Weathering Climate Change: How Farmers Learn from Forecast Outcomes

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Abstract

Weather-induced risk reduces farmers' incomes, and climate change is increasing such risk. Accurate short-to-medium-range rainfall forecasts, predicting weather zero to fifteen days ahead, can mitigate this risk by helping farmers better time activities and take precautionary measures. But, this requires that farmers accurately interpret, trust and act on forecasts. This paper evaluates how farmers in rural South India form beliefs about upcoming weather, and about forecast (in)accuracy through incentivized lab-in-the-field and real-world experiments. We find that farmers exhibit high willingness-to-pay for a subscription to a voice-call forecast service, and actively use it when available. Farmers integrate forecast information into their weather expectations. But, their trust in forecasts decreases after erroneous predictions, with less frequent use after errors. Accuracy in initial interactions mitigates this effect, highlighting the importance of initial successes for building long-term trust in a new technology. An informational intervention aimed at improving interpretation of probabilistic forecasts counters the loss in trust following incorrect predictions but introduces call fatigue, reducing overall engagement with the service. Finally, when climate change is salient, farmers are more likely to use the forecast service and are more tolerant of forecast errors, underscoring the value of forecasts in climate adaptation.

JEL Codes: C91, D81, O12, O13, Q12, Q54
Keywords: Climate Adaption, Forecasts, Agriculture, Belief Updating

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1 Introduction

Weather patterns across the world are becoming increasingly variable (Krishnan et al., 2020; Roxy et al., 2017; Auffhammer and Carleton, 2018, in India) due to global warming (Ha et al., 2020; Seneviratne et al., 2021). This amplifies agricultural production risk (Bezner Kerr et al., 2022; Hultgren et al., 2022), which reduces farmers' incomes: *ex post*, when unanticipated weather lowers yields or leads to increased costs, and *ex ante*, when farmers forgo profitable investments that may be riskier (Rosenzweig and Binswanger, 1993; Dercon, 1996; Morduch, 1999), or are unable to plan ahead. Smallholder farmers in developing countries are particularly vulnerable, making improved adaptation tools necessary for climate resilience.

Weather forecasts (at sub-seasonal and seasonal timescales) are one such technology whose skill has been steadily improving (Linsenmeier and Shrader, 2023; Haiden et al., 2023), and which is scalable at low marginal cost. When skillful, forecasts can help farmers form more accurate weather expectations to make better-informed decisions. However, this requires that farmers correctly interpret forecast information and trust the forecast service. In this paper, we study how farmers form beliefs about such new climate adaptation tools as they begin to use them. We focus on a new voice-call rainfall forecast service for coffee farmers in rural Karnataka, which provides farmers with accurate, granular, (short-to-)medium-range forecasts.[1] Such forecasts can help farmers better time agricultural activities, plan labor and input allocation, and take precautionary measures against rainfall shocks. They are especially valuable for perennial crops like coffee, which farmers commit to cultivating over multiple years.

We ask four main questions: First, how do farmers form beliefs about weather based on forecast information and forecast outcomes? Second, how do farmers form beliefs about forecast accuracy based on forecast outcomes as they repeatedly engage with forecasts? Third, do light-touch informational treatments providing training to interpret probabilities and probabilistic forecasts impact these beliefs? Finally, does vulnerability to climate change affect these beliefs?

We study this through a set of three experiments. (1) A lab-in-the-field experiment with 1,212 coffee farmers, where they play experimental games in which farmers rely on hypothetical rainfall forecasts to make incentive-compatible decisions. Prior to the games, farmers are

[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 going forward. 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/

randomly assigned to watch a video highlighting the relevance of weather forecasts in the context of a changing climate ('climate change salience video' or 'CC'), an additional video tutorial on interpreting probabilistic information ('probability training video' or 'PT'), or a placebo video.

We then partner with the Coffee Board of India to provide a real-world rainfall forecast service to over 27,000 farmers in Karnataka, most of whom already receive voice-call based agronomic advice from an existing agricultural advisory service, lending credibility to the new forecast service.[2] We rely on (2) evidence from a natural experiment in this real-world service, which arises as farmers are sent forecasts which end up being incorrect at random; and (3) from a randomized information experiment (or A/B test) in the real-world service, where 391 villages that receive probabilistic forecasts are randomized into an experimental arm receiving additional voice-calls with information on how to interpret probabilistic forecasts ('forecast interpretation treatment' or 'FI'), and another that continues to receive forecasts alone.[3]

First, we find that farmers exhibit high demand for voice-call based rainfall forecasts, both when elicited as willingness-to-pay using a Becker et al. (1964) ('BDM') mechanism prior to the launch of the real-world service, and when measured as take-up of the real-world service. In fact, farmers who were willing to pay higher amounts for the service prior to the service's launch are also more likely to have high engagement with the service (i.e., answer more than 50% of forecast calls sent to them). On average, farmers are willing to pay INR 25.55 per month (or USD 0.30 per month in 2024) for access to rainfall forecasts over voice-calls, which is significantly higher than the *average cost* of delivering forecasts to farmers in an at-scale service, INR 8 per month.[4] Farmers also update their weather expectations upon receiving weather forecasts. In hypothetical scenarios, farmers are more likely to expect rain and update their priors about the likelihood of rain occurring when rainfall forecasts communicate higher probabilities. Suggestive real-world evidence indicates that weather expectations are more accurate for farmers who receive forecasts through the forecast service than for those who do not.

[2]Many farmers who participated in the lab-in-the-field experiment were not previously on the advisory service. Both the existing advisory service, and the new forecast service are run by Precision Development (PxD) and the Coffee Board of India. The existing agricultural advisory service sends voice-calls to farmers containing educational messages designed by agronomists. There are over 120,000 coffee farmers on the service across South India.

[3]The experimental sample also consists of a small control group of villages where farmers receive no forecasts, and from whom we gather data on weather expectations. Randomization is stratified at the forecast-grid level, which is the geographical unit receiving the same forecast. Forecast grids have multiple villages in them.

[4]Back-of-the-envelope cost calculations are for providing the service to 50,000 farmers, which is the target scale of the service. At the take-up implied by the pricing the service at the average WTP, costs would be INR 15.69 per farmer

Second, we find that farmers update their subjective beliefs about forecast accuracy ('perceived forecast accuracy') after experiencing erroneous forecasts—farmers trust and rely on forecasts less, as though 'discouraged', both in the experimental games and in the real-world service. Following a round where a forecasted event fails to materialize in the lab-in-the-field experiment, farmers are less likely to choose the more accurate option when given a choice between two forecasts, updating their beliefs about the likelihood of an event to a lesser extent. Conditional on probabilities in the forecasts, farmers are less certain that a forecasted event will occur following incorrect forecasts. Farmers have similar responses in the real-world service too. Farmers are 15% less likely to answer a forecast-call if they last received a forecast that ended up being a false alarm, i.e., an incorrect forecast where rain was predicted but did not occur, and are less likely to report having relied on the service's forecasts to make decisions recently. This reduction in engagement persists both in the subsample of farmers who receive probabilistic forecasts and those who receive deterministic forecasts, indicating that it is not only the probabilistic information that contributes to the effect.

The reduction in engagement with the forecast-service is more pronounced for farmers who are risk averse, for those who grow a more weather-sensitive coffee variety, and for those with no working irrigation facilities—indicating that perceived forecast accuracy is more important for farmers who are more vulnerable to weather risks. And importantly, while these effects persist over repeat interactions with the forecast service, they are strongest when early experiences with the forecasts are error-laden. When farmers experience accurate forecasts early on, they are less likely to be discouraged by incorrect forecasts in later use—closing the 'discouragement' gap by 36%.

Our results also suggest that informational interventions to boost an understanding of the uncertainty associated with weather forecasts may mitigate the discouraging effects of incorrect forecasts. The light-touch forecast interpretation ('FI') voice-call treatment did reduce the 'discouraging' effect of incorrect forecasts on engagement with the forecast-service. However, this came at the cost of (3%) lower overall engagement due to 'call fatigue', with not only the forecast service, but also the standard educational advisory service—suggesting that other modes or media for such awareness efforts might prove more beneficial.

Finally, we find that an awareness of increasing weather variability makes forecasts more valuable to farmers. Among farmers who participated in the lab-in-the-field experiment, those who were randomly assigned to receive the climate change salience video treatment were 3 percentage points more likely to later begin using the real-world service. In addition, in the larger sample of farmers with access to the the forecast-service, those who resided in regions with high recent-historical rainfall variability (i.e., between 2000 and 2022) were less likely to reduce their engagement with the forecast-service following incorrect forecasts.

Overall, our findings indicate that medium-range rainfall forecasts are a beneficial climate change adaptation tool for farmers. In addition, farmers' consistent use of the real-world forecasts service, along with their high willingness-to-pay relative to costs of providing the service indicates substantial value to investing in providing improved, customized forecasts for farmers. However, the perceived accuracy or trust in a forecast-service is an important determinant of continued use of forecasts, regardless of objective skill, with early forecast successes boosting trust. These findings make two main contributions.

First, our findings demonstrate that the salience of climate change and weather variability increases farmers' use of forecasts, highlighting the value of medium-range forecasts as a climate adaptation tool. This contributes to the growing climate economics literature on the importance of climate adaptation Hultgren et al. (2022), particularly regarding the role of forecasts as an adaptation tool in agriculture Burlig et al. (2024). Moreover, our results show that farmers actively integrate forecast information into their weather expectations and use it to inform decision-making. This contributes more broadly to the literature on the role of forecasts in managing weather risk in developing countries: while Burlig et al. (2024); Rosenzweig and Udry (2019); Lybbert et al. (2007) demonstrate the impact of seasonal forecasts on farmer behavior, investment choices and planting strategies, Fosu et al. (2018); Rudder and Viviano (2023); Yegbemey et al. (2023) demonstrate the impact of short-range forecasts on farmer beliefs and behavior.

The value of forecasts as a climate adaptation tool arises from their ability to shape the beliefs farmers form. An emerging literature considers how individuals form environmental and climate beliefs, learn from signals around them, and learn from experiences (Kala, 2019; Patel, 2024). Our findings contribute to this by showing how experiences shape not only environmental beliefs but also trust in the information used to form these beliefs. This insight extends to beliefs about digital agricultural extension (whose impacts are studied in Fabregas et al., 2019; Cole and Fernando, 2020, and which impact farmer decision-making) and other information sources more broadly; and are critical for designing effective information and forecast services that foster trust and support adaptive decision-making.

Second, we present novel experimental evidence on how experiences shape the formation of subjective beliefs about the accuracy of new information services, specifically weather forecasts, in a developing country setting. Existing research shows that individuals are more likely to use weather forecasts with higher predictive skill across contexts (Song, 2024; Rosenzweig and Udry, 2019), yet usage is often hindered by concerns over (perceived) forecast accuracy (reviewed in Mase and Prokopy, 2014). Perceived accuracy correlates with trust in forecasts (Shafiee-Jood et al., 2021; Ripberger et al., 2015; Morss et al., 2016), and studies measuring trust directly find that individuals are more likely to act on forecast information when trust is higher (Ripberger et al., 2015; Morss et al., 2016). Together, this suggests that beliefs about forecast accuracy strongly influence forecast use, evolving as users gain experience (Shafiee-Jood et al., 2021; Millner, 2008, modeled in). Our findings contribute to this literature by experimentally demonstrating how trust and forecast use respond to forecast outcomes in both real and hypothetical scenarios.

This also aligns with findings in behavioral finance, where individuals form inflation expectations based on personal experiences, which then shape their economic choices (Malmendier and Nagel, 2016; D'Acunto et al., 2021; Malmendier, 2021). We find that farmers' experiences with correct or incorrect forecasts impacts their trust in, and use of, the forecast service. Consistent with findings about inflation in Malmendier and Nagel (2016), we also find that early experiences have a larger impact on trust and use of the service. This also relates to the literature on learning and technology adoption among farmers in developing countries (Conley and Udry, 2010), where farmers especially learn from the successes of their "information-neighbors" during the early stages of new crop cultivation.

2 Background

2.1 Study Setting

This study focuses on coffee farmers in Karnataka, India. 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.[5] 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.[6] 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.

Sixty percent of CKT's user-base is small-holder farmers, who cultivate coffee on fewer than 5 acres; while 71% of our farmers in the lab-in-the-field experiment sample are small-holders Table A1. 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.[7] In the lab-in-the-field experiment 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.

[5]Statistics from the Coffee Board of India, accessed at https://coffeeboard.gov.in/

[6]More details about CKT are in the appendix.

[7]The GSMA The Mobile Economy 2023 report indicates that this is the case.

Table 1: Coffee Krishi Taranga Users in 2018

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

2.2 Weather in Karnataka

Coffee is mainly grown in the Western Ghats region of Karnataka (in the districts of Chikmagalur, Hassan and Kodagu). The region receives three times the average rainfall in India (Varikoden et al., 2019), with definite changes in the characteristics of the monsoon rainfall, extreme rainfall, and dry spells in the region (Sreenath et al., 2022; Varikoden et al., 2019; Chandrashekhar and Shetty, 2017b; 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.

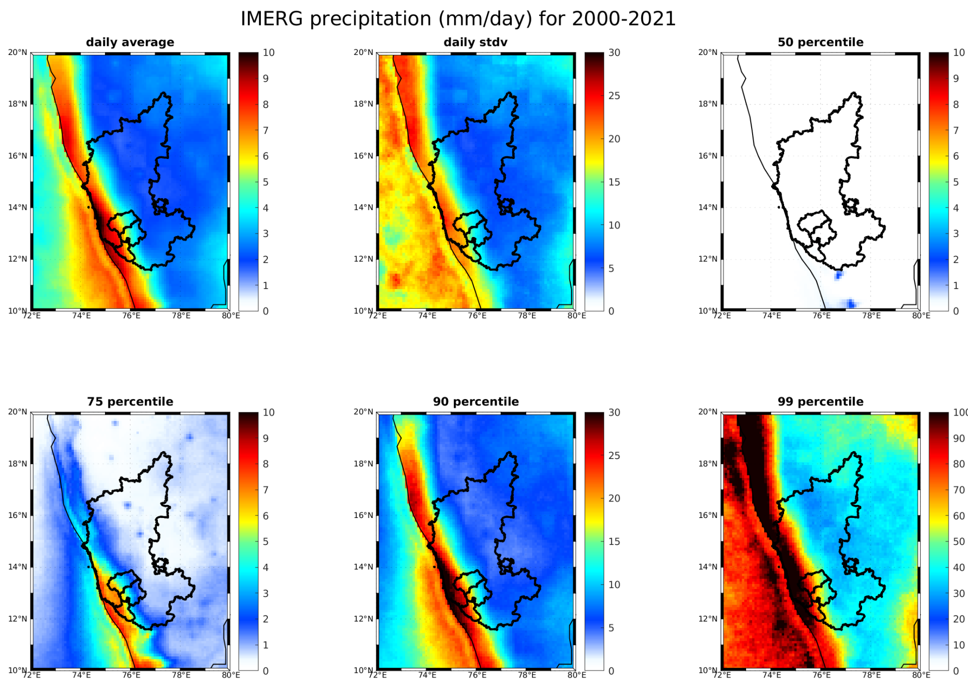


Figure 1: Daily rainfall amount and variability in Karnataka

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)

2.3 Weather Forecasts

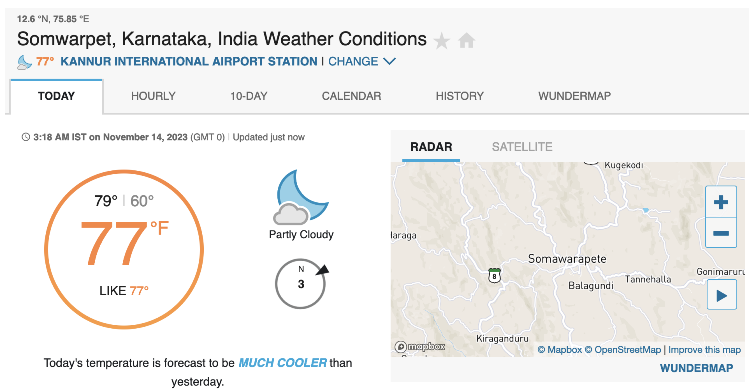
In our study sample, 49% of farmers reported typically accessing weather forecasts via television, radio, newspaper, or Kisan Call Centers. Forecasts on these media are provided by the Indian Meteorological Department (IMD), and the IMD's rainfall forecasts are deterministic predictions of expected rainfall. 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.[8] 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 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.

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

These forecasts are typically probabilistic. However, Figure 2 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.

Figure 2: A forecast for Somwarpet in Karnataka, India on Weather Underground



Notes: The figure indicates that the forecast that is presented as one for Somwarpet, Karnataka, India, is actually for the nearest weather station in Kannur International Airport, which is in the neighboring state of Kerala.

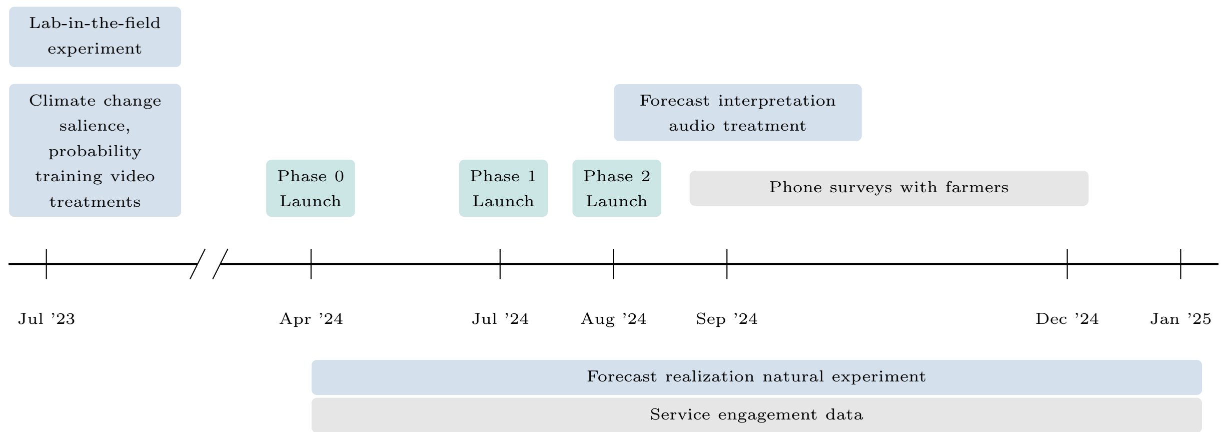
3 Experimental Design

This study consists of three experiments, with the timeline of activities described in Figure 3. First, prior to the design and launch of a real-world service, we designed and implemented a lab-in-the-field experiment with 1,212 farmers. Farmers who were willing to take-up a real-world service at the end of the lab-in-the-field experiment were then onboarded in a real-world voice-call based weather forecast service (phase 0), along with two other cohorts (phases 1, 2)—a total of over 27,000 farmers. Second, a natural experiment arises at forecasts end up being correct or incorrect at random as weather is realized. Third, an information experiment in the real-world service, with treated farmers receiving additional information about how to interpret uncertainty associated with forecasts.

3.1 Lab-in-the-Field Experiment

Sample and Randomization. We randomly selected twenty-one gram panchayats (GPs) in two blocks in Chikmagalur and Kodagu, two coffee-growing districts in Karnataka. In

Figure 3: Timeline of study activities (including on-going data collection)



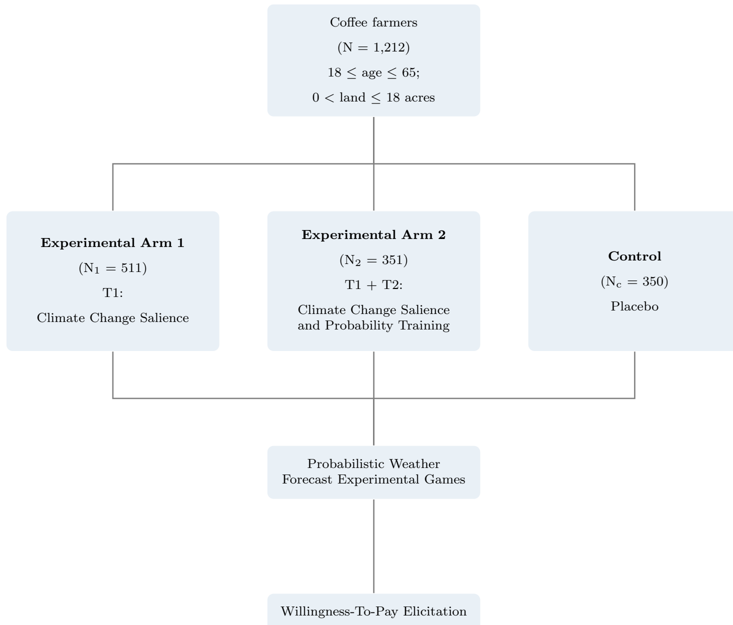
Notes: This figure presents a timeline of study activities. The lab-in-the-field experiment was conducted in-person in July and August, 2023. The service launched for the 1,212 farmers who participated in the lab-in-the-field experiment in April, 2024. The next cohort of 12,598 farmers began receiving forecasts in July, 2024; and the final cohort in our sample, of 13,410 farmers, began receiving forecasts in August, 2024. The forecast interpretation audio treatment runs between mid-August and mid-October, 2024. Phone surveys with phase 0 and phase 2 farmers arre conducted between September and December, 2024. Engagement data will be recorded until the end of January, 2025.

these GPs, 1,212 farmers were randomly sampled from the rosters of small- and medium-holder coffee farmers from the Coffee Board of India and existing users of Coffee Krishi Taranga. Farmers were randomized on-the-spot to receive light-touch video information treatments, stratified at the gram panchayat level—(1) a climate change salience treatment (T1); (2) a climate change salience and probability training treatment (T1 + T2); (3) a control group (C)—prior to playing the two experimental games.[9]

Table A1 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. 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

[9]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). This is similar to power when compared with a $\frac{1}{3}$, $\frac{1}{3}$, $\frac{1}{3}$ design which maximizes power on (T1 - C), ((T1 + T2)-C).

Figure 4: Lab-in-the-Field Experiment Design



Notes: This figure presents the design for the lab-in-the-field experiment. The study is conducted in-person, and farmers are randomized into one of three experimental arms (climate change salience video treatment; climate change salience and probability training video treatment; control). After watching the short information treatment videos, farmers play two experimental games, and finally participate in an incentive-compatible willingness-to-pay elicitation (Becker et al., 1964).

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.

Information Treatments. In the climate change salience experimental arm, farmers watch a 5.5-minute video detailing climate change effects on coffee cultivation in Karnataka, India. The video highlights challenges like rising temperatures, unpredictable rainfall, and extreme weather over the past decade, featuring firsthand accounts from farmers and presenting strategies that emphasize the importance of weather forecasts in agricultural planning and climate resilience. Farmers in the climate change salience and probability training arm watch a comprehensive 13.5-minute video that combines the climate change content with an explainer on probability concepts. Using relatable examples and visual aids, the video clarifies probability and the concept of reference classes in probabilistic predictions (Gigerenzer et al., 2009), connecting these ideas to understanding rainfall forecasts. Finally, control group farmers watch a brief video about the origins and spread of coffee farming in India.

Experimental Games. The experimental games focus on understanding whether farmers understand and act on probabilistic forecasts of events, how they update their beliefs about the likelihoods of events following probabilistic forecasts, and how these beliefs are impacted by the eventual realization of the events being forecasted.

In the first experimental game, the ‘market-choice game’, farmers choose a forecast in which they expect the event to occur with more certainty from a pair of forecasts with different event probabilities. This game is adapted from Stephens et al. (2012), with additional design features to eliminate biases that may arise due to risk aversion, that may be specific to forecast formats, and that may arise when farmers conflate a quantity of rain in a forecast with the likelihood of rainfall occurring. Rounds also randomly vary the probabilities in forecasts, the order in which rounds appear to farmers, and whether the event of interest is ‘wet’ or ‘dry’ weather.

Farmers play five incentive-compatible game-rounds (Figure 5), each set up to assist a hypothetical vendor choose a market location in which to sell a good (Figure B2, Table A3).[10] Goods considered are those such as umbrellas or a cool beverage, whose sales depend on realized weather conditions. Farmers playing the game are presented with probabilistic rainfall forecasts for each of two market-locations, and asked to recommend the location the vendor should choose in each round. To assess the certainty farmers associate with their choice of forecast, farmers also decide how many points between 1 and 5 to put at stake in a round when they recommend how much the hypothetical vendor should invest. Farmers playing the game are incentivized to maximize the vendor’s earnings and their own points.

Incentive-compatibility is ensured because the *ex ante* optimal choice is the market location or forecast where the ideal weather for a good’s sales is more likely (i.e., if a good sells better when it is a sunny day, the ideal weather is no rain), and this *ex ante* optimal choice always has higher expected earnings and lower outcome variance to remain unaffected by risk preferences. After farmers make their choices in a game round, the in-game weather outcome is revealed. They are awarded the points they staked if the ideal weather occurs, or have those points deducted if it does not. Feedback after each round helps farmers understand the impact of their decisions and the role of chance, enhancing their ability to use forecasts effectively.

In the second experimental game, the ‘agricultural decision-making game’, farmers rely on a probabilistic rainfall forecast to make hypothetical agricultural decisions (Figure B3). Farmers play six incentive-compatible game rounds (Figure 6),[11] this time set up to assist a hypothetical farmer decide whether to take an agricultural action or not, at a specific time of year, based on probabilistic rainfall forecasts. The agricultural decisions are (1) whether to irrigate coffee plants or wait for rain prior to coffee flower blossoming in the spring (March); (2) whether to apply fertilizer when there is no heavy rain or wait in the pre-monsoon period

[10] Scored rounds are played after two practice rounds to make sure farmers understand the game’s rules and scoring system.

[11] Scored rounds are played after a practice round.

Figure 5: Illustrative flow of one game-round for a scenario in Experimental Game 1: Market decision to sell tea based on expected weather

Kishore is a vendor who sells ***hot tea***. Next Sunday, there are markets in two nearby villages.

Kishore will be able to sell more tea when it **rains**.

Pick the market where you think it is **more likely to rain** so Kishore makes more profit.

The weather forecasts for the two locations are:

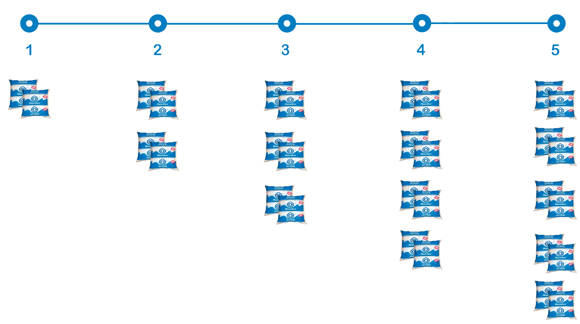
Village Market 1	**Village Market 2**
	
60% chance of any rain	90% chance of any rain

Respondent farmer chooses village market location

If it does not rain, Kishore will not be able to sell any tea, and the milk will go bad.

Depending on how certain you are about your choice, you may advise Kishore how much milk he should purchase to make tea. Milk costs Rs. 30 per liter, and Kishore makes Rs. 10 as profit per liter. How many liters of milk should Kishore purchase?

Your score will depend on Kishore's profit or loss.



Respondent farmer chooses points to put at stake

$$Stake \in \{1, 2, 3, 4, 5\}$$

Weather is realized at chosen village market location

Realization for village 1:
Draw a random number, $u \sim U(0, 1)$.
If $u < 0.6$, the event occurs; and if $u \geq 0.6$, the event does not occur.

Realization for village 2:
Draw a random number, $u \sim U(0, 1)$.
If $u < 0.9$, the event occurs; and if $u \geq 0.9$, the event does not occur.

Feedback is provided based on choice and realization

You provided good advice. Well done, it rained!

or

You provided good advice, but it did not end up raining that day!

or

This forecast predicted a lower chance of rain than the other forecast. However, on this occasion, it rained!

or

This forecast predicted a lower chance of rain than the other forecast. Unfortunately, it did not rain.

Your score for this round is, *Score*

Score is +Stake if it rains; −Stake if it does not rain

(May). The formats in which forecasts are presented vary across rounds, the probabilities in the rainfall forecast in each round randomly vary between 10% and 90%, and the order in which farmers play scenarios and rounds within scenarios is randomized.

In each scenario, farmers play two rounds with a forecast, and one round where are are asked to rely on historical rainfall patterns in their village (their priors for rainfall in that time-period). This allows us to assess whether farmers update their beliefs from their priors based on the probabilities in the forecast in forecast rounds. In each round, farmers select whether to take the relevant action or not, based on their prior beliefs about the likelihood of rain, or their posterior beliefs once they see the forecast.

The rounds are incentive-compatible since the *ex ante* optimal action is to choose the action appropriate for rain when rain is expected (with $\geq$ 50% probability), and *vice versa*. Once a decision is made, weather for the round is realized, and farmers are awarded 5 points if the action they chose was *ex post* appropriate for realized weather, and 5 points are deducted otherwise. As in the preceding game, feedback is provided after each round to help farmers assess the optimality of their decisions and the influence of chance on the outcomes

Weather forecasts and realizations. Weather forecasts in the games are designed to be realistic for the study-region, in consultation with meteorologists at CFAN. Quantities in the forecasts are from historical weather realizations for the month in the hypothetical scenarios, and probabilities vary randomly. Realizations are drawn from the probability distribution implied by the forecast, following the approach in Stephens et al. (2019). So, if a forecast indicate an 80% chance of rain, then 80% of participants who get that forecast will get a 'rain' realization, while 20% will get a 'no rain' realization (Figure 7).[12]

Incidence of incorrect forecasts. The experimental games are designed so that realizations are randomly drawn, and forecasts may be correct or wrong. This induces random variation is whether farmers encounter an incorrect forecast in a given round.

[12]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).

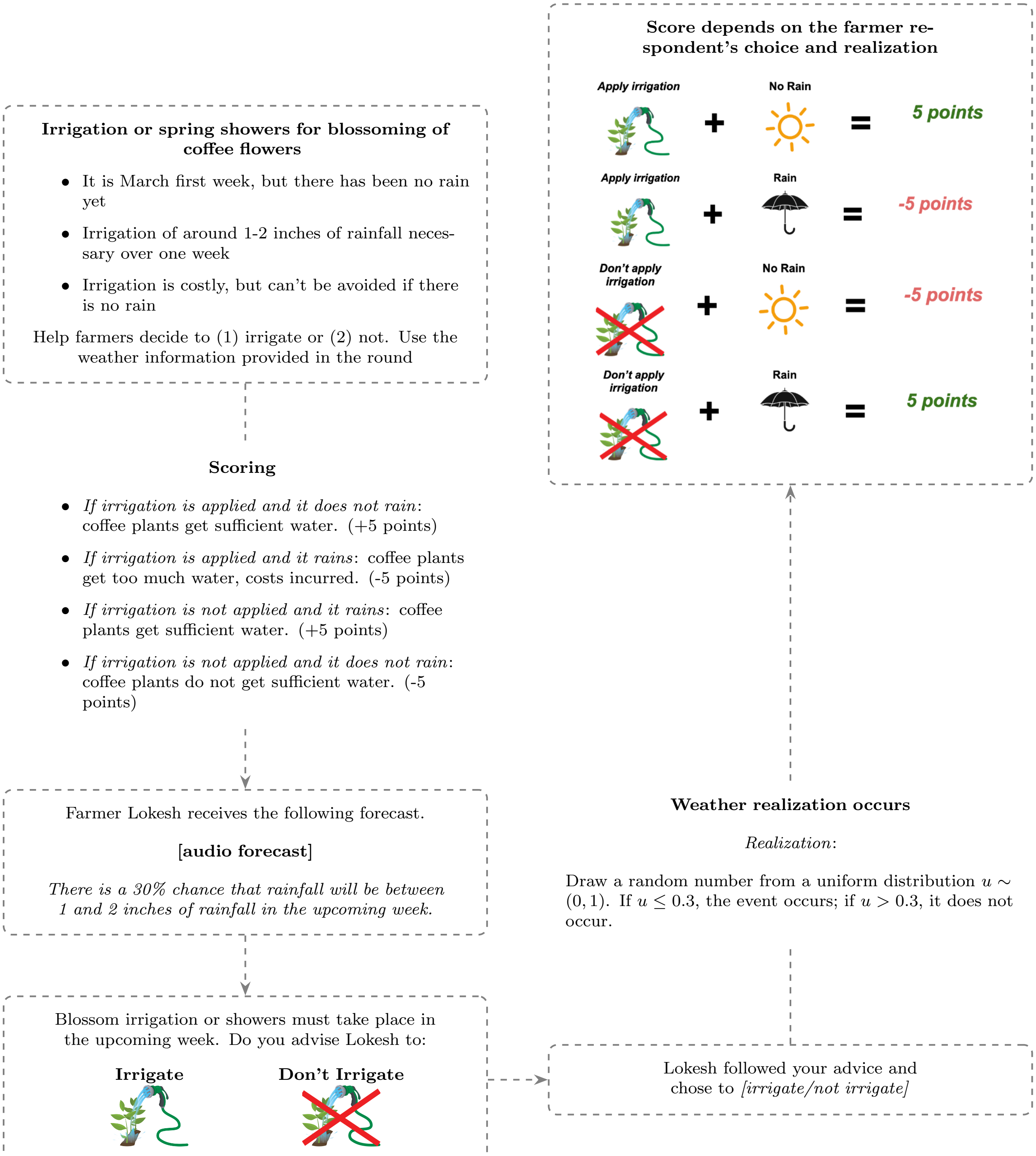


Figure 6: Illustrative flow of one game-round for a scenario in Experimental Game 2: Decision to irrigate or not prior to coffee flower blossoming based on expected weather

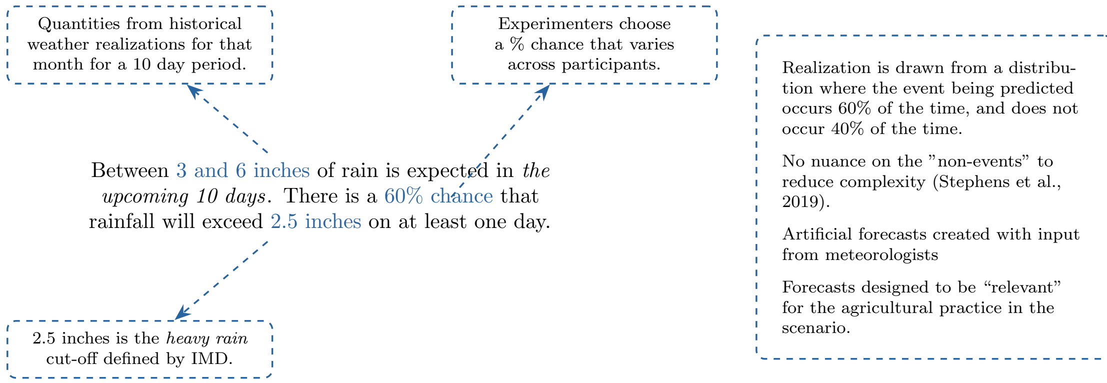


Figure 7: An example of a cumulative forecast used in experimental game 2

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. 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 et al., 1964) mechanism. An english translation of what is communicated to farmers in this exercise is below.

> *"The service being offered today is voice-call based rainfall forecasts from October 2023 to May 2024. In this service, rainfall forecasts will be provided via voice-call for the upcoming week, and will also convey the likelihood of rainfall in % chance (in addition to the quantity). The forecasts are more accurate and for a smaller (geographic) 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] of the time."*[13]

[13] Due to administrative delays, farmers eventually began receiving forecasts only in April, 2024. However, this was communicated to farmers in October, 2023. The granularity of forecasts is communicated as "for a smaller area than existing forecasts" because while the new forecast service has more granular forecasts than existing forecasts from the IMD (which are provided at the district or block level), the geographic area covered by a forecast grid-cell does not have a geographic analogue. In addition, in interviews with farmers, it became clear to us that farmers' perception was that these block or district-level forecasts were village level forecasts because certain platforms labeled them with the village's name. We discuss the change in timing of forecast delivery in Section 4. Finally, forecasts in the real-world service are for an upcoming 5-day period, rather than a week. This is because the skill of a a 5-day forecast had higher than the skill of the 7-day forecast. This change too was communicated to farmers prior to the launch of the service. The text of the introductory message sent to farmers to board them onto the service is in Figure B6.

3.2 Real-World Forecast Service

Service roll-out. Farmers who participated in the lab-in-the-field experiment and 'took-up' the service in the BDM exercise began receiving forecasts in April, 2024. Following this, the forecast-service was then rolled out in a staggered manner across blocks in Karnataka, onboarding farmers who were already registered on the CKT advisory service. Farmers in five blocks, Somwarpet, Mudigere, Sakleshpura, Belur and Alur,[14] were assigned to phase 1, and received access to the forecast-service from July, 2024 (phase 1); while farmers in six other blocks, Chikmagalur, Koppa, Narasimharajapura, Madikeri, Arkalgud, Sringeri were assigned to phase 2, and received access to the forecast-service from August, 2024. A total of 27,120, in 21 forecast-grid-cells[15] in 11 blocks are part of the sample of farmers considering in this study.

Phase 0. All 1,212 farmers, across 8 forecast-grid-cells in two blocks are onboarded onto the service. In this sample, villages (with at least 5 farmers) are randomly assigned into one of two experimental arms, stratified at the forecast-grid-cell level—(1) probabilistic forecasts only; (2) probabilistic forecasts, along with additional forecast interpretation voice-calls. This is a total of 1,145 farmers in 65 villages.

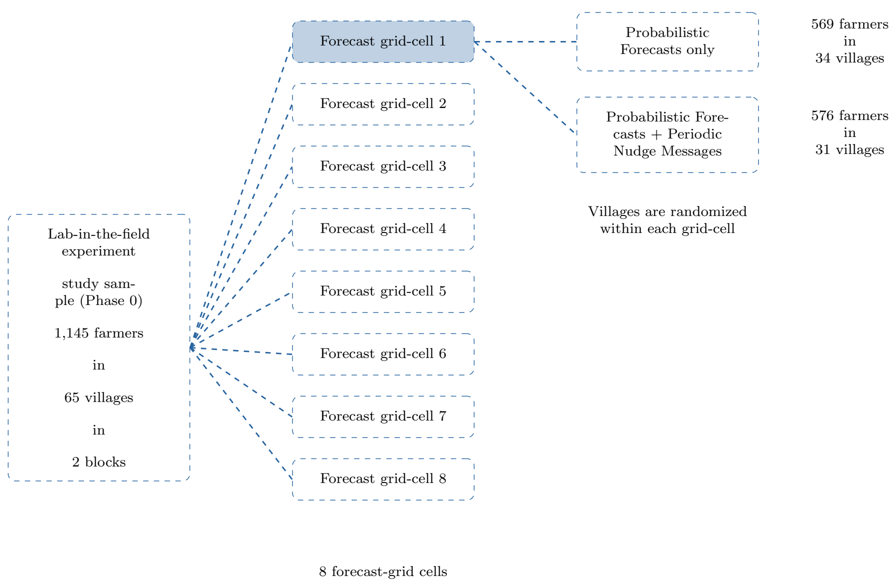


Figure 8: Forecast interpretation experiment design for Phase 0

Phase 1. A total of 14,644 farmers in 571 villages across 12 forecast-grid-cells are on the

[14]In Somwarpet and Mudigere, villages where the lab-in-the-field took place are excluded from this phase of the service roll-out to maintain the integrity of the willingness-to-pay exercise.

[15]A forecast-grid cell is a sub-block geographic area, 0.2 $\times 0.2 or 18 km \times$ 18 km (324 km^2), which is the resolution at which forecasts are currently disseminated. This is an improvement on the resolution at which widely available forecasts (such as from the IMD) are disseminated, which is at the district or block level. Blocks in the study region range from 430 km^2 to 1654 km^2.

service rosters in the five phase 1 blocks. All phase 0 villages are excluded from this sample. Villages in this phase were randomized into the one of four experimental arms, stratified at the forecast-grid-cell level—(1) probabilistic forecasts only; (2) probabilistic forecasts, along with additional forecast interpretation voice-calls; (3) deterministic forecasts only; (4) a control group. Farmers in the control group do not receive any forecasts, but continue receiving standard advisory voice-calls. Table ¡XX¿ describes characteristics of farmers in this sample.

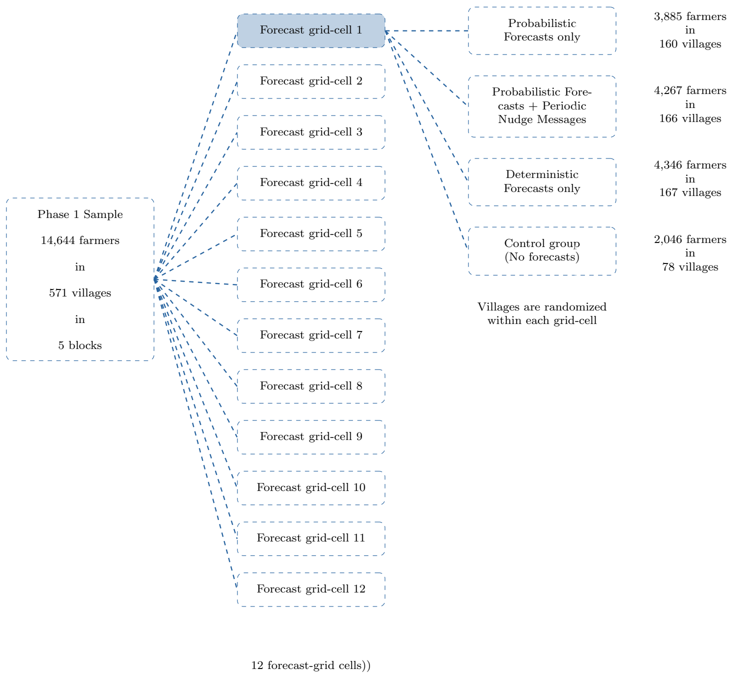


Figure 9: Forecast interpretation experiment design for Phase 1

Phase 2. A total of 15,106 farmers in 335 villages across 13 forecast-grid-cells are on the service rosters in the six phase 2 blocks. Villages in this phase were randomized into the one of five experimental arms, stratified at the forecast-grid-cell level—(1) probabilistic forecasts only; (2) probabilistic forecasts with a recommended action (or advisory); (3) deterministic forecasts only; (4) deterministic forecasts with a recommended action (or advisory); (5) a control group (which continues receiving only the regular advisory voice-calls). These farmers are part of the sample considered for the natural experiment (described below), but we do not analyze differences between these experimental groups in this paper.[16] Table ¡XX¿ describes characteristics of farmers in this sample.

Forecasts. Once farmers receive access to the service, they receive an initial onboarding call explaining the new service. Farmers then begin receiving five-day cumulative rainfall

[16]These results, comparing outcomes across the different experimental arms—comparing forecasts alone to forecasts along with recommendations—are described in our companion paper, "Customizing Weather Forecasts for Climate Change Adaptation in Rural India"

forecasts over voice calls, once every five days. Upto three call-tries are made to each farmer scheduled to receive a call. Figure Figure B8 presents the script for each type of forecast sent to farmers. To ensure comparability, the same underlying forecast is sent to all farmers in each forecast group. All forecasts present the median value of rainfall in the forecast for the upcoming five-day period. Probabilistic forecasts, in addition, provide farmers with the likelihood of rain.[17]

Forecast Realization Natural Experiment. All 27,120 farmers—across 21 forecast-grid-cells in 11 blocks—enrolled on the forecast service in phases 0, 1 and 2 are part of the sample for this pre-registered natural experiment.

Farmers receive forecasts indicating the median rainfall forecasted for the next five-days. In addition, probabilistic forecasts also indicate the likelihood of rain. Depending on the eventual realization for that five-day period, the forecast may be correct or incorrect. Since all the underlying forecasts are probabilistic in nature, whether an individual forecast is realized or not is as good as random. We rely on the random incidence of incorrect forecasts to identify their impact on farmers' subsequent engagement with the forecast service, and their beliefs about the service or its perceived accuracy.

We consider two types of incorrect forecasts that may occur: (1) a false alarm, where an event is predicted but does not occur; and (2) a missed event, where an event is not predicted, but does occur. Since all forecasts also communicate the median forecasted quantity to farmers, in our analyses, we consider two types of false alarms—one where rain is predicted but no rain occurs, and the other where rain is predicted but rain below that quantity occurs; and two types of missed events—one where no rain is predicted, but rain of any magnitude occurs, and the other where some rain is predicted, but rain far above the predicted quantity occurs.[18]

Forecast Interpretation Information Experiment. Farmers receiving probabilistic forecasts in phase 0 and phase 1, across 12 forecast-grid-cells in 5 blocks, are part of this pre-registered experiment.

Farmers assigned to receive the additional forecast interpretation treatment receive informational voice-calls every two-weeks between August and October (six in total) reiterating how to interpret forecasts and probabilities. The English translation of the script for these calls

[17]The forecast indicates the likelihood of rain above a certain threshold, which varies across months to correspond to quantities of rainfall that may be necessary for agricultural practices in a given month. For example, in the month of July, if the median forecasted rainfall in the next five days is between 0.1 and 2.5 inches, then the forecast provides the likelihood of any rain; while if the median forecasted rainfall is above 2.5 inches, the forecast provides the likelihood of rain above 2.5 inches. Rain upto 2.5 inches is ideal for the pest management activities typically undertaken in July, while rain above 2.5 inches requires other precautionary measures.

[18]Exact definitions are in the Appendix.

is below:

> *"Namaskara! This is a message from Coffee Krishi Taranga. The following is important information about understanding CKT rainfall forecast messages. Each forecast that you receive provides the total expected rainfall for the next 5 days and the likelihood of certain amounts of rain as a percentage chance. For example, an 80% chance of rain indicates that it will rain 8 out of 10 times. This means that it is very likely to rain, but it is not guaranteed to rain. Similarly, an 80% chance of 2 inches or more of rain means that it is very likely, but not certain, that rainfall will be 2 inches or more. In either case, there is also a small chance that the forecasted rainfall quantity may not occur. Weather prediction is complex, and so forecasts may occasionally be inaccurate. We recommend using the Coffee Krishi Taranga forecasts, other trustworthy local information, and your own experience to make the best decisions for your crops. We are constantly working to provide the most accurate forecast information and improve our service. If you have questions, suggestions, or need help, please contact us at [number]. Thank you for your attention and cooperation."*

3.3 Data

Lab-in-the-Field Experiment. In the lab-in-the-field experiment, apart from game outcomes, we collect data on farmer characteristics, farm characteristics, risk preferences, understanding of probabilities.

Administrative Data from the CKT service. Administrative data for the pre-existing advisory service consists of data on farmer demographics and farm characteristics for the larger sample of farmers who receive forecasts.

Service engagement data. For farmers who are enrolled in the weather-forecasting service, engagement data is automatically recorded by the service's technology platform. This consists of data on whether farmers answered a call or not, which call-try they answered, how much of a call they listened to, and the forecast that was sent. Forecasts are those generated by CFAN and described in sectionSection 2, updated on a daily-basis. In addition, we have data on actual weather realizations from NASA's Integrated Multi-satellitE Retrievals for GPM (IMERG) dataset.

Phone surveys. We conduct short phone surveys with a sub-set of farmers in phase 0, and phase 2 between September and December, 2024. These phone surveys are timed to be administered one day after a farmer is scheduled to receive a forecast. We collect data on farmers' trust in the forecast service, whether farmers relied on forecasts for agricultural decision-making in the preceding month, whether they shared forecasts with others. We also gather data on farmers' expectations of upcoming weather, comprehension of forecast message content.

Pre-registration. This research was registered on the social sciences registry. We describe deviations from the PAP in the Appendix.

4 Results

4.1 Demand for forecasts

Farmers who participate in the lab-in-the-field experiment demonstrate high demand for a new voice-call based probabilistic rainfall forecast service, with 98.43% of farmers willing to pay positive amounts and all farmers willing to take-up the service. In an incentive-compatible (Becker et al., 1964) elicitation, farmers' average willingness-to-pay for an 8-month subscription to the forecast-service is INR 204.4 (USD 2.42) or INR 25.55 (USD 0.30) per month—comparable with the willingness-to-pay for seasonal forecasts in the neighboring state of Telangana in 2022, INR 1.03 found by Burlig et al. (2024).[19]

Of the farmers who participated in this study component, 91% reported already receiving forecasts from another source, but only a them reporting trusting those forecasts.[20] Survey responses and interviews with farmers indicated that they often rely on multiple sources of weather information. Farmers also share forecast information with, and receive forecast information from, other farmers—79% of the forecast-service-users we surveyed indicated that they did share forecasts with others. So, this willingness-to-pay likely underestimates farmers' true valuation.[21]

These farmers' high demand for forecasts is also reflected in their eventual use of the real-world service. Over 96% of the same farmers answer at least one forecast-call that they receive after an initial onboarding call, and over 70% of farmers answer more than half the calls that they receive until mid-October, 2024. Farmers' willingness-to-pay also correlates with their engagement with the forecast-service (Figure 10, Table A4), as farmers with high engagement (i.e., who answered more than 50% of the forecast calls sent to them) had previously reported a 6% higher willingness to pay for the service.

Reported average willingness-to-pay is far higher than the average cost of providing the

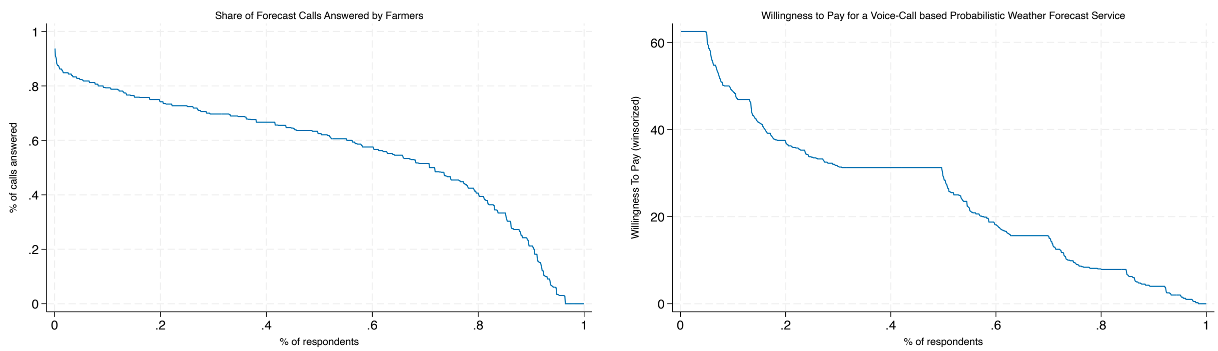
[19] This is understandably higher than the willingness-to-pay for a 9-month subscription to a voice-call based agricultural advisory service in Gujarat in 2013, INR 109 in Cole and Fernando (2020).

[20] Measured as reporting trust of 4 or 5 on a 5-point visual Likert scale.

[21] Also note that the months for which the subscription is offered in the BDM exercise, November to May, are non-rainy (or non-monsoon) months. Examples of activities that occur during this period are: (1) harvesting, and drying, when rain is undesirable; (2) coffee flowers begin to blossom in the spring, and light rain (or irrigation) is necessary. The real-world service begins in April, which includes the coffee blossoming period, and then continues onto the monsoon. Rain may be harder to predict outside the monsoon, indicating that reported willingness-to-pay may be lower for the monsoon months. Ongoing data collection will extend until January, 2025, allowing us more visibility into service-use beyond the monsoon.

service to each farmer at the target scale (of 50,000 farmers), INR 8 (USD 0.1).[22] Assuming that the demand curve implied by the willingness-to-pay reported by the farmers in the lab-in-the-field experiment applies to all farmers on the service at scale, the revenue maximizing price is INR 31.25 (USD 0.37), at which price 49.67% of farmers would take up the service (or 24,835 farmers in the at-scale service). Back of the envelope total cost calculations indicate an average cost of INR 15.69 (USD 0.19) when 24,835 farmers take up the service at price of INR 31.25, pointing to the substantial value generated by providing this service at-scale.

Figure 10: Farmer demand for a voice-call forecast service with probabilistic rainfall forecasts



Notes: The first figure represents the share of forecast calls that farmers who participated in the lab-in-the-field experiment answered between April and October, 2024. Farmers answered an average of 56.27% of calls sent to them. The second figure represents farmers' monthly willingness-to-pay for a subscription to the forecast service recorded in the BDM exercise at the end of the lab-in-the-field experiment. Farmers have an average willingness-to-pay of ₹204.4 or $2.42 for an 8-month subscription. The graph presents monthly equivalents of willingness-to-pay, which averages to ₹25.55 or $0.30 per month.

4.2 Impact of forecast information on beliefs about weather

We rely on results from the lab-in-the-field experiment and data on farmers' expectations of upcoming weather reported in phone surveys to assess how farmers rely on forecast information to form beliefs about weather.

First, we consider farmers' decisions in the 'agricultural decision-making game' from the lab-in-the-field experiment in Table 2, using the specification below.

$$\mathbb{I}(Updated\ Rainfall\ Beliefs)_{ir} = \beta_0 + \beta_1 Prob_{ir} + Order^{'}_{ir}\alpha_1 + Format^{'}_{ir}\alpha_2 + \mathbf{X}^{'}_{ir}\alpha_4 + GP_g + \epsilon_{ir} \quad (1)$$

where an observation is at the individual-round level, i, r; the outcome and regressors are described in Table 2.

[22]This is the average cost including the cost of custom private forecasts from CFAN for the coffee-growing region in Karnataka, phone service costs, and additional infrastructure and staff costs when the service is added onto an existing advisory service

Table 2: Impact of forecast information on beliefs about weather in hypothetical scenarios

(in an incentivized decision-making game with scores dependent on correctly predicting eventually realized weather)

	Irrigation		Fertilizer Application	
	|*Forecast - No forecast*|		|*Forecast - No forecast*|	
	(1)	(2)	(3)	(4)
Probability in the forecast	0.658***	0.537***	0.304***	0.244***
	(0.049)	(0.066)	(0.061)	(0.076)
Fixed Effects	No	Yes	No	Yes
N	2424	2424	2424	2424
Outcome mean, forecast prob = 0.1	0.131	0.131	0.052	0.052

Notes: The outcome is the absolute difference between the a farmer's belief about whether it will rain in a round with a forecast (posterior) and in a round without a forecast (prior) in a hypothetical decision-making game with two forecast rounds and one no-forecast round in each decision-making scenario. Regressor of interest is the probability in the forecast, which indicates the likelihood of rain being realized in that round, which randomly varies from 0.1 to 0.9. Columns 1, 3 present results which control for farmer characteristics; columns 2, 4 present results with individual fixed effects. Results with controls are from double lasso specifications, which include gram panchayat fixed effects, and controls for the forecast format, the order of the game round, game realizations in prior rounds, and whether the farmer first watched either of the informational videos prior to the experiment. Lasso controls include farmer characteristics, farm characteristics, forecast use prior to the experiment.
Robust standard errors clustered at the individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 demonstrates that farmers update their beliefs about expected weather based on information contained in a forecast in a given incentive-compatible round (rounds are described in Figure 6). Farmers in the game decide whether to irrigate (if rain is *not* expected) or not (if rain is expected), and whether to apply fertilizer (if heavy rain is *not* expected) or not (if heavy rain is expected) based on information in the forecast or their priors. Their action in a round with no forecast reflects their prior beliefs about the likelihood of rain, while their beliefs in a round with a forecast reflect their posterior beliefs based on information in the round's forecast, and the results across columns in Table 2 indicate that farmers are more likely to update their beliefs about the likelihood of rain based on a forecast, when the probability of rain in that forecast is higher. For each round in a scenario, the probability in forecasts randomly varies across participants, allowing us to interpret these results as the effect of the forecast information on beliefs. These results are not confounded by any within-scenario order effects and learning effects, which are controlled for; nor are they confounded by the method in which a forecast is delivered. The result also persists across both scenarios, where farmers are likely to have different priors—reassuring us that farmers are indeed updating their beliefs about expected weather based on a probabilistic rainfall forecast in hypothetical, controlled scenarios.

To validate whether these results translate to the real-world, we compare expectations (for a sub-sample of phase-2 farmers who we survey over the phone) between a randomly assigned control group and a randomly assigned forecast group using the following regression specification:

$$\mathbb{I}(Accurate\ Beliefs)_i = \beta_0 \ + \ \beta_1 Forecast_i \ + \ \mathbf{X}_{ir}^{'}\alpha_4 \ + \ Forecast - Grid_g \ + \ \epsilon_{ig} \quad (2)$$

where an observation is at the farmer-level, i. The outcome and regressors are described in Table 3. Suggestive evidence (from a small sample of farmers on the service) in Table 3 indicates that expectations are accurate for 14.9 percentage point more farmers in the forecast group, relative to the control group, at the 10% significance level. Sixty-five percent of the realizations in this dataset are of rainfall across categories, while 35% are of no-rain, reassuring us that the accuracy does not arise due to a lack of variation in realized weather.

Table 3: Impact of forecast information on beliefs about weather in real-world service

	$\mathbb{I}$[Expected Rainfall = Realized Rainfall]	$\mathbb{I}$[Expected Rainfall = Forecasted Rainfall]
	(1)	(2)
Receives Forecasts	0.149* (0.078)	0.106 (0.081)
N	334	334
Outcome mean, no forecast group	0.365	0.459

Notes: The outcome is an indicator, which takes the value 1 if the quantity of rainfall expected by the farmer in the next 5 days is in the same category as the realized rainfall in those 5 days. Data is from a survey with a small sample of farmers who use the real-world service, comparing those who receive forecasts with those who don't. Results are from double lasso specifications which include forecast grid, week of survey, and forecast format fixed effects. Lasso controls include age, indicator for whether a farmer is a smallholder, indicator for whether the farmer is female, indicator for whether the farmer completed higher secondary education, indicator for whether the farmer owns a smartphone, and an indicator for whether the farm has working irrigation facilities. Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Impact of forecast outcomes on beliefs about forecasts

To establish the impact of forecast outcomes on beliefs about forecasts, we rely on three sets of results: the impact of incorrect forecasts in a game-round on subsequent decisions by farmers in the lab-in-the-field experiment; the impact of incorrect forecasts in the real-world service on subsequent farmer engagement with the service; and the impact of incorrect forecasts in the real-world service on subsequent reported farmer beliefs and behavior from a phone-survey with a a sub-sample of service-users. We focus on incorrect forecasts of two types, as defined by meteorologists: *false alarms*, where rainfall is forecast but does not occur, and *missed events*, where rainfall is not forecast, but does occur (see for e.g., Ripberger et al., 2015).[23]

First, in Table 4, we analyze farmers' choices in the 'market-location choice' game from the lab-in-the-field experiment (described in Figure B2, Figure 5) using the specification below,

$$Outcome_{ir} = \beta_0 \; + \; \beta_1 Incorrect\ Forecast_{ir} \; + \; \gamma_4 Difference\ in\ Probabilities_{ir} \\ + \; \mathbf{X}'_{ir}\alpha_4 \; + \; GP_g \; + \; \epsilon_{ir} \quad (3)$$

where an observation is at the individual-round level, i, r. Outcomes and regressors are described in Table 4.

[23] A comprehensive discussion of forecast skill and verification measures is in https://www.cawcr.gov.au/projects/verification/

Table 4: Impact of incorrect forecasts on distinguishing between two probabilistic forecasts

(in an incentivized decision-making game with scores dependent on desired weather being realized)

	Chosen forecast is *ex ante* optimal		Investment		Current round score	
	(1)	(2)	(3)	(4)	(5)	(6)
Incorrect forecast in preceding round	-0.029**	-0.033***	-0.306***	-0.225***	-0.423***	-0.391***
	(0.011)	(0.012)	(0.033)	(0.029)	(0.091)	(0.093)
Difference in probabilities between forecasts in current round	0.103***	0.086***	0.334***	0.261***	1.164***	0.972***
	(0.020)	(0.020)	(0.061)	(0.052)	(0.163)	(0.164)
Individual Fixed Effects	No	Yes	No	Yes	No	Yes
N	6060	6060	6060	6060	6060	6060
Outcome mean, previous forecast correct	0.875	0.875	4.186	4.186	3.248	3.248

Notes: The outcome in columns (1), (2) is an indicator which takes the value 1 if the farmer makes the *ex ante* optimal choice, and 0 otherwise; the outcome in columns (2), (3) 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 (4), (5) is +investment if the farmer made the *ex post* optimal choice, or -investment if the farmer made the *ex post* non-optimal choice. Columns 1, 3, 5 present results which control for farmer characteristics; columns 2, 4, 6 present results with individual fixed effects. Results with controls are from double lasso specifications, which include gram panchayat fixed effects, and controls for the forecast format, the order of the game round, 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), correct choice in preceding round, whether the farmer first watched either of the informational videos prior to the experiment. Lasso controls include farmer characteristics, farm characteristics, forecast use prior to the experiment.
Robust standard errors clustered at the individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results in columns (1) and (2) in Table 4 indicate that farmers are less likely to choose the *ex ante* optimal forecast from a pair of forecasts describing predicted weather in two different market-locations, following a round where the forecasted event was not realized—an incorrect forecast. In the absence of these effects, farmers choose the *ex ante* optimal forecast more than 87% of the time, and experiencing an incorrect forecast lowers this by around 3 percentage points. Considering the high skill farmers otherwise exhibit, these results suggest a 'discouraging' effect of experiencing an incorrect forecast. Results in columns (3) and (4) further indicate that experiencing an incorrect forecast also causes farmers to stake fewer points (the investment) in subsequent rounds, reflecting lower confidence in the forecast. This directly points to a reduction in the perceived accuracy of the forecast, or trust in the forecast. Design features in the game ensure that results from this game are not confounded by biases that may arise due to a farmer conflating the quantity in a forecast with the probability in the forecast. They also ensure that merely knowing that a number is higher than another is not sufficient to make the optimal choice, since rounds require selecting either a 'more likely to rain' or 'less likely to rain' location at random. The order in which rounds are played is also randomized, as is the probabilities in the forecasts presented.

We next analyze how incorrect forecasts in the real-world impact farmers' engagement with the service, using the specification:

$$Call\ pick\ up_{i,t} = \beta_0\ +\ \beta_1 False\ Alarm_{i,t-1}\ +\ \beta_2 Missed\ Event_{i,t-1}\ + \\ (\ \beta_4 False\ Alarm_{i,t-1} \times Characteristic)\ + \\ +\ \mathbf{X}'_{ir}\alpha_4\ +\ Forecast - Grid_g\ +\ \epsilon_{ig} \quad (4)$$

The outcome and regressors are described in Table 5.

Table 5: Impact of incorrect forecasts on farmer engagement with a real-world service

	Whether a forecast voice-call is answered or not					
	(1)	(2)	(3)	(4)	(5)	(6)
Preceding forecast was a false alarm [Rain is predicted with p>0.5, but no rain occurs]	-0.092*** (0.016)	-0.045*** (0.011)	-0.094*** (0.026)	-0.072*** (0.021)	-0.086*** (0.017)	-0.111*** (0.015)
Preceding forecast was a false alarm × Risk Averse			-0.030** (0.010)			
Preceding forecast was a false alarm × Grows weather sensitive variety				-0.053** (0.023)		
Preceding forecast was a false alarm × No working irrigation facilities					-0.016*** (0.005)	
Preceding forecast was a false alarm × High rainfall variability						0.049** (0.023)
Preceding forecast was a missed event [No rain predicted, but rain of any magnitude occurs]	-0.027 (0.020)	-0.034** (0.014)	-0.018 (0.022)	-0.017 (0.021)	-0.027 (0.020)	-0.025 (0.021)
Individual Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
N	342693	342803	30885	30885	342693	342693
Outcome mean, previous forecast correct in omitted group	0.606	0.606	0.653	0.642	0.595	0.632

Notes: The outcome in all columns is an indicator which takes the value 1 if the farmer answers the forecast voice-call that is made to their number, and 0 otherwise. Columns (1) presents results which control for farmer characteristics, forecast grid, with a double lasso specification; columns (2)-(6) present results with individual fixed effects. All specifications include controls: forecast-grid, indicators for the calendar-week, indicator for number of forecast calls sent previously, indicator for forecast-type, indicators for which call-try (out of 3) was answered, the rainfall realization in the preceding forecast, current rainfall conditions, indicator for which call was last answered, indicator for whether the preceding forecast included the call-day or not. Lasso controls are an indicator for whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not. Columns (3) and (4) include only the sub-sample of farmers who participated in the lab-in-the-field experiments, and for whom data on risk aversion and crop variety exist.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As we demonstrate in Appendix C, farmers' engagement with the service reflects (or may be considered a proxy for) underlying trust in the service. Results in columns (1) and (2) of Table 5 indicate that farmers are less likely to answer a forecast-call following a forecast that ended up being a false alarm or a missed event—4.5 percentage points fewer calls are answered after a false alarm, while 3.4 percentage points fewer calls are answered after a missed event—demonstrating the 'discouraging' effect of incorrect forecasts, similar to that observed in the experimental games.[24] These effects are not driven by farmers misunderstanding or being confused about probabilities in probabilistic rainfall forecasts—**??** indicates that these effects persist for farmers in villages which receive probabilistic forecasts, and those which receive deterministic forecasts (recall that in phases 1 and 2, some villages are randomly assigned to receive deterministic forecasts, while others are randomly assigned to receive probabilistic forecasts).

This effect persists, with farmers demonstrating reduced engagement many weeks after experiencing an incorrect forecast in early forecasts (Table A7), suggesting lower perceived accuracy or trust in the forecast. Moreover, **??** clearly shows that when early forecasts are successes (i.e., there are no incorrect forecasts in the first five forecast-calls), the 'discouraging' effect of a false alarm is significantly lower in subsequent time periods. While farmers still exhibit lower engagement with the forecast-service after a false alarm, early successes narrow this effect by 4.6 percentage points, or around 7%. This corroborates the predictions in Appendix C that early experiences have lasting effects on trust-levels, even when the same number of correct forecasts have been experienced in total.

Heterogeneity. Columns (3)-(5) in Table 5 demonstrate that the reduction in engagement with the service is more pronounced for farmers who are more risk averse, for those who grow the more weather sensitive coffee variety (*Arabica*, as opposed to *Robusta*), and for those who do not have working irrigation facilities on their farms. All these factors suggest that farmers are more likely to be 'discouraged', when the stakes for them are higher. These findings reflect a similar underlying concept as that reflected in the findings in (Giné et al., 2015) which indicate that farmers with a lower ability to cope with risk, i.e., with similarly higher stakes, have accurate priors about weather.

Vulnerability to climate change. Column (6) demonstrates an important result, that farmers who are exposed to more weather variability, are less likely to be 'discouraged' by, or to lower engagement due to, incorrect forecasts. Here, blocks[25] with high recent historical rainfall variability, i.e., above median rainfall variability between 2000 and 2022, are categorized as high rainfall variability blocks, and intended to proxy for exposure to climate change—which is making weather patterns in the region more variable (Sreenath et al., 2022; Varikoden et al., 2019; Chandrashekhar and Shetty, 2017a). In high variability blocks, the reduction in engagement following a false alarm is 6.2 percentage points, as

[24] Note that there are far fewer missed events than false alarms in the dataset, since most calls are during the monsoon, leading to lower power on the missed event effects. As a result, we don't analyze heterogeneous effects with respect to missed events.

[25] geographic unit below the district level

opposed to 11.1 percentage points in other blocks—a 7.7% smaller effect where the average call-pick-up rate when the preceding forecast was correct is 63.2%. An associated results is the finding in Table 7 that the climate change salience treatment video in the lab-in-the-field experiment leads to a 3 percentage point increase in take-up of the real-world service more than six months after the treatment. This is an increase over an already high take-up rate of 95.1% in the control group from the lab-in-the-field experiment's study sample. Together, these findings demonstrate the value of improved and accessible medium-range range rainfall forecasts as a climate adaptation tool.

Survey findings. Finally, we provide provide supportive evidence from phone surveys with a little over 600 farmers who use the real-world forecast service Table 6. We analyze the impact of experiencing incorrect forecasts on subsequent trust in the forecast service, use of the forecasts in decision-making, and likelihood of sharing these forecasts with others by running the following regression specification:[26]

$$Outcome_{it} = \beta_0 + \beta_1 False\ Alarm_{i,t-1} + + \mathbf{X}'_{ir}\alpha_4 + Forecast - Grid_g + \epsilon_{ig} \quad (5)$$

where an observation is at the individual level, i. Outcomes and regressors are described in Table 6.

Table 6: Impact of incorrect forecasts in a real-world service on farmer beliefs

	Trust in forecasts used		Shared forecasts with others		Relied on forecasts for decision-making in the last month	
	Any	CKT	Any	CKT	Any	CKT
	(1)	(2)	(3)	(4)	(5)	(6)
Preceding forecast was a false alarm	-0.053	-0.031	-0.020	-0.051	0.069	-0.145**
[Rain is predicted with p>0.5, but no rain occurs]	(0.048)	(0.066)	(0.050)	(0.067)	(0.055)	(0.058)
N	589	502	590	501	614	504
Outcome mean, previous forecast correct	0.544	0.663	0.801	0.807	0.825	0.540

Notes: The outcome is columns (1) and (2) is an indicator that takes the value 1 if the farmer reports trusting forecasts at 4 or 5 on a 5-point scale, and 0 otherwise; the outcome in columns (3) and (4) is an indicator that takes the value 1 if the farmer reports having shared forecasts with others, and 0 otherwise; the outcome in columns (5) and (6) is an indicator that takes the value 1 if the farmer reports having relied on forecasts for decision-making in the last month, and 0 otherwise. Results are from double lasso specifications, including controls for forecast grid, calendar-week, the number of forecast calls answered previously,roll-out phase, forecast format, the rainfall realization in the preceding forecast, current rainfall conditions. Lasso controls are: whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Suggestive evidence in Table 6 indicates that farmers who last received a forecast that ended

[26] There are not enough missed events in the data to estimate any effects.

up being a false alarm are less likely to rely on the forecasts for decision-making—14.5 percentage fewer farmers reporting having done so after a false alarm. This finding is robust to the definition of a false alarm Table A6. In addition, using this alternate definition of a false alarm in Table A6, we find that the incidence of a false alarm also lowers reported trust in the forecasts—supporting our argument that the reduction in encouragement reflects a reduction in trust or perceived accuracy.

We also find supportive evidence in these surveys that the impact of incorrect forecasts may persist. Table A8 indicates that if the first forecast that was received was a false alarm, it reduces the likelihood that farmers rely on the service's forecasts to make agricultural decisions. Finally, corroborating our results on service-engagement and those theorized in Appendix C, Table A10 indicates that if early forecasts (in this case, the first five forecast calls sent to a farmer) are successful or correct, farmers report higher trust in the service when surveyed (at least 5-months after the service launched for phase 0 farmers, and at least two months after the service launched for phase 2 farmers). These results are statistically significant at the 95% level. However, a caveat here is that this is a sample of 502 randomly sampled farmers in phase 0 and phase 2 villages who used the service. These results, along with those in Table A9, show that early experiences with forecasts determine trust over a longer-horizon.

4.4 Impact of information treatments on beliefs about forecasts

Finally, we look at the impacts of the light-touch information treatments during the lab-in-the-field experiment, and in the real-world service. During the lab-in-the-field experiment, farmers were randomly assigned to watch a climate change salience video, a probability training video along with the climate change salience video, or a placebo video. Subsequently, once farmers being receiving calls from the real-world forecast service, villages in phases 0, and 1 are randomly assigned to receive either probabilistic forecasts alone, or probabilistic forecasts along with an information treatment, the 'forecast interpretation' treatment. The treatment intended to boost trust in the service by highlighting the uncertainty associated with forecasts, and explaining how to interpret probabilistic forecasts.

We estimate the effects of these treatments on engagement with the real-world service using the following two specifications (outcomes and regressions are in the Table 7).

$$Takeup_i = \beta_0 + \beta_1 Climate\ Change_i + \beta_2 Probability\ Training_i + \mathbf{X}_i'\alpha_4 + GP_g + \epsilon_i \quad (6)$$

$$
\begin{aligned}
Pick\ up\ \%_i = \beta_0 \ + \ \beta_1 Forecast\ Interpretation_i \ + \ \beta_2 \%\ Incorrect\ Forecasts_i \\
+ \ \beta_3 Forecast\ Interpretation_i \times \%\ Incorrect\ Forecasts_i \\
+ \ \mathbf{X}_i'\alpha_4 \ + \ Forecast - Grid_g \ + \ \epsilon_{ig} \quad (7)
\end{aligned}
$$

Table 7: Impact of information treatments on engagement with the real-world service

	Take-up	Share of calls answered				
	(1)	(2)	(3)	(4)	(5)	(6)
Climate change salience (CC)	0.034**	0.006				
	(0.015)	(0.013)				
Probability training (PT) [(CC + PT) - CC]	-0.012	-0.015				
	(0.012)	(0.014)				
Forecast interpretation (FI)			-0.031***	-0.077***	-0.035***	-0.081***
			(0.006)	(0.020)	(0.006)	(0.021)
% incorrect forecasts sent			-0.951***	-0.989***		
			(0.087)	(0.090)		
Forecast interpretation (FI) × % incorrect forecasts sent				0.074**		
				(0.029)		
% incorrect forecasts received					-0.559***	-0.598***
					(0.040)	(0.045)
Forecast interpretation (FI) × % incorrect forecasts received						0.074***
						(0.028)
N	1211	1211	9327	9327	9327	9327
Outcome mean, no video treatment	0.951	0.565	0.887	0.887	0.887	0.887

Notes: The outcome in columns (1) is an indicator which takes the value 1 if the farmer answers at least one forecast-call, and 0 otherwise; the outcome in columns (2) - (6) is the % of forecast-calls made to the farmer that are answered by the farmer. Treatment 'CC' is a video highlighting increasing weather variability and climate change adaptation measures at the start of the lab-in-the-field experiments; treatment 'PT' is a video providing probability training at the start of the lab-in-the-field experiments; treatment 'FI' is a voice-call describing how to interpret probabilistic forecasts and emphasizing that forecasts are not guarantees sent after the launch of the real-world service. Columns (1), (2) include all 1,212 farmers who participated in the lab-in-the-field experiments (phase 0), columns (3)-(6) include 1,135 phase 0 farmers, and an additional 8,192 farmers (phase 2). All results are from double-lasso specifications. Results in columns (3)-(6) include controls for the forecast-grid, phase, and number of calls made, lasso controls include whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not.
Robust standard errors (clustered at the forecast grid level in cols (2)-(6)) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As discussed previously, the climate change salience treatment significantly increases the take-up of the real-world service by 3 percentage points, more than six months after it is administered (column 1 in Table 7). The time between the treatment and the launch of the service is long enough to obfuscate any experimenter demand effects (Haaland and Roth, 2020, as in). However, column (2) indicates that it does not have a corresponding significant impact on the share of calls answered overall (by mid-October, 2024).

The 'forecast interpretation' treatment in the real-world service, on the other hand, has muted effects. The intent behind the treatment was to serve as a behavioral 'nudge', reminding farmers about uncertainty associated with forecasts and about how to interpret probabilities. This in turn was to boost trust and engagement, or at the very least mitigate the 'discouraging' effect of incorrect forecasts. These messages were sent over additional voice-calls to farmers once every two weeks from mid-August to mid-October, 2024. Results in columns (3)-(6) (Table 7) consider the share of calls answered after the start of the 'forecast interpretation' treatment, and indicate that while the treatment did mitigate the reduction in engagement (the interaction term), it came at the cost of lower overall engagement—reducing the likelihood of farmers answering the forecast-calls and the standard advisory calls (in Appendix)— due to 'call fatigue'.

5 Discussion and Conclusion

This study demonstrates that coffee farmers in rural Karnataka exhibit high demand for medium-range rainfall forecasts both through an incentive-compatible (Becker et al., 1964) mechanism to elicit their willingness to pay, and their eventual use of a real-world medium-range rainfall forecast service. We also find that the salience of climate change and weather variability boosts the use of this service. Coffee is a weather sensitive, perennial crop, and the region has highly variable (and increasingly so) weather, and taken together, our findings highlight the role of medium-range forecasts as a climate adaptation tool that helps farmers make within-season adjustments to manage agricultural risks, particularly in areas vulnerable to climate variability. This insight aligns with the growing literature on adaptation in climate economics and emphasizes that investments in scalable forecast services can have substantial benefits for smallholder farmers. In addition, the high willingness-to-pay compared to the costs of expanding access to forecasts that we observe also point to the value in investing in improved, customized climate information services for vulnerable farmers.

This study also provides experimental evidence on how farmers in developing countries form beliefs about the accuracy of weather forecasts based on their experiences, how this impacts their use of the forecast service, and how it consequently impacts their decision-making—both in a controlled lab-in-the-field experimental setting and through a natural experiment arising in a real-world service. We show that farmers' trust in the service evolves with forecast outcomes: incorrect forecasts reduce engagement with the service, and reported trust in the service. Trust (both reported, and implied by service engagement) in the service is heavily shaped by early forecast outcomes, as early positive experiences make farmer-engagement more robust to later forecast errors. This suggests a need to prioritize forecast accuracy in initial stages to foster early trust and encourage continued use, an approach that can extend to other digital extension services.

An experiment disseminating information to promote understanding of the uncertainty associated with forecasts, and to boost trust, yielded mixed results — suggesting that future research is needed to identify other strategies that boost trust in forecasts with high objective accuracy to overcome any ‘discouraging’ effects of errors. Digital information services that rely on remote delivery, such as voice-calls or text messages should also consider potential downsides of additional outreach, such as ‘call fatigue’. Finally, this study considers a relatively short time-frame: our experiments with the real-world service run a total of 10 months, and limit our ability to draw any conclusions on longer-term effects on trust, behavior or adaptation.

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A Additional Tables

Table A1: 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

Table A2: 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

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

Table A3: 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 A4: Correlation between *ex ante* WTP and use of real-world service

	Share of forecast calls answered	Farmer answered > 50% calls
	(1)	(2)
WTP for forecast service	0.025	0.068**
(in '00 ₹per month)	(0.016)	(0.034)
N	1212	1212
Outcome mean	0.563	0.707

Notes: The outcome is an indicator, which takes the value 1 if the quantity of rainfall expected by the farmer in the next 5 days is in the same category as the realized rainfall in those 5 days. Data is from a survey with a small sample of farmers who use the real-world service, comparing those who receive forecasts with those who don't. Results are from double lasso specifications which include forecast grid, week of survey, and forecast format fixed effects. Lasso controls include age, indicator for whether a farmer is a smallholder, indicator for whether the farmer is female, indicator for whether the farmer completed higher secondary education, indicator for whether the farmer owns a smartphone, and an indicator for whether the farm has working irrigation facilities. Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Impact of incorrect forecasts on farmer engagement with a real-world service

	Whether a forecast voice-call is answered or not					
	(1)	(2)	(3)	(4)	(5)	(6)
Preceding forecast was a false alarm [Rain is predicted with p>0.5, but rain below the predicted quantity occurs]	-0.032*** (0.009)	-0.012* (0.007)	0.004 (0.014)	-0.013 (0.025)	0.030*** (0.009)	-0.048*** (0.011)
Preceding forecast was a false alarm × Risk averse			-0.014* (0.006)			
Preceding forecast was a false alarm × Grows weather sensitive variety				0.013 (0.014)		
Preceding forecast was a false alarm × No working irrigation facilities					-0.004 (0.004)	
Preceding forecast was a false alarm × High rainfall variability						0.044** (0.017)
Preceding forecast was a missed event [Some rain predicted, but rain far above the predicted quantity occurs]	-0.013* (0.007)	-0.014** (0.006)	0.019* (0.009)	0.019* (0.009)	-0.012 (0.007)	-0.012 (0.007)
Individual Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
N	342693	342803	30885	30885	342693	342693
Outcome mean, previous forecast correct in omitted group	0.600	0.600	0.643	0.632	0.588	0.628

Notes: The outcome in all columns is an indicator which takes the value 1 if the farmer answers the forecast voice-call that is made to their number, and 0 otherwise. Columns (1) presents results which control for farmer characteristics, forecast grid, with a double lasso specification; columns (2)-(6) present results with individual fixed effects. All specifications include controls: forecast-grid, indicators for the calendar-week, indicator for number of forecast calls sent previously, indicator for forecast-type, indicators for which call-try (out of 3) was answered, the rainfall realization in the preceding forecast, current rainfall conditions, indicator for which call was last answered, indicator for whether the preceding forecast included the call-day or not. Lasso controls are an indicator for whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not. Columns (3) and (4) include only the sub-sample of farmers who participated in the lab-in-the-field experiments, and for whom data on risk aversion and crop variety exist.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Impact of incorrect forecasts in a real-world service on farmer beliefs

	Trust in forecasts used		Shared forecasts with others		Relied on forecasts for decision-making in the last month	
	Any	CKT	Any	CKT	Any	CKT
	(1)	(2)	(3)	(4)	(5)	(6)
Preceding forecast was a false alarm	-0.159**	-0.120*	0.005	-0.064	0.011	-0.151***
[Rain is predicted with p>0.5, but rain below the predicted quantity occurs]	(0.063)	(0.062)	(0.071)	(0.052)	(0.048)	(0.043)
Preceding forecast was a missed event	0.005	0.060	-0.062	-0.053	-0.030	0.022
[Some rain predicted, but rain far above the predicted quantity occurs]	(0.064)	(0.064)	(0.046)	(0.043)	(0.047)	(0.042)
N	589	502	590	501	614	504
Outcome mean, previous forecast correct	0.544	0.625	0.835	0.819	0.823	0.545

Notes: The outcome is columns (1) and (2) is an indicator that takes the value 1 if the farmer reports trusting forecasts at 4 or 5 on a 5-point scale, and 0 otherwise; the outcome in columns (3) and (4) is an indicator that takes the value 1 if the farmer reports having shared forecasts with others, and 0 otherwise; the outcome in columns (5) and (6) is an indicator that takes the value 1 if the farmer reports having relied on forecasts for decision-making in the last month, and 0 otherwise. Results are from double lasso specifications, including controls for forecast grid, calendar-week, the number of forecast calls answered previously,roll-out phase, forecast format, the rainfall realization in the preceding forecast, current rainfall conditions. Lasso controls are: whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Impact of incorrect forecasts on farmer engagement with a real-world service, by forecast format

	Whether a forecast voice-call is answered or not			
	Probabilistic Forecasts		Deterministic Forecasts	
	(1)	(2)	(3)	(4)
Preceding forecast was a false alarm	-0.034^{***}		-0.030^{***}	
[Rain is predicted with p>0.5, but rain below the predicted quantity occurs]	(0.009)		(0.010)	
Preceding forecast was a missed event	-0.010		-0.018^{**}	
[Some rain predicted, but rain far above the predicted quantity occurs]	(0.007)		(0.008)	
Preceding forecast was a false alarm		-0.098^{***}		-0.083^{***}
[Rain is predicted with p>0.5, but no rain occurs]		(0.016)		(0.018)
Preceding forecast was a missed event		-0.029		-
[No rain predicted, but rain of any magnitude occurs]		(0.020)		
N	214979	214979	127653	127653
Outcome mean, previous forecast correct	0.602	0.608	0.598	0.601

Notes: The outcome in all columns is an indicator which takes the value 1 if the farmer answers the forecast voice-call that is made to their number, and 0 otherwise. All columns present results with individual fixed effects, indicators for the forecast-grid, the calendar-week, which call was last answered, forecast-type, which call-try (out of 3) was answered, whether the preceding forecast included the call-day or not, and controls for the rainfall realization in the preceding forecast. Columns (1) and (2) include the sub-sample of farmers randomly assigned to received probabilistic forecasts; columns (3) and (4) include the sub-sample of farmers randomly assigned to received deterministic forecasts.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Impact of incorrect forecasts on farmer engagement with a real-world service

(Persistence of the impact of incorrect forecasts in the first call answered)

	Whether a forecast voice-call is answered or not	
	(1)	(2)
First forecast was a false alarm	-0.015***	
[Rain is predicted with p>0.5, but rain below that quantity occurs]	(0.005)	
First forecast was a missed event	-0.010*	
[Some rain is predicted with p>0.5, but rain far above that quantity occurs]	(0.006)	
First forecast was a false alarm		-0.011*
[Rain is predicted with p>0.5, but no rain occurs]		(0.006)
First forecast was a missed event		-0.039**
[No rain is predicted, but rain of any magnitude occurs]		(0.019)
N	394016	394016
Outcome mean, first forecast correct	0.570	0.550

Notes: The outcome in all is an indicator which takes the value 1 if the farmer answers the forecast voice-call that is made to their number, and 0 otherwise. Columns (1) and (2) presents results from a double lasso specification. Controls include forecast-grid, indicators for the calendar-week, indicator for number of forecast calls sent previously, indicator for forecast-type, indicators for which call-try (out of 3) was answered, the rainfall realization in the preceding forecast, current rainfall conditions, indicator for which call was last answered, indicator for whether the preceding forecast included the call-day or not. Lasso controls are an indicator for whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Impact of incorrect forecasts in a real-world service on farmer beliefs

	Trust in forecasts used		Shared forecasts with others		Relied on forecasts for decision-making in the last month	
	Any	CKT	Any	CKT	Any	CKT
	(1)	(2)	(3)	(4)	(5)	(6)
First forecast was a false alarm	-0.155	-0.186	-0.194	-0.087	0.094	-0.186**
[Rain is predicted with p>0.5, but rain below that quantity occurs]	(0.110)	(0.195)	(0.145)	(0.137)	(0.058)	(0.088)
First forecast was a missed event	0.012	-0.022	-0.034	-0.010	0.088***	-0.059
[Some rain is predicted with p>0.5, but rain far above that quantity occurs]	(0.056)	(0.078)	(0.072)	(0.022)	(0.032)	(0.076)
N	589	502	590	501	614	504
Outcome mean, first forecast correct	0.497	0.534	0.497	0.538	0.516	0.534

Notes: The outcome is columns (1) and (2) is an indicator that takes the value 1 if the farmer reports trusting forecasts at 4 or 5 on a 5-point scale, and 0 otherwise; the outcome in columns (3) and (4) is an indicator that takes the value 1 if the farmer reports having shared forecasts with others, and 0 otherwise; the outcome in columns (5) and (6) is an indicator that takes the value 1 if the farmer reports having relied on forecasts for decision-making in the last month, and 0 otherwise. Results are from double lasso specifications, including controls for forecast grid, calendar-week, the number of forecast calls answered previously,roll-out phase, forecast format, the rainfall realization in the preceding forecast, current rainfall conditions. Lasso controls are: whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Impact of incorrect forecasts on farmer engagement with a real-world service, when early forecasts received are correct relative to when they are not

	Whether a forecast voice-call is answered or not	
	(1)	(2)
Preceding forecast was a false alarm	-0.082***	
[Rain is predicted with p>0.5, but rain below that quantity occurs]	(0.017)	
Preceding forecast was a false alarm	0.051***	
$\times$ No errors in the first 5 forecast calls	(0.012)	
Preceding forecast was a missed event	-0.057***	
[Some rain is predicted with p>0.5, but rain far above that quantity occurs]	(0.014)	
Preceding forecast was a false alarm		-0.129***
[Rain is predicted with p>0.5, but no rain occurs]		(0.017)
Preceding forecast was a false alarm		0.046***
$\times$ No errors in the first 5 forecast calls		(0.012)
Preceding forecast was a missed event		-0.092
[No rain is predicted, but rain of any magnitude occurs]		(0.079)
N	267944	267944
Outcome mean, omitted group	0.612	0.601

Notes: The outcome in all is an indicator which takes the value 1 if the farmer answers the forecast voice-call that is made to their number, and 0 otherwise. Results are from specifications which control for individual fixed effects, indicators for the forecast-grid, indicators for the calendar-week, indicators for the number of forecast calls sent previously, indicator for forecast-type, indicators for which call-try (out of 3) was answered, the rainfall realization in the preceding forecast, current rainfall conditions, indicator for which call was last answered, indicator for whether the preceding forecast call included the call-day or not, indicators for the number of correct forecasts received so far.

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

Table A11: Impact of early correct forecasts in a real-world service on farmer beliefs

	Trust in forecasts used		Shared forecasts with others		Relied on forecasts for decision-making in the last month	
	Any	CKT	Any	CKT	Any	CKT
	(1)	(2)	(3)	(4)	(5)	(6)
No errors in the first 5 forecast calls	-0.010	0.170**	0.011	0.071	-0.048	-0.000
	(0.125)	(0.084)	(0.095)	(0.108)	(0.077)	(0.133)
N	589	502	590	501	614	504
Outcome mean, first forecast correct	0.548	0.552	0.547	0.550	0.552	0.552

Notes: The outcome is columns (1) and (2) is an indicator that takes the value 1 if the farmer reports trusting forecasts at 4 or 5 on a 5-point scale, and 0 otherwise; the outcome in columns (3) and (4) is an indicator that takes the value 1 if the farmer reports having shared forecasts with others, and 0 otherwise; the outcome in columns (5) and (6) is an indicator that takes the value 1 if the farmer reports having relied on forecasts for decision-making in the last month, and 0 otherwise. Specifications include controls for forecast grid, calendar-week, the number of forecast calls answered previously,roll-out phase, forecast format, the rainfall realization in the preceding forecast, current rainfall conditions, indicators for the number of correct forecasts so far. Controls from the following are selected using the double-selection LASSO method: whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Impact of video information treatments on game outcomes and willingness-to-pay

(Videos (1) highlighting increasing weather variability and climate change adaptation measures; (2) providing probability training at the start of the lab-in-the-field experiments)

	Total score	WTP	
	(1)	(2)	(3)
Climate change salience (CC)	0.441	0.256	0.166
	(1.009)	(1.132)	(1.126)
Probability training (PT) [(CC + PT) - CC]	1.436	-2.125*	-2.007*
	(1.058)	(1.167)	(1.163)
Any False Alarms in Experimental Games			-2.661***
			(0.972)
Any Missed Events in Experimental Games			0.908
			(0.970)
N	1212	1212	1212
Outcome mean, no video treatment	70.717	25.905	25.905

Notes: The outcome in all columns is an indicator which takes the value 1 if the farmer answers the forecast voice-call that is made to their number, and 0 otherwise. All columns present results with individual fixed effects. All specifications include controls: indicators for the calendar-week, indicator for number of forecast calls answered previously, indicator for the roll-out phase, indicators for number of tries made to farmers (out of 3), indicator for the forecast format, the rainfall realization in the preceding forecast, current rainfall conditions. Results in columns (1) and (2) rely on a sub-sample of farmers who participated in the lab-in-the-field experiments, for whom data on risk aversion and coffee variety is available, while other results rely on the entire sample of farmers receiving forecasts.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Impact of an audio information treatment on farmer beliefs

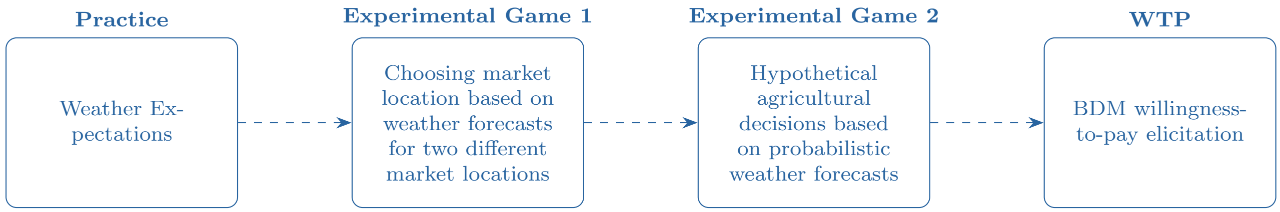
(Voice-calls describing how to interpret probabilistic forecasts and emphasizing that forecasts are not guarantees)

	Trust in forecasts used		Shared forecasts with others		Relied on forecasts for decision-making in the last month	
	Any	CKT	Any	CKT	Any	CKT
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast interpretation treatment	-0.080**	-0.059	-0.058	-0.056	-0.040	-0.068
	(0.039)	(0.074)	(0.049)	(0.042)	(0.026)	(0.054)
N	346	302	346	303	358	303
Outcome mean, no info	0.652	0.672	0.652	0.672	0.671	0.672

Notes: The outcome is columns (1) and (2) is an indicator that takes the value 1 if the farmer reports trusting forecasts at 4 or 5 on a 5-point scale, and 0 otherwise; the outcome in columns (3) and (4) is an indicator that takes the value 1 if the farmer reports having shared forecasts with others, and 0 otherwise; the outcome in columns (5) and (6) is an indicator that takes the value 1 if the farmer reports having relied on forecasts for decision-making in the last month, and 0 otherwise. Results are from double lasso specifications, including controls for forecast grid, calendar-week, the number of forecast calls answered previously,roll-out phase, forecast format, the rainfall realization in the preceding forecast, current rainfall conditions. Lasso controls are: whether the farmer is female or not, the farmer's age, whether the farmer is a smallholder with 5 acres or less of land, whether the farmer has completed higher secondary education or not, whether the farmer has a smartphone or not, whether the farmer has working irrigation facilities or not.
Robust standard errors clustered at the forecast grid level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Additional Figures

Figure B1: Flow of activities in the lab-in-the-field experiment



Experimental Game 1

Choosing a hypothetical market-location where ideal weather conditions are expected based on forecasts for two different locations

Objective

Maximize expected earnings across multiple game rounds

1. Farmers advise hypothetical vendors about where to set up a stall to sell their goods
2. Whether the vendor makes any sales depends on the weather realized, while the quantity sold depends on the points the advising farmer puts at stake in that round
3. In each round, there is only one location where the ex-ante expected earnings are maximized (i.e., where the probability of ideal weather is higher)

Game rounds

Five incentivized rounds, three of which have one-day forecasts, and two have one-week forecasts

1. Each round presents farmers with two hypothetical market locations, and forecasts for each
2. Farmers recommend a location based on the forecasts
3. They recommend how much the vendor should invest (choosing how many points to put at stake)
4. After both choices are made, in-game weather for the round is realized
5. If ideal weather is realized, points put at stake are gained, and if not, points put at stake are lost

Scenario variations to eliminate confounding

Scenarios and rounds randomly vary in certain attributes to eliminate confounding

1. Certain rounds have a pair of forecasts where the rainfall quantity is the same, and only the probability varies, while others have a pair of forecasts with both quantities and probabilities vary to control for conflating probabilities and quantities in probabilistic forecasts
2. Certain rounds require choosing a location where it is more likely to rain based on probabilistic rainfall forecasts, while others require choosing a location where it is less likely to rain based on probabilistic rainfall forecasts — to control for conflating a larger number alone with the likelihood of ideal weather
3. Order in which each round and scenario appears to control for learning over time
4. Rounds have different formats in which forecasts are presented
5. Differences in probabilities between forecast pairs randomly varies between 5% and 95%

Scoring and incentives

Farmers are incentivized to select the ex-ante optimal location in each round since their score depends on the ideal weather being realized and the number of points they choose to put at stake in a round

1. Points at stake are chosen from {1, 2, 3, 4, 5}
2. If ideal weather for the vendor's sales is realized, the stake is awarded, and if it is not realized, the stake is deducted
3. Final monetary rewards are based on points gained through all games and game-rounds, with rupees earned being the number of points scored

Figure B2: Overview of Experimental Game 1

Experimental Game 2

Choosing whether to take agricultural actions based on probabilistic rainfall forecasts in hypothetical scenarios

Objective

Maximize expected earnings across multiple game rounds

1. Farmers playing the game (player) advise a hypothetical farmer whether to take a particular agricultural action or not based on expected weather
2. Scenarios describe the time-of-year, the action, the hypothetical farmer, and in certain rounds the weather forecast
3. Once an action (or inaction) is recommended, in-game weather for the round is realized
4. In each round, there is only one action where the ex-ante expected earnings are maximized (i.e., the action or inaction that is appropriate for the weather predicted by the forecast with probability $\geq$50%)

Game rounds

Six incentivized rounds across two hypothetical agricultural scenarios

1. In each scenario, one round is played with no forecast, and 2 with forecasts
2. In each round, the agricultural scenario is described, then forecasts are provided in forecast rounds, while players are asked to recollect historical incidence of weather in their village in no-forecast rounds
3. Based on expected weather, players recommend an action/inaction
4. Following the choice of action/inaction, in-game weather for the round is realized
5. If the chosen action/inaction is appropriate for the realized weather, points are awarded; otherwise, points are deducted

Scenario variations to eliminate confounding

1. One scenario requires farmers to decide whether to irrigate their crop or not, prior to the monsoon. Irrigation is required when there is no rain, and no irrigation when there is rain
2. The second scenario requires farmers to decide whether to apply fertilizer or not during a mid-monsoon rainfall break. Fertilizer should be applied when heavy rain is not expected, and not apply fertilizer when heavy rain is expected to avoid run-off.
3. Rounds have different formats in which forecasts are presented, both audio and text/image
4. Order in which each round and scenario appears to control for learning over time
5. The probabilities in forecasts are randomly chosen from {10%, 20%, 30%, 35%, 40%, 50%, 55%, 60%, 65%, 70%, 80%, 90%}

Scoring and incentives

1. 5 points at stake in each round
2. If the chosen action/inaction is appropriate for the realized weather, points are awarded; otherwise, points are deducted
3. Final monetary rewards are based on points gained through all games and game rounds, with rupees earned being the number of points scored

Figure B3: Overview of Experimental Game 2

Figure B4: Investment choice or points put at stake in game 1

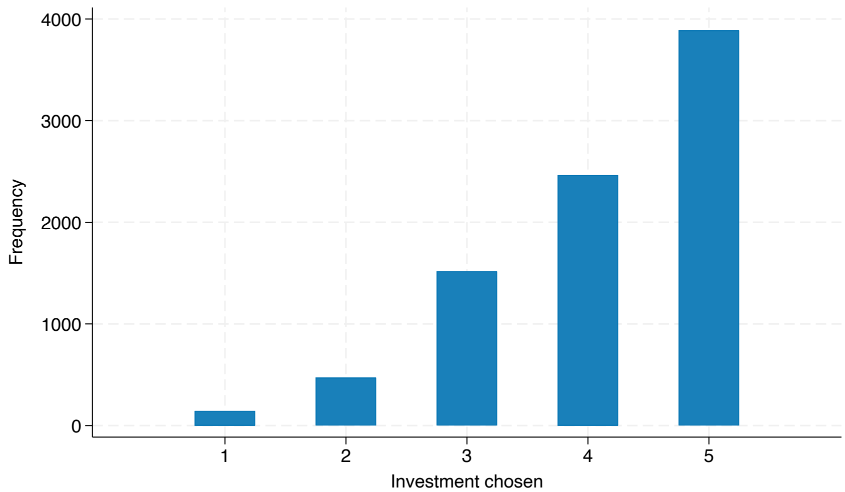


Figure B5: Rain realizations in the hypothetical Scenarios, game 1 & game 2

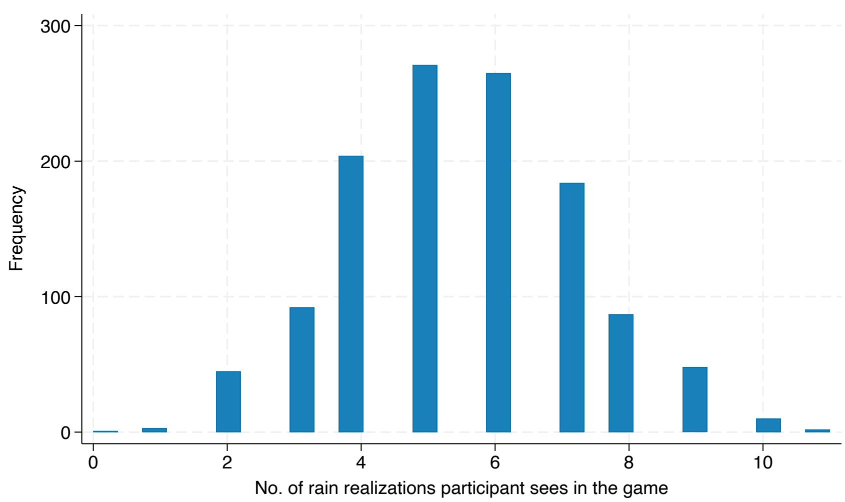


Figure B6: Onboarding messages sent on the service, translated from Kannada

Probabilistic forecasts

"Namaskara from Coffee Krishi Taranga! We are pleased to announce the launch of our weather forecast service in your village!

We will provide you with rainfall forecast messages over voice calls starting this week. The forecasts will provide the total expected rainfall for the next 5 days, and indicate how likely a certain amount of rainfall is in percentage chance terms.

Note that forecasts are not a guarantee, so if a forecast indicates that there is a 80% chance of rain, it indicates that it is highly likely to rain, but there is a small chance that the forecasted rainfall quantity may not occur.

These forecasts are more accurate and for a smaller geographic area than other forecasts commonly available to you. In the last 6 years, the forecasts correctly predicted the occurrence of any rain in the next 5-days [district-accuracy%] of the time in [district name].

In case you miss our call, you can access the latest forecast for your village by calling on [number] and replying with '5'.

We recommend you make any agriculture decisions by using information from sources that you feel are trustworthy.

If you have questions, suggestions, or need help, please contact us at [number]. Thank you for your attention and cooperation."

Deterministic forecasts

"Namaskara from Coffee Krishi Taranga! We are pleased to announce the launch of our weather forecast service for farmers in your village!

We will provide you with rainfall forecast messages over voice calls starting this week. The forecasts will provide the total expected rainfall for the next 5 days.

While forecasts are not a guarantee, these forecasts are more accurate and for a smaller geographic area than other existing forecasts commonly available to you. In the last 6 years, the forecasts correctly predicted the occurrence of any rain in the next 5-days [district-accuracy%] of the time in [district name].

In case you miss our call, you can access the latest forecast for your village by calling on [number] and replying with '5'.

We recommend you make any agriculture decisions by using information from sources that you feel are trustworthy. If you have questions, suggestions, or need help, please contact us at [number]. Thank you for your attention and cooperation."

Figure B7: Onboarding messages sent on the service, translated from Kannada

Probabilistic forecasts with related advisory

"Namaskara from Coffee Krishi Taranga! We are pleased to announce the launch of our weather forecast service for farmers in your village!

We will be providing you with rainfall forecast messages over voice calls starting this week. The messages will also indicate to you what coffee cultivation practices are recommended under the forecasted weather conditions.

The forecasts will provide the total expected rainfall for the next 5-days; and indicate how likely a certain amount of rainfall is in percentage chance terms.

Note that forecasts are not a guarantee, so if a forecast indicates that there is an 80% chance of rain, it indicates that it is highly likely to rain, but there is a small chance that the forecasted rainfall quantity may not occur.

These forecasts are more accurate and for a smaller geographic area than other existing forecasts that are commonly available to you. In the last 6 years, the forecasts correctly predicted the occurrence of any rain in the next 5-days [district-accuracy%] of the time in [district name].

In case you miss our call, you can access the latest forecast for your village by calling on [number] and replying with '5'.

We recommend you make any agriculture decisions by using information from sources that you feel are trustworthy. If you have questions, suggestions, or need help, please contact us at [number]. Thank you for your attention and cooperation."

Deterministic forecasts with related advisory

"Namaskara from Coffee Krishi Taranga! We are pleased to announce the launch of our weather forecast service for farmers in your village!

We will be providing you with rainfall forecast messages over voice calls starting this week. The forecasts will provide the total expected rainfall for the next 5-days. The messages will also indicate to you what coffee cultivation practices are recommended under the forecasted weather conditions.

While forecasts are not a guarantee, these forecasts are more accurate and for a smaller geographic area than other existing forecasts that are commonly available to you. In the last 6 years, the forecasts correctly predicted the occurrence of any rain in the next 5-days [district-accuracy%] of the time in [district name].

In case you miss our call, you can access the latest forecast for your village by calling on [number] and replying with '5'.

We recommend you make any agriculture decisions by using information from sources that you feel are trustworthy. If you have questions, suggestions, or need help, please contact us at [number]. Thank you for your attention and cooperation."

Figure B8: Examples of forecasts sent on the service, translated from Kannada

Probabilistic forecasts

For the next 5 days, that is, from May 23 to May 27, in <Pushapalli> village: There is a 70% chance of rain. 1 inch of rainfall is expected (on average).

Deterministic forecasts

For the next 5 days, that is, from May 23 to May 27, in <Pushapalli> village: 1 inch of rainfall is expected (on average).

Probabilistic forecasts with related advisory

For the next 5 days, that is, from May 23 to May 27, in <Pushapalli> village: There is a 70% chance of rain. 1 inch of rainfall is expected (on average). This forecast indicates that there might be sufficient soil moisture for pre-monsoon fertilizer application if you have not already applied fertilizer.

Provided there is sufficient soil moisture, for each acre we recommend applying 66 kg of urea, 133 kg of rock phosphate and 51 kg of muriate of potash for Arabica coffee; and 77 kg of urea, 153 kg of rock phosphate and 59 kg of muriate of potash for Robusta coffee.

Deterministic forecasts with related advisory

For the next 5 days, that is, from May 23 to May 27, in <Pushapalli> village: 1 inch of rainfall is expected (on average). This forecast indicates that there might be sufficient soil moisture for pre-monsoon fertilizer application if you have not already applied fertilizer.

Provided there is sufficient soil moisture, for each acre we recommend applying 66 kg of urea, 133 kg of rock phosphate and 51 kg of muriate of potash for Arabica coffee; and 77 kg of urea, 153 kg of rock phosphate and 59 kg of muriate of potash for Robusta coffee.

C Conceptual Framework

In this section, we present a simple conceptual framework for how farmers form beliefs about the accuracy of a forecast.

Consider a farmer, i at the start of a time-period, t, whose prior belief about the likelihood of rain in the upcoming period, t, is π_{prior}. The farmer receives a rainfall forecast, f, at time-period, t. The probability in the rainfall forecast is, π_f. The farmer forms a posterior belief, $\hat{\pi}_{posterior,t}$ about the likelihood of rain in the time-period, t using this updating rule:

$$\hat{\pi}_{posterior,t} = (1 - \tau_t)\pi_{prior,t} + \tau_t \pi_{f,t} \tag{8}$$

Here, τ_t represents a farmer's trust in the forecast, or their subjective belief about the forecast's accuracy. We, henceforth, refer to τ_t as a trust parameter, and this parameter evolves with the farmer's experiences.

$$\tau_t = (1 - \gamma_t)\tau_{t-1} + \gamma_t d_{t-1} \tag{9}$$

where $d_{t-1} \in \{0, 1\}$ represents an individual forecast's accuracy—taking the value 1 if the event the forecast predicts occurs (correct forecast), and 0 otherwise (incorrect forecast).[27] γ_t is a weighting function. Similar in spirit to the model characteristics in Malmendier and Nagel (2016), we allow the weighting function to depend on the time-period, t or the time since the farmer began using the forecasts.

$$\gamma_t = \frac{\theta}{t} \tag{10}$$

$\theta > 0$ is a constant parameter that determines the weighting on past experiences with the forecasts. This allows earlier and later experiences to have a different influence.

Call pick up. We assume that the trust parameter at a time, t, also determines the likelihood that a farmer answers a call in that period. We represent the likelihood of answering the call at a time period, t as a logistic function of the trust parameter in that period, τ_t. We assume that $\tau = 0.5$ is a trust threshold above which the likelihood of answering the call increases rapidly.

$$p_t(pick\ up) = \frac{1}{1 + e^{-\beta(\tau_t - \tau_{threshold})}} \tag{11}$$

[27]We abstract away from probabilities in forecasts, but the results hold if we consider an event to be predicted when then forecast probability is > 0.5.

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 A14 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.[28] 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.

[28]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 A14: 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

Notes: 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.

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