Weather Forecasts and Farmers' Beliefs after False Alarms*

Shawn Cole† Tomoko Harigaya‡ Vaishnavi Surendra§

June 12, 2024

Please click here for the latest version of the paper.

Abstract

Weather-induced risk reduces farmers' incomes, and climate change is increasing such risk. One promising intervention to mitigate risk is high-quality, probabilistic, short-to-medium-range rainfall forecasts, which predict weather between zero and fifteen days ahead. For forecasts to be effective, however, farmers have to understand and act on them. This paper evaluates how farmers use probabilistic forecasts and form beliefs about their accuracy in a lab-in-the-field experiment. In scenarios that mimic real-world decision making, we find that farmers update their beliefs about the (in)accuracy of forecasts following false alarms, where forecasts erroneously predict events. Farmers who experience false alarms perform worse in subsequent rounds of incentivized experimental games, and report a lower willingness-to-pay for a real-world weather forecast service in an incentive-compatible Becker–DeGroot–Marschak elicitation. Light-touch interventions to improve probability comprehension and make climate change salient have limited impact on farmer decision-making, with positive effects that are mitigated by the incidence of false alarms.

JEL Codes: C91, D81, O12, O13, Q54
Keywords: Belief Updating, Forecasts, Climate Change, Agriculture

*This research is funded by the J-PAL King Climate Action Initiative. We thank Utteeyo Dasgupta, Anjini Kochar, Subha Mani, Liz Stephens, Violeta Toma, Jessica Zhu and participants at the University of Chicago mini-conference on weather forecasting for small-holder farmers, UC Berkeley Development Lunch, SEA Annual Meeting 2023 for helpful comments and suggestions. We are grateful to Sejal Luthra for excellent research assistance, management and collaboration. We thank Kannan Sobti and Bhawna Mangla for their excellent research management and research assistance; Marcus Sander and Anshul Mauder for research assistance; Saniya T, Naveena S.P., Geetanjali A, Mangala B for research and field support; Niek de Greef and Julian Emdon for video design and editing. We also thank the Coffee Board of India, and the current and former members of the PxD team — Hannah Timmis, Aparna Priyadarshi, Sannihit Bathula, Shubham Garg, Supriya Ramanathan, Revati Vaidya, Gagandeep Kaur, Niriksha Shetty — for their inputs and support. This project was approved by the Institutional Review Boards at Harvard University, Health Media Lab (HML), and the Institute for Financial Management and Research (IFMR). The experiment is registered on the AEA RCT registry (AEARCTR-0011526).

†Harvard Business School, scole@hbs.edu

‡Precision Development (PxD), tharigaya@precisiondev.org

§Precision Development (PxD), vaishnavi.s@gmail.com

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 (Krishnan et al., 2020; 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.

(Short-to-)Medium-range weather forecasts[1] may help farmers better time agricultural activities, better plan input allocation, and take precautionary measures. However, public weather forecast providers in developing countries do not typically provide information-rich forecasts: forecasts tend to be deterministic rather than probabilistic, tend to cover larger geographic areas than forecasts in more developed countries (i.e., forecasts have coarser granularity), and are less accurate than forecasts in developed countries (Linsenmeier and Shrader, 2023). Accurate, probabilistic medium-range weather forecasts may provide farmers in developing countries with a more comprehensive picture of upcoming weather, and allow them to manage uncertainty in the forecast in a manner appropriate for their decision-making trade-offs (Fundel et al., 2019).

To begin to use probabilistic medium-range weather forecasts, farmers need to accurately comprehend (Stephens et al., 2019) and trust (Shafiee-Jood et al., 2021) forecasts. Existing evidence on probabilistic reasoning among rural populations in developing countries (reviewed in Delavande, 2014) is encouraging, indicating that farmers (and others) understand probabilities and intuitively form probabilistic beliefs about uncertain events across contexts. However, there has been limited focus on how farmers in developing countries form beliefs about the accuracy of forecasts, or learn to trust a new source of information.

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 (where farmers watch a placebo video) helps us assess

[1] We refer to forecasts with lead times of between 0 and 15 days as medium-range forecasts rather than short-to-medium-range forecasts for ease of exposition. In all cases where we refer to weather forecasts, without referring to a 'range', we refer to lead times of between 0 and 15 days. The American Meteorological Society defines short-range forecasts as those provided 0 - 2 days ahead, and medium-range forecasts as those provided between 2 and 15 days ahead. Source: https://www.ametsoc.org/index.cfm/ams/about-ams/ams-statements/archive-statements-of-the-ams/weather-analysis-and-forecasting/

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. Weather forecasts were designed with input from meteorologists, and decision-making scenarios were designed with input form agronomists and qualitative interviews with farmers. 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 1,212 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 the two incentivized experimental games. In the first game, farmers play five rounds, choosing in each round 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 they favorable weather conditions are more likely, to maximize their earnings. In the second game, farmers play six rounds in which they use available weather information to make agricultural decisions whose appropriateness depends on the realized weather, with earnings again determined by chosen action and realized weather. 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 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 rain when rain is predicted with a higher probability in the second game. All farmers are willing to take up, and 98% 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) providing weekly probabilistic weather forecasts. This is high demand for accurate, probabilistic weather forecasts over mobile phones.

Farmers assigned to watch both the probability tutorial and the video highlighting climate change perform marginally better in the probability 'test' questions, are more likely to believe that unexpected weather events 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. 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 alarm for rain (i.e., where rain is predicted with 50% probability or greater) in a round in the second game prompts farmers to be less likely to expect rain, or to expect rain only at higher forecast probabilities in the following round, reflecting a lowered trust in forecast accuracy. Conversely, unexpected rain — where rain occurs despite a low forecast probability — 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, 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 examine the 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 than when predicted events occur.

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 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 is consistent with the notion of recency bias (Tversky and Kahneman, 1974; Benjamin, 2019). 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; Janzen et al., 2020).

Our results also contribute to the literature on farmers' adaptation to increasing weather uncertainty. With limited take-up of *ex-post* strategies such as index insurance (Cole and Xiong, 2017), there has been increasing interest in expanding *ex ante* risk mitigation strategies. Existing evidence (Emerick et al., 2016; Barnett-Howell, 2021; Karlan et al., 2014) suggests that such strategies can have large effects on farmers' investment and profits. With improvements in weather forecasting skill, a near-zero marginal cost of provision, and a high potential for scaling, providing farmers with granular weather forecasts is another such potentially cost-effective mechanism (with seasonal forecasts explored in Lybbert et al. (2007); Rosenzweig and Udry (2019); Burlig et al. (2022)). Weather forecasts at the short- and medium-range can help farmers adjust factor allocation within season (Yegbemey et al., 2023; Mase and Prokopy, 2014). Short-range weather forecasts provided through mobile phones have had mixed impacts across contexts and over time (Fafchamps and Minten, 2012; Camacho and Conover, 2019; Yegbemey et al., 2023), and understanding how farmers form beliefs about the weather and about the forecast service is important for designing an effective and useful weather forecast service, and also has implications for digital extension services overall (Fabregas et al., 2019; Cole and Fernando, 2020).

Finally, we demonstrate that providing uncertainty information does help farmers in a rural developing country setting make better decisions, adding to similar research in developed country settings (Stephens et al., 2019; Roulston et al., 2006; Roulston and Kaplan, 2009). We also contribute empirical results to the literature that models how individuals learn to trust and use weather forecasts (Millner, 2008; Shafiee-Jood et al., 2021).

2 Study Setting

This study aims to understand whether conveying probabilistic rainfall forecasts to farmers will aid farmer decision-making, and focuses on a weather-sensitive crop, coffee, in a region with increasingly variable weather, Karnataka, India. This section describes our study setting and experimental design.

Setting. Coffee is a perennial crop that thrives in relatively cool, tropical weather. India is the sixth-largest coffee producer in the world, and over 70% of India's coffee is cultivated in Karnataka, our study setting.[2] Precision Development (PxD) and the Coffee Board of India operate a voice-call based agricultural advisory service, Coffee Krishi Taranga (CKT), for coffee farmers in Karnataka.[3] Around 70% of all coffee farmers in Karnataka are registered on the CKT service, and Table 1 describes characteristics of users, who were profiled in 2018.

While 60% of CKT's user-base is small-holder farmers, who cultivate coffee on fewer than 5 acres, and 71% of our study-sample are small-holders Table 2. Forty-seven percent of the CKT user-base are educated a higher secondary level or higher, while 40.9% of our study sample has attained the same level of education. In 2018, 45% of CKT-user farmers had access to a smartphone, and this is presumably far higher in 2023.[4] In our study sample, 68.9% of farmers reported access to a smartphone, despite a larger share of small-holders and smaller share of farmers with high levels of education, which are correlates of household wealth.

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

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

[2]Statistics from the Coffee Board of India, accessed at https://coffeeboard.gov.in/
[3]More details about CKT are in the appendix.
[4]The GSMA The Mobile Economy 2023 report indicates that this is the case.

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.

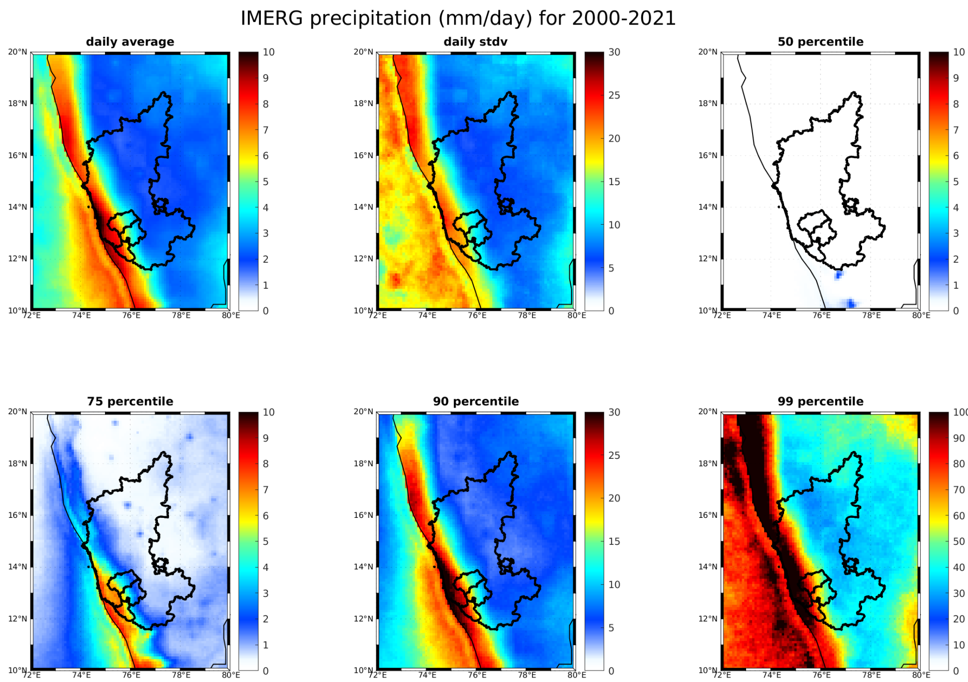


Figure 1: Daily rainfall amount and variability in Karnataka

Notes: The larger outline is the state of Karnataka. The three districts outlined within are Kodagu, Chikmagalur and Hassan. Analysis provided by Climate Forecasts Action Network (CFAN)

Weather Forecasts in Karnataka. In our study sample, 49% of farmers reported typically accessing weather forecasts via television, radio, newspaper, or Kisan Call Centers. Forecasts on these media are provided by the Indian Meteorological Department (IMD), and the IMD's rainfall forecasts are deterministic predictions of expected rainfall. Publicly available IMD weather forecasts are at the weather-station level. However, weather station coverage varies from multiple per city in large metropolises, to 1 per district in other regions.[5] Forecasts are presented to farmers at the district or the block levels in different media.

The context for this study is a new CKT weather forecast add-on service, which we offer to farmers in the willingness-to-pay exercise described in Section 3. The weather forecasts we

[5] https://mausam.imd.gov.in/imd˙latest/contents/imd-dwr-network.php

consider are short-to-medium range (i.e., at lead times of 0 to 15 days) precipitation forecasts provided by the Climate Forecast Applications Network (CFAN). CFAN calibrates forecasts generated from the European Centre for Medium-Range Weather Forecasts (ECMWF) ensemble model for increased accuracy in the study region (with three grid-cells per block, where IMD provided forecasts at the block or district levels). Apart from forecasts from the IMD, farmers may also have access to weather forecasts available online or on mobile-phone apps, and 39% of farmers in our study sample report that they do access such forecasts. These forecasts are typically probabilistic. However, Figure 8 shows that, at least in some cases, websites and apps provide forecasts for the nearest weather station location rather than the actual town. In such cases, forecasts may be perceived by farmers to have finer granularity than they actually do. Overall, CFAN's forecasts provide finer granularity, richer forecast information, and longer lead times. As part of the CKT service, raw forecasts can also be customized to be contextually relevant for coffee farmers. Such forecasts could help farmers better cope with weather variability, better allocate factor inputs, and minimize adverse consequences of weather shocks by allowing them to take precautionary actions and thus also avoid working in hazardous conditions.

3 Experimental Design

3.1 Sample and Randomization

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. We randomly selected twenty-one gram panchayats (GPs) in two blocks in the two districts. Randomly sampled farmers were initially invited to participate in the in-person study via telephone; if the recruitment goals for a gram panchayat were not achieved, subsequent recruitment was carried out in-person. Eligibility for the study required that the farmer manage a coffee farm of 18 acres or less and be aged between 18 and 65 years.

Farmers who agreed to participate during recruitment surveys were visited and enrolled in the study in-person. Upon consent, farmers were randomized on-the-spot into one of three groups: (1) an information intervention highlighting the salience of climate change in the context of coffee cultivation via video (T1); (2) information intervention highlighting climate change salience and providing basic training to improve understanding of probabilities via video (T1 + T2); (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 probability training when added to climate change information (T2 = (T1 + T2) - T1) (Muralidharan et al., 2023), while maintaining similar levels of power on the other outcomes of interest, (T1 - C), ((T1 + T2) - C).[6]

Table 2 describes the characteristics of the sample that completed the study. Overall, 1,212 farmers completed the study across the 21 GPs, with a low attrition rate of about 2% that did not significantly differ by group (Table 2). The distribution of participants across the experimental groups closely matched the intended proportions of 42%, 29%, and 29% for each treatment arm, indicating successful on-the-spot randomization. The study's participants had an average age of 48, with the majority (86%) being the primary decision-makers for their agricultural operations. Most farmers (70%) manage coffee farms of 5 acres or less, while the rest operate farms ranging from 5 to 18 acres. Smartphone access or ownership is common among 69% of the farmers, yet only 32% utilize WhatsApp for communication. Trust in available weather forecasts is relatively low, with only 35% of farmers expressing confidence in them. 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 confirms that these characteristics do not predict treatment assignment, affirming the randomization's integrity.

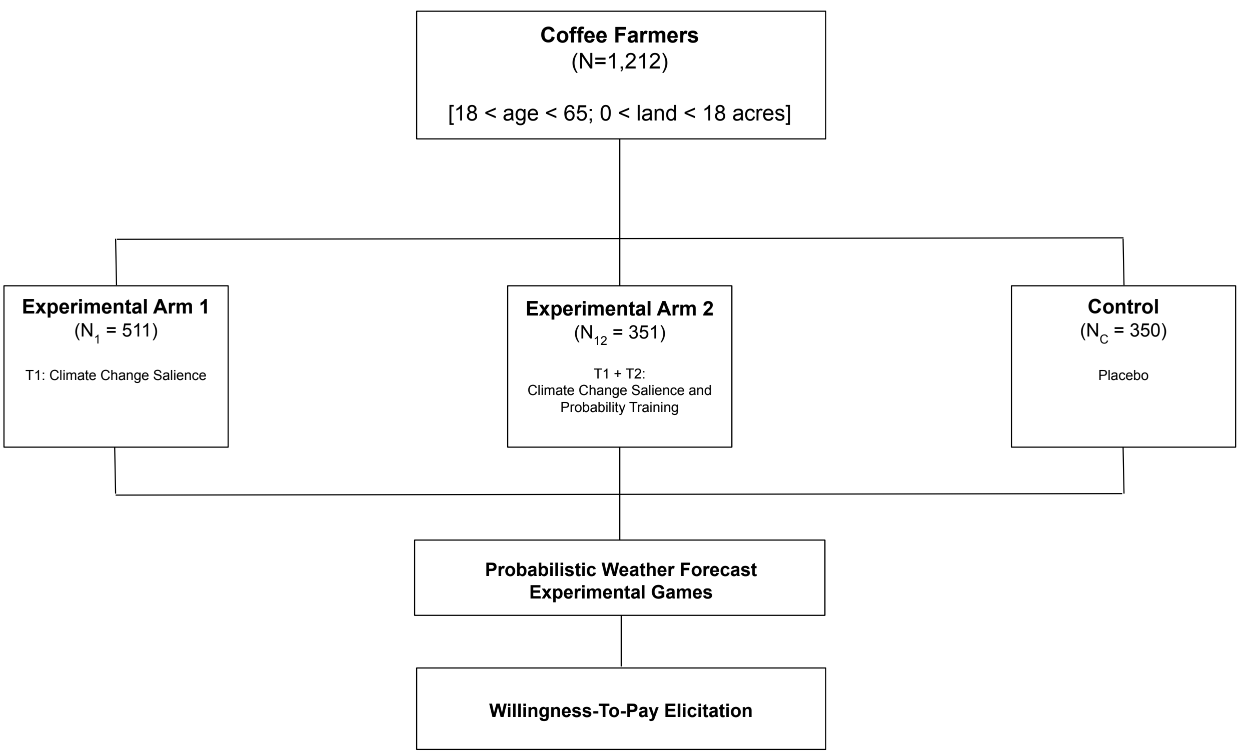


Figure 2: Experiment Design

[6]Similar levels of power when compared to a $\frac{1}{3}$, $\frac{1}{3}$, $\frac{1}{3}$ design which maximizes power on (T1 - C), ((T1 + T2)-C).

Table 2: 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

3.2 Information Treatments

Climate change salience: Farmers in the climate change salience experimental arm view a 5.5-minute video detailing climate change effects on coffee cultivation in Karnataka, India. The video outlines the increased challenges faced by local farmers due to rising temperatures, unpredictable rainfall, and extreme weather events observed in the past ten years. It features firsthand accounts from farmers, illustrating their struggles, and presents adaptive strategies, emphasizing the utility of weather forecasts in agricultural planning and climate resilience.

Climate change salience and probability training: Farmers view a comprehensive 13.5-minute video combining a primer on probability using relatable examples and visual tools, with the climate change video described above. The video makes probability concepts clear using common scenarios, interactive elements, and visual aids, connecting these ideas to their use in understanding rainfall forecasts. It further clarifies the concept of a reference class in probabilistic predictions (Gigerenzer et al., 2009).

Control: Farmers in the control group view a brief video that chronicles the origins and growth of coffee farming in India, from its inception to its current status.

3.3 Experimental Decision-Making Games

Location Choice Game: Here, farmers choose between two market locations to sell goods, with sales dependent on weather conditions. The objective is to maximize earnings by using probabilistic weather forecasts provided in both visual and textual formats. (Table B2, Table B1)

After two practice rounds, farmers engage in five incentivized rounds, choosing markets based on daily or weekly weather forecasts (Figure 4). They encounter scenarios where either 'wet' or 'dry' weather benefits sales, such as selling buttermilk on dry days or umbrellas on rainy days. The game presents forecasts with fixed rainfall and variable probabilities or with both parameters varying, challenging farmers with decisions of differing difficulty.[7] The *ex ante* correct choice, unaffected by risk preferences, always has a lower outcome variance and higher expected earnings.

Farmers choose an investment from $\{1, 2, 3, 4, 5\}$, i.e., stake points on their market choice to express confidence, with points awarded or deducted based on whether weather favorable for sales is realized or not. Feedback after each round clarifies the effectiveness of their choices and the role of chance in outcomes. This game design eliminates biases from risk aversion, forecast format, and decision-making based on rain quantity versus likelihood, ensuring a focus on the farmers' ability to use forecasts effectively.

[7] 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

Agricultural Decision-Making Game: This game challenges farmers to use weather forecasts for critical coffee farming decisions regarding irrigation and fertilizer application. After a practice round, they undergo six incentivized rounds where they must decide whether to irrigate during coffee blossoming or fertilize in the monsoon, based on probabilistic forecasts or their own judgment (Figure 5). The forecasts' probabilities vary from 10% to 90%, reflecting real-world unpredictability and testing decision-making under varying levels of uncertainty.

Farmers receive forecasts through audio, or text and image to determine the best course of action, with the game's structure designed to prevent biases from round order or forecast format. The scoring is straightforward: +5 for decisions that are ex-post appropriate, or -5 for decisions that are ex-post inappropriate. Thus, the optimal action depends only on whether the probability of rainfall is greater than or less than 50%. Feedback is provided after each round to help farmers assess the optimality of their decisions and the influence of chance on the outcomes. Details on the game's structure and scenarios are outlined in Table B2 and Table B1.

Weather forecast realizations: In the experimental games, the likelihood of forecast events occurring corresponds to the probabilities provided by the forecasts, in line with the methodology of Stephens et al. (2019).[8]

Scores and Payoffs: The scoring system incentivizes farmers to make decisions that maximize *ex ante* expected earnings/points. The rules are kept simple for ease of understanding (Haaland et al., 2023; Conlon et al., 2022), but do not constitute 'proper scoring rules' (Palfrey and Wang, 2009). Farmers earn monetary incentives equal to their total points, with a maximum possible earning of ₹110. In addition to game earnings, participants are also compensated with an in-kind benefit valued at ₹150 for their involvement in the study.

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.

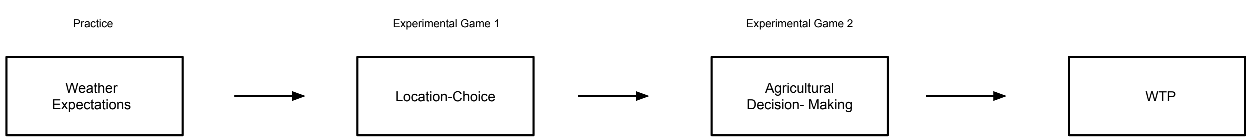


Figure 3: Experiment Flow

[8]In meteorology, a 'reliable' forecast is one where there is consistency between the forecast probabilities and the observed frequencies of weather events (Noted by the Collaboration for Australian Weather and Climate Research).

4 Experimental Results

4.1 Empirical Framework

Our empirical analysis employs a consistent strategy across different experimental games to assess the impact of information interventions and experience on farmers' decision-making.

We estimate the following general specification for outcomes at the individual level:

$$Y_i = \beta_0 + \beta_1 \mathbf{T}_i^1 + \beta_2 \mathbf{T}_i^2 + (\beta_3 \mathbf{FA}_i^{rain} + \beta_4 \mathbf{FA}_i^{no\ rain}) + \mathbf{X}_{ir}^{'} \alpha + \mathbf{G}_g + \epsilon_i \tag{1}$$

where, Y_i represents the outcome of interest for individual, i, such as total score, understanding of probability, awareness of climate change, or willingness-to-pay for probabilistic weather forecasts. T_i^1 and T_i^2 are indicators for assignment to the climate change salience video and the probability training video, respectively. In certain analyses, we include FA_{ir}^{rain}, which denotes the incidence of any false alarms (rain) in the agricultural decision-making game, occurring when rain is forecasted with a probability of 50% or higher but fails to materialize; and $FA_{ir}^{no\ rain}$, which denotes the incidence of any false alarms (no rain) in the agricultural decision-making game, occurring when rain is predicted with a probability of less than 50% yet unexpectedly occurs. X_i' is a vector of control variables selected via the double lasso method, and G_g represents gram panchayat fixed effects. We use robust standard errors in specifications at the individual level.

For the location choice game, we analyze whether farmers make the *ex ante* optimal choice, and their chosen investment. We estimate:

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

In this equation, Y_{ir} is the outcome for individual i in round r, with D_{ir} representing the difference in forecast probabilities. The vectors $Order_{ir}$, $Format_{ir}$ include fixed effects for round order, forecast format. V_{ir} indicates whether a round is a 'wet' or 'dry' round, and Q_{ir} indicates whether quantities and probabilities or only probabilities vary across the two forecasts in a round. FA_{ir} represents a false alarm experienced in the previous round, where the forecasted weather event (rain or no rain with $p > 0.5$) did not occur as predicted. Robust standard errors are clustered at the individual level to account for within-farmer serial correlation.

For the agricultural decision-making game, we consider farmers decisions, and whether farmers make the *ex ante* optimal decision. The specification for this game is similar but includes variables for false positives and negatives, as well as the probability information provided in the forecasts:

$$Y_{ir} = \beta_0 \ + \ \beta_1 \mathbf{T}_i^1 \ + \ \beta_2 \mathbf{T}_i^2 \ + \beta_3 \mathbf{FA}_{ir}^{rain} \ + \beta_4 \mathbf{FA}_{ir}^{no\ rain} \ + \ \gamma_4 \mathbf{P}_{ir} \\ + \mathbf{Order}_{ir}^{'} \alpha_1 \ + \ \mathbf{Format}_{ir}^{'} \alpha_2 \ + \ \mathbf{X}_{ir}^{'} \alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} \quad (3)$$

In this model, FA_{ir}^{rain} denotes whether the previous round had a false alarm (rain), occurring when rain is forecast with a probability of 50% or higher but fails to materialize; and $FA_{ir}^{no\ rain}$ indicates whether the previous round had a false alarm (no rain), occurring when rain is predicted with a probability of less than 50% yet unexpectedly occurs. P_{ir} reflects the forecasted probability in certain analyses and its deviation from 0.5 in others. Robust standard errors are clustered at the individual level to account for within-farmer serial correlation.

4.2 Learning from Information Treatments

We start by assessing learning from the video treatments (described in Section 3.2) by measuring farmers' understanding of probabilities, perceptions of climate change, and interpretation of weather forecasts after viewing the videos. First, we evaluate probability understanding with two 'test' questions posed immediately after the videos. The questions use classic probability puzzles: one involving choosing a bag with a better chance of yielding a black ball from a mix, and the other to identify the lottery offering higher likelihood of winning from varying ticket counts. Farmers must identify which option has a higher likelihood of a desired outcome and estimate the probability of that outcome. For climate change perceptions, we ask farmers about their expectations of the frequency of future unseasonal weather events. And, finally, to test weather forecast interpretation, we present a statement, "there is a 60% chance of rain tomorrow in your block/taluka," and assess understanding through multiple-choice answers that reflect different interpretations of probability.

While only 40% of farmers in the control group and 38% of farmers who watch just the climate change video correctly identified the more likely event in both probability questions (column 1, Table 3), the addition of probability training to the climate change salience intervention yielded a 5.8 percentage point or 14.5% relative improvement in probability comprehension (significant at the 10% level).

Regarding climate change (column 2), 42% of farmers in the control group recognize a trend towards more frequent unseasonal weather events. While the climate change salience video alone has no impact on these perceptions, 6.7 percentage points or 15.9% more farmers expect unseasonal weather more frequently in the future when probability training is added. For forecast interpretation (column 3), 16% of control farmers correctly understood the likelihood of rain, while 52% equated forecast probability with area coverage, which could still lead to a consistent interpretation of the probability of rain at specific locations.

Table 3: 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)
Climate change salience (CC)	-0.023	0.007	0.014	0.005
	(0.033)	(0.029)	(0.025)	(0.038)
Probability training (PT) [(CC + PT) - CC]	0.058*	0.067**	0.007	0.076**
	(0.033)	(0.028)	(0.026)	(0.037)
CC + PT = 0, *p-val*	0.33	0.02	0.46	0.05
N	1212	1211	1212	1211
Outcome mean, comparison group	0.400	0.420	0.160	-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 (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone.

A composite standardized index of the three learning outcomes (in column 4) shows a significant positive effect of the probability training and climate change salience videos (0.076 standard deviations), indicating a modest overall treatment impact in this arm.

4.3 Location Choice Game

In this section, we examine farmers' performance in the incentivized location-choice game (see Section 3, Table B2, Figure 4), and consider the effects of both instructional learning and experiential learning on farmers' strategic choices as the game progresses.

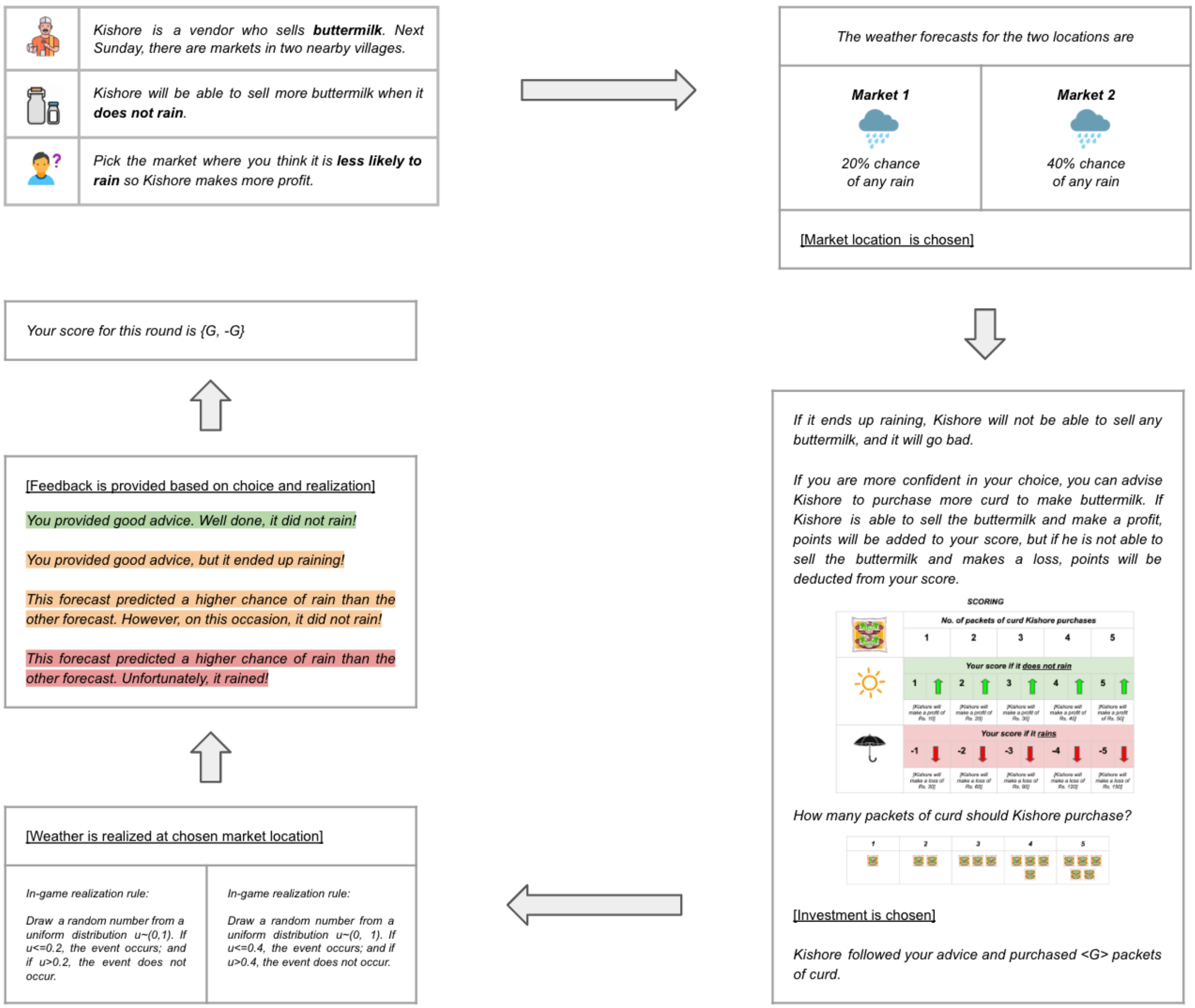


Figure 4: A single round in the location-choice game (Game 1)

Fifty-six percent of farmers in the control group consistently make the correct location choice in all game rounds. This proficiency in the game is notably higher than the proportion of farmers who answer the probability 'test' questions correctly, suggesting that weather may provide a more relatable context for understanding probability. Table 4 reveals that 85% of decisions made by farmers in the control group across all rounds are *ex ante* optimal, and farmers invest an average of 4.08 points per round. However, it also indicates that the informational interventions do not significantly impact the likelihood of making the *ex ante* optimal location choice or the number of points staked (investment).

Table 4: Outcomes in the Location Choice Game

	Ex Ante Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice	*Ex Ante* Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice	*Ex Ante* Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate change salience (CC)	-0.002	-0.007	0.004	0.001	0.025	0.034	-0.002	-0.007	0.003
	(0.013)	(0.049)	(0.116)	(0.014)	(0.050)	(0.119)	(0.013)	(0.049)	(0.117)
Probability training (PT) [(CC + PT) - CC]	0.008	0.071	0.089	0.008	0.071	0.089	0.011	0.105**	0.121
	(0.013)	(0.048)	(0.111)	(0.013)	(0.047)	(0.111)	(0.013)	(0.049)	(0.119)
False alarm in preceding round	-0.062***	-0.344***	-0.713***	-0.054***	-0.253***	-0.628***	-0.060***	-0.305***	-0.677***
	(0.011)	(0.032)	(0.091)	(0.019)	(0.058)	(0.165)	(0.013)	(0.039)	(0.105)
Climate change salience × False alarm in preceding round				-0.012	-0.126*	-0.119			
				(0.024)	(0.069)	(0.195)			
Probability training × False alarm in preceding round							-0.009	-0.132*	-0.124
							(0.025)	(0.069)	(0.202)
Difference between forecast probabilities	0.105***	0.339***	1.198***	0.105***	0.339***	1.199***	0.105***	0.338***	1.198***
	(0.020)	(0.060)	(0.164)	(0.020)	(0.060)	(0.164)	(0.020)	(0.060)	(0.164)
CC + PT = 0, *p-val*	0.65	0.21	0.46						
N	6060	6060	6060	6060	6060	6060	6060	6060	6060
Outcome mean, comparison group	0.854	4.085	2.998	0.854	4.085	2.998	0.854	4.085	2.998

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 preceding 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 (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone. The outcome in columns (1), (4), (7) is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in columns (2), (5), (8) is the investment that farmers choose in that round $\in \{1, 2, 3, 4, 5\}$, i.e., the number of points at stake; the outcome in columns (3), (6), (9) is the investment if the farmer makes the correct choice and -investment if the farmer makes the wrong choice.

Experience or experience-based learning, however, plays a critical role in shaping farmers' decisions. Table 4 and Table B3 demonstrate significant responsiveness to recent forecasting errors, with a tendency to choose less accurately and invest more conservatively in rounds following a false alarm, referring here to a forecasted event that fails to materialize as predicted. Table B3 further illustrates that the magnitude of this effect is proportional to the difference in the two forecast probabilities between two presented options in a round. Notably, column (8) of Table 4 suggests that adding probability training to the climate change salience intervention enhances investments in rounds that follow a correctly forecasted event, but this effect is entirely offset in rounds preceded by a false alarm.

Table B4 provides further insights into the learning dynamics over the course of the game.

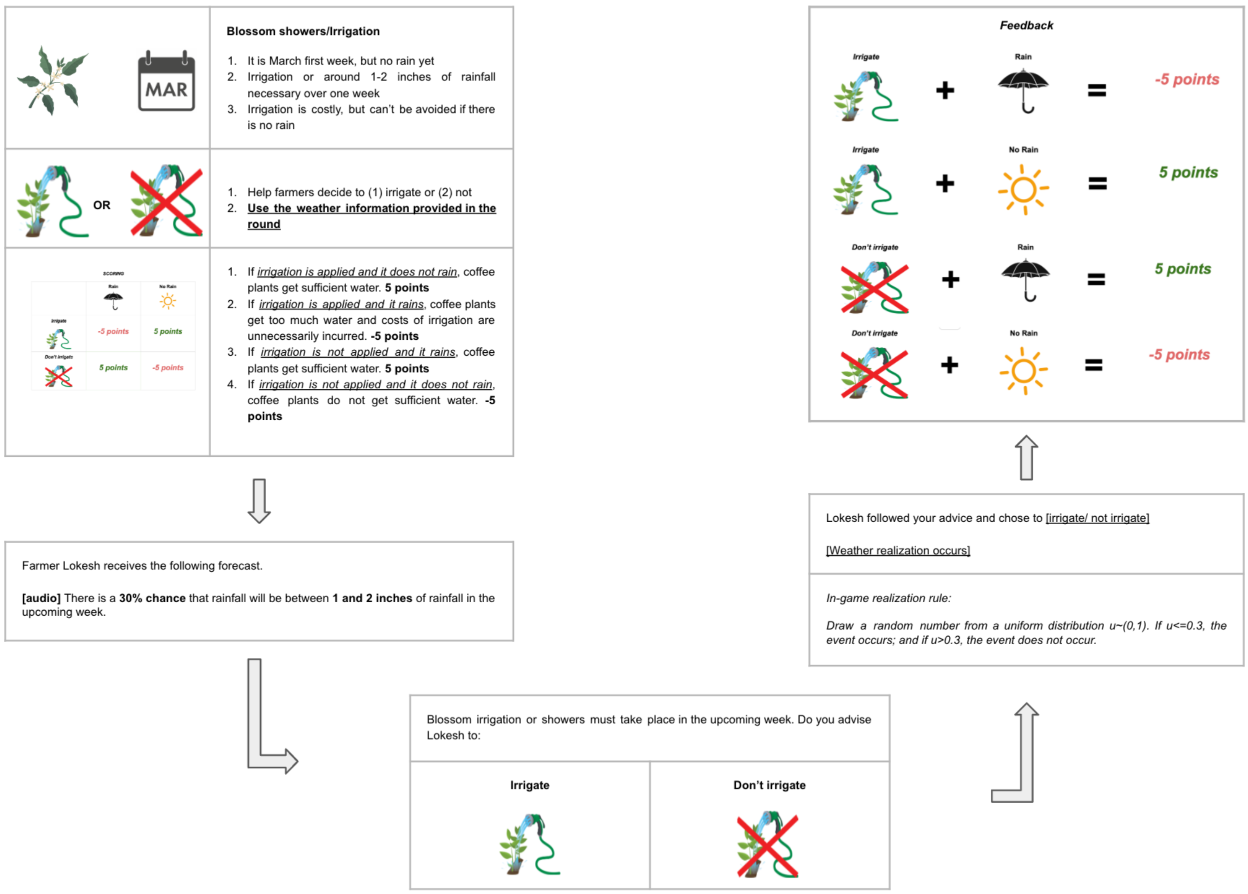


Figure 5: A single round in the agricultural decision-making game (Game 2)

Columns 7, 8, and 9 compare rounds in which farmers have already experienced with rounds where farmers have not experienced false alarms. When farmers have not encountered any false alarms in the game, there is a discernible positive trend in both investment levels and the selection of the *ex ante* optimal choice as the game progresses, although the latter is only significant at the 10% level. Conversely, this learning effect is negated once farmers experience false alarms. These result indicate that false alarms impede both learning over time, and learning from instruction, with the strong results on 'investment' suggesting that this may arise from a reduction in confidence, either in the accuracy of the forecasts or in ability to interpret the forecast.

4.4 Agricultural Decision-Making Game

Here, we examine farmers' choices in an incentivized agricultural decision-making game, which simulates real-life farming decisions that are contingent on weather. The structure and rules of the game are detailed in Section 3.3, summarized in Table B2, and an example round is in Figure 5.

We first look at farmers' decisions in rounds with no weather forecast information, where we assume that the *ex ante* optimal decision is to take an action appropriate for expected weather based on the historical weather distribution in the region. In column (1), Table 5, we see that neither informational intervention nor prior experiences with inaccurate forecasts (false alarms for rain or false alarms for no rain) significantly impact farmers' decisions. These scenarios prompted farmers to think about the historical occurrence of 'wet' versus 'dry' weather in their villages when no forecasts were provided, and reflect farmers' prior beliefs about the likelihood of 'wet' conditions on average. While 20.3% of participants recommend the action that is appropriate for 'wet' conditions in rounds without any forecasts,[9] data from NASA's IMERG precipitation dataset (which is aggregated to the block-level) indicate that the 'wet' conditions in each scenario occurred 10% of the time in the preceding twenty-two years.[10]

Columns (2) and (3) in Table 5 present results from rounds with forecasts in the second experimental game. Here, we evaluate whether farmers take decisions that maximize their expected payoff in a round *ex ante*, based on the weather forecast they receive. Farmers maximize their expected payoff in a round by selecting the action appropriate for 'wet' conditions when rain is forecasted with $p > 0.5$, and selection the action appropriate for 'dry' conditions when rain is forecated with $p < 0.5$.[11] When farmers' actions correspond to these expectations, we classify them as optimal. In column (4), we pool all forecast rounds (those where rain is predicted and where it is not), and evaluate whether farmers' take the action appropriate for 'wet' conditions alone. We do this so that we may interpret results as being indicative of farmers' belief in the likelihood of rain.

[9] Table B8 indicates that 15.4% of farmers recommended irrigation and 24.3% recommended fertilizer application in the relevant rounds.

[10] Details here: https://gpm.nasa.gov/data/imerg

[11] Either action is optimal when $p = 0.5$, which occurs in 7.5% of observations. To simplify analysis, we group $p = 0.5$ with $p > 0.5$, but results are unchanged if they are grouped with $p < 0.5$ instead. The action appropriate for 'wet' conditions is to not irrigate in the irrigation scenario, and to not fertilizer in the fertilizer application scenario. The action appropriate for 'dry' conditions is to irrigate in the irrigation scenario, and to apply fertilizer in the fertilizer application scenario.

Table 5: Outcomes in the Agricultural Decision Making Game

	Ex ante Optimal Action			**Action appropriate for 'wet' conditions**
	No Forecast	*Forecast: Rainfall ($p >= 0.5$)*	*Forecast: No Rainfall ($p < 0.5$)*	*All Forecasts (Pooled)*
	(1)	(2)	(3)	(4)
Climate change salience (CC)	-0.029	-0.002	0.036	-0.019
	(0.021)	(0.024)	(0.024)	(0.017)
Probability training (PT) [(CC + PT) - CC]	0.004	-0.000	-0.045*	0.025
	(0.020)	(0.024)	(0.025)	(0.017)
False alarm (rain) in preceding forecast round [$P[Rain] >= 0.5$ & rain NOT realized]	0.008	-0.061**	0.088***	-0.080***
	(0.024)	(0.031)	(0.031)	(0.021)
False alarm (no rain) in preceding forecast round [$P[Rain] < 0.5$ & rain realized]	-0.001	0.065**	-0.034	0.055**
	(0.025)	(0.030)	(0.031)	(0.021)
Forecast probability (deviation from 0.5) (current round)		0.520***	0.362***	
		(0.073)	(0.083)	
Forecast probability (current round)				0.501***
				(0.031)
CC + PT = 0, *p-val*	0.25	0.94	0.74	0.77
N	2424	2552	2296	4848
Outcome mean, comparison group	0.199	0.563	0.349	0.442

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 in preceding round (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 in the preceding round (no rain) represents a false negative forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p < 0.5$, and occurs, and is 0 otherwise. Climate change salience (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone.

Outcomes: In columns (1), (2), (3) 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 the action appropriate for 'wet' conditions, and 0 otherwise, while in scenarios where the forecast probability, $p < 0.5$, the outcome is 1 when the farmer recommends the action appropriate for 'dry' conditions, and 0 otherwise. In column (4), the outcome is 1 when the farmer recommends the action appropriate for 'wet' conditions, and is 0 otherwise, irrespective of the forecast, allowing us to gauge whether farmers expect rain in any round.

We see that the information treatments do not impact the likelihood of farmers' selecting the *ex ante* optimal action either in forecasts with rainfall predicted, $p >= 0.5$ or $p < 0.5$, nor when we pool results in column (4). Table 5 indicates that farmers respond to the probability in the forecasts, being more likely to recommend the action appropriate for 'wet' conditions when rainfall is forecasted with a higher probability.

Experiencing false alarms plays a critical role in shaping farmers' decision-making processes. Results across columns (2), (3) and (4) indicate that farmers adjust their expectations of rainfall based on the accuracy of previous forecasts. After a false alarms where rain was forecast ($P[rain] >= 0.5$) but did not materialize, farmers appear more skeptical about future rainfall predictions — farmers are less likely to expect rain, controlling for the forecast probability. Conversely, when unexpected rain occurs despite a low forecast probability ($P[rain] < 0.5$), farmers are more likely to expect rain, controlling for forecast probability. Together, these results suggest that farmers adjust their beliefs in the accuracy of the forecast following forecast errors or false alarms. Moreover, our analysis also indicates that farmers are most impacted by the most recent false alarms that they experience. In Table B10, we see robust evidence that the most recent false alarms significantly impact farmers' decisions across specifications where we progressively control for older false alarms. This suggests that farmers continue to update their beliefs about the accuracy of forecasts as they continue to interact with forecasts.

We next discern whether the observed effects are a direct consequence of forecast probabilities or merely the occurence of rain. First, we look at whether the magnitude of the forecasting error impacts farmers' decisions in Table B6. Here, the incidence of false alarms are weighted by the probability in the forecast that was errroneous.[12] We find that the magnitude of impact on farmers decisions is increasing in the magnitude of error, suggesting that the probability conveyed in the forecast does impact farmers' beliefs. Moreover, when controlling for the mere occurence of rain without considering whether the forecast was erroneous (Table B7), results indicate that while the absence of rain generally lowers expectations of rainfall in following rounds, the impact of a false alarm predicting rain lowers expectations even further. However, this distinction is not observed for false alarms predicting no rain, suggesting that farmers' beliefs are more adversely affected by missed forecasts of rain than by unexpected rainfall. This suggests that there is strong evidence that farmers do respond to and are discouraged by false alarms for rain in particular.

4.5 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 to be provided via the *Coffee Krishi Taranga* service run by Precision Development (PxD) with the Coffee Board of India. Willingness to pay

[12] False alarms for no rain are weighted by (1-p), while those for rain are weighted by p so that magnitudes of effects in both cases are comparable.

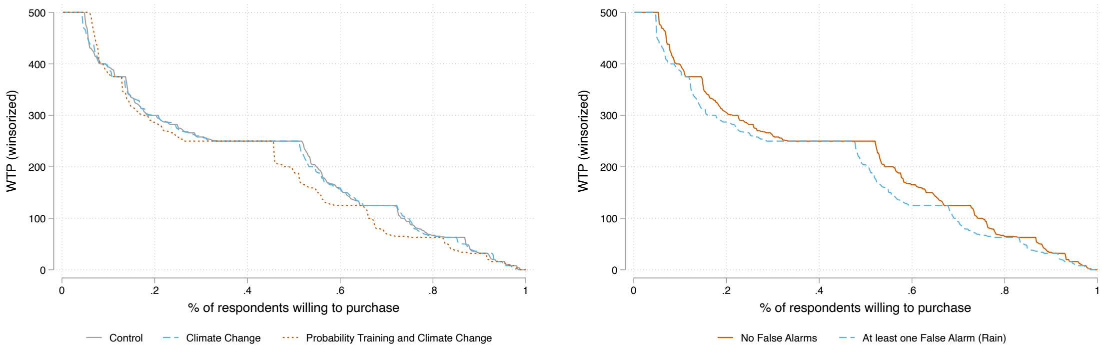


Figure 6: Willingness to Pay for Probabilistic Weather Forecasts

is elicited using an incentive compatible Becker-DeGroot-Marshak (BDM) (1964) mechanism, relying on a binary search process (following Berkouwer and Dean (2022); Burlig et al. (2022)). The weather forecasts being offered are produced by the Climate Forecast Applications Network (CFAN), and are for a period that covers critical weather sensitive activities (harvesting, blossom irrigation, pre-monsoon fertilizer application) outside of the monsoon season when rain is less frequent. Skill scores from re-forecasts over the last-six years indicate that the accuracy in each district is over 90%. These forecasts are more granular than those provided by the Indian Meteorological Department (IMD), and these forecasts are probabilistic, while those provided by the IMD are deterministic. These forecasts are also likely more granular than other forecasts available online. Farmers are told the following about the weather forecasts they may purchase in the BDM exercise:

"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]."

The accuracy referred to above refers to the hit-rate[13] for a cumulative weekly forecast, which farmers have encountered in the decision-making game's audio forecast rounds. We conduct a practice BDM round prior to the main BDM exercise. Comprehension checks in the BDM exercise for the weather forecast service indicate that most farmers understand the exercise correctly.[14]

Table 6 indicates that farmers who experience false alarms for rainfall in the agricultural-

[13]Hit-rate or Probability of detection = $\frac{hits}{hits+misses}$ (Collaboration for Australian Weather and Climate Research) or the number of correctly forecast rainfall events over the total number of rainfall events

[14]93% of farmers correctly believe that they will purchase the forecasts if the BDM secret price is lower than their final willingness to pay; and 78% correctly believe that they cannot purchase the forecasts if the BDM secret price is higher than their final willingness to pay.

Table 6: Willingness to Pay for Probabilistic Weather Forecasts

	WTP (₹ per month)		**WTP** (₹ per month, inverse hyperbolic sine)	
	(1)	(2)	(3)	(4)
Climate change salience (CC)	-0.000	-0.009	-0.001	-0.002
	(1.104)	(1.105)	(0.065)	(0.064)
Probability training (PT) [(CC + PT) - CC]	-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***	-2.546**	-0.133**	-0.141**
	(0.948)	(1.002)	(0.056)	(0.058)
Any false alarms (no rain) in game 2	0.901	0.993	0.085	0.094
	(0.955)	(0.987)	(0.056)	(0.060)
Total No. of Realizations in game 2		-0.134		-0.012
		(0.490)		(0.030)
CC + PT = 0, *p-val*	0.10	0.09	0.05	0.05
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.
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 (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone.

decision making game are willing to pay ₹2.46 less per month for the voice-call based weather service than their counterparts who do not experience these forecast errors. The response to false alarms for no rain (i.e., no rain is predicted, but rain occurs) is not significant, however. This is consistent with results in Table B7, where only forecast alarms where rain is erroneously predicted affected farmers' belief in the likelihood of rain once mere realizations were accounted for. In addition, the impact on willingness to pay suggests that the effect does reflect farmers' beliefs in the accuracy of the forecast. These results are also robust to accounting for the magnitude of the forecast error in Table B12, and to controlling for farmers' scores in the experimental games Table B13. In addition, the impact of false alarms on the total score in the preceding games in column (3) in Table B13 also indicates that the false alarms where rain is erroneously predicted in the agricultural decision-making game do not impact scores, reassuring us that neither the minimal boost in liquidity from game winnings nor discouragement from performing worse in the game is driving this result.

Finally, we consider how farmers' willingness-to-pay for real-world probabilistic weather forecasts responds to the information treatments. Recollect that Table 3 indicated that adding probability training to the climate change salience informational treatment increased farmers' understanding of probabilities, and awareness of climate change. So, a reduction in farmers' willingness to pay for forecasts by ₹2.06 per month (or 7% of the control group's mean willingness to pay, significant at the 10% level) observed in Table 6 when farmers undergo light-touch probability training is counter-intuitive. Figure 7 and Table B11 indicates that this reduction in willingness to pay for forecasts in most pronounced among the sample of farmers who report already having access to forecasts online, and who report already having access to forecasts at the block level or below. This suggests that when farmers improve understanding of probabilities and are made more aware of climate change, they may see increased value in forecasts that they already have access to through the internet, provided they are are perceived to be granular. This increased value may then result in a lower willingness to pay for a paid forecast service when compared to farmers who do not have access to such forecasts, since their second best option may now be perceived to be better.

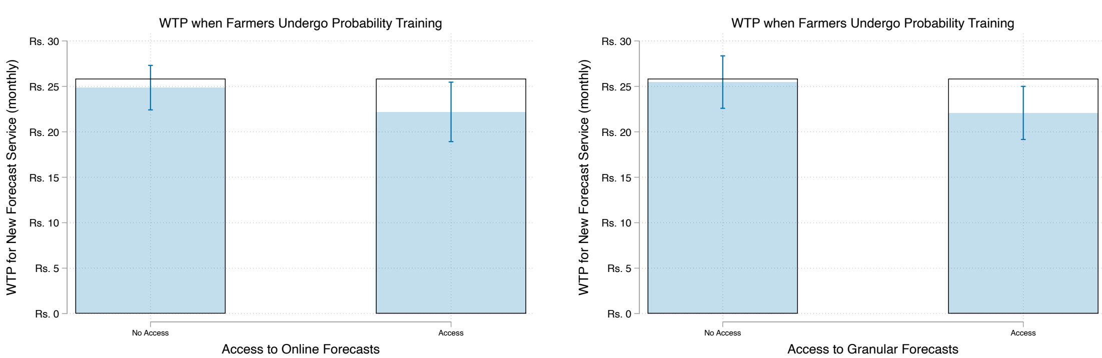


Figure 7: Willingness to Pay for Probabilistic Weather Forecasts

5 Discussion and Conclusion

We find that coffee farmers in Karnataka, India are willing to pay ₹26 per month (or 10% of the mean daily wage rate in Karnataka), on average, to receive weekly mobile-phone based, probabilistic, audio weather forecasts. Over 98% of farmers in the study sample are willing to pay non-zero amounts for these forecasts, and all farmers report interest in using such a service. This suggests that there is substantial demand for better quality better forecasts among coffee farmers in Karnataka, India.

In incentivized decision-making games, most farmers correctly act on probabilities in weather forecasts. More farmers are correct when they select a more/less likely forecast out of a pair of forecasts than they are when they answer simple 'test' probability questions (57% answer all rounds in the location-choice game correctly, while only 40% answer both 'test' questions correctly). In fact, even those farmers who do not answer all questions correctly, are correct in 66% of their choices in the location-choice game, doing better when the difference between the probabilities in the two forecasts is larger. Farmers' responses in scenarios designed to mimic real-world agricultural decision-making indicate that they are more likely to expect rain to occur when the probability of rain in the forecast is higher. Together, this reinforces findings in Delavande (2014) that rural populations in developing countries understand probabilistic information, and suggests value in providing probabilistic weather forecasts to a wider population.

While light-touch informational video on the salience of climate change has no impact on farmers, adding probability training to the treatment improves farmers' understanding of probabilities, and awareness of climate change. This impact translates into larger investments in the location choice game when farmers experience positive reinforcement, suggesting increased confidence in a concept they perhaps somewhat understand. However, this improvement is completely set-back when farmers experience an erroneous forecast.

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 an erroneous forecast. Farmers' beliefs are most impacted by erroneous forecasts of rainfall, which are most recent. This suggests that trust in forecasts can recover as farmers experience more accurate predictions, consistent with simulation results in (Shafiee-Jood et al., 2021). However, if farmers get discouraged from using following multiple consecutive forecast errors, trust in forecast accuracy may not recover, providing some insights on trust and learning in the context of adopting new technologies.

References

Alidaee, Hossein (2023). "How uncertainty about heterogeneity impacts technology adoption," *Working Paper*.

Auffhammer, Maximilian and Tamma A. Carleton (2018). "Regional crop diversity and weather shocks in india," *Asian Development Review*, 35: 113–130.

Barnett-Howell, Zachary (2021). "No small potatoes: Agricultural risk and investment under uncertainty," *Working Paper*.

Becker, Gordon M., Morris H. DeGrot, and Jacob Marschak (1964). "Measuring utility by a single-response sequential method," *Behavioral Science*, 9(3): 262–232.

Benjamin, Daniel J. (2019). "Errors in probabilistic reasoning and judgment biases," in Stefano DellaVigna B. Douglas Bernheim and David Laibson (eds.), "Handbook of Behavioral Economics: Applications and Foundations 1," volume 2, chapter 2, Elsevier, pp. 69–186.

Berkouwer, Susanna B. and Joshua T. Dean (2022). "Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households," *American Economic Review*, 112(10): 3291–3330.

Burlig, Fiona, Amir Jina, Erin M. Kelley, Gregory Lane, and Harshil Sahai (2022). "The value of forecasts: Experimental evidence from developing-country agriculture," *Pre-Analysis Plan*.

Camacho, Adriana and Emily Conover (2019). "The impact of receiving sms price and weather information on small scale farmers in colombia," *World Development*, 123.

Chandrashekhar, Vinay Doranalu and Amba Shetty (2017). "Trends in extreme rainfall over ecologically sensitive western ghats and costal regions of karnataka: an observational assessment," *Arabian Journal of Geosciences*, 11(327).

Cole, Shawn and Nilesh Fernando (2020). "Mobile'ising agricultural advice: Technology adoption, diffusion and sustainability," *The Economic Journal*, 131: 192–219.

Cole, Shawn A. and Wentao Xiong (2017). "Agricultural insurance and economic development," *Annual Review of Economics*, 9: 235–262.

Conlon, John J., Malavika Mani, Gautam Rao, Matthew W. Ridley, and Frank Schilbach (2022). "Not learning from others," *NBER Working Paper No. 30378*.

D'Acunto, Francesco, Ulrike Malmendier, Juan Ospina, and Michael Weber (2021). "Exposure to grocery prices and inflation expectations," *Journal of Political Economy*, 129: 1615–1639.

Delavande, Adeline (2014). "Probabilistic expectations in developing countries," *Annual Review of Economics*, 6: 1–20.

Emerick, Kyle, Alain de Janvry, Elisabeth Sadoulet, and Manzoor H. Dar (2016). "Technological innovations, downside risk, and the modernization of agriculture," *American Economic Review*, 106: 1537–1561.

Fabregas, Raissa, Michael Kremer, and Frank Schilbach (2019). "Realizing the potential of digital development," *Science*, 366.

Fafchamps, Marcel and Bart Minten (2012). "Impact of sms-based agricultural information on indian farmers," *The World Bank Economic Review*, 26: 383–414.

Foster, Andrew D. and Mark R. Rosenzweig (1995). “Learning by doing and learning from others: Human capital and technical change in agriculture,” *Journal of Political Economy*, 103: 1176–1209.

Fundel, Vanessa J., Nadine Fleischhut, Stefan M. Herzog, Martin Gober, and Renate Hagedorn (2019). “Promoting the use of probabilistic weather forecasts through a dialogue between scientists, developers and end-users,” *Quarterly Journal of the Meteorological society*, 145: 210–231.

Georganas, Sotiris, Paul J. Healy, and Nan Li (2014). “Frequency bias in consumers’ perceptions of inflation: An experimental study,” *European Economic Review*, 67: 144–158.

Gigerenzer, Gerd, Ralph Hertwif, Eva Van Den Broek, Barbara Fasolo, and Konstantinos V. Katsikopoulos (2009). “A 30tomorrow”: How does the public understand probabilistic weather forecasts?” *Risk Analysis*, 25: 623–629.

Giné, Xavier, Robert M. Townsend, and James Vickrey (2015). “Forecasting when it matters: Evidence from semi-arid india,” *Working Paper*.

Ha, Kyung-Ja, Suyeon Moon, Axel Timmermann, and Daeha Kim (2020). “Future changes of summer monsoon characteristics and evaporative demand over asia in cmp6 simulations,” *Gephysical Research Letters*, 47(8).

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart (2023). “Designing information provision experiments,” *Journal of Economic Literature*, 61(1): 3–40.

Janzen, Saran, Nicholas Magnan, Conner Mullally, Soye Shin, Bailey I. Palmer, Judith Oduol, and Karl Hughes (2020). “Can experimental games and improved risk coverage raise demand for index insurance? evidence from kenya,” *American Journal of Agricultural Economics*, 103: 338–361.

Karlan, Dean, Robert Osei, Isaac Osei-Skoto, and Christopher Udry (2014). “Agricultural decisions after relaxing credit and risk constraints,” *The Quarterly Journal of Economics*, 129: 597–652.

Krishnan, R., J. Sanjay, Chellappan Gnanaseelan, Milind Mujumdar, Ashwini Kulkarni, and Supriyo Chakraborty (2020). “Assessment of climate change over the indian region,” Technical report, Ministry of Earth Sciences (MoES), Government of India.

Linsenmeier, Manuel and Jeffrey Shrader (2023). “Global inequalities in weather forecasts,” *Working Paper*.

Lybbert, Travis J., Christopher B. Barrett, John G. McPeak, and Winnie K. Luseno (2007). “Bayesian herders: Updating of rainfall beliefs in response to external forecasts,” *World Development*, 35(3): 480–497.

Malmendier, Ulrike (2021a). “Experience effects in finance: Foundations, applications, and future directions,” *Review of Finance*, 25: 1339–1363.

Malmendier, Ulrike (2021b). “Fbbva lecture 2020 exposure, experience, and expertise: Why personal histories matter in economics,” *Journal of the European Economic Association*, 19: 2857–2894.

Mase, Amber Saylor and Linda Stalker Prokopy (2014). “Unrealized potential: A review of perceptions and use of weather and climate information in agricultural decision making,” *Weather, Climate and Society*, 6: 47–61.

Millner, Anthony (2008). “Getting the most out of ensemble forecasts: A valuation model based on user–forecast interactions,” *Journal of Applied Meteorology and Climatology*, 47: 2561–2571.

Muralidharan, Karthik, Mauricio Romero, and Kaspar Wüthrich (2023). “Factorial designs, model selection, and (incorrect) inference in randomized experiments,” *The Review of Economics and Statistics*, (forthcoming).

Palfrey, Thomas R. and Stephanie W. Wang (2009). “On eliciting beliefs in strategic games,” *Journal of Economic Behavior and Organization*, 71: 98–109.

Roncoli, Carla, Keith Ingram, and Paul Kirshen (2002). “Reading the rains: Local knowledge and rainfall forecasting in burkina faso,” *Society Natural Resources: An International Journal*, 15: 409–427.

Rosenzweig, Mark R. and Christopher Udry (2019). “Assessing the benefits of long-run weather forecasting for the rural poor: Farmer investments and worker migration in a dynamic equilibrium model,” *NBER Working Paper No. 25894*.

Roulston, Mark, Gary Boulton, Andrew Kleit, and Addison Sears-Collins (2006). “A laboratory study of the benefits of including uncertainty information in weather forecasts,” *Weather and Forecasting*, 21(1): 116–122.

Roulston, Mark and Todd R. Kaplan (2009). “A laboratory-based study of understanding of uncertainty in 5-day site-specific temperature forecasts,” *Meteorological Applications*, 16: 237–244.

Roxy, M.L, Subimal Ghosh, Amey Pathak, R. Athulya, Milind Mujumdar, Ragu Murtugudde, Pascal Terry, and M. Rajeevan (2017). “A threefold rise in widespread extreme rain events over central india,” *Nature Communications*, 8.

Shafiee-Jood, Majid, Tatyana Deryugina, and Ximing Cai (2021). “Modeling users’ trust in drought forecasts,” *Water, Climate and Society*, 13: 649–664.

Sreenath, A.V., S. Abhilash, P. Vijaykumar, and B.E. Mapes (2022). “West coast india’s rainfall is becoming more convective,” *npj Climate and Atmospheric Science*, 5(36).

Stephens, Elisabeth, David J. Spiegelhalter, Ken Mylne, and Mark Harrison (2019). “The met office weather game: investigating how different methods for presenting probabilistic weather forecasts influence decision-making,” *Geoscience Communication*, 2(2): 101–116.

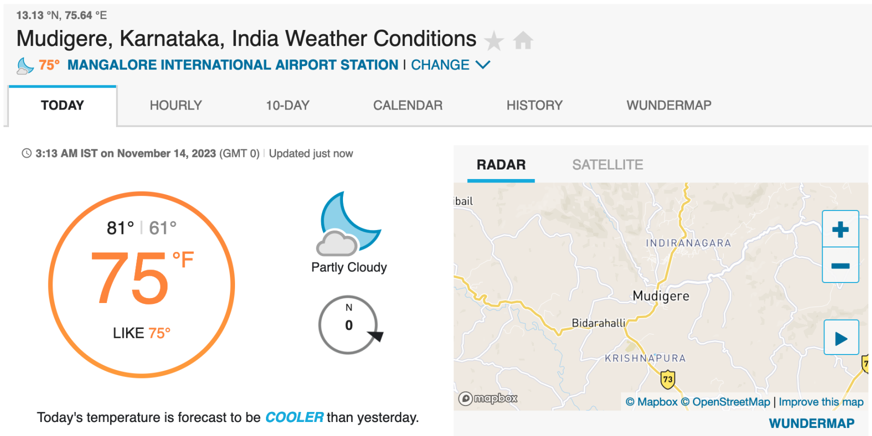
Tjernström, Emilia, Travis J. Lybbert, Rachel Hernández Frattarola, and Juan Sebastian Correa (2021). “Learning by (virtually) doing: Experimentation and belief updating in smallholder agriculture,” *Journal of Econmic Behavior and Organization*, 189: 28–50.

Tversky, Amos and Daniel Kahneman (1974). “Judgment under uncertainty: Heuristics and biases,” *Science*, 185: 1124–1131.

Varikoden, Hamza, J.V. Revadekar, J Kuttippurath, and C.A. Babu (2019). “Contrasting trends in southwest monsoon rainfall over the western ghats region of india,” *Climate Dynamics*, 52.

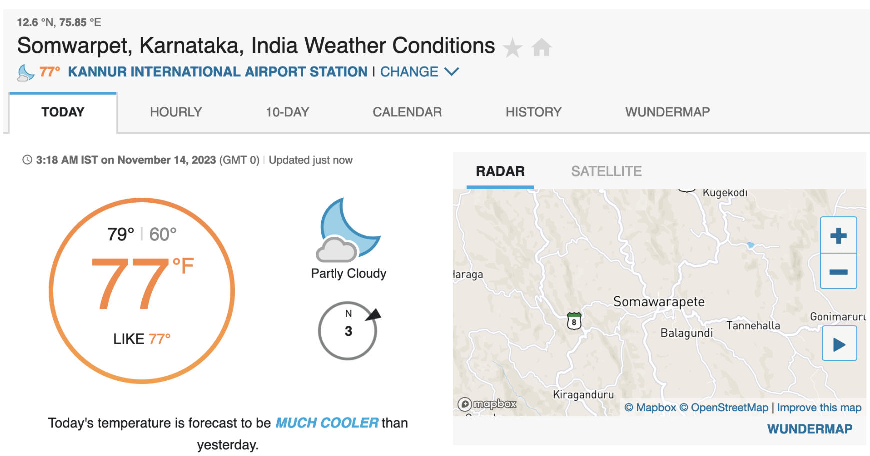
Yegbemey, Rosaine N., Gunther Bensch, and Colin Vance (2023). “Weather information and agricultural outcomes: Evidence from a pilot field experiment in benin,” *World Development*, 167: 623–629.

A Figures



Accessed at https://www.wunderground.com/weather/in/mudigere on 3.13 AM IST on Nov 14, 2023.

Mudigere is 127 kms away from Mangalore International Airport



Accessed at https://www.wunderground.com/weather/in/somwarpet on 3.18 AM IST on Nov 14, 2023.

Somwarpet is 124 kms away from Kannur International Airport

Figure 8: Forecasts for Mudigere and Somwarpet in Karnataka, India on Weather Underground

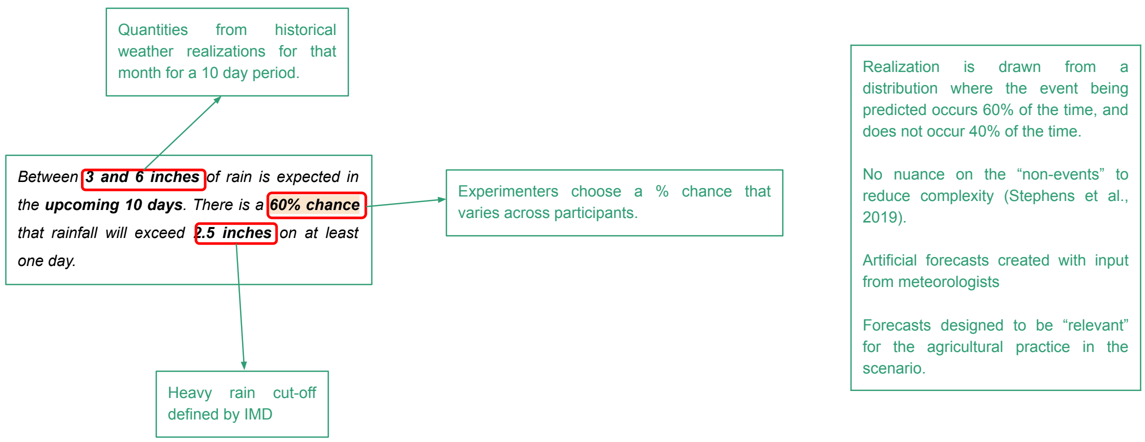


Figure 9: Examples of cumulative forecasts used in the games

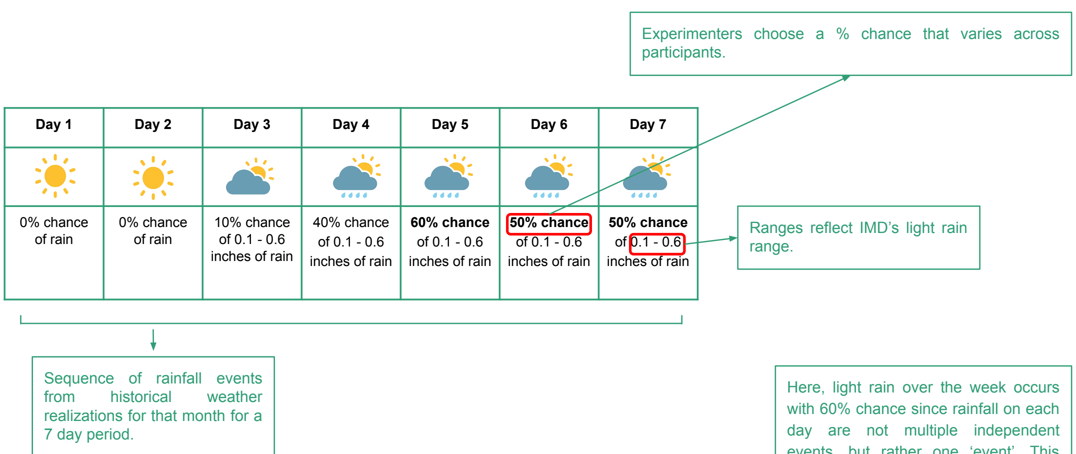


Figure 10: Examples of day-by-day forecasts used in the games

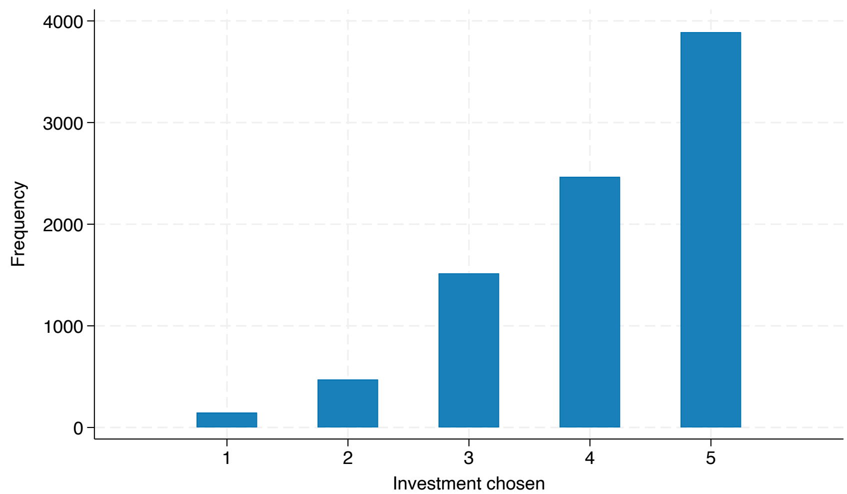


Figure 11: Investment Choices in Game 1

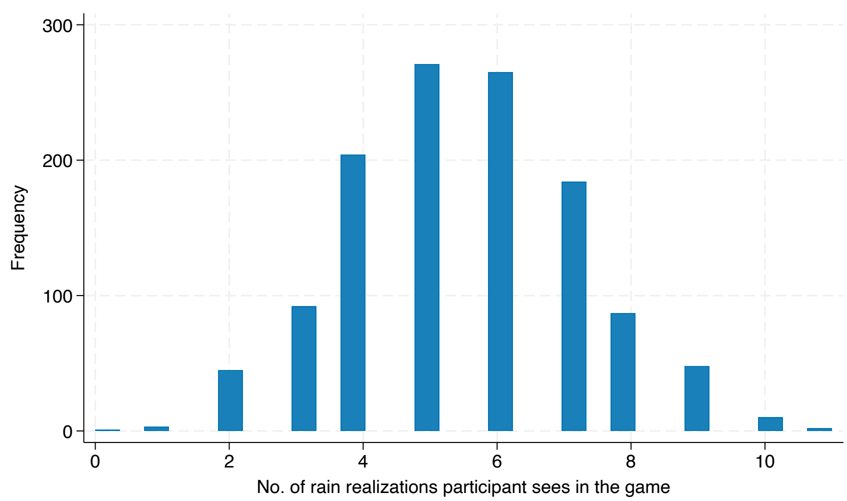


Figure 12: Rain Realizations in the Hypothetical Scenarios, Game 1 + Game 2

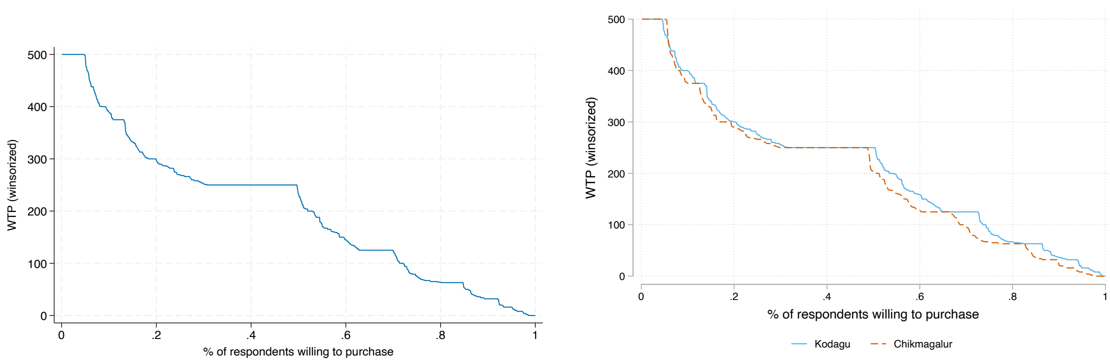


Figure 13: Willingness to Pay for Probabilistic Weather Forecasts

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: Impact of Weighted False Alarms in the Location Choice Game

	Ex Ante Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice	*Ex Ante* Optimal Choice Choice Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice	*Ex Ante* Optimal Choice Choice Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate change salience (CC)	-0.003	-0.010	-0.003	-0.002	-0.002	-0.002	-0.003	-0.010	-0.003
	(0.013)	(0.049)	(0.117)	(0.013)	(0.050)	(0.117)	(0.013)	(0.049)	(0.117)
Probability training (PT) [(CC + PT) - CC]	0.009	0.071	0.090	0.009	0.071	0.090	0.005	0.078	0.051
	(0.013)	(0.048)	(0.112)	(0.013)	(0.048)	(0.112)	(0.013)	(0.049)	(0.115)
False alarm in preceding round (weighted)	-0.115***	-0.546***	-1.279***	-0.112**	-0.470***	-1.272***	-0.129***	-0.521***	-1.423***
	(0.026)	(0.070)	(0.212)	(0.046)	(0.134)	(0.393)	(0.031)	(0.083)	(0.252)
Climate change salience × False alarm in preceding round (weighted)				-0.003	-0.107	-0.010			
				(0.054)	(0.154)	(0.456)			
Probability training × False alarm in preceding round (weighted)							0.049	-0.085	0.496
							(0.053)	(0.147)	(0.435)
Difference between forecast probabilities	0.104***	0.331***	1.184***	0.104***	0.331***	1.184***	0.104***	0.331***	1.183***
	(0.020)	(0.061)	(0.166)	(0.020)	(0.061)	(0.166)	(0.020)	(0.061)	(0.166)
CC + PT = 0, *p-val*	0.67	0.23	0.48						
N	6060	6060	6060	6060	6060	6060	6060	6060	6060
Outcome mean, comparison group	0.854	4.085	2.998	0.854	4.085	2.998	0.854	4.085	2.998

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 preceding 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 (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone. The outcome in columns (1), (4), (7) is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in columns (2), (5), (8) is the investment that farmers choose in that round $\in \{1, 2, 3, 4, 5\}$, i.e., the number of points at stake; the outcome in columns (3), (6), (9) is the investment if the farmer makes the correct choice and -investment if the farmer makes the wrong choice.

Table B4: Order Effects in the Location Choice Game

	Ex Ante Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice	*Ex Ante* Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice	*Ex Ante* Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate change salience (CC)	-0.016	-0.053	-0.059	-0.002	-0.007	0.008	-0.002	-0.008	0.008
	(0.023)	(0.070)	(0.200)	(0.013)	(0.049)	(0.116)	(0.013)	(0.048)	(0.115)
Probability training (PT) [(CC + PT) - CC]	0.008	0.071	0.097	0.003	0.101	0.132	0.010	0.078^{*}	0.112
	(0.013)	(0.048)	(0.110)	(0.024)	(0.067)	(0.199)	(0.013)	(0.047)	(0.109)
False alarm in preceding round	-0.063^{***}	-0.342^{***}	-0.707^{***}	-0.063^{***}	-0.342^{***}	-0.707^{***}			
	(0.011)	(0.032)	(0.090)	(0.011)	(0.032)	(0.090)			
Order	-0.007	-0.032^{*}	-0.046	-0.005	-0.019^{*}	-0.027	0.009^{*}	0.051^{***}	0.124^{***}
	(0.006)	(0.017)	(0.051)	(0.004)	(0.011)	(0.034)	(0.005)	(0.014)	(0.041)
Climate change salience × Order	0.005	0.016	0.022						
	(0.007)	(0.018)	(0.057)						
Probability training × Order				0.002	-0.010	-0.012			
				(0.007)	(0.018)	(0.057)			
Any false alarms in the game until current round							-0.064^{***}	-0.250^{***}	-0.635^{***}
							(0.025)	(0.068)	(0.207)
Any false alarms in the game until current round × Order							-0.005	-0.045^{**}	-0.082
							(0.007)	(0.019)	(0.058)
Difference between forecast probabilities	0.106^{***}	0.339^{***}	1.182^{***}	0.105^{***}	0.338^{***}	1.181^{***}	0.105^{***}	0.333^{***}	1.175^{***}
	(0.020)	(0.061)	(0.165)	(0.020)	(0.061)	(0.164)	(0.020)	(0.060)	(0.164)
N	6060	6060	6060	6060	6060	6060	6060	6060	6060
Outcome mean, comparison group, round 1	0.869	4.206	3.189	0.869	4.206	3.189	0.869	4.206	3.189

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, 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 preceding round is an indicator that takes the value 1 when the forecasted event in the *ex ante* optimal choice does not occur in the prior round, and 0 otherwise. Any false alarms in the game is an indicator that takes the value 1 when the farmer experience at least one false alarm across all rounds of the game. Climate change salience (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone. The outcome in columns (1), (4), (7) is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in columns (2), (5), (8) is the investment that farmers choose in that round $\in \{1, 2, 3, 4, 5\}$, i.e., the number of points at stake; the outcome in columns (3), (6), (9) is the investment if the farmer makes the correct choice and -investment if the farmer makes the wrong choice.

Table B5: Difficulty Effects in the Location Choice Game

	Ex Ante Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice	*Ex Ante* Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice	*Ex Ante* Optimal Choice	Investment Chosen	Investment Weighted *Ex Ante* Optimal Choice
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Climate change salience (CC)	-0.015	-0.014	-0.136	-0.001	-0.007	0.009	-0.001	-0.006	0.009
	(0.017)	(0.058)	(0.142)	(0.013)	(0.049)	(0.116)	(0.013)	(0.049)	(0.116)
Probability training (PT) [(CC + PT) - CC]	0.008	0.070	0.094	0.001	0.094*	0.047	0.008	0.070	0.094
	(0.013)	(0.048)	(0.111)	(0.015)	(0.056)	(0.133)	(0.013)	(0.048)	(0.111)
False alarm in preceding round	-0.062***	-0.342***	-0.708***	-0.062***	-0.341***	-0.709***	-0.055***	-0.338***	-0.668***
	(0.011)	(0.032)	(0.089)	(0.011)	(0.032)	(0.089)	(0.016)	(0.045)	(0.126)
Difference in prob <0.25	-0.053***	-0.126***	-0.594***	-0.038***	-0.103***	-0.428***	-0.031***	-0.114***	-0.384***
	(0.017)	(0.045)	(0.136)	(0.011)	(0.031)	(0.087)	(0.009)	(0.028)	(0.079)
Climate change salience × Difference in prob <0.25	0.026	0.015	0.268*						
	(0.020)	(0.055)	(0.160)						
Probability training × Difference in prob <0.25				0.013	-0.044	0.085			
				(0.019)	(0.054)	(0.154)			
False alarm in preceding round × Difference in prob <0.25							-0.013	-0.006	-0.073
							(0.022)	(0.058)	(0.178)
N	6060	6060	6060	6060	6060	6060	6060	6060	6060
Outcome mean, comparison group	0.854	4.085	2.998	0.854	4.085	2.998	0.854	4.085	2.998

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 preceding 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 (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone. The outcome in columns (1), (4), (7) is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in columns (2), (5), (8) is the investment that farmers choose in that round $\in \{1, 2, 3, 4, 5\}$, i.e., the number of points at stake; the outcome in columns (3), (6), (9) is the investment if the farmer makes the correct choice and -investment if the farmer makes the wrong choice.

Table B6: Impact of Weighted False Alarms in the Agricultural Decision Making Game

	Ex ante Optimal Action			**Action appropriate for 'wet' conditions**
	No Forecast	*Forecast: Rainfall ($p >= 0.5$)*	*Forecast: No Rainfall ($p < 0.5$)*	*All Forecasts (Pooled)*
	(1)	(2)	(3)	(4)
Climate change salience (CC)	-0.029	-0.002	0.035	-0.020
	(0.021)	(0.024)	(0.024)	(0.017)
Probability training (PT) [(CC + PT) - CC]	0.004	-0.001	-0.045*	0.025
	(0.020)	(0.024)	(0.025)	(0.017)
False alarm (rain) in preceding forecast round [$P[Rain] >= 0.5$ & rain NOT realized], weighted	0.025	-0.105**	0.136***	-0.126***
	(0.038)	(0.049)	(0.049)	(0.033)
False alarm (no rain) in preceding forecast round [$P[Rain] < 0.5$ & rain realized], weighted	0.008	0.160*	-0.137	0.191***
	(0.073)	(0.089)	(0.096)	(0.064)
Forecast probability (deviation from 0.5) (current round)		0.519***	0.359***	
		(0.073)	(0.083)	
Forecast probability (current round)				0.500***
				(0.031)
CC + PT = 0, *p-val*	0.25	0.91	0.72	0.78
N	2424	2552	2296	4848
Outcome mean, comparison group	0.199	0.563	0.349	0.442

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 in the preceding round (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 in the preceding round (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 (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone.

Outcomes: In columns (1), (2), (3) 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 the action appropriate for 'wet' conditions, and 0 otherwise, while in scenarios where the forecast probability, $p < 0.5$, the outcome is 1 when the farmer recommends the action appropriate for 'dry' conditions, and 0 otherwise. In column (4), the outcome is 1 when the farmer recommends the action appropriate for 'wet' conditions, and is 0 otherwise, irrespective of the forecast, allowing us to gauge whether farmers expect rain in any round.

Table B7: Impact of Rainfall Realizations and False Alarms in the Agricultural Decision-Making game

	Action appropriate for 'wet' conditions		
	Rain is NOT realized in preceding forecast round	*Rain is realized in preceding forecast round*	*All rounds*
	(1)	(2)	(3)
Climate change salience (CC)	-0.012	-0.033	-0.018
	(0.022)	(0.027)	(0.017)
Probability training (PT) [(CC + PT) - CC]	0.002	0.063^{**}	0.025
	(0.022)	(0.028)	(0.017)
Rain NOT realized in preceding forecast round			-0.070^{***}
			(0.018)
False alarm (rain) in preceding forecast round [$P[Rain] >= 0.5$ & rain NOT realized]	-0.048^{**}		-0.048^{**}
	(0.024)		(0.023)
False alarm (no rain) in preceding forecast round [$P[Rain] < 0.5$ & rain realized]		0.022	0.013
		(0.025)	(0.024)
Forecast probability (current round)	0.515^{***}	0.468^{***}	0.499^{***}
	(0.040)	(0.049)	(0.031)
CC + PT = 0, *p-val*	0.69	0.30	0.72
N	2964	1884	4848
Outcome mean, comparison group	0.435	0.506	0.474

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. The outcome is 1 when the farmer recommends the action appropriate for 'wet' conditions, and is 0 otherwise, irrespective of the forecast, allowing us to gauge whether farmers expect rain in any round.

Table B8: Decisions in the Agricultural Decision Making Game, by scenario

	Irrigate		**Apply Fertilizer**	
	No Forecast Round	*Forecast Round*	*No Forecast Round*	*Forecast Round*
	(1)	(2)	(3)	(4)
Climate change salience (CC)	-0.015	0.007	0.073**	-0.045*
	(0.025)	(0.024)	(0.031)	(0.024)
Probability training (PT) [(CC + PT) - CC]	-0.008	0.018	0.002	0.031
	(0.023)	(0.025)	(0.032)	(0.023)
False alarm (rain) in preceding forecast round [$P[Rain] >= 0.5$ & rain NOT realized]	-0.043	-0.138***	0.034	-0.033
	(0.027)	(0.030)	(0.040)	(0.030)
False alarm (no rain) in preceding forecast round [$P[Rain] < 0.5$ & rain realized]	-0.008	0.087***	0.010	0.024
	(0.030)	(0.029)	(0.038)	(0.031)
Forecast probability (current round)		0.693***		0.293***
		(0.040)		(0.046)
CC + PT = 0, *p-val*	0.38	0.35	0.03	0.58
N	1212	2424	1212	2424
Outcome mean, comparison group	0.154	0.500	0.243	0.463

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

Table B9: Forecast Format Effects in the Agricultural Decision Making Game

	Action appropriate for 'wet' conditions					
	Audio Forecasts	*Text & Image Forecasts*	*All Forecasts*			
	(1)	(2)	(3)	(4)	(5)	(6)
Climate change salience (CC)	-0.033	-0.007	-0.003	-0.019	-0.019	-0.019
	(0.023)	(0.023)	(0.022)	(0.017)	(0.017)	(0.017)
Probability training (PT) [(CC + PT) - CC]	0.019	0.031	0.025	0.037*	0.025	0.024
	(0.024)	(0.023)	(0.017)	(0.022)	(0.017)	(0.017)
False alarm (rain) in preceding forecast round [$P[Rain] >= 0.5$ & rain NOT realized]	-0.055*	-0.099***	-0.079***	-0.079***	-0.095***	-0.080***
	(0.032)	(0.029)	(0.021)	(0.021)	(0.029)	(0.021)
False alarm (no rain) in preceding forecast round [$P[Rain] < 0.5$ & rain realized]	0.054*	0.068**	0.055**	0.054**	0.055**	0.071**
	(0.029)	(0.031)	(0.021)	(0.021)	(0.021)	(0.031)
Forecast probability (current round)	0.624***	0.380***	0.500***	0.501***	0.501***	0.501***
	(0.044)	(0.042)	(0.031)	(0.031)	(0.031)	(0.031)
Audio Forecasts			0.020	0.004	-0.007	0.001
			(0.028)	(0.022)	(0.020)	(0.021)
Climate change salience (CC) × Audio Forecasts			-0.032			
			(0.029)			
Probability training (PT) × Audio Forecasts				-0.024		
				(0.029)		
False alarm (rain) × Audio Forecasts					0.032	
					(0.042)	
False alarm (no rain) × Audio Forecasts						-0.031
						(0.041)
N	2424	2424	4848	4848	4848	4848
Outcome mean, comparison group	0.523	0.440	0.481	0.481	0.481	0.481

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 in preceding round (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 in the preceding round (no rain) represents a false negative forecast in the preceding forecast round. The variable takes the value 1 when rainfall was forecast with $p < 0.5$, and occurs, and is 0 otherwise. Climate change salience (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone.
Outcomes:The outcome is 1 when the farmer recommends the action appropriate for 'wet' conditions, and is 0 otherwise, irrespective of the forecast, allowing us to gauge whether farmers expect rain in any round. 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 B10: Impact of False Alarms in Recent Round in the Agricultural Decision Making Game

	Action appropriate for 'wet' conditions				
	(1)	(2)	(3)	(4)	(5)
False alarm (rain) in $round_{-1}$ [$P[Rain] >= 0.5$ & rain NOT realized]	-0.093**	-0.098***	-0.086***	-0.076***	-0.080***
	(0.036)	(0.029)	(0.026)	(0.024)	(0.021)
False alarm (rain) in $round_{-2}$ [$P[Rain] >= 0.5$ & rain NOT realized]	-0.046	-0.015	0.005	-0.009	
	(0.041)	(0.032)	(0.029)	(0.027)	
False alarm (rain) in $round_{-3}$ [$P[Rain] >= 0.5$ & rain NOT realized]	-0.008	-0.020	-0.035		
	(0.039)	(0.031)	(0.029)		
False alarm (rain) in $round_{-4}$ [$P[Rain] >= 0.5$ & rain NOT realized]	-0.023	-0.023			
	(0.041)	(0.038)			
False alarm (rain) in $round_{-5}$ [$P[Rain] >= 0.5$ & rain NOT realized]	0.007				
	(0.056)				
False alarm (no rain) in $round_{-1}$ [$P[Rain] < 0.5$ & rain realized]	0.048	0.066**	0.061**	0.056**	0.055**
	(0.039)	(0.030)	(0.027)	(0.025)	(0.021)
False alarm (no rain) in $round_{-2}$ [$P[Rain] < 0.5$ & rain realized]	0.039	0.012	0.015	0.014	
	(0.043)	(0.035)	(0.030)	(0.026)	
False alarm (no rain) in $round_{-3}$ [$P[Rain] < 0.5$ & rain realized]	0.028	0.024	0.019		
	(0.040)	(0.034)	(0.030)		
False alarm (no rain) in $round_{-4}$ [$P[Rain] < 0.5$ & rain realized]	0.063	0.022			
	(0.041)	(0.033)			
False alarm (no rain) in $round_{-5}$ [$P[Rain] < 0.5$ & rain realized]	-0.021				
	(0.042)				
Climate change salience (CC)	-0.007	-0.015	-0.026	-0.017	-0.019
	(0.030)	(0.024)	(0.021)	(0.019)	(0.017)
Probability training (PT) [(CC + PT) - CC]	0.001	0.009	0.020	0.013	0.025
	(0.029)	(0.024)	(0.021)	(0.019)	(0.017)
Forecast probability (current round)	0.478***	0.456***	0.449***	0.475***	0.501***
	(0.054)	(0.044)	(0.038)	(0.034)	(0.031)
N	1592	2424	3251	4037	4848
Outcome mean, comparison group	0.404	0.430	0.446	0.442	0.442

Table B11: Willingness to Pay for Probabilistic Weather Forecasts, by Existing Access to Weather 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 (CC)	-0.057	-0.002	-0.056	-0.001
	(1.108)	(0.065)	(1.105)	(0.065)
Probability training (PT) [(CC + PT) - CC]	-3.554*	-0.246**	-3.528**	-0.235**
	(1.823)	(0.111)	(1.582)	(0.096)
No access to online forecasts	-1.262	-0.078		
	(1.902)	(0.108)		
Probability training × No access to online forecasts	2.677	0.188		
	(2.203)	(0.132)		
No access to granular forecasts			-1.993*	-0.088
			(1.183)	(0.068)
Probability training × No access to granular forecasts			3.405	0.219*
			(2.122)	(0.125)
Any false alarms (rain) in Round 2	-2.496***	-0.135**	-2.491***	-0.134**
	(0.952)	(0.056)	(0.950)	(0.056)
Any false alarms (no rain) in Round 2	0.877	0.084	0.884	0.085
	(0.955)	(0.057)	(0.955)	(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 (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone; 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.

Table B12: Willingness to Pay for Probabilistic Weather Forecasts

	WTP (₹ per month)		**WTP** (₹ per month, inverse hyperbolic sine)	
	(1)	(2)	(3)	(4)
Climate change salience (CC)	0.016 (1.105)	0.012 (1.107)	-0.000 (0.065)	-0.001 (0.064)
Probability training (PT) [(CC + PT) - CC]	-2.071* (1.136)	-2.072* (1.137)	-0.140** (0.068)	-0.140** (0.068)
Mean weighted false alarm (rain) in game 2	-8.976** (4.168)	-9.154** (4.491)	-0.581** (0.244)	-0.622** (0.260)
Mean weighted false alarm (no rain) in game 2	2.502 (7.012)	2.803 (7.342)	0.383 (0.414)	0.452 (0.442)
Total no. of realizations in game 2		-0.057 (0.511)		-0.013 (0.031)
CC + PT = 0, *p-val*	0.10	0.10	0.05	0.05
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 $\times$ 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 $\times$ probability in the forecast) across all rounds in the second game; Climate change salience (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone.

Table B13: Willingness to Pay for Probabilistic Weather Forecasts & Total Score in the Experimental Games

	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 (CC)	-0.071	-0.002	-0.144	-0.061	-0.002
	(1.100)	(0.064)	(0.938)	(1.098)	(0.064)
Probability training (PT) [(CC + PT) - CC]	-2.054*	-0.139**	1.351	-2.147*	-0.144**
	(1.137)	(0.068)	(0.978)	(1.135)	(0.068)
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 (T1) is an indicator that takes the value 1 when the farmer watches the climate change video; Probability training (T2) is an indicator that takes the value 1 when the farmer watches the probability training video, which is estimated as (T1 + T2) - T1; since the probability training video is only ever watched along with the climate change salience video, and never alone.

C Data

Variables included as possible controls in the double lasso algorithm include:

1. **Demographic characteristics:** whether the farmer is a primary decision maker in the household ; household size; farmer's age; whether the farmer is literate; whether the farmer is female; whether the farmer has access to a smartphone; whether the farmer uses WhatsApp; farmer's level of risk aversion; whether the farmer has completed at least higher secondary education.

2. **Farming characteristics:** whether coffee cultivation is the main source of income; whether the farm is irrigated; whether the farmer grows Arabica coffee; whether the farmer grows Robusta coffee; whether the farmer harvests coffee cherry preparation; whether the farmer is a small-holder (cultivating coffee on between 0 and 5 acres of land); whether the farmer reports having experienced weather-related stress in the past; whether the farmer reports having experienced unexpected losses due to weather.

3. **Individual characteristics due to sampling or attrition:** whether the farmer is different from the individual initially recruited; whether the farmer was recruited in-person or over the phone; whether the farmer is a CKT user; whether the farmer is a replacement respondent due to attrition.

4. **Existing access to weather forecasts:** Whether the farmer reports accessing forecasts online or on weather apps in the pre-experiment survey; whether the farmer reports accessing forecasts at a block-level or lower granularity in the pre-experiment survey; whether the farmer reports trust in their existing forecasts in the pre-experiment survey (a response of 4 or 5 on a 5-point Likert scale).

D Description of *Coffee Krishi Taranga*

Coffee Krishi Taranga (CKT) is a mobile-phone based agricultural advisory service for coffee farmers in India. It is operated by Precision Development (PxD) with the Coffee Board of India. In Karnataka, CKT reaches 70% of all coffee farmers. Advisory consists of voice-call based advisory messages consisting of agronomic advice, market prices, information on subsidies, etc. Agronomic messages are designed by agronomists, contrain advice on key coffee agricultural practices, and are sent out to farmers at appropriate times in the year. CKT also has an in-bound service or a hotline, where famers may dial in to record questions that may not have been addressed in the outgoing calls. Responses to these questions are recorded by agronomists, and delivered to farmers. 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 B15 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.[15] 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.

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

Table B15: Inbound Calls on Coffee Krishi Taranga between 2019 and 2022

	(1)	(2)	(3)
	Blossom	Monsoon	Harvest
	March - May	June - Sept	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.

E Conceptual Framework

We consider farmers making decisions under uncertainty about upcoming weather (over the short-to-medium term, i.e., 1-to-15 days[16]), 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.

E.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 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).[17] 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, $\alpha = 1$.

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

[17]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.

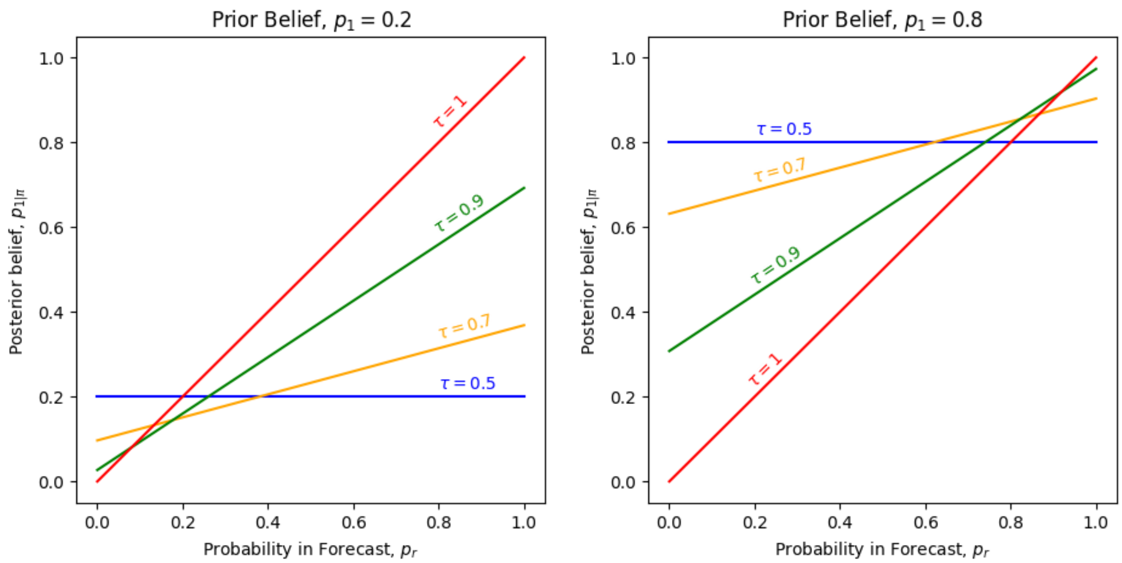


Figure 14: Posterior beliefs as forecast probability varies

The farmer's posterior belief about upcoming weather is:

$$p_{1|\pi,t} = p_t(\theta_t|\tilde{\pi}_t(\hat{\theta}_t)) = \sum_{\hat{\theta}_t \in \{0,1\}} \tilde{\pi}_t(\hat{\theta}_t) \frac{p_t(\hat{\theta}_t|\theta_t)p_t(\theta_t)}{p_t(\hat{\theta_t})} \tag{4}$$

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).[18] So,[19]

$$\begin{aligned} p_t[\theta_t = 1|\tilde{\pi}_t(\hat{\theta}_t), \tau] &= \tilde{p}_{r,t} \frac{p_t(\hat{\theta}_t = 1|\theta_t = 1)p_t(\theta_t = 1)}{p_t(\hat{\theta}_t = 1)} + (1 - \tilde{p}_{r,t}) \frac{p_t(\hat{\theta}_t = 0|\theta_t = 1)p_t(\theta_t = 1)}{p_t(\hat{\theta}_t = 0)} \\ &= \tilde{p}_{r,t} \frac{\tau p_{1,t}}{\tau p_{1,t} + (1 - \tau)(1 - p_{1,t})} + (1 - \tilde{p}_{r,t}) \frac{(1 - \tau)p_{1,t}}{(1 - \tau)p_{1,t} + \tau(1 - p_{1,t})} \end{aligned} \tag{5}$$

and,

$$p_{1|\tilde{\pi},t} = \int_0^1 p[\theta_t = 1|\tilde{\pi}_t(\hat{\theta}_t), \tau] f_t(\tau) d\tau \tag{6}$$

[18] 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 $p(\hat{\theta} = 1|\theta = 0) = p(\hat{\theta} = 0|\theta = 1) = 1 - \tau$

[19] 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 $p_{r,t}$

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,

$$p_{1,(t+1)} = \Phi(p_{1,t}, \vartheta_t) \tag{7}$$

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, $f_{t+1}(\tau) = f_t[\tau|\tilde{\pi}(\hat{\theta}), \vartheta_t]$.[20]

$$\begin{aligned} f_{t+1}(\tau) = \vartheta_t \Bigg\{ \tilde{p}_{r,t} \frac{\tau f_t(\tau)}{\mu_{\tau,t}} + (1-\tilde{p}_{r,t}) \frac{(1-\tau) f_t(\tau)}{1-\mu_{\tau,t}} \Bigg\} \\ + (1-\vartheta_t) \Bigg\{ \tilde{p}_{r,t} \frac{(1-\tau) f_t(\tau)}{1-\mu_{\tau,t}} + (1-\tilde{p}_{r,t}) \frac{\tau f_t(\tau)}{\mu_{\tau,t}} \Bigg\} \end{aligned} \tag{8}$$

$$\begin{aligned} p_{1|\tilde{\pi},(t+1)} = \int_0^1 \Bigg\{ \tilde{p}_{r,(t+1)} \frac{\tau p_{1,(t+1)}}{\tau p_{1,(t+1)} + (1-\tau)(1-p_{1,(t+1)})} \\ + (1-\tilde{p}_{r,(t+1)}) \frac{(1-\tau) p_{1,(t+1)}}{(1-\tau) p_{1,(t+1)} + \tau(1-p_{1,(t+1)})} \Bigg\} f_{t+1}(\tau, \tilde{p}_{r,t}, \vartheta_t) d\tau \end{aligned} \tag{9}$$

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

$$\max_{a_t \in \{0,1\}} \mathbb{E}_{p_{1|\tilde{\pi},t}} \Big[U(a_t, \theta_t) \Big] \tag{10}$$

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

$$\mathbb{E}_{p_{1|\tilde{\pi},t}} \Big[U(a_t = 1, \theta_t) \Big] \geq \mathbb{E}_{p_{1|\tilde{\pi},t}} \Big[U(a_t = 0, \theta_t) \Big] \tag{11}$$

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

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

receive weather forecasts. The *ex ante* value of a weather forecast requires considering all possible values that the forecast may take (Millner, 2008).

$$V_{F,t} = \mathbb{E}[V_{p_{1|\tilde{\pi},t}}] - \mathbb{E}[V_{p_{1,t}}] = \int_{\tilde{\pi}_t} \left\{ \sum_{\hat{\theta}_t \in \{0,1\}} \tilde{\pi}_t(\hat{\theta}_t) p(\theta_t|\hat{\theta}_t) U(a'_t, \theta_t) \right\} q(\tilde{\pi}_t) d\pi - \sum_{\theta_t \in \Theta} p_{1,t}(\theta_t) U(a_t, \theta_t) \tag{12}$$