Mis-Remembrance of Things Past: Memory and Adaptation to Climate Change

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Abstract

Human memory is imperfect: we often fail to recall true events and invent false experiences. I examine the economic consequences of these biases in a high-stakes field setting. I directly elicit environmental memories, beliefs, and adaptation decisions from nearly 2,300 Bangladeshi farmers. Using both natural variation in daily weather and a series of experiments embedded in the survey design, I test the predictions of a recall-driven belief formation model featuring endogenous memory revision. I find support for each step in the framework's causal chain: contemporaneous cues shape the content of recalled memories, which distort expectations, ultimately impacting economic decisions.

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> "And it never failed that during the dry years the people forgot about the rich years, and during the wet years they lost all memory of the dry years. It was always that way."
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> —*East of Eden*, John Steinbeck

1 Introduction

Our perceptions of the world around us drive our decision-making. These beliefs especially impact the well-being of households living in low- and middle-income countries, where significant information frictions limit access to the ground truth. From school quality (Andrabi et al., 2017) to prices (Jensen, 2007), medicine (Sievert, 2024) to migration (Baseler, 2023), a rich body of work documents the critical role expectations play in important economic choices. In the absence of reliable information on the true state of the world, what underpins these beliefs?

I examine one potential channel: memories. Our own experiences provide a natural source of data for learning about the unknown. Yet in contrast to a computer database seamlessly logging and retrieving information, human memory exhibits cognitive limits that systematically alter the ways in which we store past events in our mind and remember them during moments of need. We often fail to recall true aspects of our experiences and invent details that never happened, and what's more, commit these memory failures in predictable ways (Schacter, 1999; Kahana, 2012).

This paper examines the economic consequences of human memory. I begin by incorporating the cognitive regularities highlighted by psychologists into an economic model of belief formation and decision-making. In particular, I allow for *constructive* memory: the imperfect encoding of details about past experiences that our minds endogenously revise, thereby creating false perceptions of the past. The model describes a clear, causal chain: contemporaneous cues—features of the setting in which the decision-maker forms expectations—shape both which experiences come to mind and the content of those recalled memories, which in turn impact the beliefs that ultimately drive economic behavior. I then take the predictions of this framework to the high-stakes setting of rural small-holder farmers learning about and adapting to environmental threats. Equipped with data I collect on memories, beliefs, and decisions for 2,279 farmers across 250 villages in Bangladesh, I use a collage of experiments embedded in the survey design and naturally occurring variation in climate to test the predictions of the model. I find evidence that memories endogenously respond to stimuli in line with the psychology literature and systematically shape both beliefs and important economic decisions—in this case, the adoption of technology designed to address global warming's most severe threats.

The simple conceptual framework at the heart of this story illustrates the cognitive pitfalls on the path from initial experience to retrieved memory as an input to expectations and ultimately behavior. Closely following related work in economics (Mullainathan, 2002; Bordalo et al., 2023), an assumption about similarity serves as the key engine driving the model, whereby our minds more easily consider notions more similar to those already top of mind. In the set-theoretic approach to similarity I adopt here (Tversky, 1977), individual features of an experience or context determine its relation to another. Consider a farmer choosing whether or not to purchase flood insurance. Their beliefs about the likelihood of severe flooding enter as a key primitive in that decision-making process. Farmers form these beliefs amid a contemporary context—a cue—which shapes the set of memories which come to mind (Conlon and Kwon, 2025). In my framework, the cue not only changes which memories come to mind but also the *content* of those recollections, differing from previous economic models of memory by incorporating constructive memory into the cognitive process such that the mind endogenously revises features of past experiences. The similarity of the cue and set of potential features modulates how our brain edits past experiences, closely related to the simulation mechanism of Bordalo et al. (2024). For instance, a farmer may not store the exact number of days a past flood remained on their land, and thus when cued to think about devastation and destruction from long-lasting inundation by a motivated insurance salesperson, the farmer may simulate the missing feature of duration as a particularly lengthy flood event. I also allow cues to have direct association effects on beliefs independently of their role in shaping memories.

The model predicts a causal chain from the contemporaneous cue faced by the decision-maker to the ultimate economic choice. Under constructive memory, the context of the moment of recollection alters not only which experiences the decision-maker recalls but also the content of those memories. The framework suggests three key steps: (1) cues impact the nature of recalled events, (2) memories shape expectations, and (3) beliefs alter decisions.

To test the assumptions and predictions of this model, I collect three waves of surveys with rice farmers in rural Bangladesh, combining several survey experiments and a quasi-experiment arising from weather fluctuations. All of the treatments I consider echo the natural variation in cues that likely shape expectations in farmers' day-to-day lives. The 250 villages in my sample span a wide area, generating natural variation in climate experiences and weather that allow me to isolate the impact of cues and memories in shaping farmers' beliefs about future climate conditions and economic decisions. I focus on three dimensions of the local environment that directly shape agricultural production decisions: soil salinity, flooding, and monsoon intensity. For soil salinity and flooding, I speak to the economic consequences of memory by eliciting willingness-to-pay (WTP) in an incentive-compatible manner for two climate adaptation goods directly downstream of beliefs: salinity-tolerant rice seed varieties and a flood insurance contract that I offer to farmers.

I begin by testing the first step in the model's prediction: contemporaneous cues rewrite the memories that come to mind. I use a natural cue in this setting: the weather itself. I adopt a two-way fixed effects comparing farmers interviewed on days with or without rain, controlling for village fixed effects to absorb any time-invariant characteristics of a place and day fixed effects to account for any systematic forces on the interview date across villages. In essence, I compare farmers whom I happen to interview on days when it rains in their village as compared to their neighbors surveyed on days when it did not. I use enumerators' reports of rainfall to avoid the measurement error plaguing precipitation estimates based on remote-sensing data. On the farmers' side, I develop a visual method to elicit memories and beliefs about monsoon intensity in this low numeracy population by asking respondents to distribute buttons on an image illustrating alternate rainfall rates. I show that farmers' memories of monsoon intensity five and ten years ago increases when interviewed on rainy days (p-value=.018). Effects are nearly identical even for rainfall last year (p-value=.017), which one might have expected to be less vulnerable to revision given its recency. This pattern matches the model's prediction about constructive memory: cues rewrite past recollections. I also document that farmers' forecasts about future rainfall intensity increase by a similar magnitude when it happens to rain on the day they are asked the questions (p-value=.005). While this impact on expectations is consistent with memories shaping beliefs, it may also reflect a direct effect of the cue independent of memory, which motivates the experimental designs that follow which better isolate the role of memory specifically. This result echoes previous work on the psychological impacts of the weather on car purchase decisions (Busse et al., 2015).

I next turn to a simple survey experiment in the domain of soil salinity to isolate the second and third steps in the model's prediction: memories shape beliefs which can alter behavior. I ask farmers two questions, one about how salinity has changed in the last decade, and one about how they expect salinity to change in the next decade. The experiment is extremely simple: I randomize at the individual level whether I ask about the past or the future first. I repeat this randomization across three different survey rounds, giving me within farmer variation in question order. Using the leave-out-mean answers for other farmers in the same village as a proxy, I show that farmers asked about the past first in places where others report past salinity falling causes a substantial increase in the likelihood that farmers predict further declines in salinity going forward. In other words, being explicitly prompted to recall the past alters predictions about the future towards the average memory in the village.

The reverse phenomenon—future forecasts impacting past recall—does not occur. This minor change in survey protocol not only impacts farmers predictions about future trends in salinity but also their demand for climate adaptation. Farmers asked about the past first in villages where neighboring farmers recall declines in salinity have 23 percent lower WTP for salinity-tolerant seeds. These patterns hold with farmer and village-by-survey-round fixed effects. The cue induced by this survey experiment emulates the climate conversations that could easily occur in villages when farmers make climate adaptation decisions.

I next demonstrate the malleability of recall in line with constructive memory using direct elicitation of farmers' memories of floods. Asking farmers to report details about every flood they have experienced across multiple survey rounds, I show that despite the economic significance of flooding in agricultural Bangladesh, memories feature remarkable instability. Farmers disagree with their previous selves about 50 percent of the floods they report experiencing. Empirical results on the features and floods exhibiting the most accuracy line up with predictions from psychology: farmers more reliably encode salient, recent, and emotionally triggering dimensions of experiences.

To examine scope for constructive memory more directly, I randomize whether I elicit farmers' memories from oldest to most recent or vice versa. Treating the first reported memory as a cue, I show that within the same village, farmers shift details about subsequently reported memories towards the content of the first memory they report, again proxying for those features using the village leave-out-mean to avoid bias. The magnitudes of these effects are large: I cannot reject a one-for-one pass for flood length, for instance, implying that being asked first about a flood one's neighbors report being one day longer causes a one day increase in reported length of subsequent floods.

To capture all three steps of the model's predictions in a single experimental setting and isolate the impact of cues through memory separately from their potential direct priming effect, I design an information experiment around the elicitation of flood memories and WTP for flood insurance. Randomly providing farmers with government estimates about recent destructive floods elsewhere in the country prior to memory elicitation changes the content of recalled inundation events, increasing their length and damage. In turn, farmers' demand for flood insurance increases by 20 percent (p-value $< .001$). The same information provided after the memory elicitation but prior to the WTP has no effect on demand for the contract, ruling out that the information cue impacts behavior solely through priming. Together, these empirical results describe a belief formation process inherently rooted in memories and subject to the cognitive limitations plaguing human recall, even in this high-stakes setting where economic livelihoods directly depend on farmers' ability to accurately perceive the environmental conditions they face.

Related Literature This paper relates most closely to two strands of research. First, I build on a growing literature examining the role of memory in economic decisions. Following a long literature in psychology, economists have increasingly focused on memory as an important determinant of beliefs (Mullainathan, 2002; Bordalo et al., 2023). The model in this paper incorporates the psychological notion of constructive memory formally into the expectation formation process, applying the principal of similarity-based simulation from Bordalo et al. (2024) to the content of memories themselves, and thereby proposing a new channel through which cues shape beliefs (Conlon and Kwon, 2025). I then provide a series of empirical tests of this memory process. Experiments from lab settings (e.g., Enke et al. (2023)) have been recently complemented with a expanding body of field evidence. For instance, failures in retrieving information about irregular expenditures bias Zambian farmers' predictions about their budget, reducing consumption smoothing (Augenblick et al., 2024). In another example, trauma-induced memory distortions inhibit refugees in Ethiopia and post-conflict and displaced persons in Colombia from effectively simulating the future and making corresponding investments (Ashraf et al., 2025). In a similar setting to this paper, Naso (2025) studies recall about rainfall, agricultural output, and crop prices in Burundi, and presents evidence of interference: political events unrelated to agriculture increase recall error for maize and bean prices. Jiang et al. (2025) document the importance of similarity-based recall in financial markets.

Second, this paper provides evidence on the underlying determinants of adaptation to climate change (see Carleton et al. (2024) for a review). Existing work has examined a host of important frictions to individual investment in adaptation, including credit constraints (Lane, 2022), information asymmetries (Beaman et al., 2014; Mahadevan et al., 2023), financial market imperfections (Karlan et al., 2014), supply-side frictions (Emerick et al., 2016), and market structures (Bhandari et al., 2022). A growing set of evidence has established the importance of beliefs (Kala, 2019; Zappalà, 2024; Burlig et al., 2024; Patel, 2025), and this work highlights the role of memory in shaping these expectations about important environmental threats.

2 Belief Formation Model with Constructive Memory

This section presents a simple model of belief formation featuring imperfect recall and the constructive nature of memory.

2.1 Set-Up

Decision Problem A decision maker (DM) makes a binary choice $d \in \{0, 1\}$, such as whether to purchase flood insurance. Utility from this decision hinges on the state of the world $\omega \in \{0, 1\}$, such as whether there will be a devastating flood in the coming season.[1] A set of $F > 1$ features capture each state of the world, such as the length time the water sits on the land and the amount of crop damage under $\omega = 1$. Denote the DM's utility function by $U(d, \omega)$. To isolate an interior solution, I assume no Pareto dominance such that utility satisfies both of the following conditions: $U(1, 1) > U(0, 1)$—the DM would rather have insurance amid a flood than not have insurance, and $U(0, 0) > U(1, 0)$—the DM would rather not have insurance than have insurance in the absence of a flood.

Role of Beliefs The DM cannot perfectly observe the true state of the world ω that has not yet been realized—for instance, they do not yet know whether a flood will occur in the coming season. As a result, the DM makes the decision about d based on their beliefs about the state of the world, e.g. chooses whether to buy insurance based on their expectation about flood risk. Let H denote the hypothesis that the true state of the world $\omega = 1$, where H consists of the set of $F > 1$ features linked to that state of the world. A given feature $f \in F$ takes a value $\{0, 1\}$, such as an indicator for standing water lasting more than one week. The DM forms beliefs $\widehat{\theta}$ about the probability of this hypothesis. Let θ denote the true probability that $\omega = 1$. Under the previous assumptions about utility to rule out cases in which either $d = 0$ or $d = 1$ dominates in all states of the world, there exists a threshold $\theta^\star$ for which the DM chooses $d = 1$ when $\widehat{\theta} \geq \theta^\star$ and for which the DM chooses $d = 0$ when $\widehat{\theta} < \theta^\star$. In the running example, a DM will choose to purchase flood insurance when they perceive a sufficiently high risk of flooding.

Experiences The DM has a set of past experiences E consisting of $N > 1$ individual experiences $e \in E$, such as all of the monsoon seasons they have previously experienced on their land. As with the hypothesis H about the likelihood of the state of the world $\omega = 1$, a set of $F > 1$ features describe each experience, such as the nature of flooding on the DM's land during the rains.

The DM also faces a contemporary experience—a cue c—at the time they make their decision, such as the contextual setting of the day they make their prediction about flood risk and decide whether to purchase insurance. Cues share the same structure as past experiences and hypotheses, also consisting of a set of binary features.

[1] I focus on the setting with binary states of the world for simplicity but the model applies straightforwardly under an arbitrarily large set of states of the world, as in Conlon and Kwon (2025).

Similarity As in Bordalo et al. (2023), a symmetric similarity function S captures the similarity between any two objects characterized by features—a hypothesis H, past experience e, or contemporaneous cue c. Let u and v be two such objects. The similarity function $S(u, v)$ maps two sets of features into a scalar normalized to fall between $[0, 1]$, by averaging element-wise similarity as shown in Equation 1 for two objects A and B. For instance, heavy rain on the day when the DM makes their insurance decision would be more similar to past experiences of intense monsoons and future hypotheses about rain-induced flooding. Similarity increases in the feature overlap between two objects,such that $S(u, v) = 1$ when $u = v$. I take the similarity function as exogenously determined; other work has examined its microfoundations (e.g., Tversky 1977).

$$S(A, B) = \frac{1}{|A| \cdot |B|} \sum_{u \in A} \sum_{v \in B} S(u, v) \tag{1}$$

2.2 Imperfect Memory

Following a rich literature in psychology (see, for instance, Kahana 2012), I now introduce key features of human memory that interact with these building blocks of the model to shape beliefs and economic behavior.

Imperfect Encoding I allow the DM to imperfectly store information about an experience when building their memory database—a step in the cognition of memory called encoding. Consider an experience with a true set of F binary features denoted by f^* and indexed such that $e = \{f_1^*, f_2^*, \ldots, f_F^*\}$. For example, a flood experienced by the DM includes the timing, duration, water height, and damages from the inundation. Instead of encoding the true set of features for experience e in their memory database, the DM encodes e' which omits a vector m of missing features $m = \{m_i, m_j, \ldots, m_k\}$, resulting in, for instance, $e' = \{f_1^*, \emptyset, \ldots, f_F^*\}$ for $m = \{m_2\}$. In the running example, the farmer may not store the height nor color of the flood waters in their memory. These missing features can be due to absent-mindedness—insufficient attention paid to a given feature during the experience—or transience—forgetting features over time (Schacter, 1999).

Cued Recall I next allow the DM to systematically retrieve memories from their experience database based on the contemporaneous cue they face when forming beliefs about $\widehat{\theta}$ and making their decision d. Let $r(e, c)$ denote the probability that a DM recalls experience e given the cue c. As shown in Equation 2, I assume this probability scales proportionately with the relative similarity of a given experience and the cue as compared to the other experiences in the database. This yields both predictions about associative recall—that the DM will more easily recall events more similar to the cue—and interference—that successfully recalled experiences can crowd out other potentially retrievable memories. Critically, amid imperfect encoding, I assume this similarity function operates on the vector e' with its potentially missing features rather than the true experience e. I use the prime notation in Equation 2 to emphasize that this same logic applies to all memories in the database.

$$r(e, c) = \frac{S(e', c)}{\sum_{u' \in E} S(u', c)} \tag{2}$$

I assume that the DM samples $T \geq 1$ experiences from E with replacement according to Equation 2.

Constructive Memory Following recent evidence from neuroimaging studies (Schacter and Addis, 2007), I model the process of constructive memory—the filling in of missing features stored in the memory database—via simulation. I focus on the naive case in which this process all occurs "bottom up": the DM does not realize they omit certain features nor intentionally replaces them. Let $\widehat{e}$ denote a constructed memory of experience e that has been encoded as e', and let K denote the set of all possible constructed memories. Given a cue c, let $g(\widehat{e}, c)$ denote the probability of constructing a given vector of features that replaces the missing features from m. As with cued recall, the similarity function from Equation 1 also pins down simulation in this step via Equation 3. For example, a DM cued about more devastating floods may replace the missing feature of whether the water height exceeded one meter with a yes because that feature value lies closer to the cue of severe flooding in similarity space.

$$g(\widehat{e}, c) = \frac{S(\widehat{e}, c)}{\sum_{u \in K} S(u, c)} \tag{3}$$

2.3 Direct Priming

Finally, I allow the contemporaneous context of the DM's environment—their cue c—to directly shape beliefs via a priming parameter $0 \leq \gamma \leq 1$, that captures the relative role of cues directly shaping beliefs as compared to the role of memory.

2.4 Hypothesis Similarity

As a final step in closing the model, let $0 \leq \pi(x, H) \leq 1$ be a value defined according to a function σ (such as a logistic function) that increases in the similarity of an input x and the hypothesis H, according to Equation 4.

$$\pi(x,h) \equiv \sigma(S(x,H)) \tag{4}$$

Remark 1 *The DM forms beliefs $\widehat{\theta}$ about the likelihood of the state of the world $\omega = 1$ by assessing the similarity of the inputs to their decision-making process—successfully constructed memories recalled from their experience database E and the contemporaneous cue c—and the hypothesis H, according to Equation 5.*

$$\widehat{\theta}(H|E,c) = \underbrace{\gamma\pi(H,c)}_{Direct\ Priming} + \underbrace{(1-\gamma)\frac{1}{T}\sum_{e\in E} r(e,c)\sum_{u\in K} g(u,c)\pi(H,u)}_{Memory} \tag{5}$$

This expression captures the three ways through which cues shape beliefs via similarity. First, cues more similar to a hypothesis increase beliefs $\widehat{\theta}$ through a direct priming effect. Second, cues prompt certain more similar memories to come to mind more easily through the function $r(e,c)$. Third, cues change the content of recalled memories by simulated construction, making those memories more similar to the cue via the function $g(u,c)$. The key empirical challenge involves separating these three channels.

3 Empirical Tests of Constructive Memory

I now take the assumptions and predictions of this simple model to the data using a series of natural and survey experiments with farmers in Bangladesh on the front lines of climate change.

3.1 Environmental Context

I examine three environmental dimensions θ about which farmers must form beliefs $\widehat{\theta}$: soil salinity, flooding, and monsoon rainfall. This choice stems from their first-order importance in the economic lives of the Bangladeshi poor, as well as hundreds of millions of households across the globe.

Background on Soil Salinity A plot's soil salinity content can significantly affect plant growth for most crops including rice—far and away the most important crop in Bangladesh. This challenge extends worldwide, with soil salinity threatening approximately 30 percent of irrigated land (Hopmans et al., 2021). Scientists forecast that global warming will exacerbate this problem through several channels including rising sea levels, increased evaporation, droughts, and floods (Mukhopadhyay et al., 2021), significantly reducing agricultural productivity (Clarke et al., 2015; Dasgupta et al., 2015, 2018). I focus on the adaptation decision of farmers choosing whether to plant a salinity-tolerant rice variety $d = 1$ or not $d = 0$. Farmers beliefs $\widehat{\theta}$ about the salt content of their soil play a key role in this seed choice decision because the salinity-tolerant seeds do not dominate other choices in a Pareto sense: at low salt levels, farmers may be better off planting another variety which tastes better, protects against pests, or earns a higher market price, for instance, while at high salt levels, the salinity tolerant seeds still produce high yield while other varieties do not. In Patel (2025), I use two randomized controlled trials to show that beliefs play a causal role in this technology adoption and that seed choice has a large impact on farmers' agricultural profits.

Background on Flooding As the world's most common natural disaster, flooding can have catastrophic impacts on both agricultural production—by damaging crops and fields—and general well-being, destroying homes or entire villages. Climate scientists predict that under even conservative projections of global warming, much of the world will experience both higher frequency and severity of flooding (Brunner et al., 2021). These shifts pose the greatest threat to developing countries, where climate change will likely spur the largest increases (IPCC, 2022) and where floods already cause the most harm (Kahn, 2005). In Bangladesh, flooding can arise from excess rains, the breaching of riverbanks, tidal surges, and cyclones. I focus on the decision d of whether to purchase flood insurance.

Background on Monsoon Intensity The amount of rainfall during the monsoon season impacts decisions about the type of and timing of agriculture, flood risk, and the stability of agricultural production. Global warming has amplified the variability of the South Asian monsoon and increased the likelihood of extreme rainfall events (Mohan and Rajeevan, 2017).

3.2 Data Collection

I conduct a series of three in-person household surveys and several experiments with 2,279 dry season rice farmers across 250 villages in the Khulna Division of Bangladesh. Let i index farmers, t index survey round, $v(i)$ capture the village of farmer i, and $n_{v(i,t)}$ denote the total number of respondents in village $v(i)$ in survey round t. These villages span a large area amounting to approximately 15% of the surface area of Bangladesh, providing substantial natural variation in experiences and climate shocks across farmers. For more details on the survey sampling, see Appendix Section B.1 and Patel (2025). See Appendix Section B.2 for the specific survey questions used in the analyses below.

3.3 Evidence of Endogenous Memory Revision

Baseline Evidence of Imperfect Encoding To examine scope for constructive memory, I directly measure farmers' memories of past floods. One challenge is that despite advances in satellite technology to measure flooding (see Patel 2023 for details on my method to detect local flooding), significant measurement error exists. This creates a challenge in knowing the "ground truth" against which to compare recalled features to detect constructive memory. I overcome this obstacle, I use repeat recall elicitations of the same flooding events approximately eight months apart and measure discrepancies in retrieved memories and patterns in these mismatches. The intuition behind this approach is that farmers past and future selves can serve as the benchmark. Although standard reporting error could generate imperfect matches, the psychology literature points to systematic ways in which discrepancies might emerge which I directly test.[2]

I asked 638 farmers during both rounds 1 and 2 to recount every flood they could remember, randomizing whether I ask about the oldest flood or most recent flood first. Floods occur frequently in these areas, with 56.72 percent of farmers reporting ever experiencing a flood. Excluding recalled inundation events from 2022 and 2023—the years during which I conducted the surveys—I test whether the 497 farmers who could recount at least one flood in either period recount the same floods in each elicitation, allowing for a one year margin of error. As a conservative benchmark, I do not require any other aspect of the flood retrieval to match (such as the duration of the flood or the reported damages to crops and property).

The results shown in Table 4 show huge variation in recalled floods within respondent over time. Overall, farmers omit 64.69 percent of flooding events recalled in one survey from the other. This pattern largely persists even after restricting the sample to those recalling at least one flood in each period (to rule out that the effects are simply driven by differential survey fatigue) and those asked to recall events in the same order (oldest or most recent first).

Of course, some of these effects may result from standard measurement error in reporting. The psychology literature on memory suggests particular patterns consistent with a model of imperfect and constructive memory story which bear out in the data. First, the year of flooding has a U-shape relationship with the probability that a flooding event is accurately

[2] Although the phrasing of the main questions remained exactly the same in the first two survey rounds, the mechanics of the survey design changed slightly in the second round. Specifically, enumerators recorded each additional flood as part of a loop, requiring them to specifically click to add another inundation event after asking the respondent whether they could recall another one. During the baseline, the tablets allowed enumerators to proceed in error and not add another event, even if the farmer reported remembering one. I modified the survey during the baseline to prevent this type of error from occurring and exclude all responses from the baseline featuring this error.

recalled by the farmer during both survey rounds. Very old and very recent floods are both likely to be recalled, while a mass of floods in the middle—bottoming out around 20 years ago—tend to be the most likely to be imperfectly remembered. Floods with more salient features also predict more accurate recall: floods that last longer, cause more damage, or are detectable via the satellite method from Patel (2023) are more likely to be remembered twice (p-value=.046).

Even conditional on flooding events remembered during both elicitations (allowing for a two year buffer), farmers often report significantly different features along other dimensions of the flood *other* than year. On average, flood length differs by 5.4 days. Although 90 percent of the time, farmers' memories of a flood agree on whether crops were damaged, the share of crops damaged (conditional on recalling damage both times) differs by 10 percent on average. The comparable figures for house damage are 70 percent and \$570 USD, respectively (median daily consumption in Bangladesh is \$5).

Endogenous Flood Memory Survey Experiment To more directly examine the role of cues, I use a survey experiment leveraging the randomization of whether I ask farmers to recall floods from oldest to most recent or the reverse. The core idea is that the first memory farmers recount about floods serves as a cue in of itself, potentially shaping subsequent memories. The randomization of asking about the oldest vs. most recent flood first gives exogenous variation as to the nature of that initial cue. As with the salinity experiment, I use the answers from neighboring households in the village to predict the nature of that cue for a specific feature. I adopt a difference-in-difference design, comparing farmers asked about the oldest flood first to those asked about more recent floods when—according to others in the village—the oldest floods differ more along a particular feature than more recent ones. I exclude the first memory from all of these regressions as that recall serves as the cue, focusing only on subsequent memories. Let $f_{i,j,k,t}$ denote the value of feature k for the j^{th} memory recalled by farmer i in survey round t, and $OldestFirst_{i,t}$ indicate whether farmer i answered about the oldest floods they experienced first in period t. Let $\Delta f_{v(i),k,t}$ denote the leave-out-mean difference between the oldest vs. most recent floods for feature k in village $v(i)$ among the neighbors of i in period t. In other words, $\Delta f_{v(i),k,t}$ captures the degree to which people in that village systematically remember differences along feature k for the oldest vs. most recent flood. I estimate Equation 6, clustering standard errors at the farmer level and including village fixed effects $\lambda_{v(i)}$ and memory order fixed effects γ_j. The main coefficient of interest is β_3: the degree to which being asked about oldest floods first in a place where the oldest floods are systematically different along a given feature dimension changes the recalled values of those features in subsequent memories.

$$f_{i,j,k,t} = \alpha + \beta_1 OldestFirst_{i,t} + \beta_2 \Delta f_{v(i),k,t} + \beta_3 OldestFirst_{i,t} \times \Delta f_{v(i),k,t} + \lambda_{v(i)} + \gamma_j + \varepsilon_{i,j,k,t} \quad \forall j \neq 1 \tag{6}$$

Table 5 presents the main results from this design. Across all four features—flood length, an indicator for crop damage, the share of crops damaged, and an indicator for property damage—the same pattern emerges.[3] When farmers are asked about oldest floods first in places where the oldest floods stand out in a particular dimension, they shift their memories about *subsequent* floods along that same dimension. A one day increase in the reported flood length between oldest and most recent floods among neighbors in the village for instance translates into a .95 increase in flood length among subsequent floods recalled by the farmer when that farmer is asked about oldest floods first. This provides direct evidence of the malleability of features in recalled memories based on cues.

Rainfall Natural Experiment To examine the role of cues in a more naturalistic setting, I use daily variation in weather as a natural experiment in a difference-in-differences design. I compare farmers' answers about the amount of rain they remember in the past as well as forecast in the future depending on whether it happens to be raining on the day of the interview. I include fixed effects for the date of the survey and the respondents' village, thereby only leveraging identification within place and across days in whether or not it happens to be raining.

This exercise requires accurate data on very local and precisely timed rainfall exposure—information which simply does not exist even via remote sensing due to the sparsity of weather stations in Bangladesh. To overcome this empirical obstacle, I use survey enumerators' response to the question "Was it raining at any time during the day in this area?" asked at the conclusion of every survey.

To measure memories and beliefs about rainfall, I ask farmers to place 10 buttons across a visual guide that captures the number of days it rained in a two week period during the monsoon (see Appendix Section B.2 for details). I estimate Equation 7, where Y_i denotes farmer i's memory or prediction about rainfall, $RainToday_i \in \{0,1\}$ indicates whether it rained on the day of the interview, $\lambda_{v(i)}$ denotes a village fixed effect, and $\gamma_{d(i)}$ denotes a date fixed effect. I cluster standard errors at the village by date level as that is the unit at which treatment—in this case, rain on the day of the interview—is assigned. For past rainfall recollections, I also include fixed effect for the year in which rainfall is being remembered,

[3]The very skewed distribution of property damage makes it difficult to use that outcome in a regression, so I focus on these others instead.

as I randomize whether people are asked about 5 or 10 years ago.

$$Y_i = \alpha + \beta RainToday_i + \lambda_{v(i)} + \gamma_{d(i)} + \varepsilon_i \tag{7}$$

Figure 2 presents the results of this regression. Across memories of the distant past (5 to 10 years ago), the last year, and the next year, I find strong evidence in support that rain on the day of the interview cues people to remember more rain and predict more rain going forward, consistent with rain at the time of the survey serving as a cue of intense monsoons. Note however that this particular design does not allow me to tease out a priming effect from cues role in shaping memories.

4 From Cues to Memories to Behavior

To experimentally identify the role of memory in economic behavior, I run a specifically-tailored information experiment in Winter 2024/2025 linking cues, memory, and demand for flood insurance. Appendix Figure A.1 presents this design visually. The experiment involves five arms. First, there is a pure control arm with one third of respondents. In this arm, respondents report their memories of past floods and then—much later in the survey—report their WTP for a flood insurance contract. The memory elicitation follows the same procedure as described above. As in the case of the salinity-tolerant seeds, I measure WTP using BDM. As detailed further in Appendix Section B.2, I first explain flood insurance and then elicit demand for a contract that pays out 10,000 BDT in the event of a flood.

In the remaining four arms, I randomly provide respondents with information. Enumerators gave two sets of truthful information: *flood* information and *damage* information. Enumerators read the following for the flood information treatment: "Major floods struck some parts of Bangladesh in June, August, and October of this year." For the damage information treatment, they read both the flood information and the following sentence: "The government estimates that 1.1 million metric tons of rice have been destroyed by floods in Bangladesh this year."[4] Among the remaining two thirds of respondents, I randomize whether I administer only the *flood* information or also provide the *damage* information, cross-randomized with whether I provide that information before the memory elicitation or after the elicitation (yet still much before the WTP elicitation). I refer to arms where enumerators read information prior to the memory elicitation as *cues* and arms where infor-

[4] To aid with the interpretation of these results, following the experiment, I contacted a small number of respondents from the control group and measured their prior knowledge about the information disseminated in the treatment arms. The information from the flood arm was very commonly known, while essentially no farmers knew of the government's crop loss estimates from the damage arm.

mation comes after the memories as *primes*, to capture the notion that cues provided prior to the recall exercise can influence the retrieved experiences while information explained after mechanically cannot yet still can shift demand for insurance through priming. Of course, I cannot rule out that information provided after also impacts memories retrieved following the explicit flood elicitation yet conjured when respondents report their demand for insurance, and thus effects of the *prime* arms provide upper bounds on the priming channel from Equation 5. Ultimately, this provides the five arms which I refer to as control, flood cue, flood prime, damage cue, and damage prime.

I estimate Equation 8 to identify the role of constructive memory in beliefs and economic behavior. The variable $FloodCue_i \in \{0,1\}$ equals 1 if enumerators read the flood information to respondent i prior to their memory elicitation, $DamageCue_i \in \{0,1\}$ does the same for reading the damage information, and $FloodPrime_i \in \{0,1\}$ and $DamagePrime_i \in \{0,1\}$ signify the corresponding information read after the memory elicitation. I control for initial WTP for flood insurance reported by the respondent in rounds 1 or 2 and village fixed effects, captured by Ω_i. Following the pre-registration, I restrict to places where based on a machine learning algorithm's predictions, the geographic features suggest high flood risk. See Patel (2023) for further details on the construction of this flood risk measure. In the Appendix, I also report alternate specifications based on a variety of other different samples.

$$Y_i = \alpha + \beta_1 FloodCue_i + \beta_2 FloodPrime_i + \beta_3 DamageCue_i + \beta_4 DamagePrime_i + \Omega_i + \varepsilon_i \quad (8)$$

I focus on three key outcomes for Y_i. Corresponding to the economic decision d in the model, I estimate impacts on WTP for the flood insurance contract elicited much later in the survey than the memory elicitation. To understand the scope for constructive memory, I also focus on the content of the flood memories recalled by respondents. I calculate the share of memories in which the respondent reports damage to their homes and the share featuring crop loss.

Table 3 presents the main results from this experiment. A similar story holds across all sample restrictions and outcomes. First, considering the impacts on memories, I find that as expected, the primes—information provided after the memory elicitation—have no effect, with small magnitudes, none of which are statistically significant. Given that mechanically this treatment realization occurred after memories were elicited, these results are reassuring. The cues—information provided just before respondents are asked to recall their past flood experiences—tell a different story, however. Farmers told about the existence of widespread flooding in Bangladesh report a lower share of memories featuring flood damage, though these effects are relatively small and not statistically significant. Being additionally offered information about damage yields a substantial increase in recalled damage, significant at the 10 percent level in the main specification and amounting to a 10 percent increase in the case of crop damage and nearly 20 percent increase in the case of house damage relative to the control mean. Note however that the net effect combining the flood and damage information is not statistically significant. A similar pattern emerges for WTP for flood insurance, with the flood cue decreasing demand by nearly 20 percent, whereas the damage cue *increases* WTP more than 25 percent relative to a control mean.

I interpret the results of Table 3 as evidence that farmers responded to the information about widespread floods alone as a positive signal: floods occurred, as they knew, yet the information reminded them that these floods had little direct consequence on their lives. This cue therefore became more similar to non-damaging floods, lowering their demand for insurance and (suggestively) making the floods they recalled less destructive. When additionally told about the government's estimates of crop loss, the cue shifts to become more similar to damaging floods, more than offsetting that underlying effect.

4.1 Further Evidence that Memories Impact Behavior

I use a difference-in-differences design around a simple survey experiment to examine the role of memories in shaping farmers' soil salinity beliefs $\widehat{\theta}$ and subsequent seed choice decisions d. I elicit farmers' beliefs about whether "the amount of salt in the soil in the typical plot" in their village will increase, decrease, or stay the same over two different horizons: the last decade and the next decade. Figure 1 shows substantial heterogeneity to both the past and future questions across farmers, with more than a third answering increase or decrease to both future and past salinity change questions and about 15 percent answering staying the same. Farmers answered "decrease" most commonly to past salinity changes, and thus I focus on memories of salinity decreases as the main reference group. I ask these questions in all three survey rounds, yielding a total of 6,663 observations; 2,279 farmers from round 1, 2,253 from round 2, and 2,131 from round 3. However, as in Patel (2025), I exclude respondents who fail comprehension checks about the belief elicitation, resulting in 6,141 observations across 2,266 households.

Across respondents, I randomize at the farmer-by-survey round level whether this prediction about the future is asked before or after the same question asked about the past 10 years. I next incorporate heterogeneity in past memories using spatial variation across respondents. For instance, some respondents may live in villages where people systematically believe soil salinity has increased in the past, while others live in places where farmers perceive a decline in salt levels. Patel (2025) documents substantial spatial covariance within villages in both beliefs and true soil salinity levels. To capture this heterogeneity in cues, I calculate the village leave-out-mean for any given answer using the responses of i's neighbors also living in village $v(i)$ in the same survey round t.

The main empirical strategy involves a difference-in-differences design comparing (1) farmers asked about the past salinity changes before the future vs. those asked about the future prior to the past and (2) farmers living in villages where people typically believe salinity decreased in the past vs. those living in places where the common consensus holds an increase in past salinity. I consider two main outcomes denoted by $Y_{i,t}$ in Equation 9. First, I consider decision relevant beliefs about future salinity: let the binary indicator $\widehat{\theta}_{i,t} \in \{0, 1\}$ equal 1 when respondent i forecasts a decrease in soil salinity levels over the next decade in survey round t. Second, I examine willingness-to-pay (WTP) for a salinity tolerant seed, corresponding to d in the model. I elicit WTP using an ascending price list format of the Becker DeGroot Marschak (BDM) mechanism to ensure incentive compatibility. Beginning with a low price, I ask farmers if they would be willing to purchase the item for that price.[5] If they say yes, I increase the price and ask again, repeating until the respondent says no. I then randomly select a price, and if the respondent was willing to purchase the good for that amount, the transaction takes place. All else equal, I expect farmers who forecast higher salinity in the future to pay more for the packet of BRRI 67 seeds, a variety which has been explicitly designed to grow well in high salinity soil. See Patel (2025) for further details on these seed varieties.

I estimate the main specification in Equation 9, where the main coefficient of interest β_3 captures the extent to which farmers differentially perceive a decline in future salinity (or change their WTP for salinity-tolerant seeds) if they first report their recollection about past salinity changes in a place where most people report declining salinity in the past. Let $X_{i,t} \in \{0, 1\}$ equal 1 when respondent i reports a decrease in soil salinity levels over the past decade in survey round t. Let $Past_{i,t}$ denote that enumerators elicit farmer i's past salinity change first in survey round t. In all specifications, I include enumerator-by-survey round fixed effects, and I also estimate models further adding village-by-survey round fixed effects and farmer fixed effects. In the latter most stringent specification with farmer fixed effects and village-by-survey round fixed effects, identification stems from within individual variation in the order they answer questions across survey rounds. I report heteroskedasticity-robust clustered standard errors at the individual level because the randomization of the order of

[5]During piloting, it became clear that norms against accepting gifts for free distorted the results of the BDM when beginning at 0 BDT. To circumvent this issue, I begin the price list at a small positive value of 10 BDT, and only ask about 0 BDT if the respondent says no to that initial price.

questions takes place at the respondent-by-survey round level, though Appendix Table A.1 shows extremely similar results when clustering at the village level.

$$Y_{i,t} = \alpha + \beta_1 Past_{i,t} + \beta_2 \frac{1}{n_{v(i,t)-1}} \sum_{j \neq i, v(j)=v(i)} X_{j,t} + \beta_3 Past_{i,t} \times \frac{1}{n_{v(i,t)-1}} \sum_{j \neq i, v(j)=v(i)} X_{j,t} + \varepsilon_{i,t} \quad (9)$$

This design provides an empirical test for memory shaping beliefs about the future and important economic behavior. Although even those respondents asked about future salinity changes first likely draw from their own memory database about past salinity when providing their forecast, by explicitly asking about past changes, I more directly bring memories about soil salinity top of mind for the respondent. Of course, the act of being asked about the past first may change beliefs about the future and subsequent behavior in other ways: for instance, by making respondents think longer about salinity. The second difference in the difference-in-differences design helps to control for these alternate factors by studying the differential role of the specific *content* of memories, rather than just the act of reflecting on the past itself.

Table 1 presents the main results from the salinity experiment. The third row captures the main coefficient of interest β_3. Respondents' asked about the past first in a village where all of their neighbors recall a decline in soil salinity levels are 22 percent more likely to forecast a decline in salinity over the subsequent decade (column 1). This treatment effect persists under increasingly demanding fixed effects (columns 2-3), though with individual fixed effects, the estimate falls below statistical significance.

This impact on beliefs $\widehat{\theta}$ translates into real-world economic behavior d in the form of farmers' WTP for salinity tolerant seeds(columns 4-6). Although the sample shrinks because I only elicited WTP during the first two rounds of the survey. The impacts on demand almost exactly mirror the effects on beliefs, with a 23 percent decrease in WTP from the main interaction term. The magnitudes remain similar across fixed effects.

One potential concern with the interpretation of these results as the impact of memory is that the first question simply serves as a cue itself, prompting a direct priming effect through the first expression of Equation 5. To address this concern, I consider the reverse experiment: does being asked about the future first shape memories (and subsequent economic behavior)? I simply estimate Equation 9, replacing $Past_{i,t}$ with $Future_{i,t}$—an indicator for being asked about the future first, and calculating the corresponding leave-out-mean using future predictions. Table 2 presents these results. In contrast to the effects of first asking about memories, respondents giving their predictions about future salinity first show no differential impact on their recollections about past salinity (columns 1 - 3). This exercise is poorly suited to identifying constructive memory because of the coarse nature of the elicitation but does provide evidence of meaningful encoding for past experiences that cannot be shifted by the cue of prompting a respondent to forecast future trends. When examining impacts on economic behavior, the coefficients are noisy, and if anything, the coefficients go in the "wrong" direction: suggesting an *increase* in WTP for salinity tolerant seeds where we would have expected a decline. Appendix Table A.2 shows that clustering at the village level yields extremely similar results.

5 Conclusion

This paper provides evidence that memories play a fundamental role in the belief formation process and economic decision-making of farmers on the front lines of climate change. Contemporaneous cues shape the content of memories, highlighting their instability. Lowering information frictions to alleviate the cognitive demands for complex forecasting such as those facing farmers learning about their local environment could therefore substantially increase welfare.

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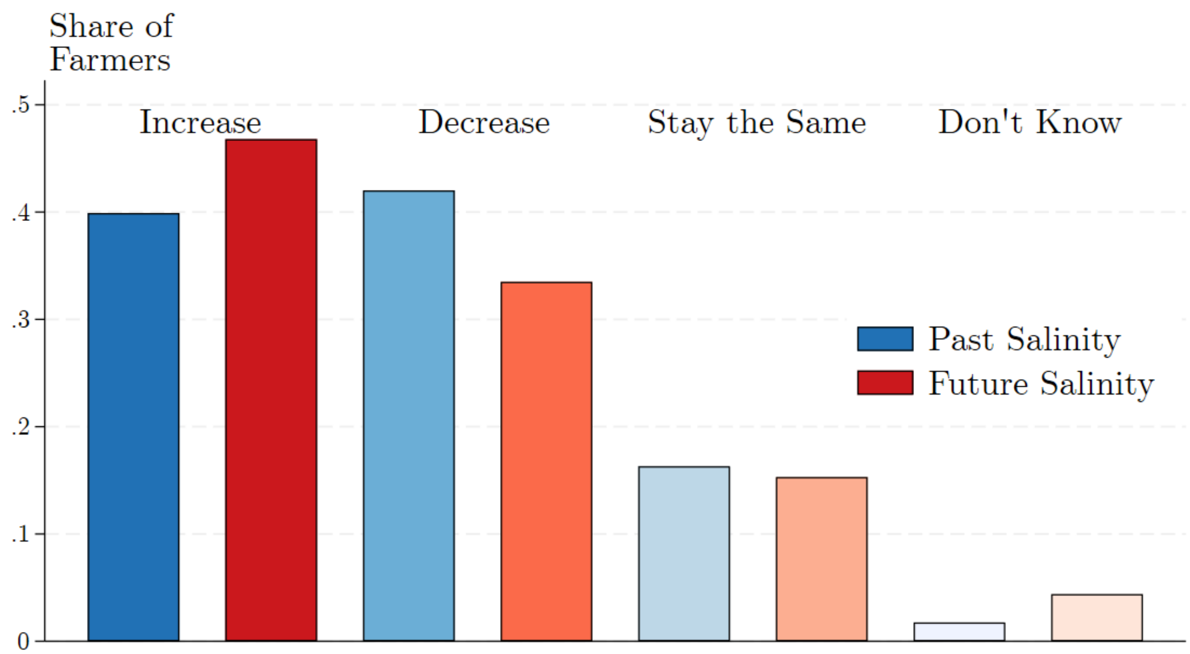
6 Figures and Tables

Figure 1: Distribution of Perceived Changes to Past and Future Salinity Levels



Note: Figure 1 plots the share of responses at the farmer-by-survey round level giving each answer to the past and future salinity change question. The past question is, "Think back to the past 10 years. Do you think the amount of salt in the soil in the typical plot in your village has increased, decreased, or stayed the same since then?" The future question is, "Think about the next 10 years.Do you think the amount of salt in the soil in the typical plot in your village will increase,decrease, or stay the same from now until then?"

Table 1: Salinity Memory Experiment Results

	$\widehat{\theta}$: Believe Future Salinity Will Decrease			d: WTP for Salinity Tolerant Seeds		
	(1)	(2)	(3)	(4)	(5)	(6)
Asked Past First	0.0140	-0.0166	-0.00658	8.900**	8.414**	5.840
	(0.0181)	(0.0158)	(0.0195)	(3.655)	(3.692)	(4.764)
Share Neighbor's Recalling Decrease	0.348***	-3.734***	-3.240***	12.14**	-3.342	42.57
	(0.0332)	(0.111)	(0.133)	(5.980)	(19.32)	(28.13)
Asked Past First × Share Neighbor's Recalling Decrease	0.0733**	0.0870***	0.0647	-16.30**	-11.38	-21.26**
	(0.0373)	(0.0336)	(0.0412)	(7.467)	(7.638)	(10.10)
Outcome Mean	0.336	0.336	0.336	71.289	71.289	71.943
Surveyor × Round F.E.	✓			✓		
Village × Round F.E.		✓	✓		✓	✓
Household × Round F.E.			✓			✓
Observations	6141	6141	6079	4116	4116	3740

Note: Table 1 presents estimates of Equation 9. All standard errors are clustered at the individual level.

Table 2: Salinity Memory Experiment Placebo Results

	Recall Past Salinity Decrease			d: WTP for Salinity Tolerant Seeds		
	(1)	(2)	(3)	(4)	(5)	(6)
Asked Future First	-0.0414**	-0.0198	-0.0366*	-6.198*	-7.961**	-4.903
	(0.0175)	(0.0159)	(0.0199)	(3.286)	(3.289)	(4.270)
Share Neighbor's Predicting Decrease	0.462***	-4.001***	-3.709***	-5.217	-9.360	-8.763
	(0.0368)	(0.119)	(0.149)	(6.707)	(20.91)	(30.53)
Asked Future First × Share Neighbor's Predicting Decrease	-0.0284	-0.0236	0.0169	12.41	12.96	24.51**
	(0.0392)	(0.0345)	(0.0432)	(7.845)	(7.922)	(11.07)
Outcome Mean	0.420	0.420	0.420	71.289	71.289	71.943
Surveyor × Round F.E.	✓			✓		
Village × Round F.E.		✓	✓		✓	✓
Household × Round F.E.			✓			✓
Observations	6141	6141	6079	4116	4116	3740

Note: Table 2 presents estimates of the placebo version of Equation 9. All standard errors are clustered at the individual level.

Table 3: Flood Memory Experiment Results

	WTP for Insurance	Share Memories With Crop Damage	Share Memories With House Damage
	(1)	(2)	(3)
Flood Cue	-7.705*	-0.0244	-0.0455
	(4.261)	(0.0361)	(0.0364)
Flood Prime	-3.194	-0.000303	-0.0328
	(4.612)	(0.0339)	(0.0384)
Damage Cue	9.974**	0.0712*	0.0819*
	(4.775)	(0.0381)	(0.0421)
Damage Prime	-0.704	-0.00292	-0.00883
	(5.672)	(0.0401)	(0.0438)
Outcome Mean	40.154	0.719	0.421
Observations	802	851	851

Note: Table 3 presents results from estimating Equation 8 restricting to villages with high flood risk.

Table 4: Recalled Flood Matches Between Baseline and Endline

Sample	All		> 0 Floods		> 0 Floods, Same Order	
Missing Round	Baseline	Endline	Baseline	Endline	Baseline	Endline
Share of Matching Floods	0.43	0.30	0.50	0.43	0.50	0.44
Number of Floods	498	717	428	500	231	263

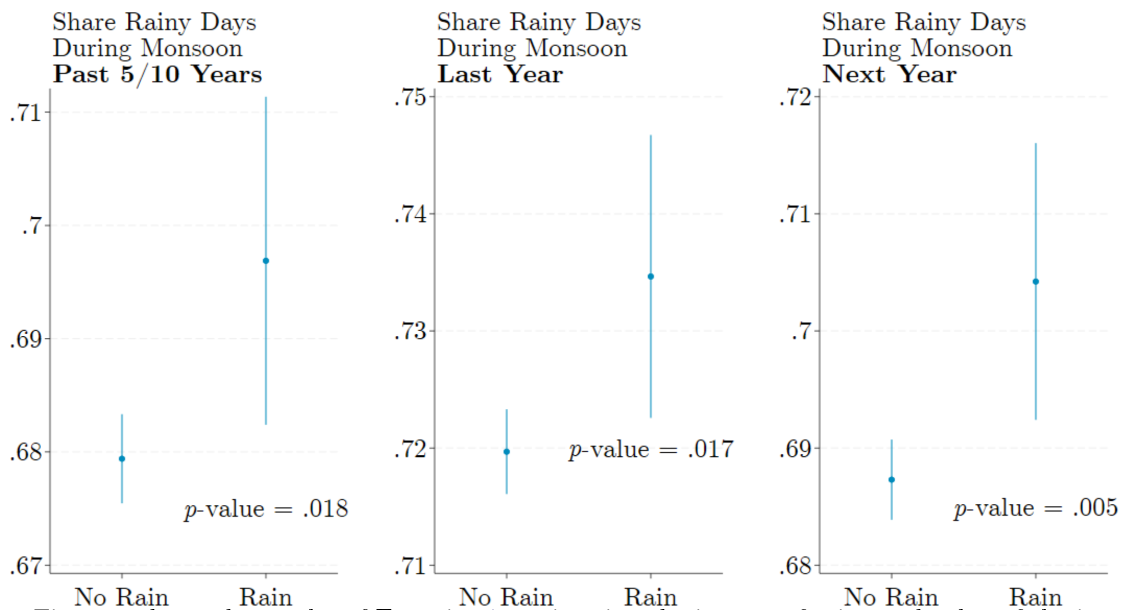
Note: Table 4 presents results on the share of floods recalled by farmers both in the endline and the baseline. The "All" sample includes only those 497 farmers who answered the flood recall questions both during the baseline and endline, did not have any enumerator issues during the baseline recall, and recalled at least one flood in either of the periods. The "> 0 Floods" sample further restricts to those farmers reporting at least one flood in both periods. The "> 0 Floods, Same Order" sample further restricts to those farmers randomly asked to recall floods in the same order (i.e. asked to recall the most recent first both times or asked to recall the oldest first both times).

Table 5: First Flood Memory as Cue

	Duration	Any Crop Damage	Share Crop Damage	Any House Damage
	(1)	(2)	(3)	(4)
Asked Oldest Flood First	-0.763	-0.00416	-0.0324**	-0.0486*
	(0.550)	(0.0171)	(0.0159)	(0.0280)
Oldest vs. Recent Feature Gap Among Neighbors	-0.396***	-0.541***	-0.927***	-0.366***
	(0.136)	(0.179)	(0.187)	(0.0983)
Asked Oldest Flood First X Oldest vs. Recent Feature Gap Among Neighbors	0.951***	1.277***	0.795***	0.809***
	(0.123)	(0.146)	(0.200)	(0.0810)
Outcome Mean	17.730	0.886	0.857	0.378
Observations	897	893	766	894

Note: Table 5 shows the impacts of the first memory recalled by farmers on features of subsequent memories using the specification in Equation 6.

Figure 2: Impact of Rain on Survey Day on Memories and Forecasts



Note: Figure 2 shows the results of Equation 7, estimating the impact of rain on the day of the interview on memories about past rainfall and predictions about future rainfall with survey date and village fixed effects.

Appendices

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A Additional Figures and Tables

Table A.1: Salinity Memory Experiment Results

	$\widehat{\theta}$: Believe Future Salinity Will Decrease			d: WTP for Salinity Tolerant Seeds		
	(1)	(2)	(3)	(4)	(5)	(6)
Asked Past First	0.0140	-0.0166	-0.00658	8.900**	8.414**	5.840
	(0.0193)	(0.0173)	(0.0200)	(4.100)	(4.118)	(4.759)
Share Neighbor's Recalling Decrease	0.348***	-3.734***	-3.240***	12.14*	-3.342	42.57
	(0.0410)	(0.151)	(0.166)	(7.165)	(19.98)	(26.98)
Asked Past First × Share Neighbor's Recalling Decrease	0.0733*	0.0870**	0.0647	-16.30**	-11.38	-21.26**
	(0.0412)	(0.0370)	(0.0420)	(8.263)	(8.367)	(9.671)
Outcome Mean	0.336	0.336	0.336	71.289	71.289	71.943
Surveyor × Round F.E.	✓			✓		
Village × Round F.E.		✓	✓		✓	✓
Household × Round F.E.			✓			✓
Observations	6141	6141	6079	4116	4116	3740

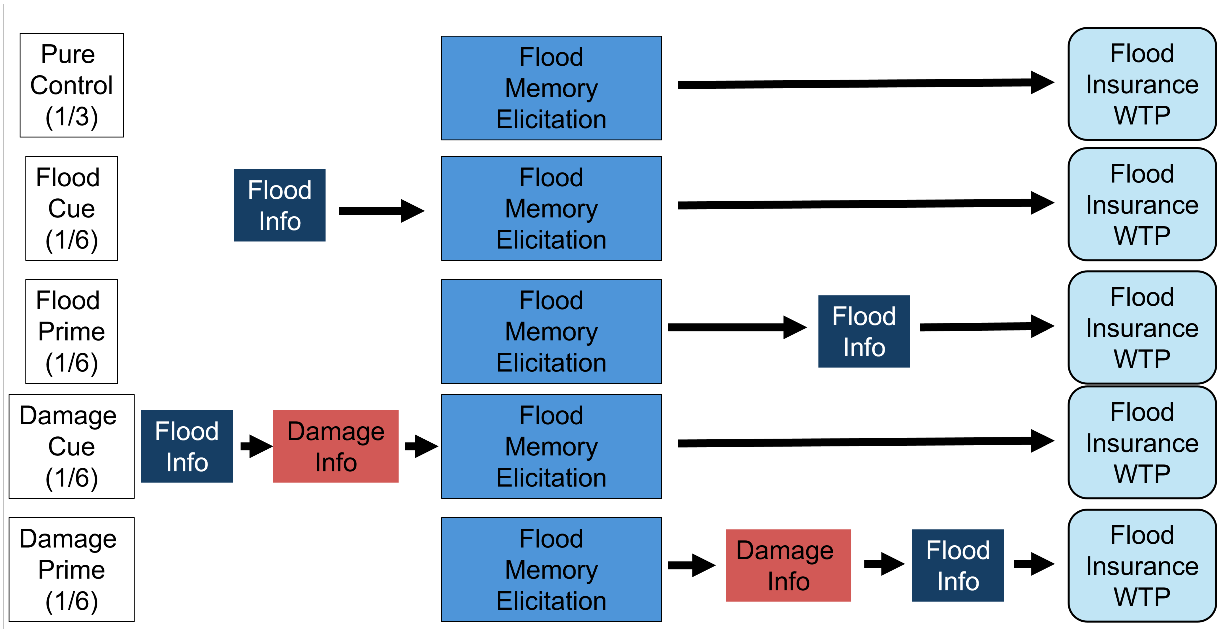
Note: Table A.1 presents estimates of Equation 9. All standard errors are clustered at the village level.

Table A.2: Salinity Memory Experiment Results

	Recall Past Salinity Decrease			d: WTP for Salinity Tolerant Seeds		
	(1)	(2)	(3)	(4)	(5)	(6)
Asked Future First	-0.0414**	-0.0198	-0.0366*	-6.198*	-7.961**	-4.903
	(0.0163)	(0.0155)	(0.0193)	(3.654)	(3.475)	(4.151)
Share Neighbor's Predicting Decrease	0.462***	-4.001***	-3.709***	-5.217	-9.360	-8.763
	(0.0455)	(0.155)	(0.178)	(7.755)	(20.49)	(29.41)
Asked Future First × Share Neighbor's Predicting Decrease	-0.0284	-0.0236	0.0169	12.41	12.96	24.51**
	(0.0421)	(0.0349)	(0.0444)	(7.794)	(8.066)	(10.35)
Outcome Mean	0.420	0.420	0.420	71.289	71.289	71.943
Surveyor × Round F.E.	✓			✓		
Village × Round F.E.		✓	✓		✓	✓
Household × Round F.E.			✓			✓
Observations	6141	6141	6079	4116	4116	3740

Note: Table A.2 presents estimates of the placebo version of Equation 9. All standard errors are clustered at the village level.

Figure A.1: Flood Survey Experimental Design



Note: Figure A.1 presents the experimental design for the flood survey experiment.

Table A.3: Flood Memory Experiment Results — No Sample Restriction

	WTP for Insurance	Share Memories With Crop Damage	Share Memories With House Damage
	(1)	(2)	(3)
Flood Cue	-5.570**	-0.0207	-0.00678
	(2.487)	(0.0227)	(0.0215)
Flood Prime	-0.0648	-0.0267	-0.0128
	(2.725)	(0.0227)	(0.0215)
Damage Cue	7.704***	0.0129	0.0345
	(2.908)	(0.0251)	(0.0249)
Damage Prime	-2.426	0.0268	0.00766
	(3.166)	(0.0269)	(0.0254)
Control Mean	37.091	0.624	0.278
Observations	2069	2118	2118

Note: Table A.3 presents results from estimating Equation 8 without sample restrictions.

Table A.4: Flood Memory Experiment Results — Simple Belief Restriction

	WTP for Insurance	Share Memories With Crop Damage	Share Memories With House Damage
	(1)	(2)	(3)
Flood Cue	-6.317**	-0.00657	-0.00248
	(2.832)	(0.0242)	(0.0237)
Flood Prime	-1.515	-0.0173	-0.0109
	(2.993)	(0.0238)	(0.0236)
Damage Cue	8.103**	0.0122	0.0316
	(3.285)	(0.0271)	(0.0273)
Damage Prime	-1.914	0.0314	0.0131
	(3.501)	(0.0285)	(0.0281)
Control Mean	38.611	0.647	0.295
Observations	1817	1866	1866

Note: Table A.4 presents results from estimating Equation 8 restricting to respondents who say that they expect a one day long flood will occur within the next five years.

Table A.5: Flood Memory Experiment Results — Button Belief Restriction

	WTP for Insurance	Share Memories With Crop Damage	Share Memories With House Damage
	(1)	(2)	(3)
Flood Cue	-4.343	-0.0000782	0.0183
	(3.143)	(0.0269)	(0.0259)
Flood Prime	-1.712	-0.00927	0.00543
	(3.385)	(0.0277)	(0.0269)
Damage Cue	6.320*	0.0373	0.0439
	(3.566)	(0.0298)	(0.0302)
Damage Prime	-1.871	0.0126	0.0135
	(3.868)	(0.0317)	(0.0314)
Control Mean	41.270	0.696	0.313
Observations	1524	1573	1573

Note: Table A.5 presents results from estimating Equation 8 restricting to respondents who place at least one button on a flood scenario in the belief elicitation of future flooding over the next five years.

Table A.6: Flood Memory Experiment Results — Baseline WTP Restriction

	WTP for Insurance	Share Memories With Crop Damage	Share Memories With House Damage
	(1)	(2)	(3)
Flood Cue	-8.023**	-0.0183	-0.00149
	(3.409)	(0.0300)	(0.0291)
Flood Prime	-4.925	-0.0121	-0.00725
	(3.708)	(0.0284)	(0.0280)
Damage Cue	12.60***	0.0450	0.0401
	(4.050)	(0.0343)	(0.0346)
Damage Prime	-3.215	0.0431	0.0170
	(4.100)	(0.0353)	(0.0338)
Control Mean	40.608	0.664	0.293
Observations	1303	1339	1339

Note: Table A.6 presents results from estimating Equation 8 restricting to respondents with at least positive WTP for the flood insurance contract in rounds 1 or 2.

B Data Appendix

B.1 Sampling

Union Sampling The survey was conducted across 250 unions in the Khulna division of Bangladesh. From the 642 unions in the Global Administrative Areas (2018) data, I exclude 32 urban areas and then select nine unions from which I have government salinity station data, 37 unions with water stations from the Bangladesh Water Development Board, 48 unions that are also included in the Bangladesh Integrated Household Survey sampling frame, and 121 unions that are also included in the 2016-2017 Bangladesh Labor Force Participation Survey sampling frame. This yields 185 unique unions. Both the Bangladesh Integrated Household Survey and the Bangladesh Labor Force Participation Survey were designed to be representative, and just 29 of the 185 initially selected unions fall outside of both of those survey's sampling frames as exclusively part of the government salinity or water stations. Then, I randomly sort the remaining unions, and choose the next 65.[6]

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

Farmer Sampling Enumerators visited each union and did an initial listing of 50 households who were planning on harvesting rice during the upcoming Boro season and made the primary agricultural decisions on their land. In almost all unions, this goal of 50 households was achieved and typically within a single village. From this initial list, farmers were randomly ordered to be selected for an interview. Initially, 10 households were selected per union, though this number was revised down to nine given survey length concerns after the first week. On average, 9.1 farmers were surveyed in each union. Before a household was deemed unavailable and a replacement household was selected from the randomized listing order, enumerators attempted to contact them multiple times over multiple days via their phone number collected during the listing. Of the endline respondents, 97.07 percent were also interviewed during the baseline; in the small number of cases when the baseline respondent was unavailable, another person from the household who makes decisions about farming was interviewed. Among the 66 households successfully interviewed in the endline but for which the primary respondent was unavailable, 28 of the baseline respondents had migrated, six had passed away, and 32 had another conflict.

Timeline Data collection took place in three main survey rounds: Fall 2022, Summer 2023,and Winter 2024/25. Villages were assigned to enumerators based on location to minimize staff travel time. Within enumerator, the order of villages was randomized for all three survey rounds. Enumerators typically completed three surveys a day, spending three days in each village.

B.2 Survey Questions

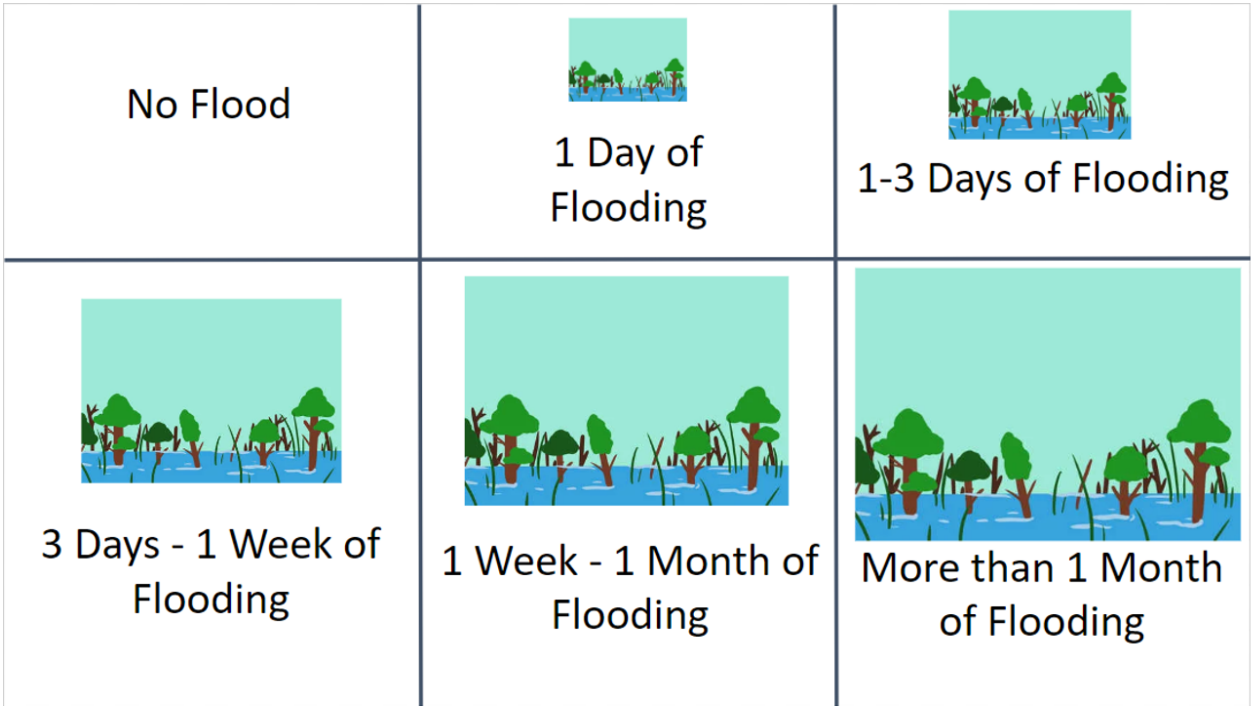
This section presents the full-text of the key questions used in this paper and describes the associated variable construction. The full survey instruments in English and Bangla can be found on my website.

Soil Salinity In the soil salinity survey experiment, enumerators asked two main questions in a random order:

1. *Past:* Think back to the past 10 years. Do you think the amount of salt in the soil in the typical plot in your village has increased, decreased, or stayed the same since then?
2. *Future:* Think about the next 10 years.Do you think the amount of salt in the soil in the typical plot in your village will increase,decrease, or stay the same from now until then?

Flooding The same random half of farmers who answered beliefs questions about precipitation also provided their expectations about flood risk by placing buttons on Figure B.1. To ensure that the categories remained mutually exclusive, enumerators instructed respondents to consider the total number of days in the case of multiple floods occurring. Farmers first provide predictions about the next 12 months, and subsequently about the next five years. As a complementary measure and an attempt to account for the difficulty in articulating small probabilities with the button method, I additionally ask farmers, "How many years do

Figure B.1: Flood Belief Elicitation Visual Tool



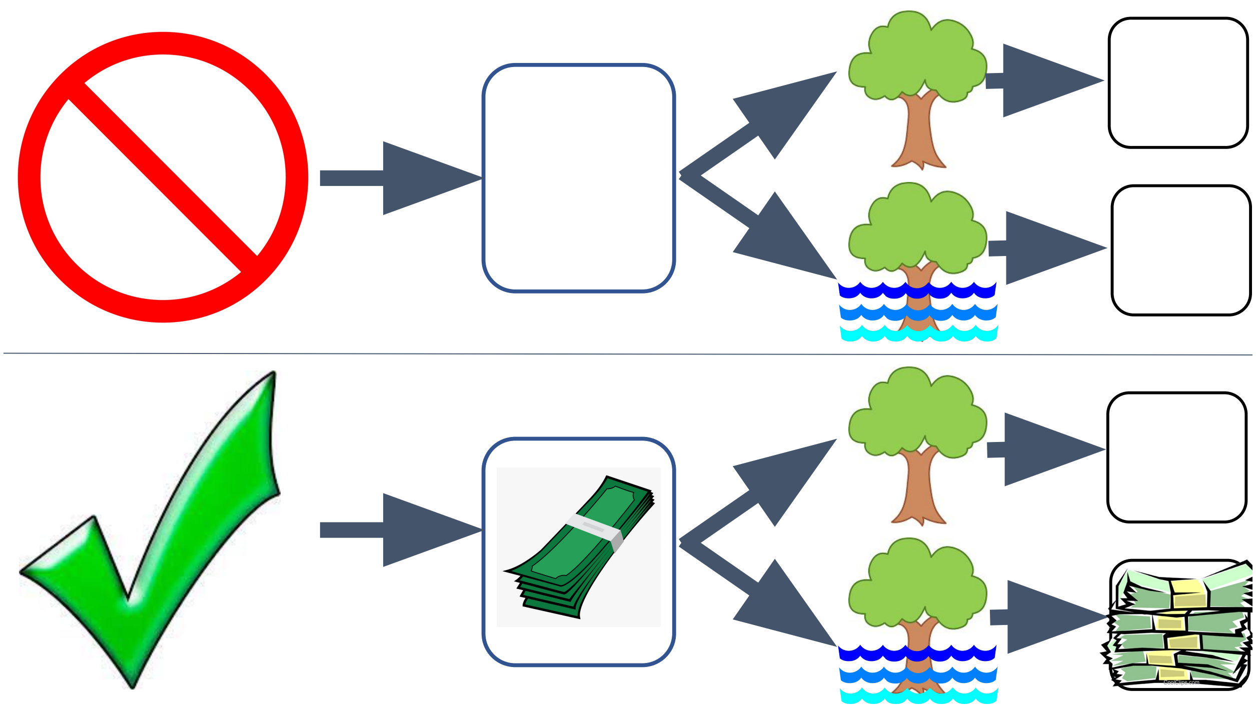
Note: Figure B.1 shows an English translation of the image used to elicit beliefs about flooding, upon which farmers allocated 10 buttons to express their expectations.

you think it would take for a [one-day/three-day/week-long/month-long] flood to happen in this village?" I winsorize these at the 99th percentile I convert these to a hazard rate by calculating the inverse.

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

To explain flood insurance as part of the BDM, enumerators read the following script using the image in Figure B.2 as a visual aid. "It is a flood insurance program. You will have the chance to purchase this insurance. In this program, people who participate will be paid a flat payment if a flood occurs on their land in the next 12 months. To understand how this works, please look at this image. In the top are people who do not participate in the payment program. That means they do not have to pay the money that is the price of joining the program. For those people, in the next season, there may or may not be a flood. Whether or not there is a flood, they will not receive any payment because they did not

Figure B.2: Flood Insurance Visual Tool



Note: Figure B.2 shows the image used to explain the flood insurance contract as part of the survey.

participate in the program. Does you have any questions about what happens if you do not participate in the program? [Answer any questions if yes.]"

"I will now discuss what happens if you do participate. If you look at the bottom, these are the people who chose to participate in the program, and so they do pay the price of joining the program. For those people, in the next season, they might experience a flood or they might not. If they do not experience a flood, then they will not receive any money from the program. In this case, they have paid the price of joining the program, but they will not receive any money back because there was no flood. If there is a flood, then these people will receive a flood payment from the program because they chose to participate and paid the fee to join. The amount of the payment is 10,000 Taka. The amount of money they receive does not depend on how much damage the flood does. They receive the same amount as long as a flood occurs. To claim the money, the participants just need to call this phone number and tell them that a flood occurred. Then the money will be sent to them through bKash to a number that they choose. The amount the participants receive if there is a flood is much more than the amount that they pay to participate in this program. Do you have any questions about what happens if you do participate in the program? [Answer any questions if yes.]"

I then ask two comprehension questions to make sure that respondents understand the contract: "Just to make sure this is clear, I'm going to ask you some questions about these scenarios. If you do not buy the insurance, how much do you get paid if there is a flood? If you do buy the insurance, how much do you get paid if there is a flood?"

Rainfall To measure farmers' perceptions of rainfall during the monsoon season, enumerators asked farmers to place buttons across the image in Figure B.3 for the random half of respondents asked about rainfall during the first survey, and across the image in Figure B.4 for the remaining survey rounds (shown in English here). This adjustment was made to address concerns about bottom-coded answers. Enumerators define a rainy day to farmers as one on which it rained for at least an hour with normal size drops. This is consistent with the U.S. Geological Survey definition. I ask farmers about how much it rained during the six months in the Bengali calendar corresponding to mid-May through mid-October. Farmers were asked to place buttons to indicate, for every two weeks during this period, on how many days they expect or recall that it rained, depending on whether the question was about the past or the future.

To convert these responses into a prediction, I assign values to buckets as follows: less than 8 days (7.5 days), less than 10 days (9.5 days), more than 12 days (12.5 days), and all bins k-$k+1$ days ($k + .5$ days).

Figure B.3: Rainfall Memory and Belief Elicitation Visual Tool—Survey Round 1

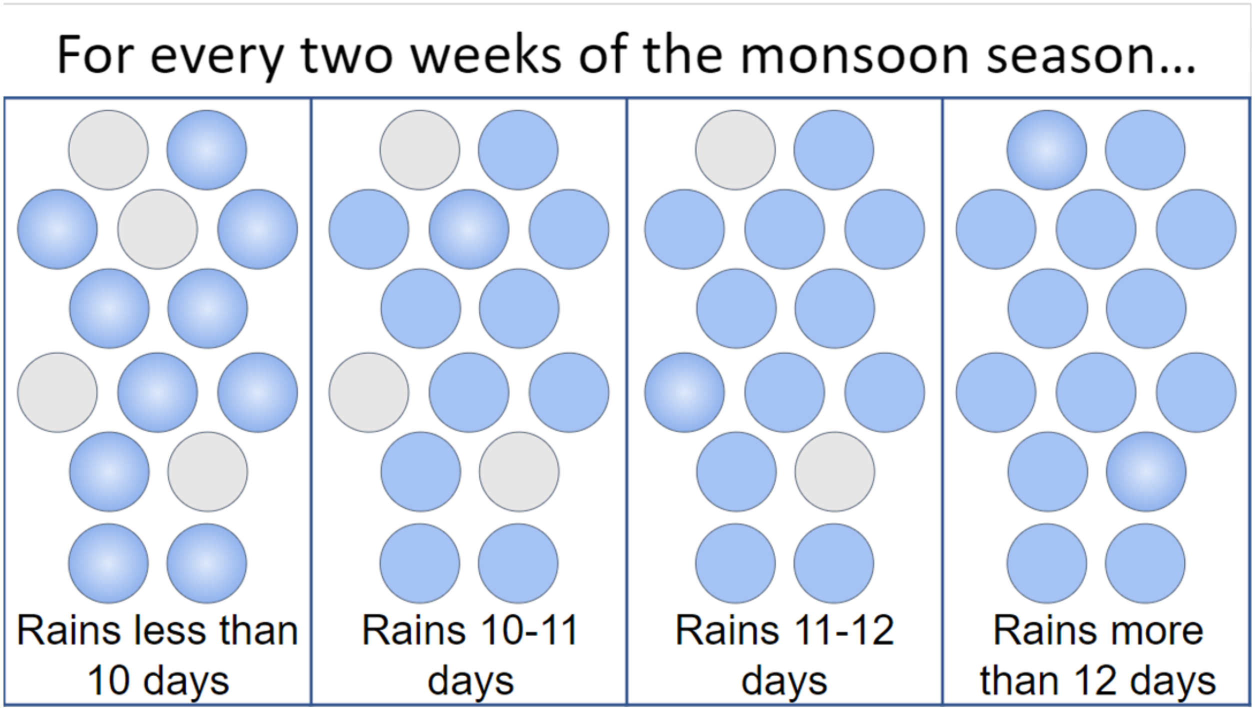
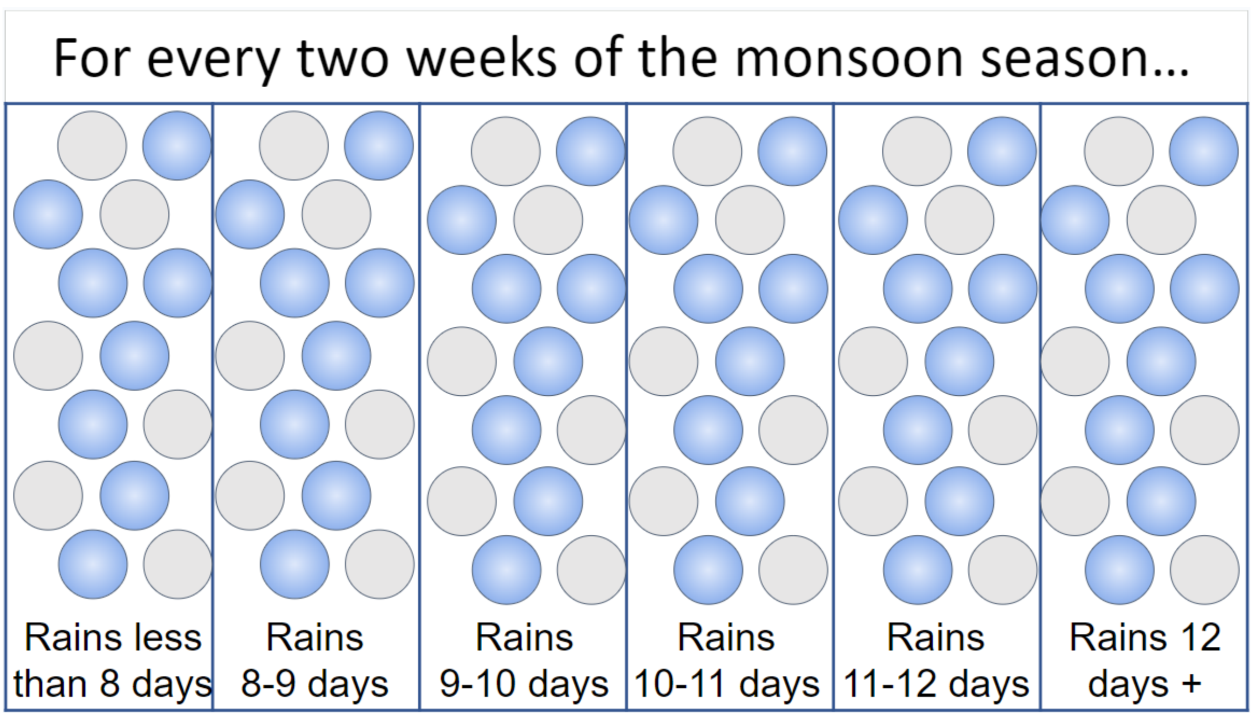


Figure B.4: Rainfall Memory and Belief Elicitation Visual Tool—Survey Round 2+



Note: Figures B.3 and B.4 show English translations of the images used to elicit beliefs about monsoon intensity. Respondents answering about their rainfall memories and beliefs during the first survey in October 2023 placed 10 buttons on Figure B.3; all remaining survey rounds used B.4.