Probabilistic Weather Forecasts and Farmer Decision Making in Rural India[*]

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Abstract

Accurate, probabilistic weather forecasts can help smallholder farmers mitigate agricultural production risk in the context of increasingly uncertain weather due to climate change. In this study, we rely on randomly assigned video information treatments and incentive-compatible experimental games to study farmers' forecast-dependent decision-making in a hypothetical setting. In the experimental games, we find that coffee farmers in rural India have relatively high probability literacy, and update their beliefs about the (in)accuracy of the weather forecast following false alarms, where predicted events do not end up occurring. Farmers who experience false alarms in the experiment also report a lower willingness-to-pay for a real-world mobile-phone based audio (probabilistic) weather forecast service in an incentive-compatible Becker–DeGroot–Marschak elicitation. Video information treatments highlighting the salience of climate change and providing probability training have limited impact on farmers' beliefs, which are are mitigated by the incidence of false alarms. These results help understand how information-based learning and experience-based learning interact.

JEL Codes: C91, D81, O12, O13, Q54
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1 Introduction

Weather uncertainty is a significant source of agricultural production risk, particularly in developing countries where farmers rely on relatively few *ex post* risk-coping strategies. Accurate expectations of upcoming weather, at seasonal and sub-seasonal time scales, can help farmers mitigate such risk (Giné et al., 2015) if their subsequent decisions are better suited to realized conditions. However, with increasing weather variability (Roxy et al., 2017; Auffhammer and Carleton, 2018, in India), forming accurate weather expectations is harder, and high quality weather and climate forecasts gain renewed importance.

Public weather forecast providers in developing countries commonly disseminate deterministic short-to-medium range weather forecasts at granularities that are coarser that those in developed countries (World Meteorological Organization). There is therefore significant scope to improve the informational content of weather forecasts in this context, provided such forecasts are accurately comprehended (Stephens et al., 2019). Existing evidence on probabilistic reasoning (reviewed in Delavande, 2014) indicates that farmers in developing country contexts understand probabilities. In fact, weather is often the intuitive example provided to farmers when discussing probabilistic beliefs. However, there has been limited focus on how farmers in developing countries may use probabilistic weather forecasts to form beliefs, both about weather and about the accuracy of the forecasts themselves.

In this paper, we rely on randomly assigned video information treatments and two incentive-compatible experimental games to study farmers' forecast-dependent decision-making in a hypothetical setting. The video treatments are designed to provide farmers with information that highlights the relevance of weather forecasts in the context of climate change, and a tutorial on interpreting probabilistic information contained in weather forecasts. Random assignment to an experimental arm where farmers watch the first video, one where they watch both videos, or a control group (who watch a placebo video) helps us assess whether information-based learning helps farmers use forecasts better in the hypothetical decision-making games that follow. In the incentive-compatible experimental games, farmers make several rounds of decisions that rely on understanding information contained in weather forecasts, observe a weather realization in each round, and earn a resultant payoff. Farmers' decisions in the two games, their earned payoffs, and a measure of their willingness-to-pay for real-world weather forecasts helps us assess whether experience-based learning in the game impacts how they use forecasts, and how they perceive forecast accuracy.

We recruit 1212 small- and medium-holder coffee farmers in Karnataka, India for this study. Farmers are randomized into one of the three experimental arms described above, watch their assigned informational videos, and then play two incentive-compatible experimental games. In the first game, farmers play five rounds in each of which they choose between two markets to sell goods, with sales outcomes depending on weather conditions. Each round requires them to interpret probabilistic weather forecasts for each of the two markets, and select the market where favorable weather conditions are more likely, to maximize their scores (and earnings). In the second game, farmers play six rounds in each of which they use available weather information to make agricultural decisions that are appropriate for expected weather conditions, with scores (and earnings) depending on the chosen action and realized weather in the round. Finally, we elicit farmers willingness to pay for a real-world voice-call based service that provides accurate, granular, probabilistic weather forecasts on a weekly basis using an incentive-compatible Becker-DeGroot-Marschak elicitation (Becker et al., 1964).

We find that that farmers in this context have high probability literacy. Though only 40% of farmers answer both probability 'test' questions in the survey correctly, 57% of farmers answer all five questions in the first experimental game correctly. In both games, farmers' choices reflect their ability to factor in the forecast probabilities into their beliefs — farmers are more likely to choose the favored market location in the first game when the difference in the probabilities in the two forecasts is larger, and are more likely to make optimal decisions for wet conditions when rain is predicted with a higher probability in the second game. Ninety-eight percent of farmers in the study sample are willing to pay more than ₹0 for a new real world voice call based weather forecast service (₹26 per month on average, or 10% of the daily casual wage rate in Karnataka). This is fairly high demand for weather forecasts over mobile phones, considering they are widely available on the internet, and through television and extension services.

Farmers assigned to watch both the probability tutorial and the video highlighting climate change perform slightly better in the probability 'test' questions, are more likely to believe that unexpected weather events are will occur more frequently in the future, and have higher scores in the first game — indicating that farmers do learn from the information in the two videos together. However, the information treatments do not impact the accuracy of farmers' choices in either game (only impacting their reported confidence in some responses in the first). Farmers assigned to watch both the probability tutorial and the video highlighting climate change, however, report an 8% lower willingness-to-pay for the real-world weather service (significant at the 10% level). This appears to be driven by those farmers who already report accessing forecasts on the internet, suggesting that improved understanding of probabilities might increase the perceived value of existing probabilistic weather forecasts.

Farmers' choices in both games are significantly impacted by their recent experiences in each game. Encountering a false alarm — where predicted weather fails to materialize despite a greater than 50% forecasted likelihood — leads to more cautious subsequent choices and a diminished belief in the accuracy of forecasts. A false positive alarm in a round in the second game prompts farmers to expect rain at higher probabilities in the following round, reflecting a lowered trust in forecast accuracy. Conversely, a false negative, unexpected rain, causes them to adjust their expectations and expect rain at lower probabilities in the following round. Experiencing false alarms in the first game appears to diminish the effects of learning from the probability tutorial. Farmers who don't experience false alarms demonstrate greater confidence in their decisions during the first game, but this boost in confidence is mitigated for those who encounter false alarms. Overall, farmers' beliefs are impacted by false alarms that are more recent than those further back in history. Finally, false alarms of unexpected dry conditions in the games also lead to a 9.5% (significant at the 1% level) decline in farmers' willingness-to-pay for the real-world service, not driven by a corresponding decrease in farmers' scores and earnings. This reduction reflects a decline in farmers' belief in the accuracy and utility of weather forecasts after experiencing such false alarms, and is consistent with their decision-making in the games.

Our findings suggest that farmers' beliefs about the accuracy and utility of weather forecasts are predominantly shaped by their recent experiences with forecast outcomes, more so than any information provided about forecast utility. Our experimental design eliminates potential biases due to order effects, forecast format effects, confusing probabilities with quantities, risk aversion, and misinterpretation of probabilities. Additionally, by including both rounds choosing rainier and drier locations in the first game, we ensure that farmers understand the distinction. Pre-game practice also confirms farmers' ability to recognize weather icons used in visual forecasts, further validating the reliability of our results in assessing their decision-making and belief formation.

The main contribution of this paper is to the literature on learning, through the finding that farmers' decisions in the experimental games are impacted more by their experiences than by information that they learn (e.g., in the psychology and economics literature, reviewed in Malmendier (2021a); Conlon et al. (2022); or in technology adoption in agriculture, such as in Foster and Rosenzweig (1995)). Similar to findings in (D'Acunto et al., 2021) or (Georganas et al., 2014), who look at impact of experienced price changes on inflation expectations, farmers in our study form beliefs about forecast accuracy based on their experiences in the study and update these beliefs to a larger extent when they experience false alarms where it does not rain despite being forecast with a high probability, than when the converse happens.

Moreover, our finding that farmers are willing to pay less for a real-world forecast when they experience false alarms in the game aligns with extensive research showing that individuals tend to overestimate the likelihood of an events they have previously experienced, regardless of their knowledge of the true probabilities (Malmendier, 2021b; Tversky and Kahneman, 1974). The tendency of farmers to be more influenced by recent false alarms rather than past ones supports the concept of recency bias Tversky and Kahneman (1974). Overall, our study also adds to the growing body of literature on the use of gamification for educational purposes in rural, developing regions (Tjernström et al., 2021; Alidaee, 2023).

Our results also contribute to the literature on the demand for digital extension services (Cole and Fernando, 2020) as well as to the literature on forecast valuation (Stephens et al., 2019; Millner, 2008; Shafiee-Jood et al., 2021).

2 Background

This study aims to understand whether conveying probabilistic information to farmers will aid farmer decision-making, and focuses on a weather-sensitive crop, coffee in a region with increasingly variable weather, Karnataka.

2.1 Setting

Coffee is a perennial crop, and so benefits from risk-mitigating strategies within the year to deal with unexpected weather. Karnataka is the largest coffee producing region in India, accounting for over 70% of the country's coffee output (Coffee Board of India). Precision Development (PxD) operates a voice-call based agricultural advisory service, Coffee Krishi Taranga (CKT), for coffee farmers in Karnataka.Table 1 describes characteristics of profiled users of the CKT service in 2018. 60% of the user-base is small-holder farmers, who cultivate coffee on fewer than 5 acres; and only 18% of the user-base cultivates more than 10 acres. Almost half the farmers are educated a higher secondary level or higher, and almost half had a smartphone in 2018 (presumably far higher in 2023).

Table 1: Coffee Krishi Taranga Users in 2018

	Mean (SD)	Obs
	(1)	(2)
Is female	0.117 (0.321)	42023
Age when profiled	51.032 (13.212)	42012
Area cultivated with coffee (acres)	8.801 (23.896)	42007
Educated to higher secondary level or above	0.475 (0.499)	30042
Cultivates Arabica	0.474 (0.499)	42022
Cultivates Robusta	0.782 (0.413)	42022
Has access to a smartphone in 2018	0.451 (0.498)	42020

2.2 Weather in Karnataka

Coffee is mainly grown in the Western Ghats region of Karnataka (in the districts of Chikmagalur, Hassan and Kodagu). The region receives three times the average rainfall in India

(Varikoden et al., 2019), with definite changes in the characteristics of the monsoon rainfall, extreme rainfall, and dry spells in the region (Sreenath et al., 2022; Varikoden et al., 2019; Chandrashekhar and Shetty, 2017; Ha et al., 2020) Some of these changes vary between the northern and southern Western Ghats (Varikoden et al., 2019). As a result, monsoon rainfall patterns in the region are likely harder for farmers to predict without high-quality weather forecasts. In addition, spatial variability of rainfall within the region is large Figure 1, making weather forecasts of finer granularity more useful for farmers as they adapt to the changing climate in the region.

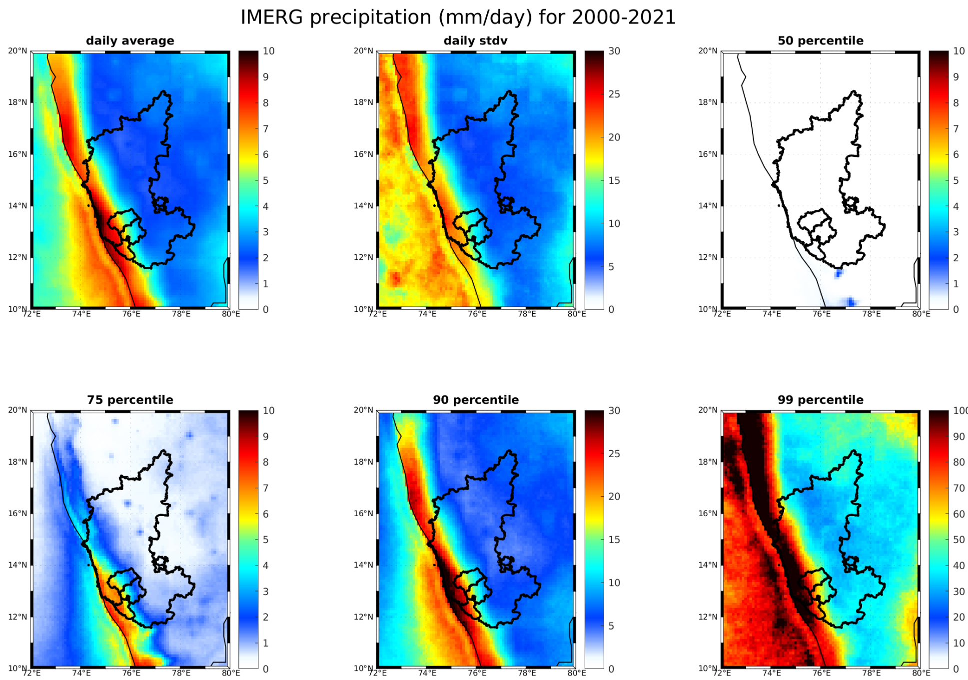

Figure 1: Daily rainfall amount and variability in Karnataka

Notes: The larger outline is the state of Karnataka. The three districts outlined within are Kodagu, Chikmagalur and Hassan.[1]

2.3 Weather and Demand for Information

With high smartphone penetration, farmers can presumably access weather forecasts on the internet. CKT does not currently provide weather forecasts to farmers on it's voice-call service beyond alerts on extreme weather events, such as cyclones and heat waves. However, CKT's administrative data on user access at the block level between 2019 and 2022 in Table 2 indicates that demand for information not provided in outgoing calls responds to weather in the preceding week. We break this down by periods that correspond to different baseline weather, and coffee practices. Between March and May, coffee plants typically blossom, and require irrigation or rainfall showers in order to do so. This is the pre-monsoon period in the region, and is typically dry with sporadic showers. Blossoming requires moderate amounts of rainfall (between 1 and 2 inches of rain over a week). Column (1) indicates that there are 18% fewer inbound calls following a week with rainfall above the 75th percentile of historical weekly rainfall distribution in that block during such a week suggesting lower demand for information when plants plausibly received enough water.[2] During the monsoon period (June - September) when baseline weather is typically rainy, column (2) indicates that inbound calls increase by 29% following a week with rainfall below the 25th percentile of historical weekly rainfall distribution in that block. Finally, during the harvest period (October - February), which is after the monsoon, rainfall is not frequent. However, unseasonal heavy rains can disrupt harvesting and make it harder for farmers to dry their harvested coffee beans. Column (3) indicates that in this period, inbound calls increase by 13% following a week with rainfall above the 75th percentile.

Table 2: Inbound Calls on Coffee Krishi Taranga between 2019 and 2022

	(1)	(2)	(3)
	Blossom March - May	Monsoon June - Sept	Harvest Oct - Feb
Preceding week rain $\geq$ 75th percentile	-8.877**	1.232	5.773**
	(3.472)	(2.889)	(2.055)
Preceding week rain $\leq$ 25th percentile	-3.490	10.148**	-2.460
	(5.719)	(3.596)	(2.824)
N	985	1265	1449
Outcome mean, omitted group	47.640	34.451	45.621

Robust standard errors clustered at the block level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The outcome is the total number of inbound calls in a week at the block-level in the specified months. All columns present the results from regressions of the outcome on a dummy indicating that rainfall in the preceding week was above the 75th percentile of the 20000 - 2022 distribution for that week in that block; a dummy indicating that rainfall in the preceding week was below the 25th percentile of the 20000-2022 distribution for that week in that block; year, week-of-year, and block fixed effects.

3 Experimental Design

This section describes the experiment design.

3.1 Sample, Randomization and Information Treatments

The sample for this study was drawn from the rosters of small- and medium-holder coffee farmers from the Coffee Board of India and existing users of Coffee Krishi Taranga in Chikmagalur and Kodagu, two coffee-growing districts in Karnataka. In each of the randomly

[2]Daily rainfall incidence at the block level comes from NASA's IMERG (Integrated Multi-satellitE Retrievals for GPM) dataset for the years 2000 - 2022.

selected twenty-one gram panchayats (GPs) in two blocks in the two districts, we randomly sampled farmers and recruited them for the in-person study on the phone. When the target sample for a GP was not met, farmers were recruited in person. Criteria for inclusion in the study sample were: cultivates coffee on 18 acres or less, and is between 18 and 65 years of age.

Farmers who agreed to participate in the study were visited in-person; and those who consented to participate in-person were randomized at the individual level (on-the-spot) into one of three experimental arms: (1) an information intervention highlighting the salience of climate change in the context of coffee cultivation via video (E1); (2) information intervention highlighting climate change salience and providing basic training to improve understanding of probabilities via video (E2); (3) a control group, with a placebo video describing the history of coffee cultivation in India (C). The experiment was designed to have 42% of the sample in the climate change salience arm, 29% of the sample in the climate change salience and probability training arm, and 29% of the sample in the control group. This design maximizes power to detect the effect of the combined treatment relative to the climate change salience treatment alone (E2 - E1 = (T1 + T2) - T1) (Muralidharan et al., 2023), while maintaining similar levels of power on the other outcomes of interest, (E2 - C), (E1 - C). Overall, 1212 farmers completed the study across the 21 GPs. Attrition among the treated sample was low (approximately 2% overall), and does not vary significantly across experimental arms (Table 3).

Table 3 describes the characteristics of the sample that completed the study. The average age of farmers in the study is 48 years, 86% of whom are primary agricultural decision makers. 70% of farmers cultivate coffee on 5 acres or fewer, with the remaining cultivating coffee on between 5 and 18 acres. Almost 69% of farmers have access to or own a smartphone, while only 32% use WhatsApp. Only 35% of farmers trust the weather forecasts that they have access to. Overall, on-the-spot randomization was implemented successfully, with shares in treatment arms close the the target 42%, 29%, 29%. The sample is well-balanced on the list of pre-specified farmer and farm characteristics with significant imbalance in the climate change salience arm on only whether coffee is the main source of income. A joint F-test of these characteristics explaining treatment assignment reassures us.

3.2 Information Treatments

Climate change salience video: Farmers assigned to the climate change salience information treatment watch a five-and-a-half-minute video discussing the impact of climate change on coffee production, particularly in Karnataka, India. It highlights the challenges posed by climate change, including increased temperatures, erratic rainfall, and extreme weather events, all of which have impacted coffee farmers in Karnataka over the last decade; provides clips of farmer experiences and challenges; and suggests adaptation and mitigation measures that may benefit farmers, including using weather forecasts to plan activities.

Table 3: Randomization Balance

	Treatments				Obs
	Mean (SD)	Coefficient (SE)		p-value	
	(1)	(2)	(3)	(4)	(5)
	Control	Climate Change (CC)	Probability Training + Climate Change (PT+CC)	CC= PT + CC = 0	Total Obs
Is the primary decision maker	0.860 (0.347)	0.013 (0.024)	0.009 (0.026)	0.857	1212
Household size	3.931 (1.419)	0.007 (0.095)	0.058 (0.109)	0.840	1212
Age	48.360 (11.084)	-0.785 (0.768)	-0.221 (0.845)	0.562	1212
Educated to higher secondary level or above	0.409 (0.492)	-0.013 (0.034)	-0.022 (0.037)	0.840	1212
Is literate	0.966 (0.182)	0.001 (0.013)	-0.014 (0.015)	0.517	1212
Is female	0.243 (0.429)	0.015 (0.030)	0.019 (0.033)	0.824	1212
Has access to a smartphone	0.689 (0.464)	0.055* (0.031)	-0.002 (0.035)	0.094	1212
Uses WhatsApp	0.320 (0.467)	0.008 (0.032)	-0.009 (0.035)	0.872	1212
Is risk averse (implied CRRA risk aversion parameter >= 1.34)	0.446 (0.498)	0.028 (0.034)	0.062 (0.038)	0.262	1212
Trusts weather forecasts	0.357 (0.480)	-0.041 (0.033)	-0.024 (0.036)	0.456	1212
Coffee cultivation is the main source of income	0.914 (0.280)	-0.048** (0.021)	-0.032 (0.022)	0.072	1211
Cultivates coffee on <= 5 acres	0.711 (0.454)	-0.022 (0.032)	0.007 (0.034)	0.616	1212
Has access to functional irrigation facility	0.474 (0.500)	-0.031 (0.033)	-0.055 (0.035)	0.303	1212
Cultivates Arabica	0.774 (0.419)	-0.010 (0.025)	-0.017 (0.026)	0.813	1212
Cultivates Robusta	0.686 (0.465)	-0.019 (0.026)	-0.047 (0.027)	0.218	1212
Cherry coffee preparation	0.474 (0.500)	-0.018 (0.020)	-0.040 (0.021)	0.148	1212
p-value of joint F-test		0.341	0.487		
Attrition	0.023 (0.150)	-0.003 (0.010)	-0.011 (0.010)	0.431	1212

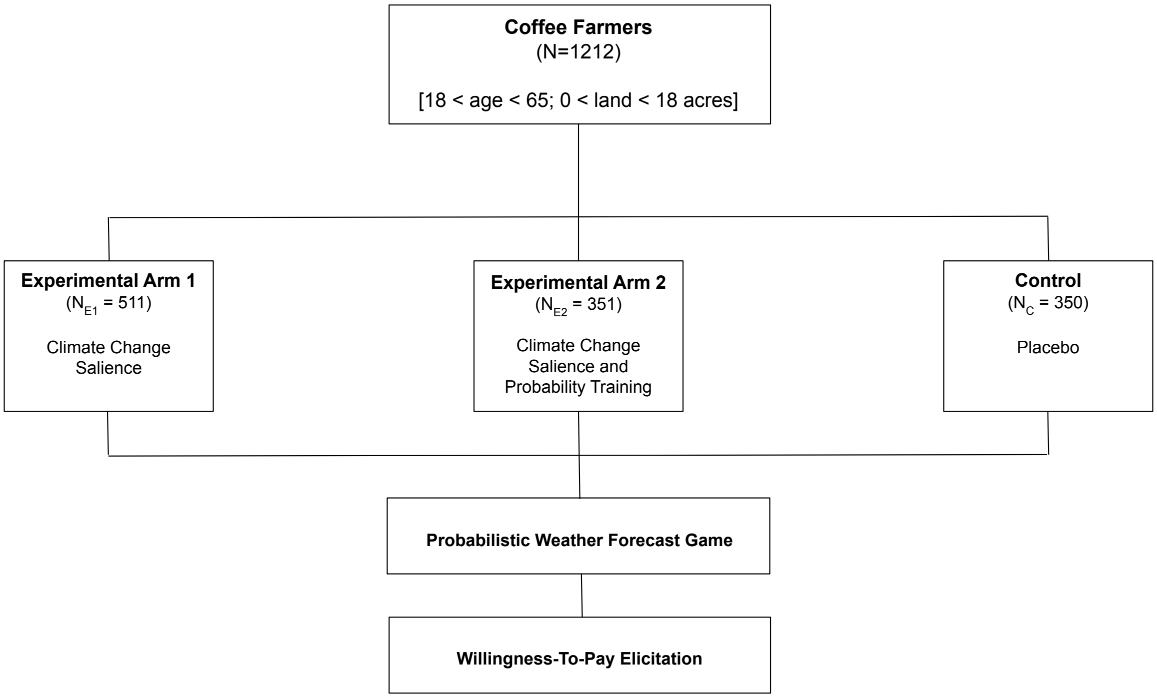

Figure 2: Experiment Design

Climate change salience and probability training video: Farmers assigned to the probability training and climate change salience information treatment watch a thirteen-and-a-half-minute video providing a tutorial on basic probability concepts, in addition to discussing the impact of climate change on coffee production. The probability training component uses everyday events to explain probabilities using visual aids and interactive activities. The video also explains probabilities in rainfall forecasts, and explains what the reference class is in a probabilistic rainfall forecast (Gigerenzer et al., 2009).

Placebo video: Farmers assigned to the control condition watch a two-and-a-half minute video about the history of coffee cultivation, it's introduction and rise in popularity in India.

3.3 Experimental Decision-Making Games

The intervention and experimental games were conducted consecutively during a single visit. After randomization into an experimental arm, farmers viewed the assigned informational videos and then played two hypothetical decision-making games designed to evaluate their comprehension of probability in the context of weather forecasts,[3] and their reliance on weather forecasts in making hypothetical decisions. These games were administered by a surveyor and farmers directly interacted with weather forecasts in the experimental games.

Location Choice Game: In this incentivized experimental game, farmers make decisions under uncertainty, mirroring real-life market choices influenced by weather conditions. Over five rounds, they are presented with pairs of probabilistic weather forecasts in image and text formats, tasked with selecting one of two market locations for selling goods. Market sales for each good depended on weather conditions, and the objective is to maximize potential earnings based on the predicted weather outcomes.

Following two practice rounds to make sure that farmers understand the game, farmers play incentivized five rounds across two scenarios — one with three rounds of daily forecasts and another with two rounds of weekly forecasts. Each scenario has two versions (one where 'wet' weather is preferred and one where 'dry' weather is preferred), one of which was presented to each farmer at random. In each round, farmers see a pair of probabilistic weather forecasts, choose a location where goods in the scenario are more likely to sell (i.e., choose the forecast where rain is more likely when 'wet' weather is preferred, and where rain is less likely when 'dry' weather is preferred). Scenarios used in the game are: selling buttermilk on a 'non-rainy' or 'dry' day, selling hot tea on a 'rainy' or 'wet' day, selling fruit juice in a 'non-rainy' or 'dry' week, selling umbrellas in a 'rainy' or 'wet' week. Forecasts were presented in two variations — one with constant rainfall amounts and varying probabilities, and another with both varying,[4] and the probabilities in each forecast pair are randomized, and so there are questions with varying difficulty (increasing as the difference between the two forecasts decreases). To ensure that the optimal choice is not confounded by risk preferences, there is only one correct choice that maximizes expected earnings regardless of a farmer's risk aversion.[5]

After selecting a market location, farmers indicate their confidence in their choice by selecting a 'stake' — the number of points they wish to risk from a set of $\{1, 2, 3, 4, 5\}$. The subsequent weather realization is random but follows the forecast probabilities (Stephens et al., 2019), i.e., when a forecast indicates that there is an 80% chance of rain, rain is realized for 80% of participants who receive that forecast. The game's scoring rules are designed to reward accuracy, points equal to the stake are added for a correct prediction and deducted for an incorrect one.

[3]Participating farmers started with a practice questions to get familiar with the game interface — this included exercises to identify weather icons, interpret sample weather forecasts in various formats, and classify rainfall intensities into distinct categories such as light, medium, heavy, or very heavy.

[4]In round variations where both quantities and probabilities in forecasts vary, higher quantities appears with a higher probability since a higher quantity of forecast rain is correlated with a higher likelihood of any rain, and so an 'incorrect' answer based on the probabilities may be a logical answer.

[5]The probabilities in each member of a forecast-pair were randomly assigned, such that the variance of outcomes in the 'correct' choice (with higher expected score) is always lower than the variance of outcomes in the 'incorrect' choice (with lower expected score)

After each round, farmers receive feedback that provides insight into the outcomes of their choices. They learn if their selection was optimal and whether the weather conditions aligned with their prediction; whether their selection was not optimal and they still experienced favorable weather by chance; whether their incorrect choice led to unfavorable weather conditions; and whether an incorrect choice coincidentally resulted in favorable weather. This feedback system is meant to help farmers understand the connection between chance and outcomes.

This design (Table B2, Table B1) allows us to rule out confounding due to round-order effects, risk aversion, forecast formats, and the ability to discern more likely from less likely events. It also tests whether farmers are basing their decisions on the likelihood or the quantity of rain, with the latter potentially leading to a conflation of the two factors in decision-making.

Agricultural Decision-Making Game: This game requires farmers to apply their understanding of weather forecasts to make strategic agricultural decisions. Over six incentivized rounds (following an unincentivized practice round), farmers advise on two key coffee farming activities: irrigation during the blossoming period and fertilizer application during the monsoon season. The game tests their ability to integrate probabilistic weather information with their knowledge of seasonal weather patterns to optimize farming outcomes.

In each scenario, farmers are presented with a decision-making task: to irrigate or not during the blossoming period, and to apply fertilizer or not during the mid-monsoon season. These decisions are informed by probabilistic weather forecasts provided in various formats — audio, visual, and textual — or by the farmers' own prior beliefs in the absence of forecasts. The game simulates real-world conditions by varying the probability of rainfall across rounds (from 10% to a high of 90%). This range allows for an assessment of decision-making under different levels of uncertainty and risk. The order of rounds within each scenario, as well as the scenarios themselves, are randomized to rule out confounding due to order and format effects. (More details in Table B2, Table B1)

Scoring in the game is straightforward: farmers earn five points for making the correct recommendation based on the weather realization and lose five points for incorrect advice. The payoffs are structured to reflect the real-life stakes of farming decisions, with the expected value of taking action (i.e., to irrigate or to apply fertilizer) being higher when the predicted likelihood of rain is low, and vice versa. This payoff structure encourages farmers to consider both the potential benefits and risks of their actions, mirroring the trade-offs they face in their agricultural practices.

The optimal decision-making strategy that maximizes payoffs within the game to to recommend taking an action (irrigation or applying fertilizer) when the probability of rain is below 50%, and to recommend not taking action when the probability of rain is at or above 50%. This threshold reflects the probability at which the expected benefits of action outweigh the risks in the game. The points accumulated translate one-for-one into monetary payoffs. Similar to the previous game, after each round, farmers receive feedback that indicating whether their choice was optimal or not, and whether weather was favorable or not by chance.

Weather forecast realizations: Throughout the experimental games, weather forecasts are 'reliable', i.e., weather realizations are drawn from the probability distribution implied by the relevant probabilistic weather forecast (following Stephens et al. (2019)).[6]

Scores and Payoffs: The scoring rules in both games imply that better outcomes result in more points, but do not constitute 'proper scoring rules' (Palfrey and Wang, 2009). This is so that the rules are easily comprehensible by the farmers (Haaland et al., 2023; Conlon et al., 2022). The rupee incentive that farmers receive is the number of points they accumulate at the end of the two games. The maximum incentive possible is ₹110. Participants also receive in-kind compensation for participation in the game (worth ₹150), apart from the total game incentive that they earn.

Willingness to Pay Elicitation: Once farmers play the two hypothetical decision-making games, we elicit their demand for a real-world audio probabilistic weather forecast service using an incentive compatible Becker-DeGroot-Marschak (BDM) (Becker et al., 1964) mechanism.

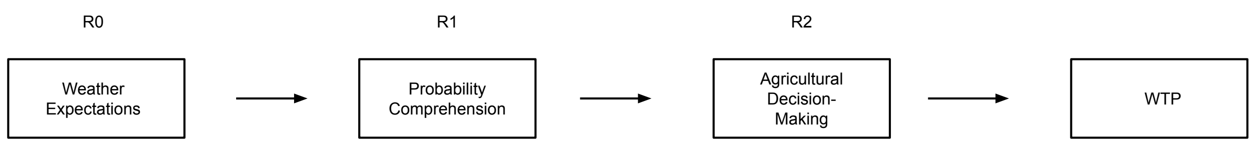

Figure 3: Experiment Flow

4 Conceptual Framework

We consider farmers making decisions under uncertainty about upcoming weather (over the short-to-medium term, i.e., 1-to-15 days[7]), when they have access to probabilistic weather forecasts (adapting Millner (2008) and Shafiee-Jood et al. (2021)). We assume that farmers are quasi-Bayesian learners, who may not accurately interpret probabilities in the weather forecasts.

4.1 Subjective beliefs about upcoming weather

We consider a representative farmer making decisions at time, t, where there are two possible states of upcoming weather, $\theta_t \in \Theta = \{0, 1\}$ — a dry state ($\theta_t = 0$), and a rainy

[6]Meteorologists define 'reliability' as there being "agreement between forecast probability and mean observed frequency". As noted by the Collaboration for Australian Weather and Climate Research.

[7]Meteorological definitions of short/medium/long range forecasts

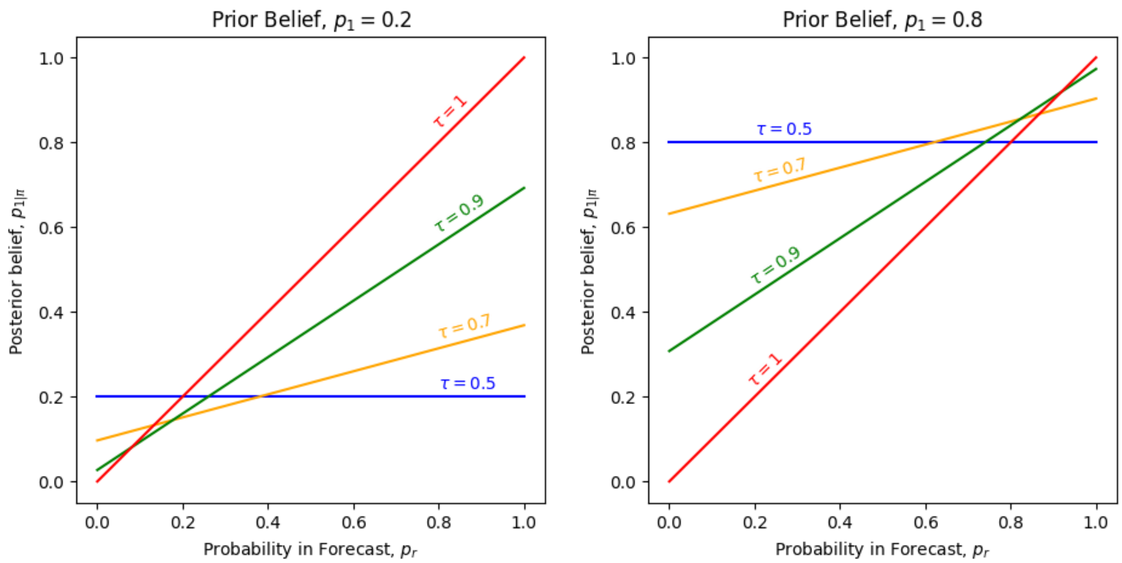

Figure 4: Posterior beliefs as forecast probability varies

state ($\theta_t = 1$). For that particular time-of-year, farmers have a prior belief about upcoming weather informed by climatology, current observations, localized knowledge, experience (Roncoli et al., 2002; Millner, 2008; Shafiee-Jood et al., 2021).[8] We denote this prior belief, $p_t(\theta_t)$, with $p_t(\theta_t = 1) = p_{1,t}$ and $p_t(\theta_t = 0) = 1 - p_{1,t}$. Farmers receive probabilistic rainfall forecasts, $\pi_t(\hat{\theta}_t)$, where $\pi_t(.)$ is a probability mass function, and $\hat{\theta}_t \in \Theta = \{0, 1\}$, $\pi_t(\hat{\theta}_t = 1) = p_{r,t}$, and $\pi_t(\hat{\theta}_t = 0) = 1 - p_{r,t}$. However, farmers may interpret the probability in the forecast, and so the the signal received by a farmer is, $\tilde{\pi}_t(\hat{\theta}_t = 1) = \tilde{p}_{r,t} = (p_{r,t})^\alpha$, where $\alpha \geq 1$. When farmers correctly interpret the probabilistic information in the weather forecast, $\alpha = 1$.

The farmer's posterior belief about upcoming weather is:

$$p_{1|\pi,t} = p_t(\theta_t|\tilde{\pi}_t(\hat{\theta}_t)) = \sum_{\hat{\theta}_t \in \{0,1\}} \tilde{\pi}_t(\hat{\theta}_t) \frac{p_t(\hat{\theta}_t|\theta_t) p_t(\theta_t)}{p_t(\hat{\theta_t})} \tag{1}$$

We assume that a farmer's belief in the accuracy of the forecast, $p_t(\hat{\theta}_t|\theta_t) = \tau \sim f_t(.)$ where $f_t(\tau)$ is a probability distribution function over $[0, 1]$ (Shafiee-Jood et al., 2021).[9] So,[10]

[8] A farmer's subjective prior belief may differ from the base rate, p_b, which we assume to be the objective historical frequency of the event occurring at a particular time-of-year.

[9] Following (Millner, 2008), we assume that τ is the same for each state of the world, i.e., $p(\hat{\theta} = 1|\theta = 1) = p(\hat{\theta} = 0|\theta = 0) = \tau$ and $p(\hat{\theta} = 1|\theta = 0) = p(\hat{\theta} = 0|\theta = 1) = 1 - \tau$

[10] This implies that when a farmer believes that the forecast is completely accurate or $\tau = 1$, $p_{1|\pi,t} = p_{r,t}$; when $\tau = 0.5$, $p_{1|\pi,t} = p_{1,t}$; and when a farmer believes that the forecast is completely inaccurate or $\tau = 0$, then $p_{1|\pi,t} = 1 - p_{r,t}$. So, when $0.5 < \tau < 1$, $p_{1|\pi,t}$ is increasing in $p_{r,t}$, and when $0 < \tau < 0.5$, $p_{1|\pi,t}$ is decreasing in $p_{r,t}$

$$
\begin{aligned}
p_t[\theta_t = 1|\tilde{\pi}_t(\hat{\theta}_t), \tau] &= \tilde{p}_{r,t}\frac{p_t(\hat{\theta}_t = 1|\theta_t = 1)p_t(\theta_t = 1)}{p_t(\hat{\theta}_t = 1)} + (1-\tilde{p}_{r,t})\frac{p_t(\hat{\theta}_t = 0|\theta_t = 1)p_t(\theta_t = 1)}{p_t(\hat{\theta}_t = 0)} \\
&= \tilde{p}_{r,t}\frac{\tau p_{1,t}}{\tau p_{1,t} + (1-\tau)(1-p_{1,t})} + (1-\tilde{p}_{r,t})\frac{(1-\tau)p_{1,t}}{(1-\tau)p_{1,t} + \tau(1-p_{1,t})} \qquad (2)
\end{aligned}
$$

and,

$$
p_{1|\tilde{\pi},t} = \int_0^1 p[\theta_t = 1|\tilde{\pi}_t(\hat{\theta}_t), \tau] f_t(\tau) d\tau \qquad (3)
$$

Updating beliefs. Once actual weather, $\vartheta_t \in \Theta = \{0, 1\}$, is realized, farmers update their subjective beliefs about the likelihood of the 'rainy' state. So,

$$
p_{1,(t+1)} = \Phi(p_{1,t}, \vartheta_t) \qquad (4)
$$

such that $p_{1,(t+1)} > p_{1,t}$ if $\vartheta_t = 1$, and $p_{1,(t+1)} < p_{1,t}$ if $\vartheta_t = 0$.

Farmers also update their beliefs about the accuracy of the forecast for the next period. So, $f_{t+1}(\tau) = f_t[\tau|\tilde{\pi}(\hat{\theta}), \vartheta_t]$.[11]

$$
\begin{aligned}
f_{t+1}(\tau) = \vartheta_t\left\{\tilde{p}_{r,t}\frac{\tau f_t(\tau)}{\mu_{\tau,t}} + (1-\tilde{p}_{r,t})\frac{(1-\tau)f_t(\tau)}{1-\mu_{\tau,t}}\right\} \\
+ (1-\vartheta_t)\left\{\tilde{p}_{r,t}\frac{(1-\tau)f_t(\tau)}{1-\mu_{\tau,t}} + (1-\tilde{p}_{r,t})\frac{\tau f_t(\tau)}{\mu_{\tau,t}}\right\} \qquad (5)
\end{aligned}
$$

$$
\begin{aligned}
p_{1|\tilde{\pi},(t+1)} = \int_0^1 \Bigg\{\tilde{p}_{r,(t+1)}\frac{\tau p_{1,(t+1)}}{\tau p_{1,(t+1)} + (1-\tau)(1-p_{1,(t+1)})} \\
+ (1-\tilde{p}_{r,(t+1)})\frac{(1-\tau)p_{1,(t+1)}}{(1-\tau)p_{1,(t+1)} + \tau(1-p_{1,(t+1)})}\Bigg\} f_{t+1}(\tau, \tilde{p}_{r,t}, \vartheta_t) d\tau \qquad (6)
\end{aligned}
$$

4.2 Decision Making

Farmers who receive weather forecasts make agricultural decisions based on their posterior beliefs about upcoming weather, $p_{1|\tilde{\pi},t}$. In this study, we consider one-shot decisions at a specific point in time, where it is optimal for farmers to take such actions when they expect

[11]Derivations are in the Appendix. $\mu_t = \int \tau f_t(\tau) d\tau$,

appropriate weather, and not take the action when they do not expect appropriate weather. The farmer's optimization problem is then:

$$\max_{a_t \in \{0,1\}} \mathbb{E}_{p_{1|\tilde{\pi},t}} \Big[U(a_t, \theta_t) \Big] \tag{7}$$

where $a = 1$ when the farmer takes the action, and $a = 0$ otherwise, and the farmer chooses to take an action iff:

$$\mathbb{E}_{p_{1|\tilde{\pi},t}} \Big[U(a_t = 1, \theta_t) \Big] \geq \mathbb{E}_{p_{1|\tilde{\pi},t}} \Big[U(a_t = 0, \theta_t) \Big] \tag{8}$$

Value of weather forecasts. Farmers value weather forecasts if their expected utility when they receive weather forecasts is larger than their expected utility when they do not receive weather forecasts. The *ex ante* value of a weather forecast requires considering all possible values that the forecast may take (Millner, 2008).

$$V_{F,t} = \mathbb{E}[V_{p_{1|\tilde{\pi},t}}] - \mathbb{E}[V_{p_{1,t}}] = \int_{\tilde{\pi}_t} \Bigg\{ \sum_{\hat{\theta}_t \in \{0,1\}} \tilde{\pi}_t(\hat{\theta}_t) p(\theta_t|\hat{\theta}_t) U(a'_t, \theta_t) \Bigg\} q(\tilde{\pi}_t) d\pi - \sum_{\theta_t \in \Theta} p_{1,t}(\theta_t) U(a_t, \theta_t) \tag{9}$$

5 Learning from Information Treatments

We first consider information-based learning from the video information treatments described in Section 3.2. Given the focus of the videos and this study, we consider three first-stage 'learning' outcomes that we measure after farmers watch the videos during the study — understanding probabilities, perceptions of climate change, interpretation of weather forecasts. We first elicit farmers' understanding of probabilities through two 'test' questions soon after they watch their assigned videos. The 'test' questions are unrelated to weather, and focus on two canonical probability scenarios: a balls-in-urn scenario, and a lottery. In both scenarios, farmers see two options, are asked to select which represents the more likely event, and indicate what the likelihood of the event is.[12] We then ask farmers whether they expect unseasonal weather more frequently, less frequently or at the same frequency in the future

[12] In the first 'test' scenario, farmers see (1) a bag with two black balls and two white balls, (2) a bag with two black balls and four white balls; in the second, they see (1) a lottery with two tickets, (2) a lottery with three tickets. In the first case, they are asked to select the bag from which they are more likely to draw a black ball if they draw a ball without looking; in the second case, they are asked to select the lottery in which a ticket holder is more likely to be selected as the winner. They are also asked to indicate the numerical likelihood of drawing a black ball in the first 'test' scenario, and the numerical likelihood of winning the lottery in the second 'test' scenario.

to gauge their perception of climate change. Finally, we ask farmers how they interpret the forecast, "there is a 60% chance of rain tomorrow in your block/taluka".[13]

Empirical strategy. We estimate the following specifications,

$$Y_i = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \mathbf{X}_i' \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_i \tag{10}$$

$$Y_i = \beta_0 \ + \ \beta_1 \mathbf{T}_i^1 \ + \ \beta_2 \mathbf{T}_i^2 \ + \mathbf{X}_i' \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_i \tag{11}$$

where, $\mathbf{Y}_i$ is the outcome of interest for individual, i; $\mathbf{E}_i^1$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 1, the climate change salience information treatment; $\mathbf{E}_i^2$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 2, the climate change salience and probability training information treatment; $\mathbf{T}_i^1$ is an indicator which takes the value, 1 when the individual is randomly assigned to watch the climate change salience informational video (either alone or along with the probability training video); $\mathbf{T}_i^2$ is an indicator which takes the value, 1 when the individual is randomly assigned to watch the probability training informational video; $\mathbf{G}_g$ is a vector of gram panchayat fixed effects; $\mathbf{X}_{ir}$ is a vector of controls selected by the double lasso algorithm. Standard errors are clustered at the individual level.

Table 4: Understanding of probabilities, climate change and weather forecasts

	Probabilities		**Climate Change**		**Weather Forecasts**		**Index**	
	Understands probability in 'test' questions		Expects unseasonal weather more frequently		Correctly interprets forecasts		First-stage Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate change salience	-0.023	-0.023	0.007	0.007	0.014	0.014	0.005	0.005
	(0.033)	(0.033)	(0.029)	(0.029)	(0.025)	(0.025)	(0.038)	(0.038)
Probability training + climate change salience	0.035		0.074**		0.020		0.082*	
	(0.036)		(0.030)		(0.028)		(0.042)	
Probability training + climate change salience relative to climate change salience alone		0.058*		0.067**		0.007		0.076**
		(0.033)		(0.028)		(0.026)		(0.037)
N	1212	1212	1211	1211	1212	1212	1211	1211
Outcome mean, comparison group	0.400	0.400	0.420	0.420	0.160	0.160	-0.000	-0.000

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. All specifications include GP fixed effects. Lasso controls are listed in the Appendix.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1); probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2); probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.

[13] The options provided in random order are: (1) "Rain will definitely occur, but not in all parts of your block/taluka (i.e., it will rain in 60% of the block/taluka)"; (2) "Rain will definitely occur, but not throughout the day in your block/taluka (i.e., it will rain for 60% of the time tomorrow)"; (3) "Rain is not certain, but rain is more likely to occur than not in all areas in your block/taluka tomorrow (i.e., there is a 6 in 10 chance of rain at all points in the block/taluka)"; (4) "Rain will definitely occur in your block/taluka, and the intensity (or heaviness) of rainfall tomorrow will be 60%"; (5) Something else

In Table 4 (columns 1 and 2), we see that 40% of farmers in the control group correctly chose the more likely event in both 'test' questions. Fifteen percent of farmers (not in the table) in the control group also expressed the likelihood of both the events occurring correctly apart from correctly selecting the more likely event. This suggests that a relatively high share of farmers already have a firm understanding of probabilities. Compared to this, we see only a modest increase in the share of farmers who correctly respond to the 'test' questions in the probability training and climate change salience experimental arm. Column (2) indicates an increase of around 6 percentage points (significant at the 10% level) or 15% relative to farmers in the climate change salience treatment arm.

Columns (3) and (4) indicate that around 42% of farmers in the control group already expect unseasonal weather to occur more frequently in the future, and around 7 percentage points (or 18%) more farmers in the probability training and climate change salience experimental arm expect the same. Columns (5) and (6) indicate that sixteen percent of farmers in the control group correctly interpret the weather forecast as a likelihood of rain (i.e., that there is a 6 in 10 chance of rain). In addition, 52% of farmers interpret the forecast as the area coverage (i.e., 60% of the area will receive rain, 52% of farmers in the overall sample). Interpreting a weather forecast in the latter manner might lead to beliefs about rainfall at a particular point that is consistent with there being 60% chance of rain at that point in the forecast period. However, neither informational video treatment impacts farmers' interpretations of weather forecasts; and the informational treatment highlighting the salience of climate change alone has no significant effect on any outcomes.

A standardized index of the three 'first-stage' outcomes (columns 7 and 8) indicates that the probability training and climate change salience video increased this measure by 0.076 standard deviation (in the control group), suggesting a small overall treatment effect in this experimental arm. To see how learning from the informational videos impacts farmers' performance in the experimental games, we look at the total points score in Table 5. Table 5 indicates that participants in the climate change and probability training combined video experimental arm score 2.33 more points than their counterparts in the control group (a 9.3% increase, significant at the 5% level) in the location-choice game. However, neither information treatment has an impact on scores in the agricultural decision-making game.

Table 5: Total points scored in the Experimental Games

	Game 1		Game 2		Total	
	(1)	(2)	(3)	(4)	(5)	(6)
Climate Change Salience	0.337	0.337	0.118	0.118	0.492	0.492
	(0.937)	(0.937)	(0.807)	(0.807)	(0.939)	(0.939)
Probability training + climate change salience	2.327**		-0.572		1.561	
	(1.055)		(0.882)		(1.046)	
Probability training + climate change salience relative to climate change salience alone		1.990**		-0.689		1.069
		(0.957)		(0.812)		(0.966)
N	1212	1212	1212	1212	1212	1212
Outcome mean, comparison group	24.974	24.974	45.743	45.743	70.717	70.717

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. All specifications include GP fixed effects. Lasso controls are listed in the Appendix.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).
Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2).
Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.

6 Experimental Game 1: Location Choice

In this section, we examine farmers' performance in the incentivized location-choice game, and consider the effects of both information-based learning as well as experience-based learning as farmers progress through the game.

Empirical strategy. Outcomes of interest in the location choice game are (1) choice, which indicates whether the farmer chooses the correct option (i.e., chooses the location where rain is less likely in rounds where 'dry' weather is favorable, and chooses the location where rain is more likely in rounds where 'wet' weather is favorable); (2) stake chosen, which indicates the number of points (from 1 to 5) that the farmer chooses to put at stake in that particular round. We estimate the following specifications,

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \beta_3 \mathbf{FA}_{ir} \ + \ \gamma_4 \mathbf{D}_{ir} \\ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{V}_{ir}^{'} \alpha_3 \ + \ \mathbf{Q}_{ir}^{'} \alpha_4 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} \end{aligned} \quad (12)$$

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{T}_i^1 \ + \ \beta_2 \mathbf{T}_i^2 \ + \beta_3 \mathbf{FA}_{ir} \ + \ \gamma_4 \mathbf{D}_{ir} \\ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{V}_{ir}^{'} \alpha_3 \ + \ \mathbf{Q}_{ir}^{'} \alpha_4 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} \end{aligned} \quad (13)$$

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \beta_3 \mathbf{FA}_{ir} \ + \ \beta_4 (\mathbf{E}_i^1 \times \mathbf{FA}_{ir}) \ + \ \beta_5 (\mathbf{E}_i^2 \times \mathbf{FA}_{ir}) \ + \ \gamma_4 \mathbf{D}_{ir} \\ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{V}_{ir}^{'} \alpha_3 \ + \ \mathbf{Q}_{ir}^{'} \alpha_4 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} \end{aligned} \quad (14)$$

where, $\mathbf{Y}_{ir}$ is the outcome of interest for individual, i in round, r; $\mathbf{E}_i^1$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 1, the climate change salience information treatment; $\mathbf{E}_i^2$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 2, the climate change salience and probability training information treatment; $\mathbf{T}_i^1$ is an indicator which takes the value, 1 when the individual is randomly assigned to watch the climate change salience informational video (either alone or along with the probability training video); $\mathbf{T}_i^2$ is an indicator which takes the value, 1 when the individual is randomly assigned to watch the probability training informational video; $\mathbf{FA}_{ir}$ indicates whether the farmer experienced a false alarm in the preceding round (i.e., the forecast event did not occur in the preceding round); $\mathbf{D}_{ir}$ is the difference in probabilities between the two options in that game round. $\mathbf{Order}_{ir}$ is a vector of dummies indicating the order in which the round appears in the game; $\mathbf{Format}_{ir}$ is a vector of dummies indicating the format in which the forecasts in that round appear; $\mathbf{V}_{ir}$ is an indicator that takes a value, 1 when the round asks farmers to select the location where rain is more likely, and 0 when the round asks farmers to select the location where rain is less likely; $\mathbf{Q}_{ir}$ is an indicator that takes a value, 1 when the two forecasts in the round have different quantities and probabilities,[14] and 0 when they have the same quantities but different probabilities. $\mathbf{X}_{ir}$ is a vector of controls selected by the double lasso algorithm. Robust standard errors are clustered at the individual level.

Results. Table 6 indicates that 85% of farmers in the control group make the correct choice, and put 4.08 points (out of a maximum of 5) at stake in each game round. This indicates high probability literacy, and this high share in the game overall is more than double the share of farmers who answer the probability 'test' questions correctly, and suggests that weather might be a more intuitive context for farmers to conceptualize probability. Columns 1 - 4 in Table 6 indicate that the information treatments don't appear to impact farmers' likelihood of selecting the correct location, nor do they impact the points farmers choose to put at stake. These results (along with those in **??**) suggest that the increase in scores in this game for individuals in the climate change salience and probability training arm observed in Table 5 is driven by an increase in the points that farmers choose to put at stake in each round, rather than an increase in farmers selecting the correct choice, particularly in 'easier' rounds, i.e., those where the difference between the two forecast probabilities is larger than 20 percentage points, and when farmers have not experienced a false alarm in the preceding round. This suggests that the probability training and climate change information treatment might reinforce understanding, or increase farmer confidence.

When it comes to experience-based learning however, Table 6 and Table B3 indicates a larger impact. Farmers are highly sensitive to false alarms (either false positive or false negative forecasts), being less likely to make the correct choice and exhibiting less confidence in rounds following a false alarm.[15] Table B3 indicates that this impact is increasing in the magnitude of the difference between the two forecasts' probabilities. Column (6) in Table 6 indicates

[14] Though the quantities and probabilities in the two forecasts differ, the forecast with the higher probability also has a higher quantity. This is in order to reduce confusion, since when higher quantities of rain are forecast, the likelihood of any rain is higher.

[15] A false alarm is an instance where the favored event (rainfall when 'wet' weather is desired and no rainfall when 'dry' weather is desired) is not realized

Table 6: Outcomes in the Location Choice Game

	Correct choice	Stake chosen	Correct choice	Stake chosen	Correct choice	Stake chosen
	(1)	(2)	(3)	(4)	(5)	(6)
Climate change salience	-0.002	-0.007	-0.002	-0.007	0.001	0.015
	(0.013)	(0.049)	(0.013)	(0.049)	(0.014)	(0.051)
Probability training + climate change salience	0.006	0.064			0.010	0.111^{**}
	(0.014)	(0.051)			(0.015)	(0.053)
Probability training + climate change salience relative to climate change salience alone			0.008	0.071		
			(0.013)	(0.048)		
False alarm in prior round	-0.062^{***}	-0.344^{***}	-0.062^{***}	-0.344^{***}	-0.054^{***}	-0.253^{***}
	(0.011)	(0.032)	(0.011)	(0.032)	(0.019)	(0.058)
Climate change salience $\times$ False alarm in prior round					-0.010	-0.087
					(0.026)	(0.077)
Probability training + climate change salience $\times$ False alarm in prior round					-0.015	-0.184^{**}
					(0.029)	(0.081)
Difference between forecast probabilities	0.105^{***}	0.339^{***}	0.105^{***}	0.339^{***}	0.105^{***}	0.339^{***}
	(0.020)	(0.060)	(0.020)	(0.060)	(0.020)	(0.060)
N	6060	6060	6060	6060	6060	6060
Outcome mean, comparison group	0.854	4.085	0.854	4.085	0.854	4.085

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix.
False alarm in the prior round is an indicator that takes the value 1 when the expected event does not occur in the prior round, and 0 otherwise.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).
Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2).
Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.
Controls that are in all specifications: GP fixed effects, order, format, an indicator for whether the round requires that farmers choose the more likely event (as opposed to the less likely event), an indicator for whether forecasts differs only in probabilities (as opposed to forecasts that differ in both quantities and probability.
The outcome in odd columns is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in even columns is the stake farmers choose in that round $\in \{1, 2, 3, 4, 5\}$

that the probability training and climate change salience information treatment increases farmer confidence, but only in rounds that do not follow a false alarm. False alarms mitigate this impact on confidence. The decline in accuracy and in confidence in rounds following a false alarm suggests that farmers update their beliefs about the accuracy of the forecast, believing them to be less accurate following a false alarm, and act accordingly.

7 Experimental Game 2: Agricultural Decision-Making

In this section, we examine farmers' decisions in an incentivized agricultural decision-making game, where they choose whether to take an action or not based on weather information over six rounds. The game is described in Section 3.3 and in Table B2.

Empirical strategy. Outcomes of interest in the agricultural decision-making game are (1) whether farmers take an action or not (serving as a proxy for their belief in the likelihood of rain in that round); (2) whether farmers choose the optimal action (i.e., the action that maximizes their expected payoff) in a round. When the outcome is whether farmers take the relevant action or not, we estimate,

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \beta_3 \mathbf{FP}_{ir} \ + \beta_4 \mathbf{FN}_{ir} \ + \ \gamma_4 \mathbf{P}_{ir} & \\ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} & \quad (15) \end{aligned}$$

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{T}_i^1 \ + \ \beta_2 \mathbf{T}_i^2 \ + \beta_3 \mathbf{FP}_{ir} \ + \beta_4 \mathbf{FN}_{ir} \ + \ \gamma_4 \mathbf{P}_{ir} & \\ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} & \quad (16) \end{aligned}$$

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \beta_3 \mathbf{FP}_{ir} \ + \beta_4 \mathbf{FN}_{ir} \ + \ \beta_5 \mathbf{E}_i^1 \times \mathbf{FP}_{ir} \ + & \\ \beta_6 \mathbf{E}_i^2 \times \mathbf{FP}_{ir} \ + \ \gamma_4 \mathbf{P}_{ir} \ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} & \quad (17) \end{aligned}$$

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \beta_3 \mathbf{FP}_{ir} \ + \beta_4 \mathbf{FN}_{ir} \ + \ \beta_5 \mathbf{E}_i^1 \times \mathbf{FN}_{ir} \ + & \\ \beta_6 \mathbf{E}_i^2 \times \mathbf{FN}_{ir} \ + \ \gamma_4 \mathbf{P}_{ir} \ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} & \quad (18) \end{aligned}$$

while in analyses where the optimal action is the outcome of interest, we estimte,

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \beta_3 \mathbf{FP}_{ir} \ + \beta_4 \mathbf{FN}_{ir} \ + \ \gamma_4 \mathbf{Dev}_{ir} & \\ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} & \quad (19) \end{aligned}$$

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{T}_i^1 \ + \ \beta_2 \mathbf{T}_i^2 \ + \beta_3 \mathbf{FP}_{ir} \ + \beta_4 \mathbf{FN}_{ir} \ + \ \gamma_4 \mathbf{Dev}_{ir} & \\ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} & \quad (20) \end{aligned}$$

$$Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \beta_3 \mathbf{FP}_{ir} \ + \beta_4 \mathbf{FN}_{ir} \ + \ \beta_5 \mathbf{E}_i^1 \times \mathbf{FP}_{ir} \ + \\ \beta_6 \mathbf{E}_i^2 \times \mathbf{FP}_{ir} \ + \ \gamma_4 \mathbf{Dev}_{ir} \ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} \quad (21)$$

$$Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{E}_i^1 \ + \ \beta_2 \mathbf{E}_i^2 \ + \beta_3 \mathbf{FP}_{ir} \ + \beta_4 \mathbf{FN}_{ir} \ + \ \beta_5 \mathbf{E}_i^1 \times \mathbf{FN}_{ir} \ + \\ \beta_6 \mathbf{E}_i^2 \times \mathbf{FN}_{ir} \ + \ \gamma_4 \mathbf{Dev}_{ir} \ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} \quad (22)$$

where, $\mathbf{Y}_{ir}$ is an indicator which is 1 when farmers do not take the action, and 0 when they do take the action, i in round, r; $\mathbf{E}_i^1$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 1, the climate change salience information treatment; $\mathbf{E}_i^2$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 2, the climate change salience and probability training information treatment; $\mathbf{T}_i^1$ is an indicator which takes the value, 1 when the individual is randomly assigned to watch the climate change salience informational video (either alone or along with the probability training video); $\mathbf{T}_i^2$ is an indicator which takes the value, 1 when the individual is randomly assigned to watch the probability training informational video; $\mathbf{FP}_{ir}$ indicates whether the farmer experienced a false alarm (rain) or false positive in the preceding round (i.e., rain was predicted with $p >= 0.5$, but did not occur); $\mathbf{FN}_{ir}$ indicates whether the farmer experienced a false alarm (no rain) or false negative in the preceding round (i.e., rain was predicted with $p < 0.5$, and occurred); $\mathbf{Dev}_{ir}$ is the absolute deviation of the probability in the forecast from 0.5; $\mathbf{P}_{ir}$ is the probability in the forecast. $\mathbf{Order}_{ir}$ is a vector of dummies indicating the order in which the round appears in the game; $\mathbf{Format}_{ir}$ is a vector of dummies indicating the format in which the forecasts in that round appear (which are different across scenarios). $\mathbf{X}_{ir}$ is a vector of controls selected by the double lasso algorithm. Robust standard errors are clustered at the individual level.

Results. Table 7 and Table B5 indicates that neither the informational treatments, not experiences of false alarms (false positives or false negatives) impacts the farmers likelihood of forgoing action (i.e., choosing to not irrigate, or not apply fertilizer) in rounds where farmers receive no forecasts. Only 20.3% of farmers choose to forgo taking the relevant action in these rounds, with 16.7% of farmers in the irrigation scenario and 24% of farmers in the fertilizer scenario not taking the relevant action Table B7. This suggests that farmers underlying prior beliefs about the likelihood of rain during the spring blossoms time is around 16.7%, while their underlying prior beliefs about the likelihood of heavy rain during the mid-monsoon fertilizer period is higher, at 24%. These prior beliefs are not very different from the historical frequency of the weather event described in the scenario.

Table 7: Optimal Strategy for Rainy Conditions in the Agricultural Decision Making Game

	No Forecast Rounds (Prior)				Forecast Rounds (Posterior)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate change salience	0.029 (0.021)	0.029 (0.021)	0.030 (0.023)	0.019 (0.022)	-0.019 (0.017)	-0.019 (0.017)	-0.023 (0.018)	-0.018 (0.018)
Probability training + climate change salience	0.025 (0.022)		0.023 (0.024)	0.022 (0.023)	0.005 (0.019)		0.008 (0.020)	0.001 (0.020)
Probability training + climate change salience relative to climate change salience alone		-0.004 (0.020)				0.025 (0.017)		
False alarm (rain)	-0.008 (0.024)	-0.008 (0.024)	-0.008 (0.041)	-0.008 (0.024)	-0.080*** (0.021)	-0.080*** (0.021)	-0.088** (0.040)	-0.079*** (0.021)
False alarm (no rain)	0.001 (0.025)	0.001 (0.025)	0.001 (0.025)	-0.035 (0.043)	0.055** (0.021)	0.055** (0.021)	0.055** (0.021)	0.049 (0.037)
Climate change salience × False alarm (rain)			-0.007 (0.054)				0.032 (0.051)	
Probability training + climate change salience × False alarm (rain)			0.012 (0.061)				-0.016 (0.055)	
Climate change salience × False alarm (no rain)				0.074 (0.059)				-0.014 (0.049)
Probability training + climate change salience × False alarm (no rain)				0.017 (0.062)				0.040 (0.057)
Probability in current forecast					0.501*** (0.031)	0.501*** (0.031)	0.501*** (0.031)	0.501*** (0.031)
N	2424	2424	2424	2424	4848	4848	4848	4848
Outcome mean, comparison group	0.203	0.203	0.203	0.203	0.440	0.440	0.440	0.440

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects, order, format.
False alarm (rain) represents a false positive forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p >= 0.5$, but does not occur, and is 0 otherwise.
False alarm (no rain) represents a false negative forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p < 0.5$, but does occur, and is 0 otherwise.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).
Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2).
Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.
The outcome is an indicator which takes the value 1 if the farmer recommends forgoing the action in the scenario (and hence believes that rain is more likely to occur than not), and 0 otherwise. Columns 1 - 4 consist of rounds where farmers do not receive a forecast. Columns 5-8 consist of rounds where farmers receive a probabilistic rainfall forecast.

When it comes to rounds where farmers receive a probabilistic weather forecast, Table 7 indicates that the informational videos continue to have no impact on farmers' actions. Farmers are more likely to forgo taking the relevant action when the probability of rain in the forecast they receive is higher, consistent with them correctly interpreting probabilities in the forecasts they receive. In addition, false alarms (both false positives and false negatives) have a significant effect on farmers' actions in subsequent rounds. Results in Table 7 and Table B5 indicate that in rounds following a one with a false positive alarm (i.e., when rainfall is forecast with a high likelihood but does not occur) farmers are less likely to forgo the relevant action, suggesting a lower belief in the likelihood of rain occurring, when controlling for all other factors, including the probability in the current round's forecast. This effect is larger when the probability in the false alarm forecast is higher Table B5. Overall, this indicates that, in such a scenario, farmers belief in the accuracy of the forecast is lower (or they increase the threshold at which they expect rain). Similarly, in rounds following one with a false negative alarm (i.e., when rainfall is forecast with a low likelihood and does occur) farmers are more likely to forgo the relevant action, suggesting a higher belief in the likelihood of rain occurring, when controlling for all other factors, including the probability in the current round's forecast. This effect is larger when the probability in the false alarm forecast is higher Table B5. Overall, this indicates that, in such a scenario, farmers' belief in the accuracy of the forecast is higher (or they lower the threshold at which they expect rain). These results are consistent with those observed in Table 6, and together we interpret this as evidence that farmers update their beliefs about the accuracy of the forecast following false alarms.

Table 8: Optimal Action in the Agricultural Decision Making Game

	Forecast: Rainfall ($p >= 0.5$)		Forecast: No Rainfall ($p < 0.5$)	
	(1)	(2)	(3)	(4)
Climate change salience	-0.002	-0.002	0.036	0.036
	(0.024)	(0.024)	(0.024)	(0.024)
Probability training + climate change salience	-0.002		-0.009	
	(0.025)		(0.027)	
Probability training + climate change salience relative to climate change salience alone		-0.000		-0.045*
		(0.024)		(0.025)
False alarm (rain)	-0.061**	-0.061**	0.088***	0.088***
	(0.031)	(0.031)	(0.031)	(0.031)
False alarm (no rain)	0.065**	0.065**	-0.034	-0.034
	(0.030)	(0.030)	(0.031)	(0.031)
Forecast probability (deviation from 0.5) (current round)	0.520***	0.520***	0.362***	0.362***
	(0.073)	(0.073)	(0.083)	(0.083)
N	2552	2552	2296	2296
Outcome mean, comparison group	0.566	0.566	0.348	0.348

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix.
Controls that are in all specifications: GP fixed effects, order, format.
False alarm (rain) represents a false positive forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p >= 0.5$, but does not occur, and is 0 otherwise. False alarm (no rain) represents a false negative forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p < 0.5$, but does occur, and is 0 otherwise. Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2). Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.
The outcome is an indicator which takes the value 1 if the farmer recommends taking the 'optimal action' in the scenario based on the probability of rainfall in the forecast they receive, and 0 otherwise. So, in scenarios where the forecast probability, $p >= 0.5$, the outcome is 1 when the farmer recommends not taking action, and 0 otherwise, while in scenarios where the forecast probability, $p < 0.5$, the outcome is 1 when the farmer recommends taking action, and 0 otherwise.

We next consider farmers choosing the action (or no action) that maximizes their expected payoff in the game round. *Ex ante*, when farmers completely trust forecasts, and rely solely on the weather forecasts provided, they maximize their expected payoff by choosing to forgo the relevant action (i.e., no irrigation, or no fertilizer application) when rain is predicted with $p >= 0.5$, and by choosing to take the relevant action (i.e., irrigate, apply fertilizer) when rain is predicted with $p < 0.5$. When farmers' chosen actions align with this, we term it an optimal action. Table 8 indicates that the information treatments have no impact on farmers' taking the optimal action. Similar to results in Table 7, false alarms (both false positives and false negative) have a significant impact on farmers' taking the optimal action. In rounds where rainfall is forecast with $p >= 0.5$, false positive alarms reduce the likelihood that farmers take the optimal action, while in rounds where rainfall is forecast with $p < 0.5$, false negative alarms increase the likelihood that farmers take the optimal action. On the other hand, in rounds where rainfall is forecast with $p >= 0.5$, false negative alarms increase the likelihood that farmers take the optimal action. In rounds where rainfall is forecast with $p < 0.5$, false negative alarms decrease the likelihood that farmers take the optimal action (but not statistically significantly in this case). These results indicate that false alarms in the preceding round cause farmers to update their beliefs about the accuracy of the forecast (or shift the threshold at which they expect rain).

8 Willingness to Pay for Probabilistic Weather Forecasts

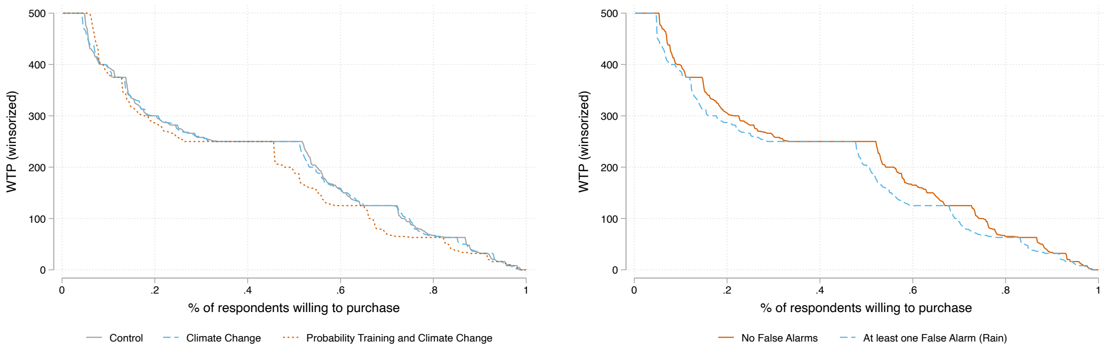

Figure 5: Willingness to Pay for Probabilistic Weather Forecasts

Once farmers complete the two games, we elicit their willingness to pay for weekly, accurate, probabilistic forecasts over voice-calls. Willingness to pay is elicited using a the Becker-DeGroot-Marshak (BDM) (1964) mechanism, using a binary search process (following Berkouwer and Dean (2022); Burlig et al. (2022)). The good being offered is:

"The service being offered today is voice-call based weather forecasts from October 2023 to May 2024. In this service, weather forecasts will be provided via voice-call for the upcoming week, and will convey the likelihood of rainfall in % chance. The forecasts are more accurate and for a smaller area than existing forecasts that are available here. In the last 6 years, the forecasts correctly predicted rain in the upcoming week 92% [in Chikmagalur]/ 96% [in Kodagu]."

While farmers comprehend the BDM exercise, measured by comprehension checks after a practice round for a pen, and in the main round, farmers do know their game scores prior to the exercise. Incentives are transferred via UPI or mobile phones recharge after the study, so farmers do not have an immediate increase in cash-at-hand.

The weather forecasts being offered are produced by the Climate Forecast Applications Network (CFAN), and the accuracy reflects their true accuracy in a given district based on skill scores from re-forecasts over the last six years. The forecast is offered for a period that covers some critical weather sensitive activities (harvesting, blossom irrigation, pre-monsoon fertilizer application) outside of the monsoon season when rain is less frequent.

We first consider how farmers' willingness-to-pay for real-world probabilistic weather forecasts responds to experiencing false alarms in the agricultural decision-making game, where false alarms have clear directionality. Table 9 indicates that farmers are willing to pay ₹2.46 per month less for a real world audio-based weather forecast service when they experienced any false (positive) alarms. This effect is increasing in the probability in the false (positive)

Table 9: Willingness to Pay for Probabilistic Weather Forecasts

	WTP (₹ per month)				WTP (₹ per month, inverse hyperbolic sine)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate change salience	-0.000	-0.000	-0.009	-0.009	-0.001	-0.001	-0.002	-0.002
	(1.104)	(1.104)	(1.105)	(1.105)	(0.065)	(0.065)	(0.064)	(0.064)
Probability training + climate change salience	-2.057*		-2.067*		-0.140*		-0.141*	
	(1.234)		(1.234)		(0.073)		(0.073)	
Probability training + climate change salience relative to climate change salience alone		-2.057*		-2.058*		-0.139**		-0.140**
		(1.136)		(1.136)		(0.068)		(0.068)
Any false alarms (rain) in game 2	-2.460***	-2.460***	-2.546**	-2.546**	-0.133**	-0.133**	-0.141**	-0.141**
	(0.948)	(0.948)	(1.002)	(1.002)	(0.056)	(0.056)	(0.058)	(0.058)
Any false alarms (no rain) in game 2	0.901	0.901	0.993	0.993	0.085	0.085	0.094	0.094
	(0.955)	(0.955)	(0.987)	(0.987)	(0.056)	(0.056)	(0.060)	(0.060)
Total No. of Realizations in game 2			-0.134	-0.134			-0.012	-0.012
			(0.490)	(0.490)			(0.030)	(0.030)
N	1212	1212	1212	1212	1212	1212	1212	1212
Outcome mean, comparison group	25.905	25.905	25.905	25.905	3.605	3.605	3.605	3.605

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects.
Any false alarms (rain) in game 2 takes the value 1 if the farmer encountered any false positive forecasts (rainfall forecast with $p >= 0.5$, but does not occur) in game 2, and 0 otherwise; any false alarms (no rain) in game 2 takes the value 1 if the farmer encountered any false negatives (rainfall forecast with $p < 0.5$, and occurs) in game 2, and 0 otherwise; total number of realizations in game 2 is the number of times rain is realized in game 2.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).
Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2).
Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.

alarm Table B10. This is consistent with the earlier results that false (positive) alarms reduce farmers' belief in the accuracy of the weather forecast. However, false (negative) alarms do not have a significant impact on farmers' willingness to pay, nor do false alarms in the first game Table B11. A concern that might arise when interpreting these results is that farmers scores are likely to be lower when they experience false alarms, reducing their earnings from the study, leading to a 'wealth effect'. However, Table B11 indicates that farmers' total score does not significantly decrease following a false (positive) alarm, while it does following false (negative) alarms in the second game, and following any false alarms in the location choice game. The false alarms which reduce willingness to pay are exactly those which do not have an impact on the score, suggesting that this is unlikely to be drive by a 'wealth effect'. Secondly, the reduction in willingness to pay persists when we directly control for the total score in the games in columns (4) and (5) in Table B11. Finally, to further reassure us, the magnitude of the decrease in willingness to pay that is reported (for an 8-month period) is an order of magnitude larger than the decrease in earnings from the study.

When next consider how farmers' willingness-to-pay for real-world probabilistic weather forecasts responds to the information treatments. Recollect that Table 4 indicated that the probability training and climate change salience treatment increased farmers' understanding of probabilities, and awareness of climate change while the climate change salience treatment alone had no impact on either. However, in Table 9, we find that the probability training and climate change salience treatment reduces farmers' willingness to pay for forecasts per month by ₹2.06 (or 7% of the control group's mean willingness to pay). This is similar in magnitude to the impact of false (positive) alarms but is puzzling when farmers seem to improve understanding probability and awareness of climate change (to a small extent). In Table 10, we look at heterogeneity by farmers' existing access to good-quality forecasts. We find that the reduction in willingness to pay for forecasts in the sample of farmers who receive the probability training and climate change salience treatment is driven by farmers who already have access to forecasts online (columns 1, 2), and who already have access to forecasts at the block level or below (columns 3, 4). This suggests that when farmers improve understanding of probabilities and are made more aware of climate change, they may also be better able to use forecasts they already have access to (for free), which in turn might reduce their willingness to pay for a paid forecast service.

9 Discussion and Conclusion

We find that coffee farmers in Karnataka, India have relatively high levels of probability literacy. More farmers interpret weather forecasts correctly (when comparing more v. less likely to occur events) than they do the two probability 'test' questions, which are similar to those often administered across surveys (85% as opposed to 40%). This reinforces findings in Delavande (2014) that rural populations in developing countries understand probabilistic information. Farmers are also willing to pay ₹26 per month, on average, to receive weekly mobile-phone based audio weather forecasts. This is around 10% of the mean daily wage in Karnataka, for information that is already publicly available from other sources (over the internet, for instance). This suggests that there is demand for more accurate weather forecasts, and farmers see these as adding value to agricultural decision-making.

Farmers randomly assigned to receive a short informational video providing basic probability training, apart from highlighting the salience of climate, do slightly better in the location-choice game, and in the probability 'test' questions. Results in the location choice game suggest that this improvement might arise from increased confidence, or reinforcement of concepts already somewhat understood. However, farmers in this experimental arm are willing to pay ₹2 per month less for the real-world weather forecasting service. Treatment effect heterogeneity suggests that this decline is driven by farmers who do not understand probability concepts (the never takers). While this suggests that short informational videos can improve understanding, it also suggests caution as heterogeneity in prior understanding could have differential effects. In this case, those 'never taker' have lower willingness to pay, they perform no worse in either game round.

Finally, and importantly, this study sheds light on how farmers build trust in a new source of information. Farmers' responses in both experimental games indicate that farmers beliefs in the accuracy of the weather forecast reduces in rounds that follow one with a false pos-

Table 10: Willingness to Pay for Probabilistic Weather Forecasts

	No access to online forecasts		**No access to granular forecasts**	
	WTP (₹ per month)	WTP (₹ per month, inverse hyperbolic sine)	WTP (₹ per month)	WTP (₹ per month, inverse hyperbolic sine)
	(1)	(2)	(3)	(4)
Climate change salience	-1.014	-0.098	-0.471	-0.058
	(1.840)	(0.109)	(1.575)	(0.092)
Probability training + climate change salience	-4.227**	-0.309**	-3.827**	-0.269**
	(2.081)	(0.125)	(1.749)	(0.105)
No access to online forecasts	-1.262	-0.078		
	(1.902)	(0.108)		
Climate change salience × No access to online forecasts	1.523	0.153		
	(2.322)	(0.136)		
(Probability training + climate change salience) × No access to online forecasts	3.608	0.282*		
	(2.591)	(0.154)		
No access to granular forecasts			-2.492	-0.157
			(1.792)	(0.102)
Climate change salience × No access to granular forecasts			0.851	0.118
			(2.242)	(0.132)
(Probability training + climate change salience) × No access to granular forecasts			3.910	0.289**
			(2.516)	(0.147)
Any false alarms (rain) in Round 2	-2.484***	-0.134**	-2.497***	-0.135**
	(0.952)	(0.056)	(0.951)	(0.056)
Any false alarms (no rain) in Round 2	0.869	0.083	0.897	0.086
	(0.956)	(0.057)	(0.956)	(0.056)
N	1212	1212	1212	1212
Outcome mean, comparison group	25.905	3.065	29.905	3.605

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects. Any false alarms (rain) in round 2 takes the value 1 if the farmer encountered any false positive forecasts (rainfall forecast with $p >= 0.5$, but does not occur) in round 2, and 0 otherwise; any false alarms (no rain) in round 2 takes the value 1 if the farmer encountered any false negatives (rainfall forecast with $p < 0.5$, and occurs) in round 2, and 0 otherwise; climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1); probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2); no access to online forecasts takes the value 1 when the farmer indicates that they do not already access weather forecasts on the internet in the pre-experiment survey, and is 0 otherwise; no access to granular forecasts take the value 1 when the farmer indicates that the weather forecasts they currently use are provided only at the district level or higher in the pre-experiment survey, and is 0 otherwise.

itive, and increases in rounds that follow false negative. That is, their threshold for which probability in the forecast indicates rain goes up after a false positive (false alarm for rain), and goes down after a false negative (false alarm for no rain). This suggests that if forecasts end up being incorrect multiple times early on (i.e., many false positives), trust in forecasts may not recover. This provides insights on one part of farming learning in the context of technology adoption.

A Figures

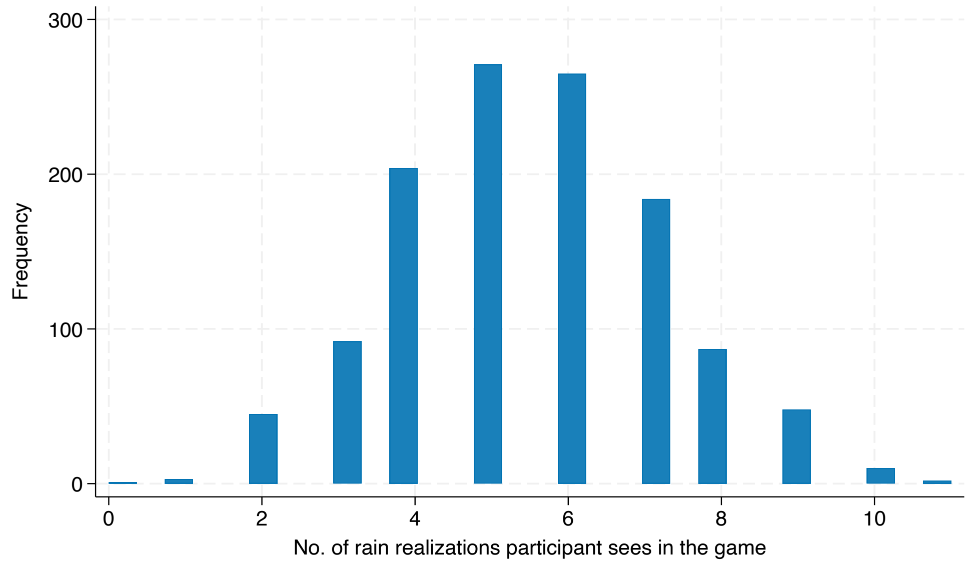

Figure 1: Rain Realizations in the Hypothetical Scenarios

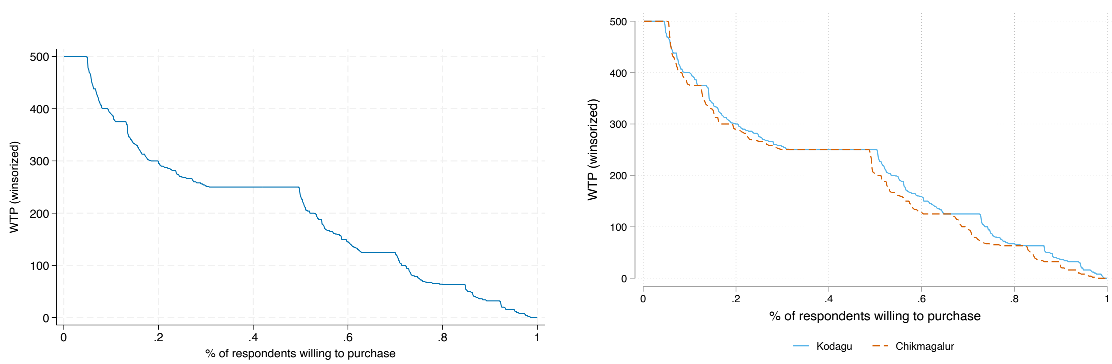

Figure 2: Willingness to Pay for Probabilistic Weather Forecasts

B Additional Tables

Table B1: Game Summary Statistics

	N	Mean	Std. Dev.	Min	Max
Round 1					
Lower probability out of the two options	6060	37.43	19.59	5.00	95.00
Higher probability out of the two options	6060	63.45	20.17	10.00	100.00
Difference in probability between the two options	6060	26.02	21.01	5.00	95.00
Rainfall realized after selecting a forecast	6060	0.49	0.50	0.00	1.00
Round 2					
Probability in the forecast	4848	49.56	22.28	10.00	90.00
Rainfall realized after choosing an action	4848	0.50	0.50	0.00	1.00

Table B2: Summary of the Experimental Games

Component	**Description**	**Details**
	I. Location Choice Game	
Objective	Maximize expected earnings	- Advise hypothetical vendors on choice of location to sell goods - Sales depend on weather realization - One correct choice for more likely to be dry (rainy)
Game Rounds	In each round: - weather forecasts for two locations are provided - farmers recommend a location - in-game weather for the round is realized	Five incentivized rounds. - Three one-day forecast rounds - Two one-week forecast rounds
Scenarios	- One-day forecast scenario - One-week forecast scenario	Randomized: order, Rainy vs. Dry location choice
Forecast Formats	Images and text only	No audio used
Variations	- Rainfall quantity constant, probability varies - Rainfall quantity and probability vary	Randomized presentation
Probability Range	Varying probabilities in forecasts	Differences in probabilities between forecast-pairs varies from 5% - 95%
Scoring	Points awarded/deducted based on accuracy, and stake chosen	- Points at stake can be selected from $\{1, 2, 3, 4, 5\}$ - If ideal weather for sale is realized, stake is awarded - If ideal weather for sale is not realized, stake is deducted
Incentives	Monetary rewards based on points	₹ earned = points scored
	II. Agricultural Decision-Making Game	
Objective	Maximize expected earnings	Advise hypothetical farmers on agricultural actions based on expected weather. Scenarios describe time-of-year, action, farmer details.
Game Rounds	In each round: - weather forecasts (or no forecasts) are provided - farmers recommend action (or inaction) - in-game weather for the round is realized	Six incentivized rounds across two scenarios. - Four rounds with forecasts - Two rounds without forecasts
Scenarios	- Blossom irrigation - Mid-monsoon fertilizer	Decisions based on probabilistic weather forecasts or expectations based on historical incidence of weather
Forecast Formats	Audio, image & text, and no forecast	Varied to test information presentation effects
Probability Range	Varying probabilities in forecasts	Forecasts predict rainfall with probabilities $\in$ $\{10\%, 20\%, 30\%, 35\%, 40\%, 45\%, 50\%, 55\%, 60\%, 65\%, 70\%, 80\%, 90\%\}$
Optimal Strategy	Farmers are incentivized to recommend (not) taking the relevant action when rain or heavy rain is (expected) not expected	*Scenario 1*: - Irrigate if rain is not expected, - don't irrigate if rain is expected *Scenario 2*: - Apply fertilizer if heavy rain is not expected, - don't apply fertilizer if heavy rain is expected
Scoring	Five points awarded when recommended action (or inaction) is appropriate for realized weather, five points deducted otherwise	*Scenario 1*: - 5 points awarded for irrigation + no rain or no irrigation + rain - 5 points deducted for irrigation + rain or no irrigation + no rain *Scenario 2*: - 5 points awarded for fertilizer application + no heavy rain or no fertilizer application + heavy rain - 5 points deducted for fertilizer application + heavy rain or no fertilizer application + no heavy rain
Incentives	Monetary rewards based on points	₹ earned = points scored

Table B3: Outcomes in the Location Choice Game

	Correct choice	Stake chosen	Correct choice	Stake chosen	Correct choice	Stake chosen
	(1)	(2)	(3)	(4)	(5)	(6)
Climate change salience	-0.003	-0.010	-0.003	-0.010	-0.000	-0.003
	(0.013)	(0.049)	(0.013)	(0.049)	(0.013)	(0.050)
Probability training + climate change salience	0.006	0.061			0.003	0.072
	(0.014)	(0.052)			(0.015)	(0.052)
Probability training + climate change salience relative to climate change salience alone			0.009	0.071		
			(0.013)	(0.048)		
False alarm in prior round (weighted)	-0.115***	-0.546***	-0.115***	-0.546***	-0.113**	-0.469***
	(0.026)	(0.070)	(0.026)	(0.070)	(0.046)	(0.134)
Climate change salience × False alarm in prior round (weighted)					-0.028	-0.087
					(0.060)	(0.166)
Probability training + climate change salience × False alarm in prior round (weighted)					0.033	-0.136
					(0.063)	(0.181)
Difference between forecast probabilities	0.104***	0.331***	0.104***	0.331***	0.104***	0.331***
	(0.020)	(0.061)	(0.020)	(0.061)	(0.020)	(0.061)
N	6060	6060	6060	6060	6060	6060
Outcome mean, comparison group	0.854	4.085	0.854	4.085	0.854	4.085

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix.
False alarm in the prior round (weighted) is a continuous variable, taking the value of the difference probabilities in the preceding round when a false alarm occurs, and zero when a false alarm does not occur.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).
Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2).
Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.
Controls that are in all specifications: GP fixed effects, order, format, an indicator for whether the round requires that farmers choose the more likely event (as opposed to the less likely event), an indicator for whether forecasts differs only in probabilities (as opposed to forecasts that differ in both quantities and probability.
The outcome in odd columns is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in even columns is the stake farmers choose in that round $\in \{1, 2, 3, 4, 5\}$

Table B4: Outcomes in the Location Choice Game

	Correct choice	Stake chosen	Correct choice	Stake chosen
	(1)	(2)	(3)	(4)
Climate change salience	-0.016	-0.077	-0.002	-0.007
	(0.025)	(0.073)	(0.013)	(0.049)
Probability training + climate change salience	-0.007	0.052	0.006	0.064
	(0.027)	(0.078)	(0.014)	(0.051)
Control group × order	-0.007	-0.032*		
	(0.006)	(0.017)		
Climate change salience × order	-0.003	-0.009		
	(0.005)	(0.013)		
(Probability training + climate change salience) × order	-0.003	-0.028*		
	(0.006)	(0.016)		
False alarm in prior round	-0.063***	-0.342***	-0.046*	-0.234***
	(0.011)	(0.032)	(0.026)	(0.072)
Difference between forecast probabilities	0.106***	0.340***	0.105***	0.336***
	(0.020)	(0.061)	(0.020)	(0.061)
No false alarm in prior round × order			-0.003	-0.013
			(0.004)	(0.011)
False alarm in prior round × order			-0.008	-0.048**
			(0.007)	(0.019)
N	6060	6060	6060	6060
Outcome mean, comparison group	0.854	4.085	0.854	4.085

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects, order, format, an indicator for whether the round requires that farmers choose the more likely event (as opposed to the less likely event), an indicator for whether forecasts differs only in probabilities (as opposed to forecasts that differ in both quantities and probability; false alarm in the prior round is an indicator that takes the value 1 when the expected event does not occur in the prior round, and 0 otherwise; climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1); probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2); probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1; order is a continuous variable that indicates the round order. The outcome in odd columns is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in even columns is the stake farmers choose in that round $\in \{1, 2, 3, 4, 5\}$.

Table B5: Optimal Strategy for Rainy Conditions in the Agricultural Decision Making Game

	No Forecast Rounds (Prior)				**Forecast Rounds (Posterior)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate change salience	0.029	0.029	0.028	0.019	-0.020	-0.020	-0.022	-0.016
	(0.021)	(0.021)	(0.023)	(0.022)	(0.017)	(0.017)	(0.018)	(0.018)
Probability training + climate change salience	0.025		0.023	0.018	0.005		0.009	0.003
	(0.022)		(0.024)	(0.023)	(0.019)		(0.020)	(0.020)
Probability training + climate change salience relative to climate change salience alone		0.029				-0.020		
		(0.021)				(0.017)		
False alarm (rain) (weighted)	-0.025	-0.025	-0.033	-0.026	-0.126***	-0.126***	-0.125**	-0.125***
	(0.038)	(0.038)	(0.063)	(0.038)	(0.033)	(0.033)	(0.063)	(0.033)
False alarm (no rain) (weighted)	-0.008	-0.008	-0.008	-0.160	0.191***	0.191***	0.191***	0.213*
	(0.073)	(0.073)	(0.073)	(0.120)	(0.064)	(0.064)	(0.064)	(0.113)
Climate change salience × False alarm (rain) (weighted)			-0.001				0.027	
			(0.085)				(0.079)	
Probability training + climate change salience × False alarm (rain) (weighted)			0.023				-0.040	
			(0.095)				(0.087)	
Climate change salience × False alarm (no rain) (weighted)				0.232				-0.098
				(0.164)				(0.144)
Probability training + climate change salience × False alarm (no rain) (weighted)				0.171				0.074
				(0.180)				(0.174)
Probability in current forecast					0.500***	0.500***	0.500***	0.501***
					(0.031)	(0.031)	(0.031)	(0.031)
N	2424	2424	2424	2424	4848	4848	4848	4848
Outcome mean, comparison group	0.203	0.203	0.203	0.203	0.440	0.440	0.440	0.440

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects, order, format.
False alarm (rain) (weighted) represents a false positive forecast in the preceding forecast round. The variable takes the value 1 × the probability in the forecast when rainfall was forecast with $p >= 0.5$, but does not occur, and is 0 otherwise.
False alarm (no rain) (weighted) represents a false negative forecast in the preceding forecast round. The variable takes the value 1 the probability in the forecast when rainfall was forecast with $p < 0.5$, but does occur, and is 0 otherwise.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).
Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2).
Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.
The outcome is an indicator which takes the value 1 if the farmer recommends forgoing the action in the scenario (and hence believes that rain is more likely to occur than not), and 0 otherwise. Columns 1 - 4 consist of rounds where farmers do not receive a forecast. Columns 5-8 consist of rounds where farmers receive a probabilistic rainfall forecast.

Table B6: Optimal Strategy for Rainy Conditions in the Agricultural Decision Making Game

	No Forecast Rounds (Prior)		Forecast Rounds (Posterior)	
	(1)	(2)	(3)	(4)
Climate change salience	0.031	0.031	-0.019	-0.019
	(0.021)	(0.021)	(0.017)	(0.017)
Probability training + climate change salience	0.028		0.005	
	(0.022)		(0.019)	
Probability training + climate change salience relative to climate change salience alone		-0.003		0.025
		(0.020)		(0.017)
False alarm (rain)	0.029	0.029	-0.058***	-0.058***
	(0.026)	(0.026)	(0.023)	(0.023)
False alarm (no rain)	-0.038	-0.038	0.027	0.027
	(0.028)	(0.028)	(0.023)	(0.023)
Rain realized in prior round	-0.004	-0.004	0.094**	0.094**
	(0.137)	(0.137)	(0.037)	(0.037)
Forecast in prior round	-0.076	-0.076	-0.016	-0.016
	(0.049)	(0.049)	(0.019)	(0.019)
Rain realized in prior round × Forecast provided in prior round	0.081	0.081	-0.019	-0.019
	(0.140)	(0.140)	(0.043)	(0.043)
Probability in current forecast			0.499***	0.499***
			(0.031)	(0.031)
N	2424	2424	4848	4848
Outcome mean, comparison group	0.238	0.238	0.471	0.471

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects, order, format. False alarm (rain) represents a false positive forecast in the preceding forecast round — the variable takes the value 1 when rainfall was forecast with $p >= 0.5$, but does not occur, and is 0 otherwise; false alarm (no rain) represents a false negative forecast in the preceding forecast round — the variable takes the value 1 when rainfall was forecast with $p < 0.5$, but does occur, and is 0 otherwise; rain realized in prior round takes the value 1 when rain is realized in the preceding round, and 0 when it is not; forecast provided in prior round takes the value 1 when the farmer receives a probabilistic weather forecast in the preceding round, and 0 when the farmer does not.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1); probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2); probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1. The outcome is an indicator which takes the value 1 if the farmer recommends forgoing the action in the scenario (and hence believes that rain is more likely to occur than not), and 0 otherwise. Columns 1, 2 consist of rounds where farmers do not receive a forecast; columns 3, 4 consist of rounds where farmers receive a probabilistic rainfall forecast.

Table B7: Optimal Strategy for Rainy Conditions in the Agricultural Decision Making Game (by Scenario)

	No Forecast Rounds (Prior)				**Forecast Rounds (Posterior)**			
	Irrigation		*Fertilizer*		*Irrigation*		*Fertilizer*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate change salience	-0.015	-0.015	0.073**	0.073**	0.007	0.007	-0.045*	-0.045*
	(0.025)	(0.025)	(0.031)	(0.031)	(0.024)	(0.024)	(0.024)	(0.024)
Probability training + climate change salience	-0.023		0.075**		0.025		-0.014	
	(0.026)		(0.034)		(0.026)		(0.026)	
Probability training + climate change salience relative to climate change salience alone		-0.008		0.002		0.018		0.031
		(0.023)		(0.032)		(0.025)		(0.023)
False alarm (rain)	-0.043	-0.043	0.034	0.034	-0.138***	-0.138***	-0.033	-0.033
	(0.027)	(0.027)	(0.040)	(0.040)	(0.030)	(0.030)	(0.030)	(0.030)
False alarm (no rain)	-0.008	-0.008	0.010	0.010	0.087***	0.087***	0.024	0.024
	(0.030)	(0.030)	(0.038)	(0.038)	(0.029)	(0.029)	(0.031)	(0.031)
Probability in current forecast					0.693***	0.693***	0.293***	0.293***
					(0.040)	(0.040)	(0.046)	(0.046)
N	2424	2424	2424	2424	4848	4848	4848	4848
Outcome mean, comparison group	0.167	0.167	0.240	0.240	0.503	0.503	0.464	0.464

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects, order, format.
False alarm (rain) (weighted) represents a false positive forecast in the preceding forecast round. The variable takes the value 1 × the probability in the forecast when rainfall was forecast with $p >= 0.5$, but does not occur, and is 0 otherwise.
False alarm (no rain) (weighted) represents a false negative forecast in the preceding forecast round. The variable takes the value 1 the probability in the forecast when rainfall was forecast with $p < 0.5$, but does occur, and is 0 otherwise.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).
Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2).
Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.
The outcome is an indicator which takes the value 1 if the farmer recommends forgoing the action in the scenario (and hence believes that rain is more likely to occur than not), and 0 otherwise. Columns 1 - 4 consist of rounds where farmers do not receive a forecast. Columns 5-8 consist of rounds where farmers receive a probabilistic rainfall forecast.

Table B8: Optimal Strategy for Rainy Conditions in the Agricultural Decision Making Game (by forecast format)

	Audio Forecasts		**Text & Image Forecasts**	
	(1)	(2)	(3)	(4)
Climate change salience	-0.033	-0.033	-0.009	-0.009
	(0.023)	(0.023)	(0.023)	(0.023)
Probability training + climate change salience	-0.014		0.022	
	(0.026)		(0.025)	
Probability training + climate change salience relative to climate change salience alone		0.019		0.031
		(0.024)		(0.023)
False alarm (rain)	-0.055*	-0.055*	-0.098***	-0.098***
	(0.032)	(0.032)	(0.029)	(0.029)
False alarm (no rain)	0.054*	0.054*	0.071**	0.071**
	(0.029)	(0.029)	(0.031)	(0.031)
Probability in current forecast	0.624***	0.624***	0.378***	0.378***
	(0.044)	(0.044)	(0.042)	(0.042)
N	2424	2424	2424	2424
Outcome mean, comparison group	0.523	0.523	0.443	0.443

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix.
Controls that are in all specifications: GP fixed effects, order, format.
False alarm (rain) represents a false positive forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p >= 0.5$, but does not occur, and is 0 otherwise; false alarm (no rain) represents a false negative forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p < 0.5$, but does occur, and is 0 otherwise; climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1); probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2). Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1. The outcome is an indicator which takes the value 1 if the farmer recommends forgoing the action in the scenario (and hence believes that rain is more likely to occur than not), and 0 otherwise.
Columns 1, 2 consist of rounds where farmers receive an audio forecast; columns 3, 4 consist of rounds where farmers receive an image/text based forecast.

Table B9: Optimal Action in the Agricultural Decision Making Game

	Forecast: Rainfall ($p >= 0.5$)		**Forecast: No Rainfall** ($p < 0.5$)	
	(1)	(2)	(3)	(4)
Climate change salience	-0.002	-0.002	0.035	0.035
	(0.024)	(0.024)	(0.024)	(0.024)
Probability training + climate change salience	-0.003		-0.009	
	(0.025)		(0.027)	
Probability training + climate change salience relative to climate change salience alone		-0.001		-0.045*
		(0.024)		(0.025)
False alarm (rain) (weighted)	-0.105**	-0.105**	0.136***	0.136***
	(0.049)	(0.049)	(0.049)	(0.049)
False alarm (no rain) (weighted)	0.160*	0.160*	-0.137	-0.137
	(0.089)	(0.089)	(0.096)	(0.096)
Forecast probability (deviation from 0.5) (current round)	0.519***	0.519***	0.359***	0.359***
	(0.073)	(0.073)	(0.083)	(0.083)
N	2552	2552	2296	2296
Outcome mean, comparison group	0.566	0.566	0.348	0.348

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix.
Controls that are in all specifications: GP fixed effects, order, format.
False alarm (rain) represents a false positive forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p >= 0.5$, but does not occur, and is 0 otherwise. False alarm (no rain) represents a false negative forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p < 0.5$, but does occur, and is 0 otherwise. Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2). Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.
The outcome is an indicator which takes the value 1 if the farmer recommends taking the 'optimal action' in the scenario based on the probability of rainfall in the forecast they receive, and 0 otherwise. So, in scenarios where the forecast probability, $p >= 0.5$, the outcome is 1 when the farmer recommends not taking action, and 0 otherwise, while in scenarios where the forecast probability, $p < 0.5$, the outcome is 1 when the farmer recommends taking action, and 0 otherwise.

Table B10: Willingness to Pay for Probabilistic Weather Forecasts

	WTP (₹ per month)		**WTP** (₹ per month, inverse hyperbolic sine)	
	(1)	(2)	(3)	(4)
Climate change salience	0.016	0.016	-0.000	-0.000
	(1.105)	(1.105)	(0.065)	(0.065)
Probability training + climate change salience	-2.055*		-0.141*	
	(1.234)		(0.073)	
Probability training + climate change salience relative to climate change salience alone		-2.071*		-0.140**
		(1.136)		(0.068)
Mean weighted false alarm (rain) in game 2	-8.976**	-8.976**	-0.581**	-0.581**
	(4.168)	(4.168)	(0.244)	(0.244)
Mean weighted false alarm (no rain) in game 2	2.502	2.502	0.383	0.383
	(7.012)	(7.012)	(0.414)	(0.414)
N	1212	1212	1212	1212
Outcome mean, comparison group	25.905	25.905	3.605	3.605

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects. Mean weighted false alarm (rain) in game 2 is the average of weighted false positives (indicator for the instance where rainfall was forecast with $p >= 0.5$ and does not occur × probability in the forecast) across all rounds in the second game; mean weighted false alarm (no rain) in game 2 is the average of weighted false negatives (indicator for the instance where rainfall was forecast with $p < 0.5$ and does occur × probability in the forecast) across all rounds in the second game; climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1); probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2); probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.

Table B11: Willingness to Pay for Probabilistic Weather Forecasts

	WTP (₹ per month)	WTP (₹ per month, inverse hyperbolic sine)	Total Score	WTP (₹ per month)	WTP (₹ per month, inverse hyperbolic sine)
	(1)	(2)	(3)	(4)	(5)
Climate change salience	-0.071	-0.002	-0.144	-0.061	-0.002
	(1.100)	(0.064)	(0.938)	(1.098)	(0.064)
Probability training + climate change salience	-2.125*	-0.141*	1.207	-2.207*	-0.146**
	(1.236)	(0.073)	(1.044)	(1.235)	(0.073)
Any false alarm (rain) in game 2	-2.432**	-0.132**	-0.820	-2.376**	-0.130**
	(0.947)	(0.056)	(0.820)	(0.947)	(0.056)
Any false alarm (no rain) in game 2	0.851	0.085	-3.122***	1.065	0.095*
	(0.952)	(0.056)	(0.817)	(0.951)	(0.056)
Any false alarms in game 1	-1.556	-0.027	-12.535***	-0.697	0.015
	(1.117)	(0.067)	(0.950)	(1.214)	(0.071)
Total score in experimental games				0.069**	0.003*
				(0.034)	(0.002)
N	1212	1212	1212	1212	1212
Outcome mean, comparison group	25.905	3.605	70.717	25.905	3.605

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications. Lasso controls are listed in the Appendix. Controls that are in all specifications: GP fixed effects.
Any false alarms (rain) in game 2 takes the value 1 if the farmer encountered any false positive forecasts (rainfall forecast with $p >= 0.5$, but does not occur) in game 2, and 0 otherwise; any false alarms (no rain) in game 2 takes the value 1 if the farmer encountered any false negatives (rainfall forecast with $p < 0.5$, and occurs) in game 2, and 0 otherwise; total number of realizations in game 2 is the number of times rain is realized in game 2.
Climate change salience indicates that the farmer is randomly assigned to the climate change salience information treatment (E1 = T1).
Probability training + climate change salience indicates that the farmer is randomly assigned to the combined information treatment (E2 = T1 + T2).
Probability training + climate change salience relative to climate change salience alone provides the coefficients for (T1 + T2) - T1.

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