these results show that environmental beliefs on the margin have large economic consequences for farmers’ bottom-line.

\textsuperscript{59} I pre-registered this experiment here.
\textsuperscript{60} Because I was delivering the seed directly to the farmer and the BDM procedure is itself quite different than the experience of purchasing in the market, the relative levels to the market price should be interpreted cautiously.
5.3 Flood Risk Information Experiment

In an additional test of whether expectations shape adaptation to climate change, I test whether farmers’ beliefs about the likelihood of flooding impacts their demand for a flood insurance contract. Weather insurance poses many attractive features for mitigating the risk associated with climate change, yet demand remains low across many developing countries for a variety of reasons, including trust, financial literacy, and present bias, among others (see Cole and Xiong (2017) for a review). In my sample, just 6.40 percent of farmers had any kind of insurance contract against weather or natural disaster shocks. Misperceptions about risk present one alternative explanation: if farmers underestimate the likelihood of flooding, then this will suppress the market even if demand would be sufficient at actuarially fair prices. I follow the literature and focus on indexed insurance contracts instead of the traditional indemnity-based products which have largely been abandoned in contexts like this one.

To measure demand for flood insurance, I elicit farmers’ willingness-to-pay (WTP) for a hypothetical contract using a price list. Because only 17.44 percent of farmers had heard about weather or natural disaster insurance, enumerators spent time explaining the basic principles of the contract, using the visual aid shown in Appendix Figure C.4 to help farmers understand. This exercise succeeded: 96.78 percent and 96.27 percent of farmers answered each of two comprehension questions correctly.\footnote{In the analysis that follows, I exclude farmers who answer these comprehension questions incorrectly in addition to those who fail the beliefs elicitation checks. For the full text of the explanation and these checks, see Appendix Section C.3.} With equal probability, I randomized the insurance payout between 10,000 and 30,000 BDT in increments of 5,000, and then elicited the highest willingness-to-pay for a monthly premium of that contract.\footnote{I winsorize the willingness-to-pay values at 200 BDT per month, which affects 4 farmers.} Half of farmers answered these questions during the baseline, and half answered during the endline.

Farmers’ expectations about the likelihood of experiencing a flood strongly predict their demand for this hypothetical contract. I present results using an aggregate index of flood risk, though all results are robust to using the individual components.\footnote{I consider each of the following measures. First, I use the expected number of flood days in the next year and the next five years based on the farmers’ answers to the flood risk belief elicitation questions. Second, I calculate hazard rates from the number of years until farmers expect to have experienced a flood that lasts for one day, three days, a week, or a month. Third, I use farmers’ responses to the questions about whether flood risk has increased in the past 10 years, will increase in the next 10 years, and the order those two questions were asked. I combine these into a single index following the procedure in Kling et al. (2007), and standardize the resulting measure based on the control group mean and standard deviation.} To visualize the link between beliefs and WTP, Figure 10 plots demand curves by quintile of this flood index. The graph shows clear differences non-parametrically in the share of farmers willing to purchase the insurance contract at a given price, particularly at low prices where the bulk of consumers
are marginal. What makes these demand curves look so different? To shed light on that question, I calculate price elasticities using a log-log specification, interacting price with beliefs. For statistical power, I pool the first and second quintiles into one category and the third, fourth, and fifth into a second. Figure 11 plots these elasticities. Farmers with higher beliefs about flood risk exhibit significantly higher price elasticities (p-value = 0.016).

The absence of true flood risk presents one clear challenge to interpreting the link between expectations and WTP shown in those graphs. Of course, farmers’ beliefs likely reflect—at least in part—their true exposure to flooding, and that could be driving demand. To speak to this issue, Table 12 presents simple linear regressions predicting stated WTP using the flood risk index and a battery of measures of flood risk, described in detail in Appendix Section B.1. In all specifications, I include an indicator for the survey round, farmers’ WTP for a plate from the BDM of the survey (following Dizon-Ross and Jayachandran (2022)), and fixed effects for the insurance payout amount. I report heteroskedasticity-robust standard errors. Column (1) presents the simple relationship between perceived flood risk and demand. Columns (2) through (6) show how this coefficient changes with the addition of various proxies for flood risk. Across all specifications, the coefficient remains either effectively the same or in fact increases in magnitude, suggesting that beliefs shape demand above and beyond the true local propensity for flood exposure. Column (7) embraces this logic one step further with the inclusion of union fixed effects, testing whether beliefs help explain WTP conditional on all other aspects that might shape demand within the village, including the common component of expectations. Although the estimates are significantly noisier, I cannot reject that the point estimate matches that of Columns (1) through (6), even in this particularly conservative specification.

One concern with a causal interpretation of these patterns is that an omitted variable might be correlated with both perceived flood risk and insurance demand. In an attempt to better isolate the causal impact of beliefs, I implemented an information experiment among the half of the sample that answered these questions during the endline survey. Enumerators told a random half of farmers about historical flood incidence in their area based on the analysis of satellite imagery described earlier in this paper. Specifically, the information included the number of unions in their upazila that experienced a flood since 2002 according to that measurement, and conditional on at least one union having a flood, the frequency of floods at an annual level. Table 13 presents the results from this experiment.

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64 I pre-registered this design here. The script introducing the information included language about the limitations of this methodology: “As part of this project, we measured flooding in each union using data from satellites. These measures are not perfect, but they can help us understand how frequently floods occur.” Because treatment status does not vary within the baseline, I omit that control from the analysis of this experiment.
To measure the impact of information on beliefs, I first recalculate the flood index using only those questions asked after the potential information treatment. This alternative measure strongly predicts WTP, echoing the results in Table 12 as shown in Column (1). On average, farmers update their beliefs about flood risk downwards after receiving this information, as shown in the first-stage results in column (2). Though noisy, the reduced form and two-stage least squares results of columns (3) and (4) suggest a causal link between perceived flood risk and demand for index insurance.

How large is this effect of beliefs? To help quantify the magnitude, I use the random variation from the insurance payout amount as a benchmark, as interpreting levels from price lists like this one can be misleading. Despite the huge variation in potential compensation (10,000 - 30,000 BDT, or approximately $93 - $279 USD), I find no evidence that farmers demand responds to this amount. In an OLS regression controlling for survey round and farmers’ WTP for a plate during the BDM, the coefficient is very close to zero and statistically insignificant (p-value = 0.77). Appendix Figures A.11 and A.12 plot demand curves and price elasticities by contract, again showing no difference across payouts. In the context of the belief results, this underscores that the magnitude of the effect of expectations dwarfs the impact of even a tripling of the insurance payout amount.

The hypothetical nature of this elicitation method raises concerns with this analysis if farmers’ answers do not reflect meaningful variation in their willingness-to-pay. Like with the incentivized Becker-DeGroot-Marschak method, I refrain from interpreting the levels from these price lists, relying instead on relative differences across farmers. Nevertheless, the results described above could still be biased if some additional factor—such as experimenter demand—correlates with both the stated willingness-to-pay and farmers' expectations about flood risk. The information experiment helps to alleviate this concern: such an omitted variable would also have to be impacted by the treatment providing historical flood incidence in the area. As a further validation of the hypothetical method, however, I implement a separate survey among a small sample of farmers in some of the same villages as the main survey sample, drawing from the initial household listing. I elicit both the hypothetical willingness-to-pay using the same questions as the main survey and additionally conduct a Becker-DeGroot-Marschak elicitation of demand for a 10,000 BDT flood insurance contract. I find a strong, statistically significant relationship between the incentivized and unincentivized

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65 This null is consistent with a model in which damages from floods poorly correlate with flood incidence, resulting in considerably less responsive utility gains to shifts in the financial payout. Indeed, I find evidence of this mechanism in farmers’ answers to their expected financial damages to their homes conditional on experiencing floods lasting for different amounts of time. On average, the standard deviation across these five flood length categories is 51,425.74 BDT, highlighting the uncertainty farmers hold about potential harm caused by flooding events.
versions of the question, a reassuring sign that the WTP I elicited on the main sample captures a real dimension of demand.\textsuperscript{66}

6 Learning Counterfactuals and Policy Simulations

How large of a role do beliefs play in adaptation to climate change? The experimental results show that environmental expectations have large causal impacts on choice, but characterizing the overall magnitude is challenging from those reduced form estimates alone for several reasons. First, my primary outcome is willingness-to-pay as captured via the BDM mechanism. The nature of this elicitation (for instance, giving farmers 500 BDT immediately prior to the measurement) likely introduces level effects, as suggested by the significant share of people willing to pay above market price. Second, the impact of environmental beliefs on seed choice is non-linear. Third, the experiment captures how demand for salinity-tolerant seeds varies with beliefs about next season’s salinity, measured over the summer. Farmer’s beliefs likely evolve between the endline and the actual planting decision in the winter as they observe more information about their land, and the ideal elasticity relates to beliefs at the time of planting. Fourth, I can only identify the local average treatment effect of those farmers whose beliefs were influenced by the experiment.

Because of those limitations, in this section I turn to a structural model of demand for climate adaptation. Specifically, I estimate a random utility model of seed choice (McFadden, 1974; Train, 2009). In doing so, I can explicitly account for the non-linear role of beliefs to answer questions like: how would seed choice change if farmers had completely accurate beliefs about soil salinity? What would happen if farmers learned from subtle shifts in the same way as salient shocks? How effective would a government information intervention policy be at increasing climate adaptation?

6.1 Model of Seed Choice

I expand the set-up from Section 3 to allow farmers indexed by $i$ living in village $v$ to choose among $J_v$ dry-season rice varieties. To simplify the estimation, I focus on the seed choice that each farmer plants on the largest share of their land, such that each farmer chooses one seed among the set $J_v$. Because I cannot observe the true set of potential seed choices faced by each farmer, I define $J_v$ to be the superset of all seeds planted on any amount of land by any farmer $i \in v$.

Equation 8 captures the indirect utility of farmer $i$ choosing seed $j$, where $x_{ij}$ is a vec-

\textsuperscript{66}For details on this data collection and result, see Appendix Section C.3.
tor of seed-specific characteristics, $\beta_i$ are random coefficients that vary over farmers in the population, $w_{ij}$ is a vector of seed-specific characteristics, $z_i$ is a vector of farmer-specific characteristics, $c_j$ are intercepts, and $\varepsilon_{ij}$ are unobserved random taste shocks, which I model as independent type I (Gumbel-type) extreme-value random variables.

$$U_{ij} = V_{ij} + \varepsilon_{ij} = x_{ij}\beta_i + w_{ij}\alpha + z_i\delta_j + c_j + \varepsilon_{ij} \tag{8}$$

By including random coefficients, I allow for correlation of choices across alternatives and therefore do not have to assume independence of irrelevant alternatives. I do not directly estimate $\beta_i$ but rather assume they have a multivariate normal distribution $\beta_i \sim N(\mu, \Sigma)$ and estimate $\mu$ and $\Sigma$. Given this utility function, the probability of the $i$th farmer choosing seed $j$ is given by equations 9 and 10. Because the integral in Equation 10 has no closed-form solution, I compute it using maximum simulated likelihood.

$$P_{ij}(\beta) = \frac{e^{V_{ij}}}{\sum_{k \in J} e^{V_{ik}}} \tag{9}$$

$$P_{ij} = \int P_{ij}(\beta)f(\beta)d\beta \tag{10}$$

### 6.2 Estimating the Demand Model

To estimate this model, I begin by building a database of seed characteristics. For the vector $w_{ij}$, I include seed price, indicators for whether the modal farmer I survey reported that a feature of that seed was processing ease, market demand, good taste, and nice color, along with whether the modal farmer reported that seed being resistant to pests and resistant to salinity.\(^{67}\) For the vector $x_{ij}$, I include the interaction of salinity-tolerant status with the error in farmers’ beliefs about the amount of salt in their soil. In my default specification, I do not include any further farmer-specific controls $z_i$. I cluster all standard errors at the farmer level. I estimate the model exclusively among the treatment group from the seed experiment, and always exclude those who fail the beliefs elicitation comprehension checks at baseline. This provides a natural out-of-sample goodness-of-fit test by examining how the predictions of this model perform among the control group.

The results show that the model performs well and that beliefs about salinity levels strongly impact adoption of salinity tolerant seeds. First, coefficients in general tend to be consistent with our priors about how adoption should respond to seed attributes. Market demand for the harvested rice and the associated selling price are both strongly positively

\(^{67}\)Note that I use farmers’ beliefs about seeds because that is the characteristic of the variety upon which they make their decision.
related with seed adoption, for example. Second, the standard deviation of the random coefficients for the interaction of salinity tolerance and belief error is positive and statistically different from zero, allowing me to reject that independence from irrelevant alternatives would apply in this setting. Third, the model’s predictions out of sample in the control group strongly predict farmers’ actual behavior in that population. Table 9 presents simple regressions of actual seed choice on the model’s predicted probabilities, separately for the treatment group in the seed experiment (upon which the demand model was estimated) and the control group. In both cases, I cannot reject a coefficient of 1: in other words, as the model’s prediction about whether seed is selected increase by 1, so to does the actual behavior of farmers.

How does seed adoption change under alternative beliefs? I estimate these counterfactuals by calculating the marginal predicted choice probability for each seed under alternative variables using the structure of the demand model. Figure 9 plots these predicted adoption probabilities by error separately for farmers whose soil salinity initially fell below the government recommended threshold of 4.00 dS/m for switching to salinity tolerant seeds and those for whom their measurement fell above. Those facing high salinity levels always exhibit higher adoption rates regardless of their beliefs, reflecting differences in the seed market across places. Yet for both groups, beliefs play a large role in shaping adoption. On average, moving from the 10\textsuperscript{th} percentile to the 90\textsuperscript{th} percentile in belief error corresponds to an 80.87 percent increase in the probability of adoption a salinity-tolerant seeds.

7 Conclusion

This paper has documented the importance of environmental beliefs in shaping adaptation to climate change.

One clear policy recommendation emerging from these results is the value of collecting and disseminating information about local climate conditions. From a policy perspective, providing farmers with soil salinity information collected from their own plots presents a significant cost—requiring individual-level analysis of farmers’ own plots. Instead, providing farmers with aggregate averages at a higher-geographic level presents an appealing possible alternative. In this context, upazila represents the relative geographic level for this policy question as the administrative unit at which the Bangladesh government currently collects and reports soil salinity data. The success of this type of policy hinges on the answer to two questions. First, do true salinity conditions covary enough within these areas to meaningfully speak to farmers’ own agricultural decisions? I examine this question using the new soil salinity data I collected, and find that for the most part, the aggregate value
accurately captures farmers’ own experiences. The correlation between the salinity measured from farmers’ own plots and the mean value across all plots from which I collect data in their upazila is 0.81. To put this magnitude in perspective, I provide two benchmarks. First, the correlation between a farmers’ own plot and their village average is 0.92. Second, I take advantage of the three measurements taken by enumerators on each plot during each round of soil salinity data collection. This gives me six pairwise correlations of salinity on the same land on the same date, helping to provide a sense of the maximum correlation given the sensor’s measurement error. On average, the average pairwise correlation from these measurements is 0.90. To view this another way, the government threshold for switching to saline tolerant seeds is 4.5; the recommendation based on data from a farmer’s own plot disagrees with that from the upazila average just 2.57 percent of the time.

Do farmers themselves recognize this strong agronomic link between their own plots and that of their peers in the upazila? To speak to that second key question for this overall policy, I consider two types of evidence. First, I directly measure farmers’ subjective views of the similarity of their plots to that of their neighbors, both within their village and within their larger upazila. Consistent with the soil salinity measurements, farmers perceive a lower spatial covariance at higher geographic levels: 25.48 percent say that the salt on their plot is extremely or very similar to their village average, as compared to 9.23 percent for the upazila average. In fact, farmers for whom the difference in absolute value between their plot and their upazila mean minus the absolute value of their plot and village mean are also significantly more likely to qualitatively answer that their salt is more similar to their village neighbors ($p$-value = 0.02). Second, I take a revealed preference approach and embed an additional arm within the information experiment, offering a random 75 percent of farmers information both about their own soil salinity and the average salt levels for all farmers in their upazila, while the remaining farmers could only purchase information about the latter upazila mean figure. I find no evidence that farmers value these aggregate figures less than data about their own plots. Appendix Figure A.9 plots the distribution of farmers’ demand for information separately by those offered the upazila-average only compared to those offered their own plot’s data as well, and the distributions almost entirely overlap. In OLS regressions predicting demand for information conditional on WTP for the plate, I find no strong evidence of a systematic impact of the format of information provided, with a 95 percent confidence interval of -6.53 to 2.61. Overall, these results suggest that although farmers indeed recognize that information at higher geographic aggregates applies

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68 Note that both the upazila and village correlations are upwardly biased towards the truth because of imputations used replace missing salinity measurements (due to flooding or farmer unavailability), though this procedure reflects a reasonable implementation of this policy in practice.
less to their own agricultural conditions, providing this (much less costly) information can nevertheless still shift beliefs.
References


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Rentzschler, Jun, Melda Salhab, and Bramka Arga Jafino, “Flood Exposure and Poverty in 188 Countries,” *Nature Communications*, 2022, 13 (3527).


— and __. “The best of both worlds: combining randomized controlled trials with structural modeling,” Journal of Economic Literature, 2023, 61 (1), 41–85.


8 Figures and Tables
Figure 1: Soil Salinity Beliefs vs. Agronomic Truth

![Figure 1: Soil Salinity Beliefs vs. Agronomic Truth](image)

**Note:** Figure 1 plots a binned scatter plot of farmers’ beliefs about the 2022-23 season’s average soil salinity against the ground truth based on direct agronomic readings of their soil. The dashed gray line denotes the 45-degree line. Figure 2 plots a histogram of the errors in beliefs. The dashed vertical red line denotes perfect accuracy. Mass to the right of that line captures overestimation, and mass to the left captures underestimation.

Figure 2: Histogram of Belief Errors

![Figure 2: Histogram of Belief Errors](image)
### Table 1: Soil Salinity Beliefs vs. Agronomic Truth

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Salinity Truth</strong></td>
<td><strong>Salinity Belief</strong></td>
<td><strong>Salinity Belief</strong></td>
</tr>
<tr>
<td>Salinity Truth</td>
<td>0.786***</td>
<td>0.805***</td>
</tr>
<tr>
<td></td>
<td>(0.121)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.999*</td>
<td>0.913*</td>
</tr>
<tr>
<td></td>
<td>(0.547)</td>
<td>(0.504)</td>
</tr>
<tr>
<td>Include Comp. Check Failures</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Outcome Mean</td>
<td>4.617</td>
<td>4.633</td>
</tr>
<tr>
<td>Observations</td>
<td>2,068</td>
<td>2,271</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.034</td>
<td>0.038</td>
</tr>
<tr>
<td>$p$-value: $\beta$ True Salinity = 1</td>
<td>0.078</td>
<td>0.080</td>
</tr>
<tr>
<td>$p$-value: $\beta$ Constant = 0</td>
<td>0.068</td>
<td>0.070</td>
</tr>
</tbody>
</table>

**Note:** Table 1 presents bi-variate regressions of farmers’ beliefs about salinity on the true soil salinity measurements. The agronomic truth is based off of the best prediction of seasonal exposure given the fall 2022 measurements. The outcome in each regression is farmers’ beliefs, which captures farmers’ expectations about soil salinity over the course of the 2022-23 season, measured during the fall. Column (1) includes the pre-specified cut of excluding those farmers who fail the comprehension checks during the belief elicitation practice. Column (2) includes the full sample. All specifications report heterogeneity-robust standard errors.
Table 2: Planting Behavior and Salinity Belief Errors

<table>
<thead>
<tr>
<th></th>
<th>(1) Intend To Plant Salinity-Tolerant Seeds</th>
<th>(2) Actual Share Land Planted With Salinity-Tolerant Seeds (Perceived Status)</th>
<th>(3) Actual Share Land Planted With Salinity-Tolerant Seeds (Actual Status)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Salinity Belief - Truth</td>
<td>0.0384*** (0.00355)</td>
<td>0.0207*** (0.00365)</td>
<td>0.0181*** (0.00294)</td>
</tr>
<tr>
<td>True Salinity</td>
<td>0.180*** (0.0164)</td>
<td>0.123*** (0.0167)</td>
<td>0.135*** (0.0146)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,068</td>
<td>2,008</td>
<td>2,008</td>
</tr>
<tr>
<td>Outcome Mean</td>
<td>0.412</td>
<td>0.168</td>
<td>0.168</td>
</tr>
</tbody>
</table>

Figure 3: Planting Behavior and Salinity Belief Errors

(a) Salinity-Tolerant Seed Intention
(b) Share Land with Salinity-Tolerant Seeds

Note: Table 2 presents regressions of the farmers’ planting behavior on the error in their salinity beliefs (defined as beliefs minus the truth) and the true agronomic salinity on their plots. Column (1) uses as an outcome whether farmers report intending to plant any salinity-tolerant variety on their plot. Column (2) reports the total share of land across all plots on which farmers planted a seed that they consider to be salinity-tolerant. Column (3) shows the same, this time using my assessment of whether the seed is salinity-tolerant based on official agronomic records as opposed to the farmers’ own reports. All regressions exclude those who fail the beliefs comprehension checks during the practice elicitation and report heteroskedasticity-robust standard errors. Figures 3a and 3b visualize the relationships in Columns (1) and (2) of Table 2 using binned scatter plots.
Figure 4: The Spatial Concentration of Salinity Belief Errors

Note: Figure 4 plots cumulative distribution functions at the village level of the probability that two randomly drawn people from that village have opposite signed salinity bias, calculated as 1 minus the Hirschman-Herfindahl Index where the group shares are the proportion of people over- and underestimating the salinity on their plot. The blue line shows the true data. The gray lines plot the cumulative distribution functions for 100 placebo distributions after randomly re-assigning villages.
<table>
<thead>
<tr>
<th>Salinity Beliefs - Truth</th>
<th>(Standardized)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Log Plot Area</td>
<td>-0.119***</td>
</tr>
<tr>
<td></td>
<td>(0.0146)</td>
</tr>
<tr>
<td>Age (10 years)</td>
<td>-0.0881***</td>
</tr>
<tr>
<td></td>
<td>(0.0126)</td>
</tr>
<tr>
<td>Peers View</td>
<td></td>
</tr>
<tr>
<td>Extremely</td>
<td></td>
</tr>
<tr>
<td>Knowledgeable</td>
<td>-0.251***</td>
</tr>
<tr>
<td></td>
<td>(0.0914)</td>
</tr>
<tr>
<td>Peers Follow</td>
<td></td>
</tr>
<tr>
<td>Seed Advice</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.674***</td>
</tr>
<tr>
<td></td>
<td>(0.0706)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,008</td>
</tr>
<tr>
<td>Outcome Mean</td>
<td>-0.020</td>
</tr>
</tbody>
</table>

Note: Table 3 presents regressions prediction the absolute value of salinity beliefs minus the agronomic truth, normalized to have mean equal to 0 and standard deviation equal to 1. Column (1) regresses this outcome on the log of total harvested land as measured in the endline survey. Column (2) regresses this outcome on the farmer’s age, scaled by 10 years for readability. Column (3) regresses this outcome on the share of other farmers in the village who say that the respondent is extremely knowledgeable about farming. Column (4) regresses this outcome on the share of other farmers in the village who say that they would consider following the respondent’s advice about what seed to plant. All specifications include the true salinity level interacted with fixed effects for each ventile. All regressions exclude those who fail the beliefs comprehension checks during the practice elicitation and report heteroskedasticity-robust standard errors.
Figure 5: Simulated Belief Movement in Conceptual Framework

(a) Absolute Changes in Beliefs: High Yield
(b) Absolute Changes in Beliefs: Low Yield

(c) Relative Changes in Beliefs: High Yield
(d) Relative Changes in Beliefs: Low Yield

Note: Figure 5 shows changes in beliefs for simulated data based on the model. In all simulations, I assume $\rho = .33$, that is their is an equal chance of a high, low, and neutral productivity shock. The left column corresponds to observing high yield in the first period, and the right column corresponds to observing low yield. Figures 5a and 5b illustrate how beliefs change after observing the new data, where the arrows begin at the prior. Figures 5c and 5d scale this change to account for the mechanical limitations of belief updating given the bounds, shading based on the relative change in beliefs at each prior.
Table 4: Impact of Climate Shocks on True Salinity and Salinity Beliefs

<table>
<thead>
<tr>
<th></th>
<th>True Salinity</th>
<th>Salinity Beliefs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Flood × Saltier</td>
<td>0.157***</td>
<td>0.909**</td>
</tr>
<tr>
<td></td>
<td>(0.0531)</td>
<td>(0.395)</td>
</tr>
<tr>
<td>Closer to Ocean × Sea Level Rise × Ocean Salinity</td>
<td>0.113*</td>
<td>0.194</td>
</tr>
<tr>
<td></td>
<td>(0.0581)</td>
<td>(0.190)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>Clusters</th>
<th>Control Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2075</td>
<td>250</td>
<td>4.605</td>
</tr>
<tr>
<td></td>
<td>2075</td>
<td>250</td>
<td>4.605</td>
</tr>
<tr>
<td></td>
<td>2068</td>
<td>250</td>
<td>4.617</td>
</tr>
<tr>
<td></td>
<td>2068</td>
<td>250</td>
<td>4.617</td>
</tr>
</tbody>
</table>

Note: Table 4 displays only the main interaction term of the difference-in-differences. Standard errors are clustered at the village level. The outcome in columns (1) and (2) is the true soil salinity as measured by agronomic sensors. The outcome in columns (3) and (4) is farmers’ mean belief about soil salinity. Independent variables Saltier, Closer to Ocean, Sea Level Rise, and Ocean Salinity are all measured in standard deviations. Sample restricted to farmers who passed belief comprehension checks.

Figure 6: Impact of Climate Shocks on True Salinity and Salinity Beliefs

Note: Figure 6 plots the coefficients from Table 4 and reports $p$-values testing for equality between coefficients.
Table 5: Impact of Climate Shocks on Interpretation of Environmental Signals

<table>
<thead>
<tr>
<th></th>
<th>Use of Generic Signals to Learn About Salinity</th>
<th>Attribution of Salinity Symptoms To Other Causes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Closer to Ocean × Sea Level Rise × Ocean Salinity</td>
<td>-0.0474  (0.0646)</td>
<td>0.457** (0.187)</td>
</tr>
<tr>
<td>Flood × Saltier</td>
<td>0.187*** (0.0529)</td>
<td>-0.0413 (0.198)</td>
</tr>
</tbody>
</table>

| Observations | 2056 | 2056 | 2056 | 2056 |
| Clusters     | 250  | 250  | 250  | 250  |
| Control Mean | 1.074| 1.074| 2.451| 2.451|

Note: Table 5 displays only the main interaction term of the difference-in-differences. Standard errors are clustered at the village level. The outcome in columns (1) and (2) is the sum of indicators for whether the farmer reports using the height of plants or plant death as an indicator from which they can learn about soil salinity. The outcome in columns (3) and (4) is the total number of other potential causes that farmers report saying could exhibit the same symptoms as high soil salinity. Independent variables Saltier, Closer to Ocean, Sea Level Rise, and Ocean Salinity are all measured in standard deviations. Sample restricted to farmers who passed belief comprehension checks.

Table 6: Dynamic Impacts of Climate Shocks on Learning

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Closer to Ocean × Sea Level Rise × Ocean Salinity</td>
<td>0.00342 (0.0140)</td>
<td></td>
</tr>
<tr>
<td>Flood × Saltier</td>
<td>0.0621* (0.0335)</td>
<td></td>
</tr>
</tbody>
</table>

| Observations | 20655 | 20655 |
| Farmers      | 2075  | 2075  |
| Clusters     | 250   | 250   |
| Control Mean | 0.141 | 0.141 |

Note: Table 6 displays only the main interaction term of the difference-in-differences in the natural experiments, interacting additionally with indicators for the endline survey and the true cause of the image being about soil salinity. Standard errors are clustered at the village level. Outcome is the whether the farmer answered the question correctly. Independent variables Saltier, Closer to Ocean, Sea Level Rise, and Ocean Salinity are all measured in standard deviations. Sample restricted to farmers who passed belief comprehension checks.
Figure 7: Impact of Climate Shocks on Interpretation of Environmental Signals

Note: Figure 7 plots the coefficients from Table 5 and reports \( p \)–values testing for equality between coefficients.

Table 7: Impact of Salinity-Tolerant Seeds

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tolerant Seed Share (FS)</td>
<td>Profits (OLS)</td>
<td>Profits (RF)</td>
<td>Profits (IV)</td>
</tr>
<tr>
<td>Offered Free Seeds</td>
<td>0.0898***</td>
<td>-0.0918**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0143)</td>
<td>(0.0428)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Salinity Tolerant Seed Share</td>
<td>-0.388***</td>
<td>-1.022**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0605)</td>
<td>(0.483)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control Mean</td>
<td>0.124</td>
<td>0.021</td>
<td>0.021</td>
<td>0.021</td>
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<tr>
<td>First Stage F-Stat</td>
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<td></td>
<td>39.938</td>
</tr>
</tbody>
</table>

Note: Table 7 presents results on the salinity-tolerant seed experiment. All specifications exclude those farmers who fail the baseline belief elicitation checks and report heteroskedasticity robust standard errors. Agricultural profits in Columns (2) through (4) have been standardized.
Table 8: Random Coefficients Demand Estimates

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seed Price (100s BDT)</td>
<td>0.962</td>
<td>0.963</td>
</tr>
<tr>
<td></td>
<td>(0.0391)</td>
<td>(0.0395)</td>
</tr>
<tr>
<td>Salinity Tolerant</td>
<td>1.040</td>
<td>1.026</td>
</tr>
<tr>
<td></td>
<td>(0.145)</td>
<td>(0.147)</td>
</tr>
<tr>
<td>Salinity Tolerant × Belief Error (dS/m)</td>
<td>1.112**</td>
<td>1.115**</td>
</tr>
<tr>
<td></td>
<td>(0.0385)</td>
<td>(0.0418)</td>
</tr>
<tr>
<td>Selling Price (100s BDT)</td>
<td>1.030</td>
<td>1.030</td>
</tr>
<tr>
<td></td>
<td>(0.0191)</td>
<td>(0.0195)</td>
</tr>
<tr>
<td>Growth Duration</td>
<td>0.999</td>
<td>0.999</td>
</tr>
<tr>
<td></td>
<td>(0.00477)</td>
<td>(0.00480)</td>
</tr>
<tr>
<td>Processing Ease</td>
<td>0.686</td>
<td>0.683</td>
</tr>
<tr>
<td></td>
<td>(0.539)</td>
<td>(0.541)</td>
</tr>
<tr>
<td>Market Demand</td>
<td>2.611***</td>
<td>2.645***</td>
</tr>
<tr>
<td></td>
<td>(0.365)</td>
<td>(0.381)</td>
</tr>
<tr>
<td>Good Taste</td>
<td>0.643***</td>
<td>0.642***</td>
</tr>
<tr>
<td></td>
<td>(0.0771)</td>
<td>(0.0774)</td>
</tr>
<tr>
<td>Nice Color</td>
<td>0.399*</td>
<td>0.387*</td>
</tr>
<tr>
<td></td>
<td>(0.179)</td>
<td>(0.180)</td>
</tr>
<tr>
<td>Pest Tolerant</td>
<td>1.192</td>
<td>1.189</td>
</tr>
<tr>
<td></td>
<td>(0.160)</td>
<td>(0.162)</td>
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<td>/Normal</td>
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<td></td>
</tr>
<tr>
<td>sd(seed_saltolbelief)</td>
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<td>1.201</td>
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<tr>
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<td>4469</td>
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<tr>
<td>Farmers</td>
<td>724</td>
<td>724</td>
</tr>
</tbody>
</table>

Note: Table 8 presents the estimates from the random coefficients demand estimation of seed choice. The sample only includes farmers in the treatment group from the seed experiment and excludes all those who fail the baseline belief elicitation comprehension checks. I report odds-ratios, but the stars denote statistical significance of the original coefficients (unexponentiated). I allow random coefficients for the interaction between salinity tolerant seeds and belief errors, where belief errors are defined as the difference between farmers’ predictions of soil salinity on their plots for 2022-23 and the best agronomic prediction for the same period based on the fall EC-meter readings.
Table 9: Demand Model Out-of-Sample Performance

<table>
<thead>
<tr>
<th></th>
<th>(1) Control (Out-of-Sample)</th>
<th>(2) Treatment (In-Sample)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Prediction</td>
<td>0.981***</td>
<td>1.034***</td>
</tr>
<tr>
<td></td>
<td>(0.0359)</td>
<td>(0.0364)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.00310</td>
<td>-0.00547</td>
</tr>
<tr>
<td></td>
<td>(0.00579)</td>
<td>(0.00592)</td>
</tr>
<tr>
<td>Observations</td>
<td>4678</td>
<td>4455</td>
</tr>
<tr>
<td>Farmers</td>
<td>754</td>
<td>725</td>
</tr>
</tbody>
</table>

Note: Table 9 provides out-of-sample tests for the performance of the demand model. The outcome is a binary indicator for whether that seed is the one that farmer’s planted the largest share of their land in the 2022-23 season. The predictor is the model’s predicted probability of that seed being chosen.

Figure 8: Demand Model Out-of-Sample Performance

Note: Figure 8 plots a binned scatter plot comparing actual seed choice to the predicted probability of selecting a seed from the structural demand model, separately by the seed experiment treatment group (on which the model was estimated) and the control group. Those who failed the baseline belief comprehension checks are excluded.
Note: Figure 9 uses the marginal predicted choice probability from the structure of the model to evaluate the predicted choice probabilities for the primary salinity tolerant seed used in my sample under alternative belief errors. Here, belief error is defined as the gap between farmers’ prediction for soil salinity over the 2022-23 season and the best agronomic prediction based on the fall reading.
Table 10: Soil Salinity Information Experiment: First-Stage

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prior</strong></td>
<td>1.361***</td>
<td>1.403***</td>
<td>1.377***</td>
</tr>
<tr>
<td></td>
<td>(0.0829)</td>
<td>(0.0863)</td>
<td>(0.0894)</td>
</tr>
<tr>
<td><strong>Own Truth - Prior</strong></td>
<td>1.108***</td>
<td>1.153***</td>
<td>1.134***</td>
</tr>
<tr>
<td></td>
<td>(0.0881)</td>
<td>(0.0924)</td>
<td>(0.0942)</td>
</tr>
<tr>
<td><strong>Own Treatment</strong></td>
<td>0.268</td>
<td>0.229</td>
<td>0.329</td>
</tr>
<tr>
<td></td>
<td>(0.190)</td>
<td>(0.203)</td>
<td>(0.211)</td>
</tr>
<tr>
<td><strong>Own Treatment x (Own Truth - Prior)</strong></td>
<td>-0.832***</td>
<td>-0.865***</td>
<td>-0.842***</td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td>(0.218)</td>
<td>(0.228)</td>
</tr>
<tr>
<td><strong>Own Treatment x (Upa Truth - Prior)</strong></td>
<td>0.980***</td>
<td>0.997***</td>
<td>0.992***</td>
</tr>
<tr>
<td></td>
<td>(0.210)</td>
<td>(0.220)</td>
<td>(0.230)</td>
</tr>
<tr>
<td><strong>Upa Treatment</strong></td>
<td>0.244</td>
<td>0.180</td>
<td>0.305</td>
</tr>
<tr>
<td></td>
<td>(0.283)</td>
<td>(0.296)</td>
<td>(0.313)</td>
</tr>
<tr>
<td><strong>Upa Treatment x (Upa Truth - Prior)</strong></td>
<td>0.243***</td>
<td>0.255***</td>
<td>0.276***</td>
</tr>
<tr>
<td></td>
<td>(0.0813)</td>
<td>(0.0845)</td>
<td>(0.0872)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>1.162***</td>
<td>1.069***</td>
<td>1.119***</td>
</tr>
<tr>
<td></td>
<td>(0.228)</td>
<td>(0.238)</td>
<td>(0.247)</td>
</tr>
<tr>
<td><strong>Sample</strong></td>
<td>Full</td>
<td>Pass EL</td>
<td>Pass BL+EL</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>2245</td>
<td>2035</td>
<td>1864</td>
</tr>
<tr>
<td>($\beta_3 + \beta_4$) = $\beta_5 : p - val$</td>
<td>0.262</td>
<td>0.165</td>
<td>0.162</td>
</tr>
<tr>
<td><strong>$R^2$</strong></td>
<td>0.138</td>
<td>0.148</td>
<td>0.140</td>
</tr>
<tr>
<td><strong>F-statistic</strong></td>
<td>44.390</td>
<td>43.905</td>
<td>38.274</td>
</tr>
</tbody>
</table>

Note: Table 10 presents the first-stage regressions of the impact of receiving information about soil salinity over the 2022-23 season on farmers’ predictions about soil salinity over the 2023-24 season. Column (1) includes all respondents; column (2) includes only those farmers who passed the endline belief elicitation comprehension checks; and column (3) includes only those who passed both the baseline and the endline comprehension checks. All specifications report heteroskedasticity robust standard errors.
Figure 10: Demand Curves for Index Insurance by Perceived Flood Risk

![Demand Curves for Index Insurance by Perceived Flood Risk](image)

Figure 11: Flood Insurance Elasticity by Perceived Flood Risk

![Flood Insurance Elasticity by Perceived Flood Risk](image)

**Note:** Figure 10 plots demand curves for the hypothetical flood index insurance product by quintile of the perceived flood risk index (see Appendix Section C.2 for details). Figure 11 plots the price elasticity for the hypothetical flood insurance contract separately by two categories of perceived flood risk. To calculate the elasticity, I estimate a log-log specification interacting belief category with price. The first pools the first and second quintiles of the flood risk belief index, and the second pools the third, fourth, and fifth quintiles.
Table 11: Soil Salinity Information 2SLS: Demand for Salinity-Tolerant Seeds

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Salinity Belief 2023-24</td>
<td>3.043**</td>
<td>3.012**</td>
<td>3.136*</td>
</tr>
<tr>
<td></td>
<td>(1.487)</td>
<td>(1.513)</td>
<td>(1.602)</td>
</tr>
<tr>
<td>Observations</td>
<td>2245</td>
<td>2035</td>
<td>1864</td>
</tr>
<tr>
<td>First Stage F-statistic</td>
<td>50.62</td>
<td>49.91</td>
<td>43.07</td>
</tr>
</tbody>
</table>

Note: Table 11 regresses demand for salinity-tolerant seeds as measured via the BDM against farmers beliefs about soil salinity in the upcoming season, instrumenting for beliefs using the experimental variation from the information treatment shown in Table 10. Regressions control for their willingness-to-pay for salinity-tolerant seeds at baseline and treatment status in the seed experiment. Column (1) includes all respondents; column (2) includes only those farmers who passed the endline belief elicitation comprehension checks; and column (3) includes only those who passed both the baseline and the endline comprehension checks. All specifications report heteroskedasticity robust standard errors.
Table 12: Perceived Flood Risk and Willingness-to-Pay for Index Insurance

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Flood Risk Index</td>
<td>2.421***</td>
<td>2.587***</td>
<td>2.724***</td>
<td>2.354***</td>
<td>2.411***</td>
<td>2.703***</td>
<td>1.246</td>
</tr>
<tr>
<td></td>
<td>(0.814)</td>
<td>(0.831)</td>
<td>(0.857)</td>
<td>(0.825)</td>
<td>(0.837)</td>
<td>(0.863)</td>
<td>(1.098)</td>
</tr>
<tr>
<td>True Flood Risk Controls</td>
<td>None</td>
<td>Past</td>
<td>Govt.</td>
<td>Neighbors</td>
<td>ML Pred.</td>
<td>All</td>
<td>Union F.E.s</td>
</tr>
<tr>
<td>Observations</td>
<td>1811</td>
<td>1811</td>
<td>1811</td>
<td>1811</td>
<td>1811</td>
<td>1811</td>
<td>1809</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.031</td>
<td>0.033</td>
<td>0.039</td>
<td>0.032</td>
<td>0.031</td>
<td>0.045</td>
<td>0.245</td>
</tr>
</tbody>
</table>

Table 13: Perceived Flood Risk and Willingness-to-Pay for Index Insurance

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived Flood Risk Index (Post Treatment)</td>
<td>2.054**</td>
<td>-0.268***</td>
<td>-2.424</td>
<td>9.057</td>
</tr>
<tr>
<td></td>
<td>(0.821)</td>
<td>(0.0514)</td>
<td>(1.851)</td>
<td>(7.033)</td>
</tr>
<tr>
<td>Flood Information Treatment</td>
<td></td>
<td></td>
<td></td>
<td>1655</td>
</tr>
<tr>
<td>Observations</td>
<td>1655</td>
<td>1655</td>
<td>1655</td>
<td>1655</td>
</tr>
<tr>
<td>First Stage F-statistic</td>
<td></td>
<td></td>
<td></td>
<td>21.98</td>
</tr>
</tbody>
</table>

Note: Table 12 presents OLS regressions predicting farmers’ willingness-to-pay (WTP) for the hypothetical index insurance product using an index capturing their beliefs about future flood risk (see Appendix Section C.2 for details). All specifications include controls for survey round, farmers’ WTP for a plate during the BDM elicitation, and fixed effects for the contract payout amount. Column (1) presents the regression of WTP on beliefs without additional controls for true flood risk. Columns (2) through (6) add in controls for flood risk, which are detailed further in Appendix Section B.1. Column (2) includes linear controls for the historical daily flood hazard rate, country-wide ranking of that value, and indicators for ever experiencing floods of of the same length categories as the belief elicitation, all at the union-level. Column (3) includes measures of flood hazard and fixed effects for flood proneness calculated from shapefiles produced by the Bangladesh Agricultural Research Council. Column (4) includes the average daily hazard rate of all neighboring polygons to that farmers’ union. Column (5) includes the prediction of flood hazard ranking from the supervised machine learning algorithm described in Section B.1. Column (6) includes all of these measures of flood risk together in one regression. Column (7) includes union fixed effects. Table 13 presents results from the information experiment providing farmers information about the historical incidence of flooding on their land. All specifications include fixed effects for the payout amount in the index insurance contract and the farmers’ willingness-to-pay (WTP) for a plate during the BDM elicitation. Column (1) presents an ordinary least squares regression showing the link between WTP for flood insurance and beliefs. Column (2) shows the first-stage results of how beliefs vary by information status. Column (3) shows the reduced form impact of treatment on WTP. Column (4) instruments for beliefs using treatment assignment.
# Appendices

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<td>F.1 Methodology</td>
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</tr>
<tr>
<td>F.2 Qualitative Evidence Motivating Modeling Assumptions</td>
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</tr>
<tr>
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<td>109</td>
</tr>
</tbody>
</table>

## A Additional Figures and Tables
Figure A.1: Farmers’ Beliefs About the Returns to Switching to Salinity-Tolerant Seeds

Note: Figure A.1 plots how farmers’ beliefs about the returns to planting salinity-tolerant seeds as measured as a share of their total expected yield relates to their belief about the salt content of their soil. The vertical dashed gray line denotes the threshold above which the government recommends adopting salinity-tolerant varieties.
Figure A.2: Beliefs about Flood Risk: Elicitation #1

![Cumulative Probability](chart1)

**Horizon**
- Next Year
- Next Five Years

**Expected Number of Days of Flooding**

Figure A.3: Beliefs about Flood Risk: Elicitation #2

![Expected Years Until...](chart2)

**Expected Years Until...**
- 1 Day Flood
- 3 Day Flood
- 1 Week Flood
- 1 Month Flood

**Note:** Figures A.2 and A.3 present farmers' beliefs about flood risk. Figure A.2 plots the cumulative distribution function across farmers of expected number of flood days averaging across bins in the button elicitation. Figure A.3 plots the distribution of farmers' responses to the question, “How many years do you think it would take for a [TIME] long flood to happen in this village?” where [TIME] is one-day, three-day, week, and month.
Figure A.4: Flood Perceptions Compared to Past Inundation Exposure

Note: Figure A.4 plots a binned scatter plot comparing farmers’ beliefs about flooding next year against the satellite-derived measure of their past flooding exposure in the village. The coefficient and intercept from a bi-variate regression with robust standard errors are shown. The sample excludes farmers who fail the belief comprehension checks for the round in which the flooding question was asked.
Table A.1: Farmer Survey Demographics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household Size</td>
<td>4.7</td>
<td>4</td>
</tr>
<tr>
<td>Female</td>
<td>.033</td>
<td>0</td>
</tr>
<tr>
<td>Age</td>
<td>46</td>
<td>45</td>
</tr>
<tr>
<td>Years of Schooling</td>
<td>6.4</td>
<td>5</td>
</tr>
<tr>
<td>No Schooling</td>
<td>.21</td>
<td>0</td>
</tr>
<tr>
<td>Fewer than 5 Years of Schooling</td>
<td>.52</td>
<td>1</td>
</tr>
<tr>
<td>Completed Primary Schooling</td>
<td>.31</td>
<td>0</td>
</tr>
<tr>
<td>High School or Above</td>
<td>.13</td>
<td>0</td>
</tr>
<tr>
<td>Annual Earnings (USD)</td>
<td>1,656</td>
<td>1,365</td>
</tr>
<tr>
<td>Number of Plots</td>
<td>2.9</td>
<td>2</td>
</tr>
<tr>
<td>Survey Plot Size</td>
<td>46</td>
<td>33</td>
</tr>
<tr>
<td>Years Farming</td>
<td>22</td>
<td>20</td>
</tr>
<tr>
<td>Years Farming on Survey Plot</td>
<td>13</td>
<td>10</td>
</tr>
<tr>
<td>Lived Elsewhere in Past</td>
<td>.049</td>
<td>0</td>
</tr>
<tr>
<td>N</td>
<td>2,261</td>
<td></td>
</tr>
</tbody>
</table>

Note: Table A.1 presents summary statistics for the main sample of farmers. The survey plot is the plot on which most of the survey questions focused, which was randomly selected with weights proportional to size.
Table A.2: Signs Used by Farmers to Assess Soil Salinity

<table>
<thead>
<tr>
<th>Share Using Sign</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Look for white powder on the ground</td>
<td>0.432</td>
</tr>
<tr>
<td>Taste the soil</td>
<td>0.027</td>
</tr>
<tr>
<td>Taste the water</td>
<td>0.086</td>
</tr>
<tr>
<td>Red patches on the leaves</td>
<td>0.354</td>
</tr>
<tr>
<td>White patches on the leaves</td>
<td>0.072</td>
</tr>
<tr>
<td>Brown patches on the leaves</td>
<td>0.105</td>
</tr>
<tr>
<td>Brown leaves</td>
<td>0.108</td>
</tr>
<tr>
<td>Small plants/stunted height</td>
<td>0.549</td>
</tr>
<tr>
<td>Plant death</td>
<td>0.232</td>
</tr>
<tr>
<td>Use sensor</td>
<td>0.002</td>
</tr>
<tr>
<td>Ask Agricultural Officer/Dealer</td>
<td>0.004</td>
</tr>
<tr>
<td>Ask friends/family members/neighbors</td>
<td>0.026</td>
</tr>
<tr>
<td>Other</td>
<td>0.057</td>
</tr>
<tr>
<td>Don’t use any signs</td>
<td>0.070</td>
</tr>
<tr>
<td>N</td>
<td>2,279</td>
</tr>
</tbody>
</table>

Note: Table A.2 presents the share of farmers using each indicator as a sign to assess soil salinity on their plots, as measured during the baseline survey. These answers come from the question, “What signs do you use to figure out the amount of salt in the soil?” Enumerators were instructed not to read out possible answers to the respondents.

Table A.3: Farmers’ Perceptions of Symptoms of High Soil Salinity

<table>
<thead>
<tr>
<th>Share Using Sign</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Red Patches on the Leaves</td>
<td>0.641</td>
</tr>
<tr>
<td>White Patches on the Leaves</td>
<td>0.084</td>
</tr>
<tr>
<td>Brown Patches on the Leaves</td>
<td>0.128</td>
</tr>
<tr>
<td>Brown Leaves</td>
<td>0.134</td>
</tr>
<tr>
<td>Small Plants/Stunted Height</td>
<td>0.784</td>
</tr>
<tr>
<td>Plant Death</td>
<td>0.503</td>
</tr>
<tr>
<td>N</td>
<td>2,253</td>
</tr>
</tbody>
</table>

Note: Table A.3 presents the share of farmers mentioning each response to the question, “If you had too much salt in your soil, how do you think that would impact what your rice plants look like?” in the endline survey.
Table A.4: Role of Measurement Error in Salinity Belief Inaccuracy

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Binary Belief</td>
<td>Continuous Belief</td>
<td>Continuous Belief</td>
</tr>
<tr>
<td>Beliefs - Truth</td>
<td>0.0286***</td>
<td>0.454***</td>
<td>1.180***</td>
</tr>
<tr>
<td>(0.00396)</td>
<td>(0.141)</td>
<td>(0.126)</td>
<td>(0.0140)</td>
</tr>
<tr>
<td>True Salinity</td>
<td>0.454***</td>
<td>0.454***</td>
<td>0.454***</td>
</tr>
<tr>
<td>(0.141)</td>
<td>(0.141)</td>
<td>(0.141)</td>
<td>(0.141)</td>
</tr>
<tr>
<td>Leave-Out Mean Salinity</td>
<td>1.180***</td>
<td>1.180***</td>
<td>1.180***</td>
</tr>
<tr>
<td>(0.126)</td>
<td>(0.126)</td>
<td>(0.126)</td>
<td>(0.126)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.381***</td>
<td>2.262***</td>
<td>-0.821</td>
</tr>
<tr>
<td>(0.0140)</td>
<td>(0.644)</td>
<td>(0.567)</td>
<td>(0.0140)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,068</td>
<td>1,151</td>
<td>2,068</td>
</tr>
<tr>
<td>Outcome Mean</td>
<td>0.444</td>
<td>4.364</td>
<td>4.617</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.025</td>
<td>0.012</td>
<td>0.053</td>
</tr>
</tbody>
</table>

Note: Table A.4 presents regressions testing for the role of measurement error in explaining the lack of explanatory power of true soil salinity on farmers’ beliefs. Column (1) regresses whether farmers answered “Yes” in response to the question, “Do you think the soil on plot [X] is salty?” on the error between farmers’ continuous belief and the agronomic measure. Columns (2) and (3) both use this continuous belief as the outcome. In column (2), the specification restricts to only those farmers who say they were not at all confused during the belief elicitation. In column (3), the predictor is the village leave-out mean of the agronomic soil salinity. All regressions exclude those who fail the beliefs comprehension checks during the practice elicitation and report heteroskedasticity-robust standard errors.

Table A.5: Examples of Salient Shocks and Subtle Shifts for Different Environmental Threats

<table>
<thead>
<tr>
<th>Environmental Risk</th>
<th>Salient Shock</th>
<th>Subtle Shift</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flood risk</td>
<td>Flood</td>
<td>Marginal riverbank erosion</td>
</tr>
<tr>
<td>Soil salinity</td>
<td>Saline flood</td>
<td>Salinity intrusion into groundwater</td>
</tr>
<tr>
<td>Rainfall</td>
<td>Drought</td>
<td>Fewer days of rain</td>
</tr>
<tr>
<td>Temperature</td>
<td>Heat wave</td>
<td>Slightly higher temperatures</td>
</tr>
<tr>
<td>Cyclone risk</td>
<td>Cyclone</td>
<td>More intense storms in ocean</td>
</tr>
<tr>
<td>Air Pollution</td>
<td>Vision-impairing pollution</td>
<td>Marginally higher pollution</td>
</tr>
<tr>
<td>Wildfire risk</td>
<td>Wildfire</td>
<td>Longer periods without rain</td>
</tr>
</tbody>
</table>

Note: Table A.5 provides examples of salient shocks and subtle shifts across a host of different environmental threats.
Figure A.5: Distribution of Soil Salinity Beliefs

Note: Figure A.5 plots the distribution of farmers’ mean salinity belief as elicited during the baseline survey.
Figure A.6: Distribution of Rainfall Intensity Beliefs

Note: Figure A.6 plots the distribution of farmers’ beliefs about the share of rainy days during the monsoon season for three different periods: the past (five or ten years earlier than the elicitation), the present (the most recent season), and the future (10 years from the elicitation year).
Note: Figure A.7 maps the average soil salinity level within each union based on the measurements collected directly from farmers’ plots over the course of the 2022-2023 season.
Figure A.8: Change in Soil Salinity over 2022-23 Season

Note: Figure A.8 graphs the distributions of the best prediction of the average soil salinity on farmers' plots. The blue bars denote the histogram of seasonal salinity predicted based on the fall soil readings only. The red bars denote the same, now including the spring readings into the prediction as well.
Figure A.9: Distribution of Farmers’ Willingness-to-Pay for Soil Salinity Information

Figure A.10: Figure A.9 plots histograms showing the distribution of farmers’ WTP for the soil salinity information as elicited via the Becker-DeGroot-Marschak price list. The blue bars denote the distribution for farmers offered information about both the average soil salinity level for all farmers in their distribution and their own plots, while the red bars shows the equivalent for farmers only offered information about the upazila average. For the purposes of this graph, I winsorized WTP at 200 BDT.
Figure A.11: Demand Curves for Index Insurance by Perceived Flood Risk

Figure A.12: Flood Insurance Elasticity by Perceived Flood Risk

Note: Figure A.11 plots demand curves for the hypothetical flood index insurance product by payout amount of the contract. Figure A.12 plots the price elasticity for the hypothetical flood insurance contract separately by this same amount. To calculate the elasticity, I estimate a log-log specification interacting payout with price.
Figure A.13: Illustration of Rising Sea Levels’ Impact on Soil Salinity

Note: Figure A.13 presents a diagram from the United States Environmental Protection Agency illustrating the dynamics between rising sea levels and the contamination of irrigation sources.
Table A.6: Salient Shock: Salty Flood Impacts on True Soil Salinity

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Flood</strong></td>
<td>-0.314*</td>
<td>-0.309*</td>
<td>0.0377</td>
</tr>
<tr>
<td></td>
<td>(0.181)</td>
<td>(0.167)</td>
<td>(0.0842)</td>
</tr>
<tr>
<td><strong>Saltier</strong></td>
<td>0.406***</td>
<td>0.517***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0862)</td>
<td>(0.0905)</td>
<td></td>
</tr>
<tr>
<td><strong>Flood × Saltier</strong></td>
<td>0.157***</td>
<td>0.117**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0531)</td>
<td>(0.0557)</td>
<td></td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>4.644***</td>
<td>4.650***</td>
<td>4.613***</td>
</tr>
<tr>
<td></td>
<td>(0.0405)</td>
<td>(0.0386)</td>
<td>(0.0349)</td>
</tr>
<tr>
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<td>2075</td>
<td>2075</td>
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<tr>
<td><strong>Clusters</strong></td>
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<td>250</td>
<td>250</td>
</tr>
<tr>
<td><strong>Control Mean</strong></td>
<td>4.605</td>
<td>4.605</td>
<td>4.605</td>
</tr>
<tr>
<td><strong>Flood Risk Controls</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

**Note:** Table A.6 presents results from the difference-in-differences specification comparing the differential impact of salty floods on the agronomic measure of soil salinity. Column (1) presents regression results of the impact of floods alone, controlling for the machine learning generated flood risk measure. Columns (2) and (3) estimate the full difference-in-differences specification, where saltier is measured in terms of standard deviations. Column (2) is my preferred specification; column (3) does not control for baseline flood risk. All standard errors are clustered at the village level. Regressions exclude farmers who failed the baseline beliefs elicitation comprehension checks.
Table A.7: Subtle Shift: Salinity Intrusion’s Impact on True Soil Salinity

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<tr>
<td>Sea Level Rise</td>
<td>0.286***</td>
<td>0.284***</td>
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<tr>
<td></td>
<td>(0.0913)</td>
<td>(0.0991)</td>
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<tr>
<td>Ocean Salinity</td>
<td>-0.441***</td>
<td>-0.372***</td>
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<tr>
<td></td>
<td>(0.0927)</td>
<td>(0.103)</td>
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<tr>
<td>Sea Level Rise × Ocean Salinity</td>
<td>0.192***</td>
<td>0.0432</td>
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<tr>
<td></td>
<td>(0.0541)</td>
<td>(0.0638)</td>
</tr>
<tr>
<td>Closer to Ocean</td>
<td>0.179**</td>
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</tr>
<tr>
<td></td>
<td>(0.0711)</td>
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<tr>
<td>Closer to Ocean × Sea Level Rise</td>
<td>0.181**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0911)</td>
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</tr>
<tr>
<td>Closer to Ocean × Ocean Salinity</td>
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<td></td>
<td>(0.0976)</td>
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<tr>
<td>Closer to Ocean × Sea Level Rise × Ocean Salinity</td>
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</tr>
<tr>
<td></td>
<td>(0.0581)</td>
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<td>4.530***</td>
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<tr>
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<td>Clusters</td>
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</tr>
<tr>
<td>Control Mean</td>
<td>4.605</td>
<td>4.605</td>
</tr>
</tbody>
</table>

Note: Table A.7 presents results from the triple difference-in-differences specification comparing the differential impact of being closer to the coast while being exposed to relatively higher sea levels and ocean salinity on the agronomic measure of soil salinity. Column (1) presents regression results of a difference-in-difference specification ignoring distance to the coast and just isolating the shocks to sea level elevation and ocean salinity. Column (2)—my preferred specification—additionally interacts with distance to the coast. All standard errors are clustered at the village level. Regressions exclude farmers who failed the baseline beliefs elicitation comprehension checks. All variables are measured in terms of standard deviations.
Table A.8: Salient Shock: Salty Flood Impacts on Soil Salinity Beliefs

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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<tbody>
<tr>
<td>Flood</td>
<td>0.433</td>
<td>0.143</td>
<td>0.661</td>
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<tr>
<td></td>
<td>(0.776)</td>
<td>(0.763)</td>
<td>(0.503)</td>
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<tr>
<td>Saltier</td>
<td>0.466</td>
<td>0.737**</td>
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<tr>
<td></td>
<td>(0.346)</td>
<td>(0.352)</td>
<td></td>
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<tr>
<td>Flood × Saltier</td>
<td>0.909**</td>
<td>0.811**</td>
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<tr>
<td></td>
<td>(0.395)</td>
<td>(0.396)</td>
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<tr>
<td>Constant</td>
<td>4.563***</td>
<td>4.569***</td>
<td>4.520***</td>
</tr>
<tr>
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<td>(0.166)</td>
<td>(0.167)</td>
<td>(0.151)</td>
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<td>2068</td>
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<td>Control Mean</td>
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<td>4.617</td>
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<tr>
<td>Flood Risk Controls</td>
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<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Note: Table A.8 presents results from the difference-in-differences specification comparing the differential impact of salty floods on farmers’ beliefs about soil salinity on their plots. Column (1) presents regression results of the impact of floods alone, controlling for the machine learning generated flood risk measure. Columns (2) and (3) estimate the full difference-in-differences specification, where saltier is measured in terms of standard deviations. Column (2) is my preferred specification; column (3) does not control for baseline flood risk. All standard errors are clustered at the village level. Regressions exclude farmers who failed the baseline beliefs elicitation comprehension checks.
Table A.9: Subtle Shift: Salinity Intrusion’s Impact on Soil Salinity Beliefs

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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<tbody>
<tr>
<td>Sea Level Rise</td>
<td>0.274</td>
<td>0.383</td>
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<tr>
<td></td>
<td>(0.344)</td>
<td>(0.470)</td>
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<tr>
<td>Ocean Salinity</td>
<td>-1.169***</td>
<td>-1.100**</td>
</tr>
<tr>
<td></td>
<td>(0.348)</td>
<td>(0.433)</td>
</tr>
<tr>
<td>Sea Level Rise × Ocean Salinity</td>
<td>0.00356</td>
<td>-0.300</td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
<td>(0.217)</td>
</tr>
<tr>
<td>Closer to Ocean</td>
<td>0.413*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.244)</td>
<td></td>
</tr>
<tr>
<td>Closer to Ocean × Sea Level Rise</td>
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</tr>
<tr>
<td></td>
<td>(0.439)</td>
<td></td>
</tr>
<tr>
<td>Closer to Ocean × Ocean Salinity</td>
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<tr>
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<td>(0.400)</td>
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<tr>
<td>Closer to Ocean × Sea Level Rise × Ocean Salinity</td>
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<tr>
<td>Control Mean</td>
<td>4.617</td>
<td>4.617</td>
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</tbody>
</table>

Note: Table A.9 presents results from the triple difference-in-differences specification comparing the differential impact of being closer to the coast while being exposed to relatively higher sea levels and ocean salinity on farmers’ beliefs about the amount of salt in their soil. Column (1) presents regression results of a difference-in-difference specification ignoring distance to the coast and just isolating the shocks to sea level elevation and ocean salinity. Column (2)—my preferred specification—additionally interacts with distance to the coast. All standard errors are clustered at the village level. Regressions exclude farmers who failed the baseline beliefs elicitation comprehension checks. All variables are measured in terms of standard deviations.
Figure A.14: Photograph of Salt Visible on Soil Surface

Note: Figure A.14 shows a photograph I took of soil with salt visible on the surface from a village in Khulna.
B   Environmental Data

B.1   Estimating Flood Risk

This section describes the approach I use to calculate true flood risk for each union. Perhaps the simplest measure is simply the historical incidence of flooding in each polygon, which I calculate using the new measure of flooding that I derived from remote sensing data. The primary challenge with relying on that measure is that idiosyncratic factors may have caused a flood in one area and not the other in recent years, yet both places could still have the same fundamental flood risk in the future. The goal therefore is to use existing data to identify sets of locations where floods might happen using an objective scale. In addition to the simple historical exposure rates, I consider three separate types of indicators. First, I calculate “traditional” measures of exposure based on standard hydrological models. Second, I use my new measure of flood exposure derived from satellites to build a measure of flood risk. Third, I take a model-free approach by linking other geographic data with that historical measure and using supervised machine-learning to generate a flood risk measure.

For the first set, I defer to the government’s estimates and calculate flood hazard and proneness from shapefiles produced by the Bangladesh Agricultural Research Council (BARC). When controlling for this set of flood risk, I include fixed effects for each of the government’s flood proneness categories and quadratic polynomials of the flood hazard measure.

For the second, I calculate—for each union—the average flood exposure of its neighbors. The intuition behind this method is that neighboring areas likely experience very similar flood risk, and thus by calculating the average incidence among them, I can proxy for a given union’s own flooding likelihood without giving undue influence to one place’s own historical experience. I calculate two measures: one that includes the primary union’s own past incidence in addition to its neighbors, and one that does not.

Finally, I calculate a predicted measure of flood risk using machine learning to dictate how underlying geographic features impact flood risk. This approach has the advantage of not relying on hydrological models, which can often be quite sensitive in their predictions, while also allowing me to let the data tell me which unions are comparable with one another. To flexibly estimate predicted flood, I train an algorithm to predict true flood experience based on geographic characteristics. First, I calculate the daily flood hazard rate based on the full panel of flooding experience. To account for the long tail of the distribution, I assign each union its percentile rank in this distribution of hazard rates, though results are broadly similar using the raw value. This variable constitutes the main flood risk outcome that I predict in the algorithm. As inputs, I calculate the mean and standard deviation of elevation in each union, binned latitude and longitude at the tenth of a degree level, the length of major rivers through that union, average drainage characteristics and flooding depth from BARC shapefiles, and each of the flood measures from the first set described in the previous paragraph. I then randomly split the sample of 5,158 unions into a training dataset and a testing dataset, with 20 percent reserved for the latter. Finally, I train a random forest algorithm to predict flood rank using the full set of inputs. Applying this model out of sample to the hold-out unions, I can explain 0.71 percent of the variation in true historical incidence ranking using my predicted measure. The fact that this $R^2$ is less than one can be
viewed as an advantage in this case because I can always control for the true past experience. This measure, by contrast, captures a data-driven notion of similarity.

B.2 Soil Salinity

I focus on two complementary data sources to measure soil salinity.

**Direct Agronomic Data Collection** First, enumerators took soil salinity measurements on the randomly selected plot using handheld soil sensors that measure electrical conductivity, with a range from 0 to 10 dS/m. For each plot, measurements were taken in three places, at least six inches from the edge of the soil, three feet apart from one another. I calculate the average reading from these three samples to measure each plot’s salinity on a given day. For repeat measurements, enumerators use photographs, GPS readings, and the farmer’s location to return to the same point in each plot and collect follow-up data. Figure B.1 shows an image from the baseline survey of enumerators using the soil sensors to measure salinity. Enumerators used Yieryi EC-98361 Digital Soil EC Meter Testers with a resolution of 0.01 ms/cm.

Salinity evolves over the course of the dry season, but due to budget restrictions, high-frequency salinity measurement was not possible. Instead, enumerators took salinity measurements twice: first during the baseline survey, and second during a midline visit during the season. Based on multiple photos and detailed GPS coordinates taken during each measurement, I verify that the enumerators indeed returned not only to the same plot but to the same point in each plot. Ideally, measurements would be taken continually during the growing season to understand average exposure. Given budget restrictions, the midline was timed to maximize predictive power of the average soil salinity from November through April. Most of the baseline survey measurements took place in November. Based on data from the SRDI’s soil monitoring sites described further below, the additional month that maximizes predictive power in a simple linear regression is March, with an $R^2$ of .901. The second round of measurements was timed so as to collect as much data as possible in March, subject to constraints around the timing of Ramadan and the geographic scope required of enumerators, with some data collected in the second-half of February.

To convert these snapshots of salinity into a measure of seasonal exposure, I estimate

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69 Additionally, enumerators measured salinity from a random sample of 30 villages during a third visit at the end of May and beginning of June. These data confirm the trends shown from the second-round of measurements.
the link between seasonal average and the relevant calendar months using the 142 full seasons of salinity from the SRDI data and apply this relationship out of sample to the soil measurements I collect. For a small number of households, enumerators could not collect salinity measurements during one of the two visits: 164 during the baseline (largely due to flooding making the plot inaccessible) and 31 during the midline (typically because of migration or other household unavailability). For these households, I replace the missing measurement with the mean village value prior to predicting seasonal salinity exposure; if the entire village lacks the measurement, then I use the mean for the upazila.

The gold-standard method for measuring soil salinity requires taking soil samples to a lab for analysis—prohibitively expensive at the scale of this study. This raises an important concern with the handheld sensors used to measure salinity in this sample of farmers: any systematic bias in these sensors would distort the results. In particular—given that the salinity levels I measure tend to be systematically lower than historical salinity levels measured by the SRDI—one might worry that my sensors underestimate the truth, especially at higher salt levels. To test the scope of this potential issue, I conduct laboratory tests with the handheld sensors used in the study and compare the results to other more expensive sensors available in the market. This approach features the advantage of being able to know the ground truth: by carefully measuring out grams of NaCl and mixing it with a solution of distilled water, I can calculate the exact electrical conductivity of the solution and compare the measured values to this ground truth. Of course, these sensors are designed for direct soil measurement as opposed to this controlled solution, and thus discrepancies could indicate differences in the type of sample instead of indicating errors with the sensor.

I test for differences in measurement across sensors and salinity levels in these lab experiments. I conduct the evaluations in 250 milliliter solutions featuring grams of NaCl ranging from 0 to 1.5 in increments of .1 grams, equivalent to a dS/M range of 0 to 10.27. I compare three sensors used in the field, two sensors of the same model but brand new (in case the sensors change over time or by use), and two brand new high-end models. I randomized the order in which each sensor was placed in the solution, and include fixed effects for this order. I first document that among the high-end models—which are much too expensive to feasibly be used at scale—the salinity sensors nevertheless tend to overestimate the objective salinity level by an average value of (0.73 dS/m). The sensors I use during the midline overestimate by a smaller amount, with a mean of 0.69 dS/m. To help put this magnitude in perspective, the within

Figure B.2: Salinity Sensor Lab Experiments

Note: Figure B.2 shows an image of one of the soil salinity sensors used in this study being tested in a solution of distilled water and NaCl.

70 Specifically, the gram molecular weight (GMW) of sodium (Na) is 22.99, the GMW of chloride is 33.45, so I calculate the true conductivity as grams of NaCL divided by 58.44 times 1000 divided by milliliters of distilled water.

71 One of the high-end models top-codes at 2.00 dS/m, and thus I exclude all measures above that point for that model.
plot, within day standard deviation in measured salinity in my sample is 0.15 ds/M on average. In a regression specification allowing for a differential linear bias in true salinity, I find no statistically significant evidence that the cheaper sensors I use perform differently than the more expensive ones. The fact that the overall discrepancy suggests that if anything, the sensors I used overestimate salinity, contrary to what would be expected given the low levels I observe in the field compared to historical trends.

**Government Salinity Panel** Second, SRDI provided measurements from monthly soil samples from 11 monitoring sites in and around Khulna. Most of these samples date back to 2004. Figure B.3 visualizes the average salinity value during the Boro season for these sites over time. The graph illustrates the considerable variation both over time and across places in soil salinity. Figure B.4 presents the simple average time series in annual salinity among a constant sample of stations. Salt levels also exhibit significant variation within the year in predictable seasonal patterns. Figure B.5 plots this seasonal variation using data from the government’s soil stations.

The government’s data provide reassurance that the patterns in seasonal salinity I document are true. Figures B.6 and B.7 show that consistent with my readings, February and March of the 2022-23 season were abnormally low. This is particularly surprising given the low amounts of rainfall, but the results are striking even in this relatively underpowered analysis.

**B.3 Water Salinity**

To measure the local water salinity, I combine two data sources.

First, I obtain monthly water salinity levels from 133 river station monitoring sites maintained by the Bangladesh Water Development Board (BWDB). Figure B.10a maps these stations, which I assign to unions based on the closest centroid. I acquire all available data since 2011, yielding 5,955 observations total. For each station and month, I observe the maximum, minimum, and average salinity at high tide. Figure B.8 plots the average values across month, illustrating substantial seasonal variation.

Second, I estimate exposure to ocean salinity levels every day since January 1st, 2002 by first calculating surface sea water salinity from the Hybrid Coordinate Ocean Model (HY-
Figure B.4: Trends in Annual Soil Salinity—SRDI Soil Stations (Constant Sample)

![Graph showing trends in annual soil salinity over years.]

Figure B.5: Seasonal Patterns in Soil Salinity—SRDI Soil Stations

![Graph showing seasonal patterns in soil salinity across calendar months.]

Note: Figure B.5 plots the average soil level across the 11 locations monitored monthly by the Bangladesh government’s Soil Resource Development Institute. Seven of the stations have data for most months since 2004; four new ones were added in 2018. Figure B.4 takes the constant sample of these stations with data available for all twelve months of each year, and plots the average salinity for all available years.
Figure B.6: 2022-23 Soil Salinity Anomaly: SRDI Soil Sites Raw Data

Figure B.7: 2022-23 Soil Salinity Anomaly: SRDI Soil Sites Raw Data

Note: Figures B.6 and B.7 use data for the 10 sites for which I have historical data from the SRDI to assess the extent to which 2022-23 exhibit abnormal soil salinity patterns. Figure B.6 plots the raw means of the 2022-23 season against the historical average by calendar month across all sites. Figure B.7 plots coefficients from a regression of calendar month interacted with a dummy for the 2022-23 season controlling for site and calendar month fixed effects, clustering standard errors by site.
COM) along 10 kilometer-wide grids off the Bangladeshi coast (Cummings and Smedstad, 2013). Figure B.10b illustrates the coastal grids over which I calculate daily ocean salinity from this remote sensing data in red, and the nearest straight line distance to unions in blue.

The BWDB does not collect data during all months of the year—and in particular, not during the critical flooding times of the monsoon season. To overcome this missing data challenge, I train a supervised machine learning algorithm to predict river salinity using predictors constructed from ocean salinity measurements, which are available year-round. I first construct a vector of predictors from the ocean salinity data. Following Guimbeau et al. (2023), I identify the five closest coastal polygons to each BWDB station, and then construct five month leads and lags of mean and maximum ocean salinity from those five polygons. I include features for both the unweighted salinity, weighted according to the inverse squared distance of the five closest locations, and a final set multiplying this weighted version by the minimum distance from the salinity station to the coast. Using a random forest to predict the truth, I can explain 82.41 percent of the variation in a 20 percent hold-out testing sample.

### B.4 Sea-Level Rise

To measure village-level exposure to sea-level rise, I again use data from the Hybrid Coordinate Ocean Model (HYCOM) along 10 kilometer-wide grids off the Bangladeshi coast (Cummings and Smedstad, 2013). I calculate the sea surface elevation anomaly relative to the modeled elevation mean. Figure B.11 plots the evolution of average elevation across these polygons over time, with darker colors denoting earlier years, to illustrate the variation I use in the natural experiments.
Figure B.8: River Station Salinity Data

Figure B.9: Ocean Salinity Over Time

Note: Figure B.8 plots the average maximum, minimum, and mean salinity at high tide across river stations by calendar month using the data I obtained from the Bangladesh Water Development Board. Figure B.9 plots average ocean salinity across polygons for three sample years over the course of the calendar year.
Figure B.10: Mapping Water Salinity Sources

(a) BWDB River Salinity Stations
(b) Linking Unions to Coastal Grids

Note: Figure B.10a maps the BWDB river salinity stations from which I obtain data. Figure B.10b illustrates the ways I link unions to coastal grids via the closest cell. Figure B.11 plots how sea levels have risen along the coast of Bangladesh based on my calculations from satellite data of the HYCOM (Cummings and Smedstad, 2013), averaging across the 10 kilometer-wide grids I have created off the Bangladeshi coast.
C  Farmer Perceptions Survey

C.1  Sampling

**Union Sampling**  The survey was conducted across 250 unions in the Khulna division of Bangladesh. From the 642 unions in the Global Administrative Areas (2018) data, I exclude 32 urban areas and then select nine unions from which I have government salinity station data, 37 unions with water stations from the Bangladesh Water Development Board, 48 unions that are also included in the Bangladesh Integrated Household Survey sampling frame, and 121 unions that are also included in the 2016-2017 Bangladesh Labor Force Participation Survey sampling frame. This yields 185 unique unions. Both the Bangladesh Integrated Household Survey and the Bangladesh Labor Force Participation Survey were designed to be representative, and just 29 of the 185 initially selected unions fall outside of both of those survey’s sampling frames as exclusively part of the government salinity or water stations. Then, I randomly sort the remaining unions, and choose the next 65.\(^{73}\)

**Farmer Sampling**  Enumerators visited each union and did an initial listing of 50 households who were planning on harvesting rice during the upcoming Boro season and made the primary agricultural decisions on their land. In almost all unions, this goal of 50 households was achieved and typically within a single village. From this initial list, farmers were randomly ordered to be selected for an interview. Initially, 10 households were selected per union, though this number was revised down to nine given survey length concerns after the first week. On average, 9.1 farmers were surveyed in each union. Before a household was deemed unavailable and a replacement household was selected from the randomized listing order, enumerators attempted to contact them multiple times over multiple days via their phone number collected during the

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\(^{73}\) The original sampled list included 250 unions. After enumerators attempted to conduct the listing exercise, they could not find a sufficient number of Boro rice farmers in either Nalian Range or Satkhira Range, reducing the total sample to 248, which was the pre-registered sample size. During the course of the baseline survey, it was discovered that in two additional unions, farmers had a different interpretation of the term “Boro” and did not harvest rice during the relevant season, reducing the sample size to 246. After additional funding was received partway through data collection, however, four new replacement unions were added to bring the total back to 250, following the initial randomization order.
Figure C.2: Data Collection Timeline

Note: Figure C.2 shows the timeline of data collection activities along with farmers’ typical planting and harvest times.

listing. Of the endline respondents, 97.07 percent were also interviewed during the baseline; in the small number of cases when the baseline respondent was unavailable, another person from the household who makes decisions about farming was interviewed. Among the 66 households successfully interviewed in the endline but for which the primary respondent was unavailable, 28 of the baseline respondents had migrated, six had passed away, and 32 had another conflict.

Timeline Data collection spanned from Fall 2022 through Summer 2023, as pictured in Appendix Figure C.2. Villages were assigned to enumerators based on location to minimize staff travel time. Within enumerator, the order of villages was randomized for both the baseline and endline surveys. Enumerators typically completed three surveys a day, spending three days in each village.

C.2 Variable Construction

Please visit the following links to view the complete survey instruments: Baseline (English translation), Baseline (Bangla translation), Endline (English translation), and Endline (Bangla). The plot-specific questions and the salinity measurements took place on a plot selected at random with a probability proportional to the plot size.

Demographics I construct a continuous years of education measure based on the categorical answers given to the education question as follows: no schooling or informal education only (0), class 5 or below (5), class 8 or below (8), SSC/Dakhil or below (10), HSC/Alim
or below (12), Degree (12), Graduate (16), Technical/Vocational education (16), and Post-graduate (18).

Environmental Knowledge  Salinity:  Respondents were first asked, “Does the amount of salt in the soil change throughout the year?” Those who answered yes were then asked in which month the salt in the soil was highest and lowest. Based off of monthly data from the Bangladesh Soil Resource Development Institute’s soil stations in Khulna and nearby areas, I classify correct answers generously: any month between mid-March to mid-June (in the Bangla calendar) for the peak and any month between mid-July and mid-November for the trough.

Environmental Beliefs  Salinity:  To elicit beliefs about soil salinity, I ask farmers to distribute buttons across the picture shown in Figure C.3a. I first introduce this image by telling farmers, “This image shows pictures of rice plants at the end of the season, once they are fully grown. They are arranged from the best growing to the worst growing. The smallest ones grew the worst. The biggest plants grew the best. Plant number 1 is the least healthy, and plant number 7 is the most healthy.” To ensure that farmers do not simply misinterpret the question as asking about last year’s or next year’s crops, I next ask, “First, think about last year. Which of these pictures best matches the plants that grew on your plot last year? I would now like to know how you think your own crops will fare this year. Think about the end of the season. What are your guesses about what your grown plant will look like on your plot? Place the highest number of buttons on the image that best matches your guess. Remember, plant 7 is the healthiest and plant 1 is the least healthy.” Then, I introduce the salinity study specifically by instructing farmers, “This is not a picture of your own plant, it is taken from a previous study. Researchers have grown rice seedlings under different conditions. This rice variety is not specially adapted for saline soils. Instructions: Point to picture that has the biggest plant. This picture shows the seed grown in soil with the least amount of salt. Instructions: Point to picture that has the smallest plant. This picture shows the seed grown in soil with the most amount of salt. Instructions: Point to the pictures in the middle. These pictures show seeds grown in increasing amounts of salt, from largest to smallest. Do you have any questions about these plants?” After answering any lingering questions, the main belief elicitation question asks farmers, “This photo comes from researchers who planted rice that is not saline tolerant in different soils with different amounts of salt. If they used your soil from your plotplot, which of these pictures do you think would look most like the plant at the end of the season? We are asking this question because we are trying to understand how much salt you think is in your soil. You should assume that the researchers copy all aspects of your soil, such as the water and fertilizers you use over the season and the weather on your plot. Please place more buttons on the pictures that you think are more likely.” In follow up questions, I elicit beliefs about soil conditions five years in the past and in the future.

The image from Figure C.3a comes from the field experiments testing salinity’s impact on rice yield from Grattan et al. (2002). Based on the growing conditions from that paper, I convert beliefs into average salinity perceptions based on equation 11, where $s^k_i$ denoting the number of buttons places on the $k^{th}$ rice plant, where the healthiest plant is 7 and the
Figure C.3: Belief Elicitation Visual Aids

(a) Soil Salinity Image
(b) Flooding Image
(c) Monsoon Intensity Image—Baseline
(d) Monsoon Intensity Image—Endline

Note: Figure C.3 shows English versions of the images used to elicit beliefs in the survey. Figure C.3a shows the image for measuring expectations about soil salinity among farmers, which comes from field experiments run to test the impact of salinity on rice yield from Grattan et al. (2002). Figure C.3b shows the image for flooding. Figures C.3c and C.3d show the images used in the monsoon intensity elicitation during the baseline and endline, respectively.

least healthy is 1. This equation incorporates both the conversion from the plant health to the seasonal average of field water salinity and the translation of field water salinity to salinity from the top three inches of soil. In both steps, Grattan et al. (2002) find strong linear relationships with high $R^2$.

$$\text{Expected Salinity}_i = \hat{s}_i = 1.17 \times \left( \frac{\sum_{i=1}^{7} \left( .3 + 1.95(7-k) \right) s^k_i \right)}{10} + 1.2 \quad (11)$$

Due to the discrete nature of the button elicitation method, farmers cannot express beliefs that span the complete support of possible salinity expectations. To account for this measurement error, I adjust beliefs under the following structural assumption. This ensures that any bunching I observe in the data is not an artifact of the elicitation method. Let $s^r$ denote a possible salinity expectation that can be expressed using buttons, where $r$ ranks values from smallest to largest. The key assumption I make is that the true expected belief $s^*_i$
equals their reported value $\tilde{s}_i = s^{r(i)}$ plus an adjustment drawn from a uniform distribution spanning between ranks, following equation 12, yielding the final belief in equation 13.

$$\mu_i \sim U \left( \frac{s^{r(i)-1} - s^{r(i)}}{2}, \frac{s^{r(i)+1} - s^{r(i)}}{2} \right)$$

$$s^*_i = \tilde{s}_i + \mu_i$$

One limitation of this measurement approach is bottom-coding from the Grattan et al. (2002) experiments. Indeed, I find soil salinity levels below the lowest amount considered in that study on several hundred plots. To account for this, when comparing beliefs to the truth, I also bottom-code the true salinity level at the same level as these beliefs.

**Flooding Beliefs** The same random half of farmers who answered beliefs questions about precipitation also provided their expectations about flood risk by placing buttons on Figure C.3b. To ensure that the categories remained mutually exclusive, enumerators instructed respondents to consider the total number of days in the case of multiple floods occurring. Farmers first provide predictions about the next 12 months, and subsequently about the next five years. As a complementary measure and an attempt to account for the difficulty in articulating small probabilities with the button method, I additionally ask farmers, “How many years do you think it would take for a [one-day/three-day/week-long/month-long] flood to happen in this village?” I winsorize these at the 99th percentile I convert these to a hazard rate by calculating the inverse.

To construct an index of flooding beliefs, I calculate the expected number of days of flooding next year and in the next five years, hazard rates from the questions of the form “How many years...”, and farmers answers to the questions about whether flooding risk increased the past 10 years, will increase the next 10 years, and the order of those two questions. I combine these measures following the procedure in Kling et al. (2007), and then standardize the resulting measure based on the control group mean and standard deviation, where here the control group excludes those who randomly received the flood information. To analyze the information treatment, I construct this same index only using the hazard rate questions which were asked after enumerators potentially provided the information to respondents.

**Rainfall Beliefs** To measure farmers’ perceptions of rainfall during the monsoon season, enumerators asked farmers to place buttons across the image in Figure C.3c for the random half of respondents asked about rainfall during the baseline survey, and across the image in Figure C.3d for the other half asked during the endline. This adjustment was made to address concerns about bottom-coded answers. Enumerators define a rainy day to farmers as one on which it rained for at least an hour with normal size drops. This is consistent with the U.S. Geological Survey definition. I ask farmers about how much it rained during the six months in the Bengali calendar corresponding to mid-May through mid-October. Farmers were asked to place buttons to indicate, for every two weeks during this period, on how many days they expect or recall that it rained, depending on whether the question was about the past or the future.
To convert these responses into a prediction, I assign values to buckets as follows: less than 8 days (7.5 days), less than 10 days (9.5 days), more than 12 days (12.5 days), and all bins \(k-k+1\) days (\(k + .5\) days).

### Perceived Returns to Salinity-Tolerant Seeds
To measure beliefs about the returns to salinity-tolerant seeds, I first ask farmers to estimate the amount of rice they expect to harvest from the target survey plot. Then, I ask them by how much they expect this harvest to change if they switched to a salinity-tolerant seed. If they already intend to plant a salinity-tolerant seed, then I instead ask about switching to a non-salinity tolerant seed. In all questions, I use the visual belief elicitation method described above that uses buttons to elicit probabilistic beliefs. I simply use the mean return scaled by the total mean expected harvest in the analysis of the returns to salinity-tolerant seeds.

### Agricultural Profits
Capturing agricultural profits presents a variety of challenges in this setting. I therefore calculate several complementary measures, each with its own advantages and drawbacks.

Separately from farmers’ self-reported profits, I calculate a measure of greenness based on satellite data. First, I take the average latitude and longitude of each farmers’ plots from the salinity sensor readings. Second, I construct a circle around this point of .0005 degrees, or approximately 55 meters. Note that because plots vary in size and the soil salt measurements did not occur in the middle of the plot, this step certainly generates measurement error, though it should be independent of treatment status. Third, I calculate a normalized difference vegetation index (NDVI) using remote sensing data from the Sentinel-2 satellite. I use the Harmonized MultiSpectral Instrument Level 2-A series made available on Google Earth Engine. From the endline survey, I take the harvest week of the Boro crop and calculate average greenness in the three weeks leading up to that date.

I compile every satellite image between February 15th and March 15th 2023. I calculate the average value of the red and near infra-red (NIR) wavelengths for each image, excluding any observations with any cloud coverage. Finally, I calculate the NDVI on each day according to equation 14 and take the average value across this time period for each plot.

\[
\text{NDVI}_i = \frac{NIR - RED}{NIR + RED} \tag{14}
\]

\[
EVI = \frac{2.5 \times (NIR - RED)}{NIR + 6 \times RED - 7.5 \times BLUE + 1} \tag{15}
\]

### Agricultural Issues: What Comes to Mind?
The first question asked to respondents after the consent form was: “What are the biggest issues that you face in cultivating

---

\[74\] I use responses from the 98.33 percent of farmers who report a date between the second half of February and the first half of June. For the others (including those who did not harvest in Boro), I assign them the modal date from their treatment status by village response. There is no difference between treatment and control group in reporting an answer within the relevant date (\(p\)-value=0.922). In one village, all harvest dates are missing, and I exclude respondents from this village from this analysis.
Boro rice?” I recorded the audio of farmers’ responses to this question, and then coded up their answers according to the issues mentioned by each farmer. I construct 13 categories, in addition to an other category: Pests/Disease, Salinity, Input prices, Non-salinity water problems, Input shortages, Seed issues, Rice sale price, Non-salinity soil problems, Other rice plant health problems, Farmers’ own health, Floods, Rain/droughts, and Temperature.

C.3 Flood Insurance Details

This section provides details on the elicitation of willingness-to-pay for flood insurance. Enumerators explained the hypothetical contracts to farmers using the following script: “In some places, there are insurance contracts for bad weather or natural disasters. For example, there may be an insurance contract for the amount of rain. In that case, farmers like you will pay some money to the insurance company at the beginning of the season. If there is not enough rain in that season, the insurance company will refund the money paid to the farmers at the beginning of the season with interest. And if there is enough rain in the season, then the insurance company will not pay any money at the end of the season. I’m now going to ask you about a hypothetical insurance contract. Suppose there is an insurance company offering insurance for flooding. You should imagine that the insurance company is extremely trustworthy. If you accept the contract, that means that every month, you would have to pay a fixed amount to that company. If there is a flood that occurs on your land, then they will pay you a large amount of money. If there is no flood, then you do not receive any money. Does this make sense?”

Then, enumerators point to the relevant parts of the visual aid in Figure C.4 and read the following, where the randomized values for \(\text{Fee}\) and \(\text{Payout}\) were automatically filled in\(^{75}\): “Now let’s see an example. The insurance company offers you a contract for \(\text{Fee}\) Taka per month. If there is a flood, then the company pays you \(\text{Payout}\) Taka. Let’s walk through two scenarios. First, imagine that you do not buy the contract. That is shown by the top row. Then each month, you do not have to pay anything to any company. If no flood occurs, then you never receive any payment from the company and you never have to pay anything. However, if there is a flood, then that might damage your house or your crops. In that case, you would also not receive anything from the company, but you might have damages that might cost you some money. Now, imagine that you do buy the contract. That is shown by the bottom row. Then each month, you have to pay \(\text{Fee}\) taka. If there is no flood, then you do not get paid anything by the company. If there is a flood, it might damage your house.

\(^{75}\) The example fee has no predictive power for explaining farmers’ willingness-to-pay in the price list that follows.
or your crops. But the company also pays you [Payout] Taka. Of course, it is hard to know in advance if or when a flood will occur.”

To check farmers’ comprehension of this type of contract, enumerators asked two questions: “Just to make sure this is clear, I’m going to ask you some questions about these scenarios. If you do not buy the insurance, how much do you get paid if there is a flood? If you do buy the insurance, how much do you get paid if there is a flood?”

Finally, prior to the elicitation, enumerators reiterated the format of the contract: “It is important to remember that it is hard to predict if and when a flood might occur. That means that if you buy insurance, the number of months you have to pay the fee before a flood occurs could be small, could be large, or a flood might never occur. Does that make sense?” Then, enumerators implemented the price list to elicit demand using the same value of [Payout] as the example. The format of the questions mirrored the BDM procedure conducted earlier in the survey.
D Additional Data Sources

D.1 New Seed Database

Rice farmers in Bangladesh plant a large number of different seeds, many of which are local varieties. Unfortunately, no systematic data includes information on these different varieties. To overcome this issue, I construct a new database of seed characteristics by compiling data from several different sources. I take records from the Digital Herbarium of Crop Plants from the Department of Crop Botany at Bangabandhu Sheikh Mujibur Rahman Agricultural University, which itself aggregates information from the seed developers. I supplement these data with information from three government sources: the Bangladesh Ministry of Agriculture Bangladesh Agricultural Research Council’s Agri-Advisory Portal, the Seed Certification Agency, and the Bangladesh Rice Research Institute. I add additional information on the growth duration of each seed from the Food and Agriculture Organization on Bangladesh. I execute online searches for each variety and, in some cases, call the seed importers directly to collect additional information.76 Finally, local varieties constitute an important share of planted seeds in this setting, yet official records detailing their characteristics do not exist. I use phone surveys with four seed dealers from across the Khulna division in an attempt to fill in this data gap. I focus on salinity tolerance status, the most important seed characteristic for my analysis.77

The complete set of seeds for which I attempt to find data spans 330 different varieties, of which I classify 17 as salinity tolerant. As a benchmark, I classify 42 as resistant to at least one pest. Table D.1 presents information on how other seed characteristics vary by whether the variety is tolerant to saline soil. Salinity-tolerant seeds tend to produce smaller yields and enter the market more recently.

76 The Hera-2 seed is somewhat salinity-tolerant, but the original Hera seed is not. However, because farmers sometimes use the term “Hera” to refer to either, I defer to their judgment on a case-by-case basis as to whether their variety of “Hera” is indeed resistant to high salinity levels.

77 The information from seed dealers sometimes contradicts the official government records or one another for this feature, and thus I only defer to the seed dealers’ classification in the case of local varieties for which no official source exists, and when at least two dealers report the same seed being saline tolerant.

Table D.1: Seed Characteristics by Salinity Tolerance Status

<table>
<thead>
<tr>
<th></th>
<th>(1) Boro Yield (Tons/Hectare)</th>
<th>(2) Plant Height (cm.)</th>
<th>(3) Release Year</th>
<th>(4) Growth Duration (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Salinity Resistant</td>
<td>-1.024*</td>
<td>-1.841</td>
<td>14.36***</td>
<td>4.508</td>
</tr>
<tr>
<td></td>
<td>(0.536)</td>
<td>(3.070)</td>
<td>(2.969)</td>
<td>(3.302)</td>
</tr>
<tr>
<td>Non-Resistant Mean</td>
<td>6.689</td>
<td>109.832</td>
<td>1997.891</td>
<td>135.824</td>
</tr>
<tr>
<td>Observations</td>
<td>64</td>
<td>119</td>
<td>147</td>
<td>139</td>
</tr>
</tbody>
</table>

Note: Table D.1 presents ordinary least squares regressions of key seed characteristics against each variety’s salinity tolerance, based on the new database I assemble. Observations vary depending on what information I am able to track down for each seed.
D.2 Bangladesh Climate Change Adaptation Survey

This section describes the cleaning and definitions of relevant variables from the Bangladesh Climate Change Adaptation Survey. I focus on two primary questions asked in the second round to 805 households. First, respondents were asked, “Have you noticed any changes in the average rainfall or the number of rainfall days over the last 20 years?” I construct a variable indicating whether respondents answered that rainfall had decreased to this question. Second, they were asked, “Have you noticed any long term changes in rainfall variability over the last 20 years? If yes, what changes have you noticed?” I classify responses to this question under six categories: longer droughts, an increase in floods, more erratic rainfall, later rainfall, earlier rainfall, and heavier rainfall.

E Conceptual Framework Appendix

E.1 Proofs of Theoretical Results

This section provides a formal treatment of the results from Section 3. To make this section self-contained, I begin by repeating the key notation from the set-up as discussed in the main text and then derive the main predictions.

Set-Up Farmer grows rice in two periods, \( t \in \{1, 2\} \). Output in period \( t \) is given by the binary indicator \( y_t \in \{0, 1\} \), where \( y_t = 0 \) denotes low harvest, and \( y_t = 1 \) denotes high harvest. Harvest is subject to a random productivity shock \( \xi \) that can be either negative \((\xi = -1)\), positive \((\xi = 1)\), or neutral \((\xi = 0)\). I assume productivity shocks are distributed symmetrically with mean zero such that the positive and negative shocks occur with equal, positive probability denoted by \( \rho > 0 \) and that neutral shocks occur with positive probability such that \( \rho < .5 \). In the first period, farmers make no decisions about inputs and plant the standard seed. In the second period, salinity tolerant seeds are introduced, and farmers decide whether to plant salinity tolerant seed or plant the standard seed. This decision is given by the binary indicator \( d_t \in \{0, 1\} \). Planting a standard seed is given by \( d_t = 0 \), where \( d_1 = 0 \) by default because salinity tolerant seeds are not available in the first period. In the second period, farmers may plant a salinity tolerant seed, denoted by \( d_2 = 1 \). Seed choice costs \( c(d_t) \), where I normalize such that planting a non-salinity tolerant seed is free \( c(d_t = 0) = 0 \). I assume planting a salinity tolerant seed costs \( c(d_t = 1) \) is positive yet small to capture the notion that salinity tolerant seeds perform relatively better in high salt environments yet relatively worse than standard seeds amid low salinity. Two independent and unchanging environmental conditions denoted by the set \( \{S, B\} \) can impact harvest, where \( S \) is the soil salinity and \( B \) is blast, an important fungus threatening rice. I use lower case letters to denote the true, binary environmental states in these respective domains, given by \( s \in \{0, 1\} \), where \( s = 0 \) denotes low salt levels and \( s = 1 \) denotes high salt levels, and by \( b \in \{0, 1\} \), where \( b = 0 \) denotes no blast and \( b = 1 \) denotes the presence of blast. I assume the agricultural production function follows a particular, simple functional form given by Equation 16. The maximization and minimization expressions ensure the binary support of output \( y_t \in \{0, 1\} \). Planting salinity tolerant seeds \( d_t = 1 \) mitigates the damage from soil with high salt content \((s = 1)\).
$y_t(s, b, d_t) = \max \left( \min \left( 1 - (s - d_t)^2 - b + \xi, 1 \right), 0 \right)$ (16)

I assume farmers cannot directly observe the environmental states. As a result, farmers are uncertain about how their decision $d_2$ impacts their output $y_2$ entering the second period. This uncertainty is captured by their prior over the states of soil salinity and blast. I use $\cdot$ and lower case letters to denote beliefs, such that $\hat{s}_t$ denotes a farmer’s belief entering period $t$ about the probability that true salinity levels are high $\hat{s}_t = P(s = 1)$, and $\hat{b}_t$ denotes a farmer’s belief in period $t$ about the probability that blast is present $\hat{b}_t = P(b = 1)$. I assume that farmers use Bayes’ rule to learn about these unobserved environmental conditions by updating using the harvest in period 1. Risk-neutral farmers choose seeds to maximize output in period 2 given their beliefs, as shown in Equation 17.

$$U = \max_{d_2} \mathbb{E} \left[ y_2(\hat{s}_2, \hat{b}_2, d_2) - c(d_2) \right]$$ (17)

Finally, I define the default domain to be the environmental domain $E \in \{S, B\}$ corresponding to the most likely threat $\hat{\xi} = \max(\hat{s}, \hat{b})$.

**Learning About the Environment** To characterize farmers’ posterior beliefs entering the second period, I simply apply Bayes’ rule. First, consider the case shown in Equation 18 of updating about the likelihood of high salinity after observing a bad harvest.

$$\hat{s}_2 = P(s = 1|y_1 = 0) = \frac{P(s_1)P(y_1 = 0|s = 1)}{P(y_1 = 0)}$$ (18)

I now derive each of these components. The first term is simply farmers’ priors about salinity $P(s_1) = \hat{s}_1$. The second and third terms can be calculated using the agricultural production function, as shown in Equations 19 and 20, respectively.

$$P(y_1 = 0|s = 1) = \hat{b}_1 + (1 - \hat{b}_1)(1 - \rho)$$ (19)

$$P(y_1 = 0) = \hat{b}_1 \hat{s}_1 + \hat{s}_1(1 - \hat{b}_1)(1 - \rho) + \hat{b}_1(1 - \hat{s}_1)(1 - \rho) + (1 - \hat{b}_1)(1 - \hat{s}_1)\rho$$ (20)

Substituting these expressions into Equation 18 gives Equation 21.

$$\hat{s}_2 = \frac{\hat{s}_1 \hat{b}_1 + \hat{s}_1(1 - \hat{b}_1)(1 - \rho)}{\hat{s}_1(1 - \hat{b}_1)(1 - \rho) + \hat{b}_1(1 - \hat{s}_1)(1 - \rho) + (1 - \hat{b}_1)(1 - \hat{s}_1)\rho}$$ (21)

This expression can be simplified to Equation 22.

$$\hat{s}_2 = \frac{\hat{s}_1 - \rho \hat{s}_1 + \rho \hat{b}_1 \hat{s}_1}{\hat{b}_1 + \hat{s}_1 + \rho + 3\rho \hat{b}_1 \hat{s}_1 - \hat{b}_1 \hat{s}_1 - 2\rho \hat{b}_1 - 2\rho \hat{s}_1}$$ (22)

The difference between posterior and prior beliefs about salinity is then given by Equation 23.

$$\hat{s}_2 - \hat{s}_1 = \frac{\hat{s}_1 - 2\rho \hat{s}_1 - \hat{b}_1 \hat{s}_1 + 3\rho \hat{b}_1 \hat{s}_1 - (\hat{s}_1)^2 + 2\rho (\hat{s}_1)^2 + \hat{b}_1 (\hat{s}_1)^2 - 3\rho \hat{b}_1 (\hat{s}_1)^2}{\hat{b}_1 + \hat{s}_1 + \rho + 3\rho \hat{b}_1 \hat{s}_1 - \hat{b}_1 \hat{s}_1 - 2\rho \hat{b}_1 - 2\rho \hat{s}_1}$$ (23)
The expression for the difference between posterior and prior beliefs about blast is given by the symmetric expression, substituting \( \hat{b}_t \) for \( \hat{s}_1 \) and vice versa. Note that the denominators are identical and always positive since it is simply \( P(y_1 = 0) \), so I focus exclusively on the numerator.

Due to the bounds of beliefs \( 0 \leq \hat{s}_t, \hat{b}_t \leq 1 \), the amount that a farmer can update depends on their prior. To account for this mechanical limitation, the numerator from Equation 23 can be scaled to become a share of the potential scope for belief updating; in other words, by dividing by \( |1 - y_t - \hat{s}_1| \).

\[
\frac{\hat{s}_2 - \hat{s}_1}{|1 - y_t - \hat{s}_1|} \propto \frac{\hat{s}_1 - 2 \rho \hat{s}_1 - \hat{b}_1 \hat{s}_1 + 3 \rho \hat{b}_1 \hat{s}_1 - (\hat{s}_1)^2 + 2 \rho (\hat{s}_1)^2 + \hat{b}_1 (\hat{s}_1)^2 - 3 \rho \hat{b}_1 (\hat{s}_1)^2}{1 - \hat{s}_1} \quad (24)
\]

I factor out \((1 - \hat{s}_1)\) from the numerator in Equation 25 to arrive at the simplified Equation 26.

\[
\frac{\hat{s}_2 - \hat{s}_1}{|1 - y_t - \hat{s}_1|} \propto \frac{(1 - \hat{s}_1)\hat{s}_1 + (1 - \hat{s}_1)(-2 \rho \hat{s}_1) + (1 - \hat{s}_1)(-\hat{b}_1 \hat{s}_1) + (1 - \hat{s}_1)(-3 \rho \hat{s}_1 \hat{b}_1)}{1 - \hat{s}_1} \quad (25)
\]

\[
\frac{\hat{s}_2 - \hat{s}_1}{|1 - y_t - \hat{s}_1|} \propto \hat{s}_1 - 2 \rho \hat{s}_1 - \hat{b}_1 \hat{s}_1 - 3 \rho \hat{s}_1 \hat{b}_1 \quad (26)
\]

Since the expression for blast is symmetric, the expression for the relative difference between posterior and prior beliefs along the two unobserved environmental dimensions is therefore given by Equation 27.

\[
\frac{\hat{b}_2 - \hat{b}_1}{|1 - y_t - \hat{b}_1|} - \frac{\hat{s}_2 - \hat{s}_1}{|1 - y_t - \hat{s}_1|} \propto \hat{b}_1 \hat{s}_1 (1 - 2 \rho) \quad (27)
\]

Since \( \rho < .5 \) by assumption, the sign depends on the term \((\hat{b}_1 - \hat{s}_1)\). When prior beliefs about the likelihood of high salinity exceed initial beliefs about the chance of blast, then observing low yield leads the farmer to disproportionately increase their beliefs about salinity relative to blast.

Now, consider updating about the likelihood of high salinity after observing a good harvest.

\[
\hat{s}_2 = P(s = 1|y_1 = 1) = \frac{P(s_1)P(y_1 = 1|s = 1)}{P(y_1 = 1)} \quad (28)
\]

Following the same procedure as in the case of a bad harvest, the posterior likelihood of salt levels being high is given by Equation 29.

\[
\hat{s}_2 = \frac{\hat{s}_1(1 - \hat{b}_1) \rho}{\hat{s}_1(1 - \hat{b}_1) \rho + \hat{b}_1 (1 - \hat{s}_1) \rho + (1 - \hat{s}_1)(1 - \hat{b}_1)(1 - \rho)} \quad (29)
\]

\[
\hat{s}_2 = \frac{\hat{s}_1 \rho - \hat{b}_1 \rho \hat{s}_1}{1 - \hat{b}_1 - \hat{s}_1 - \rho + 2 \hat{b}_1 \rho + 2 \hat{b}_1 \hat{s}_1 + \hat{s}_1 \rho + \hat{b}_1 \rho - 3 \hat{b}_1 \rho \hat{s}_1} \quad (30)
\]

Again noting that the denominator is always positive and identical in the case of salinity and
blast since it is simply $P(y_1 = 1)$, I focus on the numerator. The change in salinity beliefs is given by Equation 31.

$$\hat{s}_2 - \hat{s}_1 \propto (\hat{s}_1)^2 + 2\hat{s}_1 \rho - 2\hat{b}_1 \rho \hat{s}_1 - \hat{s}_1 + \hat{b}_1 \hat{s}_1 - (\hat{s}_1)^2 \rho - 2\hat{b}_1 \rho \hat{s}_1 - 2\hat{b}_1 (\hat{s}_1)^2 + 3\hat{b}_1 \rho (\hat{s}_1)^2 \quad (31)$$

Scaling to account for the mechanical restrictions due to the bounds on beliefs gives Equation 33.

$$\frac{\hat{s}_2 - \hat{s}_1}{1 - y_1 - \hat{s}_1} \propto \hat{s}_1 + 2\rho - 2\hat{b}_1 \rho - 1 + \hat{b}_1 - \hat{s}_1 \rho - 2\hat{b}_1 \rho - 2\hat{b}_1 \hat{s}_1 + 3\hat{b}_1 \rho \hat{s}_1 \quad (32)$$

As before, the change between posterior and prior beliefs about the likelihood of blast is symmetric, substituting $\hat{b}_1$ for $\hat{s}_1$ and vice versa. The relative change is given by Equation 33.

$$\frac{(\hat{b}_2 - \hat{b}_1)}{|1 - y_1 - \hat{b}_1|} - \frac{(\hat{s}_2 - \hat{s}_1)}{|1 - y_1 - \hat{s}_1|} \propto (\hat{b}_1 - \hat{s}_1)3\rho \quad (33)$$

As before, the sign of this expression hinges on $\hat{b}_1 - \hat{s}_1$. Because this is the case of experiencing a low yield (and thus farmers update their beliefs downward), the relative reduction in likelihood for the default domain is smaller than that in the non-default domain. In other words, a farmer who thinks salinity is more likely than blast going into period 1 will still think that salinity is more likely than blast going into period 2 after observing a good yield, even though both posteriors will be lower than the priors.

Combining the results from Equations 27 and 33 illustrates that after observing either low yield or high yield, the rank ordering of beliefs is preserved. In other words, the default domain exhibits path dependence and will always be the default domain. This proves Remark 1.

### E.2 Extensions to Learning About Rainfall and Flooding

I have thus far focused on the case of learning about soil salinity (and other unobservable environmental factors impacting agricultural production) from crop yield. The same intuition can be easily extended to the cases of flooding and rainfall—the other main beliefs I study in this paper—among other important decision-relevant dimensions of the environment.

In the case of flooding, farmers observe whether or not it floods in a given year. This observed data—the equivalent of $y_t$ in the conceptual framework—can be consistent with both high flood risk state and low flood risk state, particularly given the relatively low hazard rate of flooding even in areas with high latent risk. These two dimensions are equivalent to the blast fungus $b$ and soil salinity $s$. Farmers face the same type of identification problem, and their priors about whether latent flood risk is high or low will shape how they interpret either the presence or absence of a flood.

Similarly, in the case of rainfall, farmers form predictions about the upcoming monsoon season to inform important agricultural decisions. The truth is unobservable to farmers, and thus instead they must rely on past experiences when forming their beliefs. The latent rainfall distribution can be either high or low, and yet because any given observed rainfall in a year could have been drawn from the support of either distribution, farmers face a similar identification problem and will exhibit the same kind of path dependence.
F Qualitative Evidence

F.1 Methodology

Main Sample Open-Ended Response Audio Recordings

I focus on audio recordings of four open-ended questions asked to the main sample during the endline survey:
1. What are the biggest issues that you face in cultivating Boro rice?
2. How do you learn about the amount of salt in the soil of your plots?
3. What do you find hard about figuring out how much salt is in your soil? What do you find easy about figuring out how much salt is in your soil?
4. Are you worried or not worried about salinity on your plots? Why or why not?
I transcribe and translate the responses to these questions.

Qualitative Interview Data Collection

I conducted qualitative interviews in six villages in the same upazilas of the main survey, but no farmer in the main sample lived in any of these villages. The sampling frame mirrored the main survey to include all Boro season rice farmers, though within that set, the 40 farmers constituting the qualitative interview sample were recruited by convenience instead of randomization from a listing. Interviews were conducted in June 2023, coinciding with the launch of the endline survey. Most interviews lasted between 20 and 30 minutes and were held outside, typically in common areas of the village. Shahriaz Ahmed—a lecturer in Development Studies at Khulna University—conducted consecutive translation to facilitate the interviews between myself and the farmers. All interviews were recorded, and the transcriptions of these interviews form the basis of the data used in the coding procedure.

Interviews followed an in-depth narrative approach, which has a long and rich history in social science research (see DeLuca et al. (2016) for more on this method and Bergman et al. (Forthcoming) for a recent example from the economics literature). This method—which emphasizes a natural, in-depth conversation over a series of questions and short answers—has been shown to allow a wide range of responses to emerge through initial, open-ended questions that lead to targeted follow-up. In the case of this study, the conversations primarily focused on how farmers made agricultural decisions and their related economic concerns. All interviews started and ended with the same pair of questions. I began by asking each farmer, “How did your harvest go?” and concluded by asking “Do you have anything else to share?” In between, the conversation ranged but largely focused on what farmers identified as their biggest agricultural challenges, the choices they make to adapt to these obstacles, and how they gather information to arrive at these decisions.

Qualitative Interview Data Coding Protocols

I took an inductive approach to coding the qualitative data, by first reviewing the corpus of all interviews and noting the aspects of decision-making and learning that emerged as most salient from farmers’ own accounts. I then coded all transcripts according to these
themes, recording the frequency with which they were mentioned across all farmers in the sample. The following paragraphs provide further detail on the coding protocols for each theme.

**Inference by Harvest Outcome:** This code describes farmers who use the outcome of their harvest to assess the degree of environmental threats on their land. I code interviews under this theme even if farmers also use other signals to formulate their beliefs, as long as they mention this particular data point explicitly as well.

**Low Belief Uncertainty:** This code covers farmers who reported who—when describing environmental conditions on their land or the effectiveness of technology—emphasized the certainty of their expectations. For instance, when describing the amount of salt on their soil, a farmer in this classification would be very confident in their assessment.

**Unwillingness to Switch from Boro Cultivation:** This code captures farmers who—when discussing potential margins of adaptation to environmental threats on their land—stressed their unwillingness to ever stop cultivating rice during the Boro season, even if conditions become particularly dire.

**Confidence in Success of Salinity Adaptation Methods:** This code applies to farmers who report taking an adaptation step that they say fully corrects the salinity problem after pointing out salinity issues on their land. Note that by construction, this code can only possibly apply to farmers who recount a salt threat to their agricultural productivity. Farmers falling under this category explicitly acknowledge that salinity would harm their output had it not been for some measure they take, which they say has fully eradicated the potential harm.

**Reliance on Social Learning:** This code includes farmers explicitly pointing to input from others as the major factor in determining their agricultural decisions. I further classify interviews by the source of this information: neighbors or family members in the same village, or relevant local agricultural figures (agricultural extension officers or seed/fertilizer dealers). Farmers typically mention this in the context of seed, fertilizer, and pesticide decisions.

**Demand for Government Assistance:** This code covers any farmer who brought up a request for government support. This typically—though not always—was directly related to agricultural production, and in particular often in the form of financial assistance, either directly or through price controls for inputs. Sometimes, this also included demand for information provided by the government. I also classify farmers under this theme if they hold a pessimistic attitude towards government assistance; that is, they say bring up the topic in the context of decrying the government’s current activities (for instance, in the case of providing some farmers with free seeds but not others through a opaque or unfair procedure).
F.2 Qualitative Evidence Motivating Modeling Assumptions

This section presents additional quotations motivating the modeling assumptions used in my theoretical framework. I organize the quotes based on the the same points made in the set-up of Section 3.

Farmers cannot directly observe salinity

“How do we understand the amount of salt in the soil? We are not engineers. No, we have no way of knowing whether the soil has salinity or not.”
“I find it difficult to estimate the level of salinity in the soil. I don’t understand easily because I don’t have a machine.”
“I don’t have a soil test or salinity tester, and I can’t tell the salinity of the land by looking at the soil.”
“If there is a machine then the matter of measuring salinity is easy. And if there is no salt measuring machine then the matter seems difficult to me.”
“It is impossible to understand without testing the salinity. And we can’t understand by looking.”
“We can’t understand if there is salinity in the land where there is grass without testing the machine.”
“We do not have the equipment to test. So we find it difficult to estimate the salinity level.”
“It is difficult to understand salinity by looking at bare land.”

Farmers rely on harvest output and physical plant characteristics to infer salinity

“It seems difficult to estimate the salinity level if the crop is good in the field. I can easily estimate the level of salinity by looking at the appearance of the crop and the color change of the soil.”
“When the paddy of my land is red in color, I can easily understand that my land is definitely affected by salt. I don’t find anything difficult here. I can tell by looking at the rice plant that it is affected by salt.”
“If the rice plant does not grow when planted in the land, the rice plant turns red and dies, it is easy to understand that there is salinity in the land. It is difficult to understand salinity by looking at bare land.”
“When the bunch of paddy plant turns red, we know that there is salinity in the land. Besides, paddy plants become smaller and white salt floats on the ground. By looking at these I basically estimate the salinity of the land.”
“We can understand the salinity level of the land by looking at the appearance of the crops on the land. When the leaves of the rice plant turn red, white spots appear on the soil and the rice plants wither. Then it is easy to understand that there is salinity in the land.”
“Rice plants do not grow due to salinity, rice plants turn red and rice plants die. Then I realized that the amount of salt in the land is high.”
“The amount of salt in the soil can be understood. White salt appears on the soil after planting rice plants when the rice plants die and the soil dries up. Then it is understood that the salt content in the land is high. The amount of salt is estimated by looking at
these two things: soil and crops.”

“After planting the rice plant, when the rice plant becomes small, we understand that the salt content in the land is high. And in saline land, the soil becomes excessively muddy and soft. Besides, earthworm infestation is seen in saline land. By looking at these two signs, we basically estimate the amount of salinity.”

“I find it difficult to understand salinity by looking at bare land. And when crops are planted in the land and the appearance of the crops, the salinity of the land can be easily understood. By seeing the crop after planting, we can tell whether the land is salinity or not.”

The link between these signals and salinity is indirect

“When the leaves of paddy plants turn red in the land, it is easy to understand that there is salinity in the land. And when rice plants are not growing well, it becomes difficult to know whether the problem is due to salinity, soil or fertilizer.”

“After planting rice plants in the land, when the rice plants turn brown, it is easy to understand that the salinity of the land has increased. And when the paddy plant gets a little bigger and then if the paddy plant does not grow, it seems difficult to know whether the problem is due to salinity or some other reason.”

“If white substance like salt is seen in the soil then it is easy to understand that salinity level is high. And when the paddy plant dies, it becomes difficult.”

“After planting rice in the land, when the rice plants do not grow and are small in size, it is easy to understand that there is salinity in the land. But when the paddy leaves turn red, I find it difficult whether the problem is due to salinity or some other reason.”

“When the rice turns red it is easy to understand that it is due to salinity. When after planting paddy in the land and applying proper fertilizers it is found that the crop is not growing well and the crop is not being nourished then it is difficult to understand whether it is actually due to salinity or some other reason.”

“If a white substance like salt appears in the soil when the soil is dry, it is easy to understand that the salinity level is high. And if a disease occurs after planting paddy in the land, it is difficult to understand whether the problem is due to salinity or for some other reason.”

“If after planting paddy in the land, if the paddy does not grow and the paddy plants are stunted, then it is easy to understand that the land has salinity. But when rice plants turn yellow due to insect attack, it is not easy to understand whether the problem is due to salinity or insect attack.”

G Structured Ethics Appendix

Following the guidance of Asiedu et al. (2021), this section presents a discussion of the ethical considerations of the human subjects research conducted as part of this paper. I discuss the two experiments involved in this project separately: RCT #1, the randomization of saline tolerant seed prices as part of the BDM procedure of the baseline, and RCT #2, the random provision of information about soil salinity during the endline survey.
Policy Equipoise  Is there policy equipoise? That is, is there uncertainty regarding participants’ net benefits from each arm of the study relative to the other arms and to the best possible policy to which participants could have access? If not, ethical randomization requires two conditions related to scarcity: (1) Was there scarcity, i.e., did the inclusion of multiple arms change the expected aggregate value of the programs delivered? (2) Do all ex-ante identifiable participants have equal moral or legal claims to the scarce programs?

For RCT #1, policymakers hold genuine uncertainty as to how effective these saline-tolerant seeds can be in real-world settings, and in particular, how the productivity may vary with saline level. The scale of this experiment provides substantial new evidence outside of controlled lab settings or example plots to assess the relative efficacy in a vulnerable population preserving their agricultural techniques and decision-making for other inputs.

For RCT #2, while there can be little doubt that providing more information to farmers is weakly beneficial, it remains an open policy question as to the magnitude of these benefits and the format of delivery. The cost-benefit calculation behind a policy to collect soil salinity data and provide that information to farmers hinges on the extent to which that information might lead to meaningful behavior change and whether farmer-specific soil measurement is necessary for achieving this impact or whether averages at higher geographic levels can also be effective. This experimental design targets both parameters.

Role of Researchers with Respect to Implementation  Are researchers “active” researchers, i.e. did the researchers have direct decision making power over whether and how to implement the program? If YES, what was the disclosure to participants and informed consent process for participation in the program? Providing IRB approval details may be sufficient but further clarification of any important issues should be discussed here. If NO, i.e., implementation was separate, explain the separation.

The researcher is considered “active” and had direct decision-making power over all aspects of the experimental design for both RCT #1 and RCT #2. Informed consent was elicited from all participants, as approved by Harvard’s IRB board.

Potential Harms to Participants or Non-Participants from the Interventions or Policies  Does the intervention, policy or product being studied pose potential harm to participants or non-participants? Related, are participants or likely affected non-participants particularly vulnerable? Also related, are participants’ access to future services or policies changed because of participation in the study? If yes to any of the above, what is being done to mitigate such risks?

For RCT #1, one potential concern is that the specific seed variety which I provide to farmers as part of the BDM procedure could cause harm to farmers’ output. Several factors help alleviate this worry. First, the government is actively trying to distribute these same seed varieties in many of the areas I survey, often by giving out 10 kilogram packets for free. Due to scarce government resources however, the scope of this effort is significantly limited. In one sense, this experiment can be viewed as an extension of an existing government program, albeit at a smaller scale. Second, the enumerator instructions deliberately avoid making any normative statements about whether the farmer should use the seed. Instead, they simply report that “this seed has been designed to grow well even if the soil has a
lot of salt in it", echoing the description used by the government’s Agricultural Information Service when describing this variety. Third, the WTP elicitation for the seed comes after the BDM mechanisms for a pen, a plate, and a store voucher. To the extent that these standard goods do not have a clearly interpretable normative position, farmers were primed to treating the exercise as a true willingness-to-pay. Fourth, while BRRI 67 grows well in high salinity environments, it grows no worse in low salinity environments. Therefore, even if farmers are overestimating the amount of salt in their soil, their harvest will not be especially negatively impacted if they use the seed. However, it should be noted that other seeds that farmers may use instead in the case of a low saline soil could have other appealing attributes, such as taste or relatively higher yield, and thus harvest may still be lower compared to the counterfactual seed choice. Finally, by only providing one kilogram of seeds, I further help to mitigate this risk, as farmers would likely diversify to other seeds if they had not been planning on using BRRI 67 already.

For RCT #2, one potential concern is that I might accidentally provide erroneous information about soil salinity to respondents. This is particularly relevant given the surprising results of the handheld EC-meters showing low levels of salinity: if salinity is in fact higher than I measure, then I may inadvertently mislead farmers, which could result in worse decisions in the future. I take several steps in an attempt to mitigate this risk. First, I take considerable steps to ensure that the soil salinity measures accurately capture the amount of salt on each farmer’s plot. These steps—detailed further in section B.2—include repeated measurements and validation using a controlled lab test. Second, when providing the information to farmers, enumerators emphasize the generalizability of the measurement, saying: “These numbers are based off of the measurements we took this past season. The amount of salt in the soil can change, so it may be different next year.” Third, the records I obtain from the government’s soil measurements (noting that they only collect data from 10 plots) match the same patterns I find, indicating that indeed, the 2022-23 season exhibited strikingly low salinity levels.

### Potential Harms to Research Participants or Research Staff from Data Collection or Research Protocols

Are data collection and/or research procedures adherent to privacy, confidentiality, risk-management, and informed consent protocols with regard to human subjects? Are they respectful of community norms, e.g., community consent not merely individual consent, when appropriate? Are there potential harms to research staff from conducting the data collection that are beyond “normal” risks?

Yes. This research received IRB approval from Harvard University. Data collection posed no unusual risks to research staff.

### Financial and Reputational Conflicts of Interest

Do any of the researchers have financial conflicts of interest with regard to the results of the research? Do any of the researchers have potential reputational conflicts of interest?

No.

### Intellectual Freedom

Were there any contractual limitations on the ability of the researchers to report the results of the study? If so, what were those restrictions, and who were
they from?
No.

Feedback to Participants or Communities

Is there a plan for providing feedback on research results to participants or communities? If yes, what is the plan? If not, why not?
Yes. The results of both experiments and the trends in salinity over the 2022-23 season were shared with participants prior to the 2023-24 Boro planting. I consulted with G. M. Mustafizur Rahman of the Soil Research Development Institute to ensure that the information I provided farmers was consistent with the best available guidance from the government. The text of the script read by enumerators is as follows: “The amount of soil salinity can change from year to year. Last year, the amount of soil salinity in Khulna division was much lower than it had been in previous years. It is difficult to know whether it will be low again in the future. But it is clear that last year was low relative to what it had been in the past. Because last year’s salinity levels were so low, the farmers who planted more of their land with salinity-tolerant seeds actually earned less money than the farmers who planted different seeds. If the amount of salinity on the soil had been higher, then it might have been better to plant the salinity tolerant seeds. But because it was low, that year, those seeds were not as profitable. It is hard to know what the soil salinity will be next year. In general, when soil salinity is very high, it is better to plant salinity tolerant seeds, and when soil salinity is very low, it is better to plant a different kind of seed. In coastal areas, the government recommends planting salinity tolerant seeds.”

Foreseeable Misuse of Research Results

Is there a foreseeable and plausible risk that the results of the research will be misused and/or deliberately misinterpreted by interested parties to the detriment of other interested parties? If yes, please explain any efforts to mitigate such risk.
No.

Other Ethics Issues to Discuss

Are there any other issues to discuss?
No.