Probabilistic Weather Forecasts and Farmer Decision Making in Rural India*

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Abstract

With increasing weather uncertainty in the context of climate change, accurate, probabilistic weather forecasts can potentially help smallholder farmers mitigate associated agricultural production risk. In this paper, we study how coffee farmers in Karnataka, India make decisions using probabilistic weather forecasts in a lab-in-the-field experiment that relies on hypothetical decision-making games. Farmers demonstrate relatively high probability literacy, responding to probabilities conveyed in hypothetical weather forecasts and express demand for a real-world mobile-phone based audio weather forecast service in an incentive compatible Becker–DeGroot–Marschak (BDM) exercise. Farmers update their beliefs about the (in)accuracy of the weather forecast following false alarms (where forecast events do not end up occurring), and farmers who experience more false alarms in the experiment report lower willingness-to-pay for the real-world service.

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

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1 Introduction

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

Evidence across disciplines and methodological approaches suggest that weather forecasts benefit farmers (Meza et al., 2014; Mase and Prokopy, 2014; Rosenzweig and Udry, 2019), and that there is substantial demand for seasonal Burlig et al. (2022) and sub-seasonal weather information (Fosu et al., 2020). Other interventions that reduce farmers' *ex ante* agricultural risk have been shown to have large effects on profits, crowding in investment (Barnett-Howell, 2021; Emerick et al., 2016; Karlan et al., 2014), and if accurate forecasts that are customized for farmers' understanding and contexts are provided at scale, they have the potential to do so too. While most studies so far have focused on the provision of deterministic weather forecasts, there is potential for farmers to take better decisions when they may also assess the certainty associated with the forecast. However, providing farmers with informationally rich forecasts only makes sense if such forecasts are accurately comprehended (Stephens et al., 2019).

Prior literature on probabilistic reasoning (Delavande, 2014) indicates that farmers in developing country contexts do understand probabilities, and in fact, weather is often the intuitive example provided to farmers when discussing probabilistic beliefs. In this study, we focus on probabilistic weather forecasts for farmers in rural Karnataka, and ask how farmers understand, interpret, use and form beliefs about probabilistic weather forecasts. We do this in a lab-in-the-field experimental set-up. We recruit small- and medium-holder coffee farmers in Karnataka, India. Farmers are randomized into one of three experimental arms: (1) an information intervention highlighting the salience of climate change in the context of coffee cultivation via video; (2) information intervention highlighting climate change salience and providing basic training to improve understanding of probabilities via video; (3) a control group, with a placebo video describing the history of coffee cultivation in India (C). Farmers watch the assigned informational videos, and then play two hypothetical decision-making games where decisions rely on understanding information contained in weather forecasts. Finally, we elicit farmers willingness to pay for a voice-call based service that provides accurate, granular, probabilistic weather forecasts on a weekly basis.

We find that farmers have relatively high probability literacy, and perform better in the weather forecast games than in probability 'test' questions that rely on the canonical balls-in-urn example or on lotteries. In the experimental games, farmers take decisions that are consistent with their beliefs updating to incorporate the probabilities conveyed in forecasts. Farmers who are randomly assigned to the probability training (and climate change salience) information treatment perform slightly better in probability 'test' questions, and exhibit higher confidence in their choices in the location-choice game. Farmers randomly assigned to the probability training (and climate change salience) information treatment also believe that unexpected weather events are increasingly likely after the information treatment. Farmers also exhibit reasonably high willingness to pay for a new real world voice call based weather forecast service (₹26 on average, or 10% of the daily casual wage rate in Karnataka), considering forecasts are widely available on the internet.

Over the course of the experimental games, farmers also continuously update their beliefs about the accuracy of the weather forecasts in the game. We find that farmers update their beliefs (downward) about the accuracy of forecasts following false alarms (where rainfall is predicted with high probability, but does not occur), and that farmers who experience false alarms in the game have a significantly lower willingness to pay for the real-world weather service.

2 Background

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

2.1 Setting

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

Table 1: Coffee Krishi Taranga Users in 2018

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

2.2 Weather in Karnataka

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

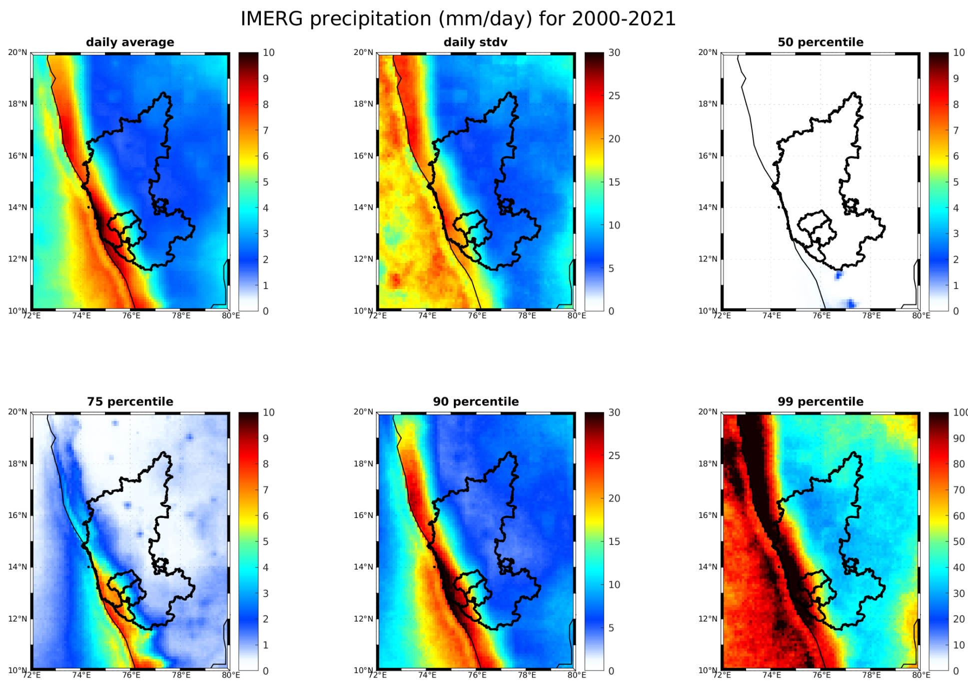

Figure 1: Daily rainfall amount and variability in Karnataka

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

2.3 Weather and Demand for Information

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

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

rains can disrupt harvesting and make it harder for farmers to dry their harvested coffee beans. Column (3) indicates that in this period, inbound calls increase by 13% following a week with rainfall above the 75th percentile.

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

	(1)	(2)	(3)
	Blossom	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

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

3 Experimental Design

This section describes the experiment design.

3.1 Sample, Randomization and Information Treatments

The sample for this study was drawn from the rosters of small- and medium-holder coffee farmers from the Coffee Board of India and existing users of Coffee Krishi Taranga in Chikmagalur and Kodagu, two coffee-growing districts in Karnataka. In each of the randomly selected gram panchayats (GPs) in two blocks in the two districts, we randomly sampled farmers and recruited them for the in-person study on the phone. When the target sample for a GP was not met, farmers were recruited in person. Overall, 1212 farmers completed the study.

In person, farmers who are successfully recruited are randomized at the individual level (on-the-spot) into one of three experimental arms: (1) an information intervention highlighting the salience of climate change in the context of coffee cultivation via video (E1); (2) information intervention highlighting climate change salience and providing basic training to improve understanding of probabilities via video (E2); (3) a control group, with a placebo video describing the history of coffee cultivation in India (C). The experiment was designed to have unequal shares across treatment arms (42% in the climate change salience arm, 29% in the climate change salience and probability training arm, and 29% in the control group) to maximize power to detect the effect of the combined treatment relative to the climate change salience treatment alone (Muralidharan et al., 2023). Attrition among the treated sample is low (approximately 2% overall), and does not vary significantly across experimental arms (Table B1).

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

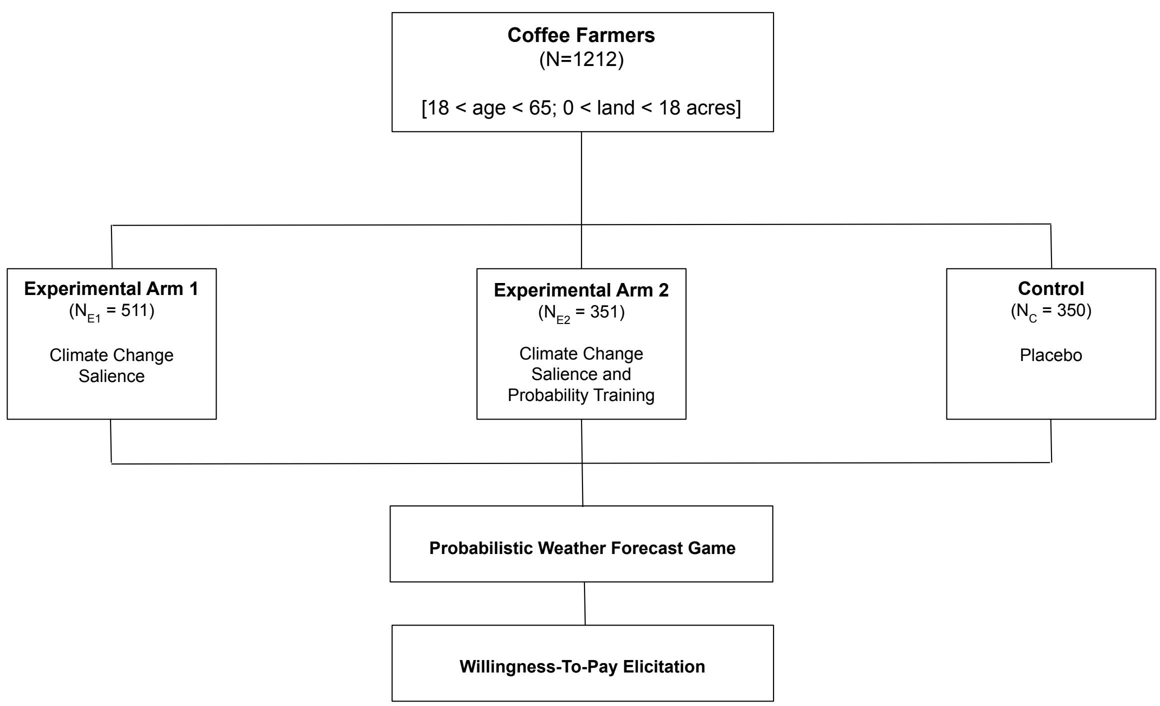

Figure 2: Experiment Design

Table 3: Randomization Balance

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

3.2 Experimental Games: Hypothetical Decision-Making and Weather Forecasts

The intervention and experimental games took place during the same visit. Once farmers are randomized into an experimental arm. Farmers then watch the assigned videos, and then play two hypothetical decision-making games that rely on weather forecasts. The games are designed to test farmer's understanding of probabilities and administered by the surveyor, with the farmer viewing/listening to the weather forecasts themselves.

Practice: To get accustomed to the interface, farmers first answer a few questions indicating their familiarity with weather icons, interpreting sample weather forecasts in varying formats, and classifying rainfall quantities into categories (light, medium, heavy, very heavy).

Location choice game: Each round in the game consists of a pair of weather forecasts in a different format, the order in which these rounds appear is randomized. All forecasts in this round use images and text only (i.e., no audio). There are five rounds across two scenarios, one scenario consists of three one-day forecast pair rounds; while the other consists of two one-week forecast pair rounds. There are two versions of each scenario that are chosen by the game at random — one asking farmers to select a rainy (more likely to rain) location, and the other asking farmers to select a dry (less likely to rain) location. All forecasts are probabilistic rainfall forecasts. In addition, each forecast pair has two versions that appear at random — one where the quantities of rainfall in both forecasts are the same, with only probabilities varying, and the other where quantities and probabilities both vary.[3] These game elements allow us to control for confounding due to round-order, forecast format, differences in ability to select more like as opposed to less likely events. If participants were to perform far better in the versions of forecasts where quantities vary than where they do not, it might indicate conflating likelihoods with quantities. The probabilities in each forecast pair are randomized, and so there are questions with varying difficulty (increasing as the difference between the two forecasts decreases). While probabilities in each round are randomly assigned, we ensure that probabilities are such that the optimal choice is not confounded by risk preferences (so there is only one correct choice, irrespective of risk preferences). Table B2 provides some game details. Finally, as in Stephens et al. (2019), the forecast event is realized with the probability in the weather forecast (i.e, if a forecast in the games indicates that there is an 80% chance of rain, rain is realized with 80% chance, i.e, 8 out of 10 participants who see that forecast will have a rainfall realization, and 2 out of 10 participants will have a no rainfall realization. Forecasts are simplified to have only two possible outcomes (event being realized, or event not being realized).

Game 1: Farmers play the first hypothetical decision-making game, comprising five incentivized rounds across two scenarios unrelated to coffee cultivation after two unincentivized

[3] Quantities in these version are such that a higher quantity appears with a higher probability. This is done because a higher quantity of forecast rain is correlated with a higher likelihood of any rain, and so an 'incorrect' answer based on the probabilities may be a logical answer.

practice rounds. In each round, farmers are presented with a scenario where a vendor has to choose one of two market locations with different weather forecast (i.e. probability of rain) to maximize the sales of vendor's goods, where the expected sales depend on weather realization. For instance, one of the practice scenarios is that of a vendor who sells fresh fruit juice, which sells better on a sunny (or non-rainy) day. In this case, the participant farmer chooses a location for the vendor based on weather forecasts. Once this choice of location is made, participant farmers then indicate their confidence in their choice by selecting a 'stake', or the amount the vendor should plan to sell in the selected location. A weather realization occurs after these choices are made, and scores depend on the outcomes and chosen 'stakes'. Each forecast pair consists of forecasts in a different format, the order in which they appear is randomized, and across participants, forecast-pairs in the sub-rounds vary in the probabilities of the forecasted event, and in some cases, the amounts of rainfall predicted.

Game 2: Participant farmers next play a second hypothetical decision-making game where they recommend agricultural actions to hypothetical farmers following a weather forecast. Participant farmers are presented with two hypothetical coffee-cultivation activity scenarios. In one, they assist three hypothetical farmers decide whether to irrigate coffee plants or not during the crucial blossoming period; and in the other, they assist three hypothetical farmers decide whether to apply fertilizer or not. The hypothetical farmers in each scenario have access to different weather information (forecasts in different formats or no forecast). In each round, in-game weather is realized after participant farmers recommend an action, and scores depend on the weather realization and action chosen. Across participants, forecasts in sub-rounds vary in the probabilities of the event being forecast, and the order of sub-rounds is randomized. In each round, participant farmers are awarded five points when their action is appropriate for realized weather, and lose five points when their action is not.

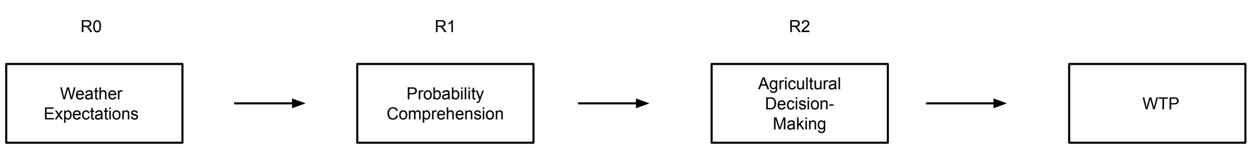

Figure 3: Experiment Flow

Weather forecast realization: Throughout the experiment, weather forecasts are 'reliable', i.e., weather realizations are drawn from the probability distribution implied by the relevant probabilistic weather forecast (following Stephens et al. (2019)).[4]

Willingness to Pay Elicitation: Willingness to pay is elicited using the Becker DeGroot Marschak (1964) or BDM mechanism.

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

4 Conceptual Framework

We consider farmers making decisions under uncertainty about upcoming weather (over the short-to-medium term, i.e., 1-to-15 days[5]), when they have access to probabilistic weather forecasts (adapting Millner (2008) and Shafiee-Jood et al. (2021)). We assume that farmers are quasi-Bayesian learners, who may not accurately interpret probabilities in the weather forecasts.

4.1 Subjective beliefs about upcoming weather

We consider a representative farmer making decisions at time, t, where there are two possible states of upcoming weather, $\theta_t \in \Theta = \{0, 1\}$ — a dry state ($\theta_t = 0$), and a rainy state ($\theta_t = 1$). For that particular time-of-year, farmers have a prior belief about upcoming weather informed by climatology, current observations, localized knowledge, experience (Roncoli et al., 2002; Millner, 2008; Shafiee-Jood et al., 2021).[6] We denote this prior belief, $p_t(\theta_t)$, with $p_t(\theta_t = 1) = p_{1,t}$ and $p_t(\theta_t = 0) = 1 - p_{1,t}$. Farmers receive probabilistic rainfall forecasts, $\pi_t(\hat{\theta}_t)$, where $\pi_t(.)$ is a probability mass function, and $\hat{\theta}_t \in \Theta = \{0, 1\}$, $\pi_t(\hat{\theta}_t = 1) = p_{r,t}$, and $\pi_t(\hat{\theta}_t = 0) = 1 - p_{r,t}$. However, farmers may interpret the probability in the forecast, and so the the signal received by a farmer is, $\tilde{\pi}_t(\hat{\theta}_t = 1) = \tilde{p}_{r,t} = (p_{r,t})^{\alpha}$, where $\alpha \geq 1$. When farmers correctly interpret the probabilistic information in the weather forecast, $\alpha = 1$.

The farmer's posterior belief about upcoming weather is:

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

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

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

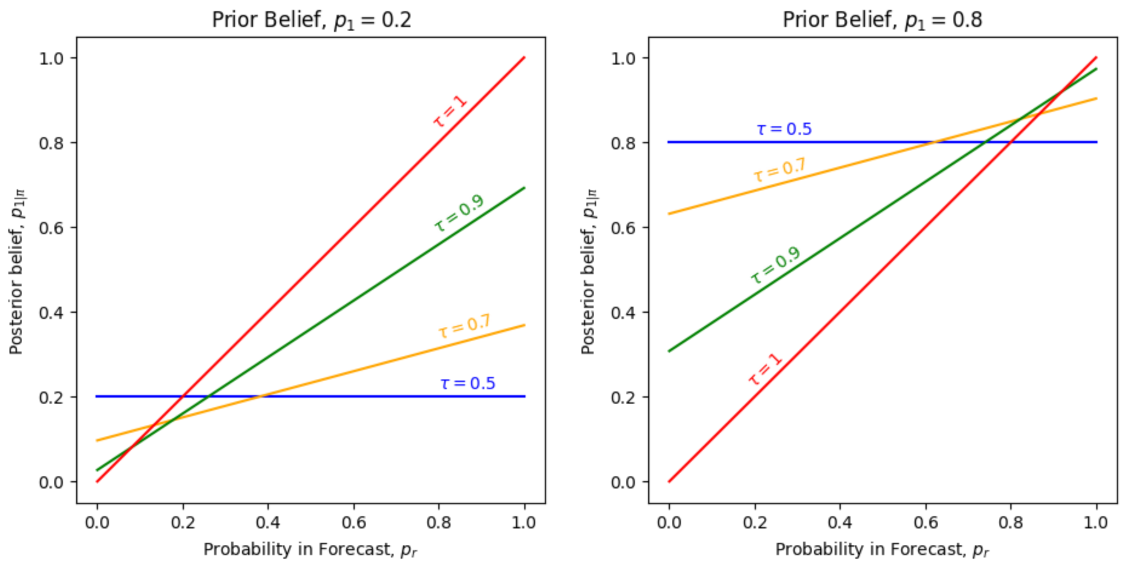

Figure 4: Posterior beliefs as forecast probability varies

We assume that a farmer's belief in the accuracy of the forecast, $p_t(\hat{\theta}_t|\theta_t) = \tau \sim f_t(.)$ where $f_t(\tau)$ is a probability distribution function over $[0, 1]$ (Shafiee-Jood et al., 2021).[7] So,[8]

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

and,

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

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

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

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

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

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

Farmers also update their beliefs about the accuracy of the forecast for the next period. So, $f_{t+1}(\tau) = f_t[\tau|\tilde{\pi}(\hat{\theta}), \vartheta_t]$.[9]

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

$$p_{1|\tilde{\pi},(t+1)} = \int_0^1 \left\{ \tilde{p}_{r,(t+1)} \frac{\tau p_{1,(t+1)}}{\tau p_{1,(t+1)} + (1-\tau)(1-p_{1,(t+1)})} + (1-\tilde{p}_{r,(t+1)}) \frac{(1-\tau) p_{1,(t+1)}}{(1-\tau) p_{1,(t+1)} + \tau(1-p_{1,(t+1)})} \right\} f_{t+1}(\tau, \tilde{p}_{r,t}, \vartheta_t) d\tau \quad (6)$$

4.2 Decision Making

Farmers who receive weather forecasts make agricultural decisions based on their posterior beliefs about upcoming weather, $p_{1|\tilde{\pi},t}$. In this study, we consider one-shot decisions at a specific point in time, where it is optimal for farmers to take such actions when they expect appropriate weather, and not take the action when they do not expect appropriate weather. The farmer's optimization problem is then:

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

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

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

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

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

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

5 Empirical Framework

The experimental games are both incentivized. In the first location-choice game, farmers choose a stake (between 1 and 5) corresponding to how confident they are in their choice being correct. If the desired weather is realized (at random, according to the probability in the chosen forecast), points equal to the stake are added to the farmers' scores, while if the desired weather is not realized (at random), points equal to the stake are deducted from the farmers' scores. In the second, agricultural decision-making game, farmers get 5 points when the action they recommend is appropriate for (randomly, according to the probability in the weather forecast) realized weather, and lose 5 points when it is not. These scoring rules imply that better outcomes result in more points, but do not constitute 'proper scoring rules'. This is in order to ensure that the rules are easily comprehensible by the farmers (Haaland et al., 2023; Conlon et al., 2022). The rupee incentive that farmers receive is the number of points they accumulate at the end of the two games. The maximum incentive possible is ₹110. Participants also receive in-kind compensation for participation in the game (worth ₹150), apart from the total game incentive that they earn.

The second agricultural decision-making game consists of 6 incentivized rounds across two agricultural scenarios: blossom irrigation and mid-monsoon fertilizer application. In each scenario, farmers play 2 rounds (4 in all) where they choose an action (irrigate or not; apply fertilizer or not) after a probabilistic weather forecast, and 1 (2 in all) where they choose an action without a forecast, but relying on their priors about the weather pattern in their villages at that time-of-year (specified in each scenario). Rounds with forecasts have forecasts in varying formats (audio, image, text). The order of rounds in each scenario, and of the scenarios themselves are randomized to control for format and order effects. The probabilities in forecasts vary across participants, and are drawn from {10%, 20%, 30%, 35%, 40%, 45%, 50%, 55%, 60%, 65%, 70%, 80%, 90%}. In both scenarios, taking the action (irrigate or apply fertilizer) is optimal when there is no rain, and not taking the action is optimal when there is rain. Payoffs (described above) are designed such that the expected value of taking an action (no action) is higher when the likelihood of rain is lower (higher), and taking an action in the game is optimal with respect to game payoffs when the likelihood of rain is $\leq$50%.

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

	Probabilities		Climate Change	Weather Forecasts		Index
	(1)	(2)	(3)	(4)	(5)	(6)
	Correctly chooses more likely (non-weather) event	Correctly chooses more likely (non-weather) event and provides correct probability	Expects unseasonal weather more frequently	Correctly interprets % chance in forecast	Does not interpret % chance as rainfall intensity	Combined standardized first stage index
Climate change salience	-0.015	0.034	0.008	0.012	0.032	0.026
	(0.033)	(0.025)	(0.028)	(0.025)	(0.025)	(0.034)
Probability training + climate change salience	0.036	0.050*	0.077**	0.018	0.039	0.108***
	(0.036)	(0.028)	(0.030)	(0.028)	(0.026)	(0.038)
Probability training + climate change salience relative to climate change salience alone	0.051	0.016	0.069**	0.006	0.007	0.080**
	(0.033)	(0.027)	(0.028)	(0.026)	(0.023)	(0.033)
N	1212	1212	1211	1212	1212	1211
Outcome mean, comparison group	0.400	0.149	0.420	0.146	0.840	0.000

5.1 Probability, Climate Change Perceptions, Interpreting Weather Forecasts

We first consider 'first-stage' impacts of the information treatment videos on farmers understanding of probabilities, and their perceptions of climate change. Understanding of probabilities is elicited using two 'toy' scenarios where farmers pick the more likely out of two events (unrelated to weather). After selecting the more likely event, farmers are then asked to report the likelihood of the described event occurring. In Table 4, we see that 40% of farmers choose the more likely event in both questions; while 15% of farmers in the control group also express the likelihood of the events occurring correctly. Column (2) indicates that the climate change salience and probability training video increases farmers' probability understanding by 5 percentage points (significant at the 10% level) or 33%. Farmers' perception of climate change is measured as whether they expect unseasonal weather more frequently, less frequently, at the same frequency in the future, or whether they cannot say. In column (3), responses of more frequently are interpreted as reflecting more awareness of climate change, and we see that the combined video increases this measure by almost 8 percentage points (or 18%). Across columns, the climate change salience video alone has no significant effects on outcomes.

Table 5 indicates that participants in the climate change and probability training combined video experimental arm score 2.9 more points than their counterparts in the control group (a 11.6% increase, significant at the 1% level). The information treatments have no impact on scores in the second game.

Table 5: Total points scored in the Experimental Games

	(1) Game 1	(2) Game 2	(3) Total
Climate Change Salience	0.515	0.482	1.202
	(0.986)	(0.862)	(1.066)
Probability training + climate change salience	2.902***	-0.390	2.115*
	(1.109)	(0.935)	(1.174)
Probability training + climate change salience relative to climate change salience alone	2.387**	-0.872	0.913
	(1.038)	(0.853)	(1.110)
N	1212	1212	1212
Outcome mean, comparison group	24.974	45.743	70.717

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

6 Experimental Game 1: Location Choice

In this section, we examine farmers' performance in the incentivized location-choice game, where they choose which of two given locations are more likely to experience the desired weather based on weather forecasts in each of five rounds.

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

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1\mathbf{E}_i^1 \ + \ \beta_2\mathbf{E}_i^2 \ + \beta_3\mathbf{FA}_{ir} \ + \ \gamma_4\mathbf{D}_{ir} \\ + \mathbf{Order}_{ir}^{'}\alpha_1 \ + \ \mathbf{Format}_{ir}^{'}\alpha_2 \ + \ \mathbf{V}_{ir}^{'}\alpha_3 \ + \ \mathbf{Q}_{ir}^{'}\alpha_4 \ + \ \mathbf{X}_{ir}^{'}\alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} \end{aligned} \quad (10)$$

$$\begin{aligned} Y_{ir} = \beta_0 \ + \ \beta_1\mathbf{E}_i^1 \ + \ \beta_2\mathbf{E}_i^2 \ + \beta_3\mathbf{FA}_{ir} \ + \ \beta_4(\mathbf{E}_i^1 \times \mathbf{FA}_{ir}) \ + \ \beta_5(\mathbf{E}_i^2 \times \mathbf{FA}_{ir}) \ + \ \gamma_4\mathbf{D}_{ir} \\ + \mathbf{Order}_{ir}^{'}\alpha_1 \ + \ \mathbf{Format}_{ir}^{'}\alpha_2 \ + \ \mathbf{V}_{ir}^{'}\alpha_3 \ + \ \mathbf{Q}_{ir}^{'}\alpha_4 \ + \ \mathbf{X}_{ir}^{'}\alpha_4 \ + \ \mathbf{G}_g \ + \ \epsilon_{ir} \end{aligned} \quad (11)$$

where, Y_{ir} is the outcome of interest for individual, i in round, r; $\mathbf{E}_i^1$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 1, the climate change salience information treatment; $\mathbf{E}_i^2$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 2, the climate change salience and probability training information treatment; $\mathbf{FA}_{ir}$ indicates whether the farmer experienced a false alarm in the preceding round (i.e., the forecast event did not occur in the preceding round); $\mathbf{D}_{ir}$ is the difference in probabilities between the two options in that game round. $\mathbf{Order}_{ir}$ is a vector of dummies indicating the order in which the round appears in the game; $\mathbf{Format}_{ir}$ is a vector of dummies indicating the format in which the forecasts in that round appear; $\mathbf{V}_{ir}$ is an indicator that takes a value, 1 when the round asks farmers to select the location where rain is more likely, and 0 when the round asks farmers to select the location where rain is less likely; $\mathbf{Q}_{ir}$ is an indicator that takes a value, 1 when the two forecasts in the round have different quantities and probabilities,[10] and 0 when they have the same quantities but different probabilities. $\mathbf{X}_{ir}$ is a vector of controls selected by the double lasso algorithm. Standard errors are clustered at the individual level.

Results. Columns (1) and (4) in Table 6 indicate that the increase in scores in this game for individuals in the climate change salience and probability training arm observed in section 5.1 is driven by an increase in the points that farmers choose to put at stake in each round, rather than an increase in farmers selecting the correct choice. This increase in points put at stake is particularly stark in 'easier' rounds, i.e., those where the difference between the two forecast probabilities is larger than 20 percentage points. This suggests that probability training reinforces understanding, or increases farmer confidence.

Table 6: Outcomes in the Location Choice Game

	All rounds		Difference between forecast probabilities > 20 %		Difference between forecast probabilities ≤ 20 %	
	(1)	(2)	(3)	(4)	(5)	(6)
	Choice	Stake Chosen	Choice	Stake Chosen	Choice	Stake Chosen
Climate Change Salience	-0.003	0.008	-0.012	-0.012	0.020	0.016
	(0.013)	(0.047)	(0.016)	(0.058)	(0.017)	(0.054)
Probability training + climate change salience	0.009	0.088*	-0.005	0.102*	0.028	0.073
	(0.014)	(0.050)	(0.017)	(0.061)	(0.018)	(0.057)
Probability training + climate change salience relative to climate change salience alone	0.012	0.081*	0.007	0.114**	0.008	0.057
	(0.012)	(0.046)	(0.016)	(0.058)	(0.017)	(0.053)
False alarm in prior round	-0.057***	-0.325***	-0.058***	-0.328***	-0.066***	-0.322***
	(0.011)	(0.032)	(0.015)	(0.044)	(0.016)	(0.041)
Difference between forecast probabilities	0.084***	0.329***	0.087	0.368**	0.189	0.956***
	(0.031)	(0.091)	(0.055)	(0.167)	(0.117)	(0.330)
N	6060	6060	2765	2765	3295	3295
Outcome mean, comparison group	0.854	4.085	0.881	4.151	0.830	4.029

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications.
The outcome in odd columns is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in odd columns is the stake farmers choose in that round $\in \{1, 2, 3, 4, 5\}$
Controls that are in all specifications: GP fixed effects, order, format, an indicator for whether the round requires that farmers choose the more likely event (as opposed to the less likely event), an indicator for whether forecasts differs only in probabilities (as opposed to forecasts that differ in both quantities and probability)
Lasso controls: household size, age, farmer is the primary decision-maker, literacy, female, farmer uses a smartphone, farmer uses WhatsApp, coffee is the main source of income, access to irrigation, cultivates Arabica, cultivates Robusta, harvests cherry coffee, land owned in acres, experienced weather related stress, experienced weather related losses, source of weather forecasts, level at which weather forecasts are provided, knowledge of weather forecast symbols

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

Table 7: Outcomes in the Location Choice Game

	All rounds		Difference between forecast probabilities > 20 %		Difference between forecast probabilities ≤ 20 %	
	(1) Choice	(2) Stake Chosen	(3) Choice	(4) Stake Chosen	(5) Choice	(6) Stake Chosen
Climate Change Salience	-0.002	0.027	0.001	-0.005	0.012	0.049
	(0.013)	(0.050)	(0.017)	(0.063)	(0.018)	(0.057)
Probability training + climate change salience	0.012	0.128**	0.013	0.130**	0.021	0.120**
	(0.014)	(0.052)	(0.019)	(0.066)	(0.019)	(0.059)
False Alarm in Prior Round	-0.051***	-0.247***	-0.014	-0.298***	-0.086***	-0.203***
	(0.019)	(0.056)	(0.025)	(0.082)	(0.030)	(0.073)
Climate Change Salience × False Alarm in Prior Round	-0.005	-0.084	-0.053	-0.015	0.029	-0.150
	(0.025)	(0.076)	(0.035)	(0.107)	(0.038)	(0.097)
(Probability training + climate change salience) × False Alarm in Prior Round	-0.014	-0.143*	-0.076*	-0.100	0.029	-0.179*
	(0.029)	(0.080)	(0.040)	(0.115)	(0.043)	(0.104)
Difference between forecast probabilities	0.081***	0.320***	0.083	0.370**	0.184	0.931***
	(0.031)	(0.090)	(0.055)	(0.166)	(0.117)	(0.331)
N	6060	6060	2765	2765	3295	3295
Outcome mean, comparison group	0.869	4.052	0.895	4.051	0.839	4.055

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications.
The outcome in odd columns is an indicator which takes the value 1 if the farmer makes the correct choice, and 0 otherwise; the outcome in odd columns is the stake farmers choose in that round $\in \{1, 2, 3, 4, 5\}$
Controls that are in all specifications: GP fixed effects, order, format, an indicator for whether the round requires that farmers choose the more likely event (as opposed to the less likely event), an indicator for whether forecasts differs only in probabilities (as opposed to forecasts that differ in both quantities and probability)
Lasso controls: household size, age, farmer is the primary decision-maker, literacy, female, farmer uses a smartphone, farmer uses WhatsApp, coffee is the main source of income, access to irrigation, cultivates Arabica, cultivates Robusta, harvests cherry coffee, land owned in acres, experienced weather related stress, experienced weather related losses, source of weather forecasts, level at which weather forecasts are provided, knowledge of weather forecast symbols

Table 6 also indicates that farmers are sensitive to false alarms, being less likely to make the correct choice and exhibit less confidence in rounds following a false alarm.[11] In addition, Table 7 indicates that experiencing a false alarm in the preceding round also mitigates the effect of the probability training and climate change salience information treatment. Together, we interpret this as evidence that farmers update their beliefs about accuracy of the forecast (as described in section 4) downward following false alarms.

Finally, farmers' likelihood of selecting the correct choice, and the 'stake' they chose is increasing in the difference between forecast probabilities in that round, which is consistent with farmers understanding the probabilities conveyed in the forecasts. It is also important to note here that a high share of farmer responses are correct — 86% of farmers in the control group are correct, with the share being 83% for the more difficult forecast-pairs. This suggests high probability literacy, even higher than that implied by the 'toy' scenarios in Table 4.

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

7 Experimental Game 2: Agricultural Decision-Making

In this section, we examine farmers' performance in the incentivized agricultural decision-making game, where they choose whether to take an action or not based on weather information in each of six rounds. The game consists of two scenarios — one where farmers advise hypothetical farmers on whether to irrigate crops or not; and the other where farmers advise hypothetical farmers on whether to fertilizer their crops or not. Each scenario has 3 rounds — one where farmers recommend an action relying on their prior beliefs about the likelihood of rain at the time-of-year specified in the scenario; and two where farmers recommend an action after a weather forecast. This set-up allows us to understand how farmers update their beliefs about the accuracy of the forecast, and whether they update their prior beliefs over rounds.

7.1 Subjective beliefs about upcoming weather

Empirical strategy. We first estimate the impact of the informational treatments, and of false alarms, on the likelihood of farmers recommending forgoing the action in a game round. We focus here on 'forgoing the action', since both scenarios that we consider have actions that are optimal when there is no rain. Focusing on a lack of action then reflects farmers' subjective posterior beliefs in the likelihood of rain in each game round. In Table 8, we focus on all game rounds, both where farmers receive a probabilistic weather forecast, and where they do not. We assume that in rounds where farmers do not receive a weather forecast, they rely on their subjective prior beliefs about the likelihood of rain in the scenario alone; while in rounds where they do receive a weather forecast, they update their subjective beliefs based on the signal in the forecast, and prior signals about the accuracy of the forecast.

An important caveat here is that farmers in the game do not have real world information, such as observations of clouds or other weather phenomena, to rely on while forming beliefs. As a result, their subjective 'priors' here likely only partially represent those that would be formed in a real-world setting. Nevertheless, their responses to the weather forecasts themselves are informative for real-world settings. We estimate,

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

where, Y_{ir} is an indicator which is 1 when farmers do not take the action, and 0 when they do take the action, i in round, r; $\mathbf{E}_i^1$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 1, the climate change salience information treatment; $\mathbf{E}_i^2$ is an indicator which takes the value, 1 when the individual is randomly assigned to experimental arm 2, the climate change salience and probability training information treatment; $\mathbf{FA}_{ir}$ indicates whether the farmer experienced a false alarm in the preceding round (i.e., the forecast event did not occur in the preceding round); **Forecast** is an indicator which is 1 in rounds where farmers receive a probabilistic weather forecast, and 0 in rounds where they do not receive any weather forecast; $\mathbf{P}_{ir}$ is the probability in the forecast. $\mathbf{Order}_{ir}$ is a vector of dummies indicating the order in which the round appears in the game; $\mathbf{Format}_{ir}$ is a vector of dummies indicating the format in which the forecasts in that round appear (which are different across scenarios). $\mathbf{X}_{ir}$ is a vector of controls selected by the double lasso algorithm. Standard errors are clustered at the individual level.

In this specification, we interpret the outcome, likelihood of 'forgoing action' in a round, as reflecting a farmer's posterior belief in the likelihood of rainfall in that round. We interpret the impact of the information treatments and of false alarms on the outcome in rounds with no forecasts as impacts on farmers' subjective prior beliefs, which in turn impact their subjective posterior beliefs.

Results. The last row in Table 8 provides the share of farmers in the control group who choose not to act in rounds with no forecasts, this indicates the average farmers' belief in the likelihood of rain in each scenario. Column 3 (rows 1 and 2) indicates that the climate change salience information treatment, and the information treatment combining probability training with climate change salience increase farmers' likelihood of forgoing action when they receive no forecast in the fertilizer application scenario. We interpret this as an increase in their prior belief about the likelihood of rainfall during the window for fertilizer application (within the monsoon). Farmers prior beliefs are not very different from the historical frequency of the weather event described in the scenario.

In rounds with forecasts, this effect is mitigated. We interpret this as

A false alarm in the preceding round (Table 8, rows 6 & 7)) (i.e., rainfall did not occur in the preceding round), reduces the likelihood of forgoing action in rounds with a forecast as well as rounds without a forecast. The larger reduction in rounds with forecasts suggests that false alarms reduce farmers' beliefs in the accuracy of the forecast. This is consistent with the evidence in Table 6 & Table 7, where false alarms reduce both the likelihood of choosing the correct forecast option, and farmers' confidence in that forecast.

Finally, in the last row in Table 8, we see that farmers' likelihood of forgoing action (reflecting their posterior belief in the likelihood of rain) in increasing the probability of rain in the forecast. Results indicate the likelihood of forgoing action is 0.5 when the likelihood of rain increases from 0 to 1. Again, this corroborates evidence in Table 6 and Table 7 that farmers interpret probabilities reasonably well.

8 Willingness to Pay for Probabilistic Weather Forecasts

Once farmers complete the two games, we elicit their willingness to pay for weekly, accurate, probabilistic forecasts over voice-calls. Willingness to pay is elicited using a the

Table 8: Forgoing Action in the Agricultural Decision Making Game

	(1)	(2)	(3)
	All rounds with forecasts	Scenario 1 Irrigation	Scenario 2 Fertilizer
Climate Change Salience	0.030	-0.018	0.077**
	(0.021)	(0.025)	(0.031)
Probability training + climate change salience	0.027	-0.032	0.079**
	(0.022)	(0.027)	(0.034)
Forecast	0.086***	0.086**	0.059
	(0.032)	(0.037)	(0.042)
Climate Change Salience × Forecast	-0.049*	0.020	-0.119***
	(0.026)	(0.034)	(0.039)
(Probability training + climate change salience) × Forecast	-0.023	0.044	-0.092**
	(0.029)	(0.037)	(0.043)
False alarm in preceding round	-0.040**	-0.055**	-0.022
	(0.018)	(0.022)	(0.027)
False alarm in preceding round × Forecast	-0.051**	-0.056*	-0.049
	(0.024)	(0.030)	(0.036)
Probability in the Forecast	0.500***	0.674***	0.292***
	(0.031)	(0.040)	(0.047)
N	7272	3636	3636
Outcome mean, comparison group	0.199	0.154	0.243

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications.
The outcome is an indicator which takes the value 1 if the farmer recommends forgoing the action , and 0 otherwise.
Only includes observations with no forecasts. Controls that are in all specifications: GP fixed effects, order, format
Lasso controls: household size, age, farmer is the primary decision-maker, literacy, female, farmer uses a smartphone, farmer uses WhatsApp, coffee is the main source of income, access to irrigation, cultivates Arabica, cultivates Robusta, harvests cherry coffee, land owned in acres, experienced weather related stress, experienced weather related losses, source of weather forecasts, level at which weather forecasts are provided, knowledge of weather forecast symbols

Becker-DeGroot-Marshak (BDM) (1964) mechanism, using a binary search process (following Berkouwer and Dean (2022); Burlig et al. (2022)). The good being offered is:

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

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

Table 9: Willingness to Pay (per month) for Probabilistic Weather Forecasts

	(1) WTP	(2) WTP (inverse hyperbolic sine)
Climate Change Salience	-0.603	-0.002
	(1.151)	(0.065)
Probability training + climate change salience	-2.655**	-0.143*
	(1.309)	(0.073)
Probability training + climate change salience relative to climate change salience alone	-2.052*	-0.141**
	(1.148)	(0.068)
Any high probability forecasts resulting in no rain in the game (False alarms)	-2.344**	-0.131**
	(0.978)	(0.056)
Any low probability forecasts resulting in rain in the game	0.731	0.086
	(0.977)	(0.056)
N	1212	1212
Outcome mean, comparison group	26.408	3.608

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

Table 9 and Figure 2 indicate that farmers' willingness to pay is lower for those in the climate change salience and probability training experimental arm. Consistent with results in both games, experiencing false alarms (of rainfall forecasts) in the games reduces farmers' willingness to pay for the weather forecasting service and the more false alarms a farmer faces, the lower the willingness to pay (add this table). This, again, suggests that farmers update their beliefs about the accuracy of weather forecasts following false alarms.

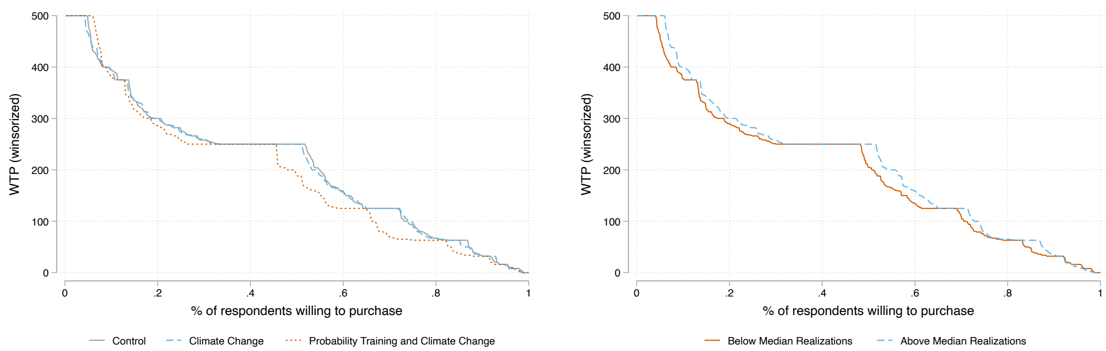

Figure 5: Willingness to Pay for Probabilistic Weather Forecasts

9 Discussion and Conclusion

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

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

Finally, and importantly, this study sheds light on how farmers build trust in a new source of information. Farmers' responses in both experimental games indicate that farmers beliefs in the accuracy of the weather forecast reduces in rounds that follow one with a false positive, and increases in rounds that follow false negative. That is, their threshold for which probability in the forecast indicates rain goes up after a false positive (false alarm for rain), and goes down after a false negative (false alarm for no rain). This suggests that if forecasts end up being incorrect multiple times early on (i.e., many false positives), trust in forecasts may not recover. This provides insights on one part of farming learning in the context of technology adoption.

A Figures

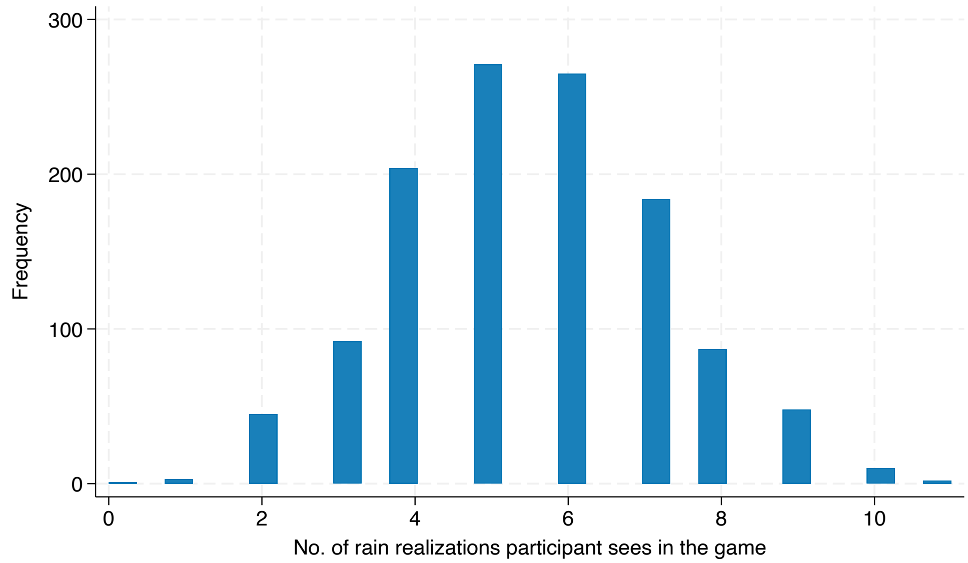

Figure 1: Rain Realizations in the Hypothetical Scenarios

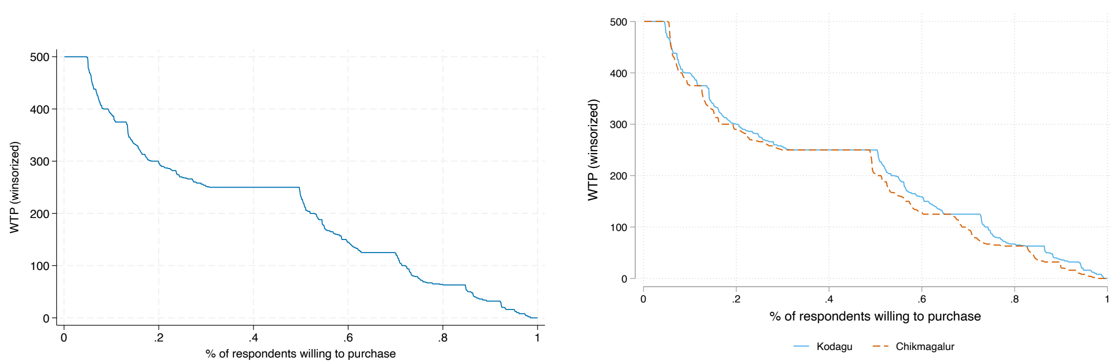

Figure 2: Willingness to Pay for Probabilistic Weather Forecasts

B Additional Tables

Table B1: Attrition

	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
Attrition	0.023 (0.150)	-0.003 (0.010)	-0.011 (0.010)	0.431	1212

Table B2: 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 B3: Optimal action taken in Agricultural Decision Making Game

	(1) All rounds with forecasts	(2) Forecasts with 'large' probabilities {10%, 20%, 30%, 70%, 80%, 90%}	(3) Forecasts with 'small' probabilities {35%, 40%, 45%,50%,55% 60%, 65%}
Climate Change Salience	0.017	-0.030	0.046**
	(0.017)	(0.024)	(0.023)
Probability training + climate change salience	-0.006	0.002	-0.018
	(0.018)	(0.025)	(0.026)
Probability training + climate change salience relative to climate change salience alone	-0.023	0.030	-0.064***
	(0.017)	(0.024)	(0.024)
False alarm in preceding round	0.010	0.009	0.008
	(0.016)	(0.023)	(0.022)
Forecast probability (deviation from 0.5)	0.472***	0.212*	0.125
	(0.055)	(0.119)	(0.199)
N	4848	2246	2602
Outcome mean, comparison group	0.593	0.672	0.527

Robust standard errors, clustered at the individual level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All columns report results from a double lasso specifications.
The outcome is an indicator which takes the value 1 if the farmer recommends the action that maximizes their expected payoff in the round, and 0 otherwise
Controls that are in all specifications: GP fixed effects, order, format
Lasso controls: household size, age, farmer is the primary decision-maker, literacy, female, farmer uses a smartphone, farmer uses WhatsApp, coffee is the main source of income, access to irrigation, cultivates Arabica, cultivates Robusta, harvests cherry coffee, land owned in acres, experienced weather related stress, experienced weather related losses, source of weather forecasts, level at which weather forecasts are provided, knowledge of weather forecast symbols

Table B4: Optimal action taken in Agricultural Decision Making Game

	(1)	(2)	(3)
	All rounds with forecasts	Forecasts with 'large' probabilities {10%, 20%, 30%, 70%, 80%, 90%}	Forecasts with 'small' probabilities {35%, 40%, 45%,50%,55% 60%, 65%}
Climate Change Salience	-0.021	-0.093**	0.038
	(0.028)	(0.040)	(0.039)
Probability training + climate change salience	-0.075**	-0.039	-0.108**
	(0.030)	(0.043)	(0.042)
Risk Averse	-0.046*	-0.053	-0.029
	(0.025)	(0.037)	(0.036)
Climate Change Salience × Risk Averse	0.069**	0.108**	0.014
	(0.035)	(0.051)	(0.049)
(Probability training + climate change salience) × Risk Averse	0.120***	0.073	0.143***
	(0.038)	(0.055)	(0.054)
False alarm (rain forecast)	0.011	-0.006	0.020
	(0.027)	(0.040)	(0.037)
False alarm (no rain forecast)	0.002	-0.030	0.024
	(0.022)	(0.032)	(0.031)
Forecast probability (deviation from 0.5)	0.478***	0.208*	0.087
	(0.055)	(0.118)	(0.198)
N	4848	2246	2602
Outcome mean, comparison group	0.593	0.672	0.527

References

Auffhammer, Maximilian and Tamma A. Carleton (2018). "Regional crop diversity and weather shocks in india," *Asian Development Review*, 35: 113–130. [2]

Barnett-Howell, Zachary (2021). "No small potatoes: Agricultural risk and investment under uncertainty," *Working Paper*. [2]

Berkouwer, Susanna B. and Joshua T. Dean (2022). "Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households," *American Economic Review*, 112(10): 3291–3330. [22]

Burlig, Fiona, Amir Jina, Erin M. Kelley, Gregory Lane, and Harshil Sahai (2022). "The value of forecasts: Experimental evidence from developing-country agriculture," *Pre-Analysis Plan*. [2, 22]

Chandrashekhar, Vinay Doranalu and Amba Shetty (2017). "Trends in extreme rainfall over ecologically sensitive western ghats and costal regions of karnataka: an observational assessment," *Arabian Journal of Geosciences*, 11(327). [4]

Conlon, John J., Malavika Mani, Gautam Rao, Matthew W. Ridley, and Frank Schilbach (2022). "Not learning from others," *NBER Working Paper No. 30378*. [14]

Delavande, Adeline (2014). "Probabilistic expectations in developing countries," *Annual Review of Economics*, 6: 1–20. [2, 23]

Emerick, Kyle, Alain de Janvry, Elisabeth Sadoulet, and Manzoor H. Dar (2016). "Technological innovations, downside risk, and the modernization of agriculture," *American Economic Review*, 106: 1537–1561. [2]

Giné, Xavier, Robert M. Townsend, and James Vickrey (2015). "Forecasting when it matters: Evidence from semi-arid india," *Working Paper*. [2]

Ha, Kyung-Ja, Suyeon Moon, Axel Timmermann, and Daeha Kim (2020). "Future changes of summer monsoon characteristics and evaporative demand over asia in cmp6 simulations," *Gephysical Research Letters*, 47(8). [4]

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart (2023). "Designing information provision experiments," *Journal of Economic Literature*, 61(1): 3–40. [14]

Karlan, Dean, Robert Osei, Isaac Osei-Skoto, and Christopher Udry (2014). "Agricultural decisions after relaxing credit and risk constraints," *The Quarterly Journal of Economics*, 129: 597–652. [2]

Mase, Amber Saylor and Linda Stalker Prokopy (2014). "Unrealized potential: A review of perceptions and use of weather and climate information in agricultural decision making," *Weather, Climate and Society*, 6: 47–61. [2]

Meza, Francisco J., James W. Hanse, and Daniel Osgood (2014). "Economic value of seasonal climate forecasts for agriculture: Review of ex-ante assessments and recommendations for future research," *Journal of Applied Meteorology and Climatology*, 47: 1269–86. [2]

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

[11, 12, 13]

Muralidharan, Karthik, Mauricio Romero, and Kaspar Wüthrich (2023). “Factorial designs, model selection, and (incorrect) inference in randomized experiments,” *The Review of Economics and Statistics*, (forthcoming). [7]

Roncoli, Carla, Keith Ingram, and Paul Kirshen (2002). “Reading the rains: Local knowledge and rainfall forecasting in burkina faso,” *Society Natural Resources: An International Journal*, 15: 409–427. [11]

Rosenzweig, Mark R. and Christopher Udry (2019). “Assessing the benefits of long-run weather forecasting for the rural poor: Farmer investments and worker migration in a dynamic equilibrium model,” *NBER Working Paper No. 25894*. [2]

Roxy, M.L, Subimal Ghosh, Amey Pathak, R. Athulya, Milind Mujumdar, Ragu Murtugudde, Pascal Terry, and M. Rajeevan (2017). “A threefold rise in widespread extreme rain events over central india,” *Nature Communications*, 8. [2]

Shafiee-Jood, Majid, Tatyana Deryugina, and Ximing Cai (2021). “Modeling users’ trust in drought forecasts,” *Water, Climate and Society*, 13: 649–664. [11, 12]

Sreenath, A.V., S. Abhilash, P. Vijaykumar, and B.E. Mapes (2022). “West coast india’s rainfall is becoming more convective,” *npj Climate and Atmospheric Science*, 5(36). [4]

Stephens, Elisabeth, David J. Spiegelhalter, Ken Mylne, and Mark Harrison (2019). “The met office weather game: investigating how different methods for presenting probabilistic weather forecasts influence decision-making,” *Geoscience Communication*, 2(2): 101–116. [2, 9, 10]

Varikoden, Hamza, J.V. Revadekar, J Kuttippurath, and C.A. Babu (2019). “Contrasting trends in southwest monsoon rainfall over the western ghats region of india,” *Climate Dynamics*, 52. [4]