Environmental Beliefs and Adaptation to Climate Change

Dev Patel

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Environmental Beliefs $\Rightarrow$ Climate Adaptation Decision $\Rightarrow$ Profits

Research Questions

#1. How accurate are environmental beliefs?

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#3. How do environmental beliefs impact climate change adaptation?

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- Panel surveys & experiments with 2,279 rice farmers in 250 Bangladeshi villages
- Focus on **soil salinity**
  - Soil salinity affects $\approx$ 30% of irrigated land worldwide (Hopmans et al. 2021)
  - Climate change projected to increase soil salinity through many channels (Mukhopadhyay et al. 2021)
  - Particularly well-suited to studying environmental beliefs

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- Farmers recognize spatial covariance of salinity
  - **RCT #1:** Equal WTP for neighbors' info vs. neighbors' info + own plot
- Opportunity to free ride lowers info demand
  - **Natural Experiment:** Same farmer has lower WTP when surveyed relatively later in village
  - **RCT #2:** Lower WTP when neighbor told environmental data

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Puzzle: why are such high-stakes beliefs incorrect in equilibrium?

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$\Rightarrow$ Bayesian farmers with perfect knowledge of production function can still hold incorrect beliefs in equilibrium

$\Rightarrow$ **Identification problem:** ambiguous signals $\rightarrow$ priors endogenously shape interpretation of new data $\rightarrow$ (rational) path dependence in beliefs

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Lab-in-the-Field:

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- Climate change characterized by **subtle** shocks and **salient** shocks
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- Framework predicts different environmental events with the same *true* impact on salinity...

⇒ can have different impacts on *beliefs* (e.g., subtle shock goes unnoticed)

⇒ cause persistent errors by endogenously changing how farmers learn from **new** data

- Confirm using quasi-random variation in **subtle** and **salient** salinity shocks combined with survey data

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Salinity Beliefs ⇒ Seed Choice

Method:

- **Info RCT:** Information on true soil salinity

Results:

- **Beliefs Matter:** A 1 S.D. ↑ in soil salinity beliefs causes a **41%** ↑ in demand for salinity tolerant seeds

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Method:

- Simple structural model of seed demand

Results

- If farmers had **perfect** salinity beliefs ⇒ agricultural profits would increase **16%**

Roadmap

1. **How accurate are environmental beliefs?**

   - Background on soil salinity
   - Measuring true salinity conditions
   - The missing market for salinity measurement *Skip today for time*
   - Measuring beliefs about salinity conditions
   - Address potential concerns with belief elicitation
   - Comparing salinity beliefs to true conditions

2. How do people learn about their environment?
3. How do environmental beliefs shape adaptation to climate change? *Skip today for time*

Background on Soil Salinity in Bangladesh

- **Problem:** Too much salt in the root bed harms plant growth, especially for rice
  - Persistence: site's salinity type matches last year 84% of time in (small) govt. series
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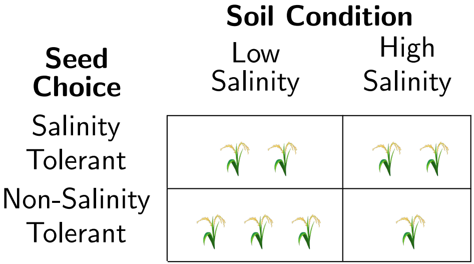

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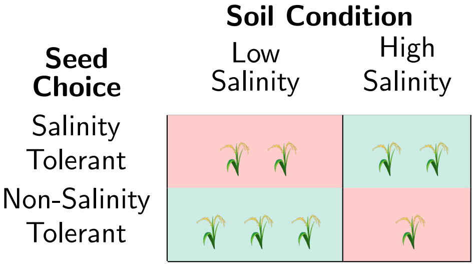
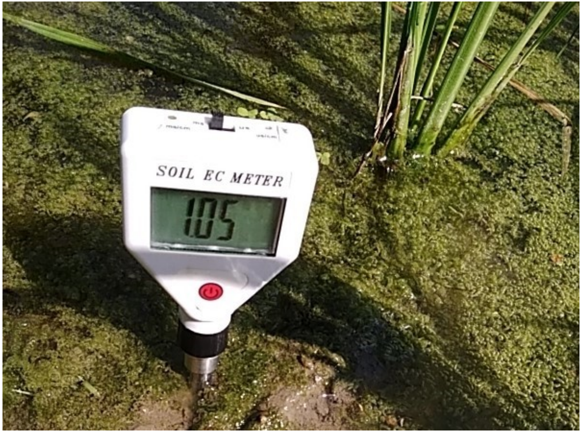


Measuring True Soil Salinity Conditions

- Essentially no existing soil salinity data
- I use agronomic sensors to directly measure salinity on 2,279 plots
  - Validate sensors with chemistry tests & "gold-standard" lab analyses of soil samples



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- **Solution:** Use image from a soil RCT
  - Other researchers randomized the soil salinity across rice plants
  - Can match picture to corresponding agronomic measurement in the same units as sensors

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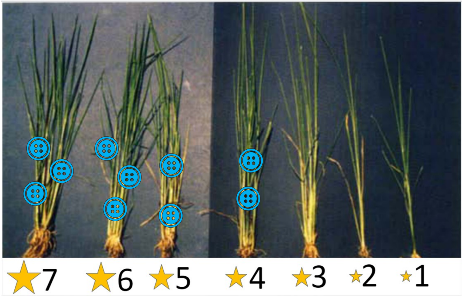
- Visually elicit full histogram of farmers' beliefs

Comprehension



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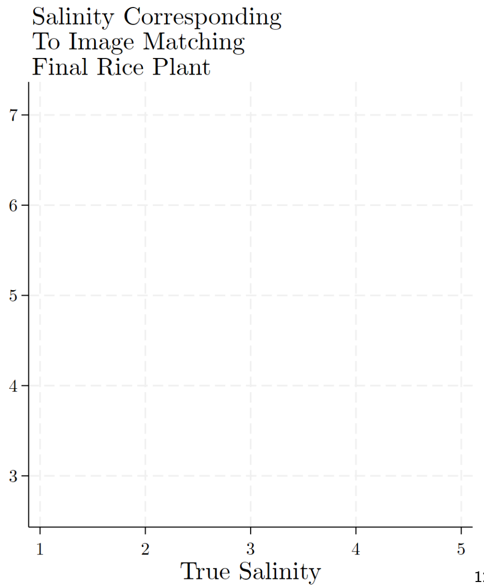
⇒ Primarily focus on *relative* treatment effects

- Correlation between plant health and underlying salinity is different in Bangladesh

⇒ Ask farmers in endline which picture best matched their crop

⇒ Regress the corresponding salinity measurement on the final salinity exposure



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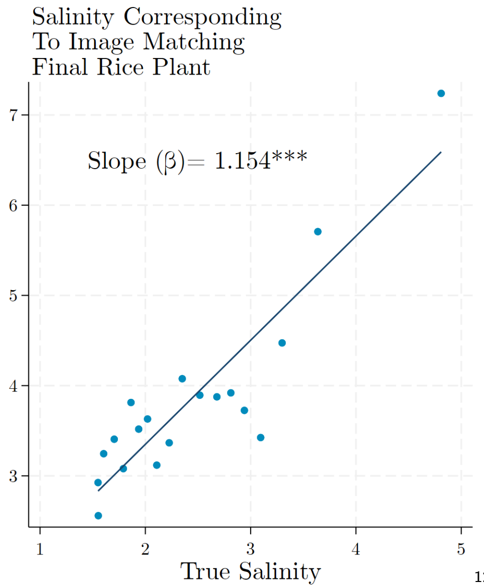

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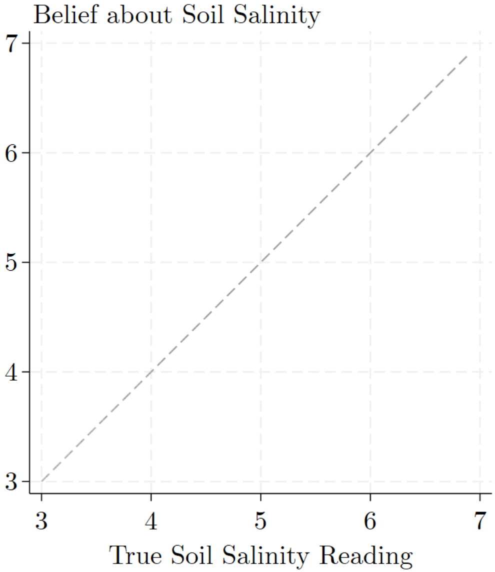

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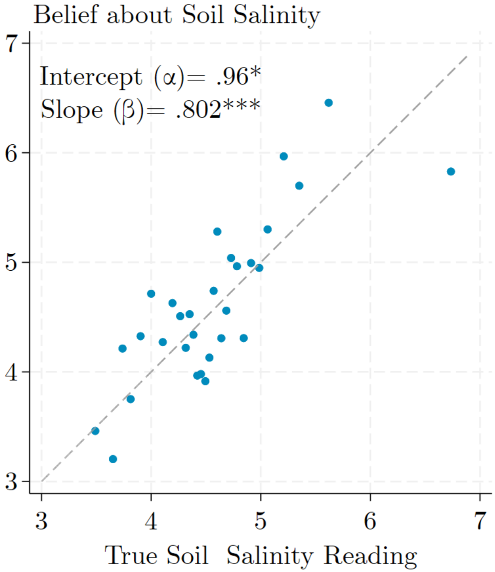

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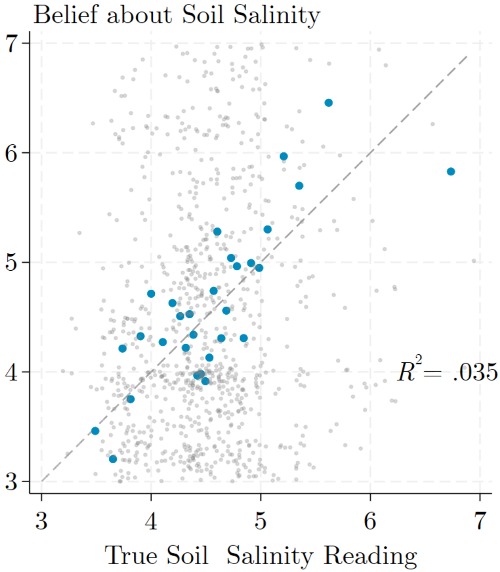
- Cannot reject $\alpha = 0$ and $\beta = 1$ Table



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- Averages mask significant heterogeneity in accuracy
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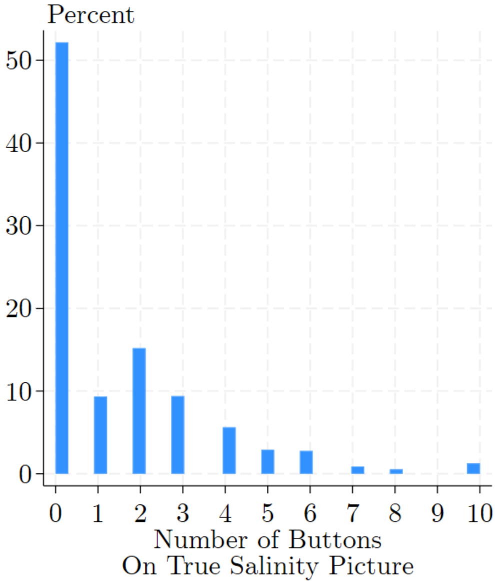
    - Beliefs exhibit strong spatial covariance *Details*
    - Better farmers, older farmers, farmers with more land $\Rightarrow$ more accurate *Details*
    - Errors strongly predict seed choice *Details*



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  - Errors strongly predict seed choice *Details*
- Does not reflect uncertainty

Roadmap

1. How accurate are environmental beliefs?

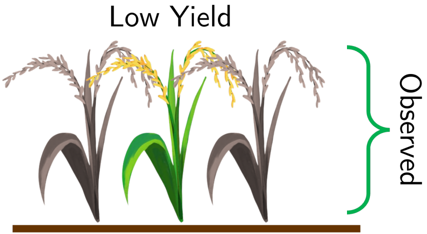
2. **How do people learn about their environment?**

   - Overview of simple conceptual framework
   - Lab-in-the-field exercise to illustrate identification problem
   - Natural experiments testing framework's predictions

3. How do environmental beliefs shape adaptation to climate change?

Learning About Environmental Conditions

- Bayesian farmers, no misspecification of agricultural production function
- Farmers observe yield



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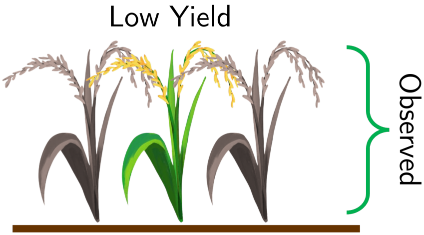

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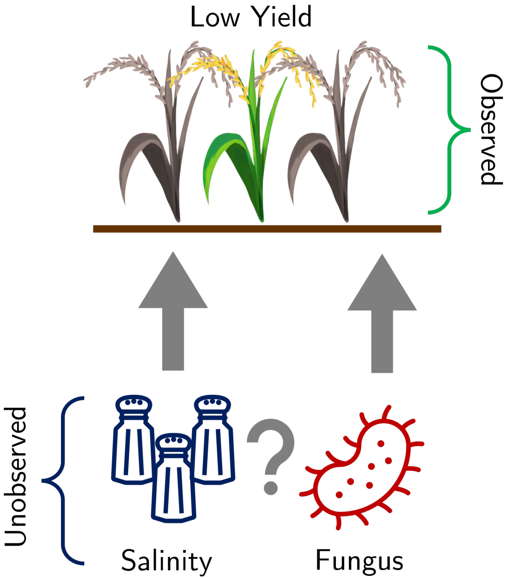

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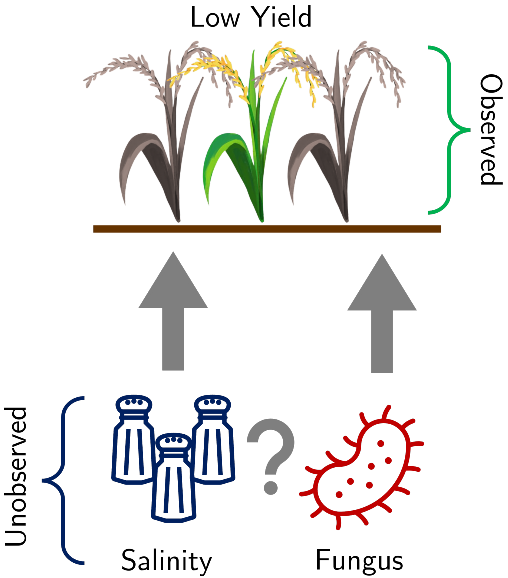
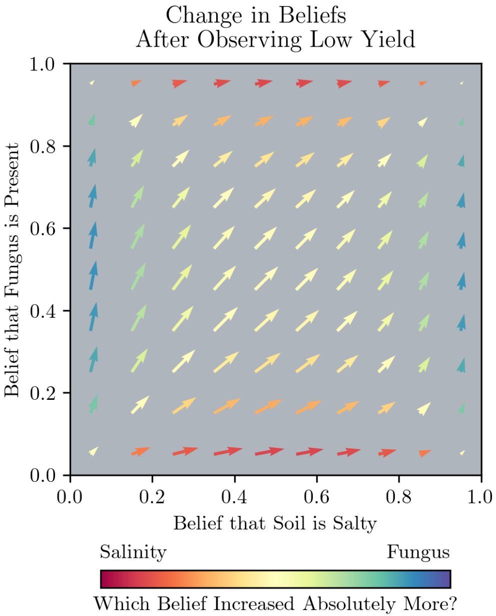
⇒ **Path dependence**: most likely threat stays the most likely
Math *Formal Statement*

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0.2
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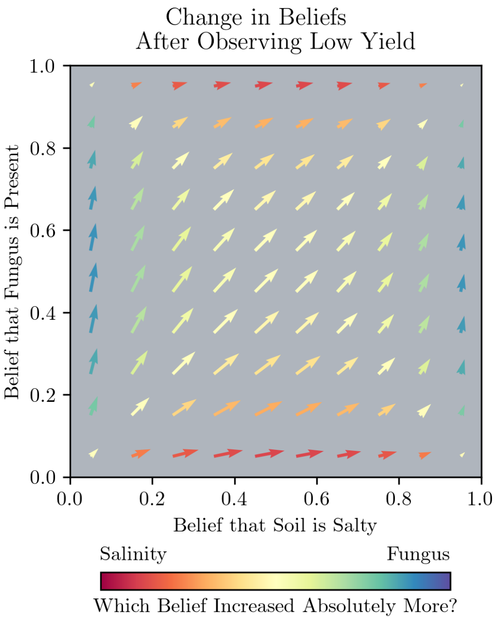
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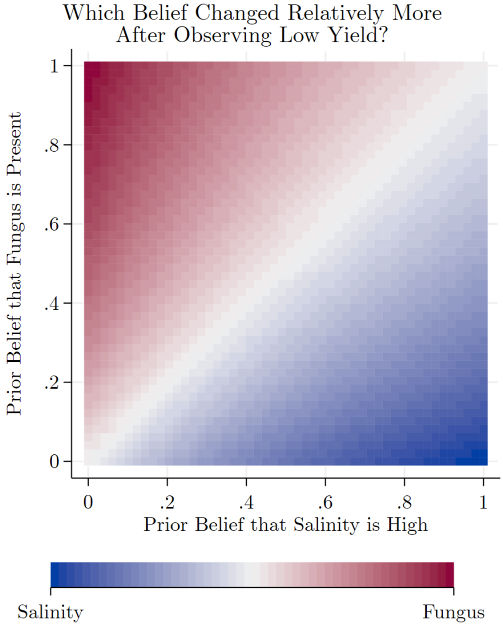
Which Belief Changed Relatively More
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.6
.8
1
Prior Belief that Salinity is High
Salinity
Fungus

Lab-in-the-Field Evidence of Identification Problem

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"What might make the plant look like this?"

Example: **Blast Fungus**

Example: **Salinity**

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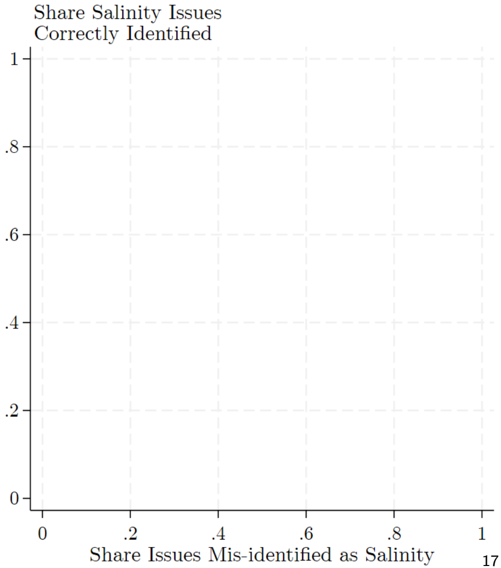


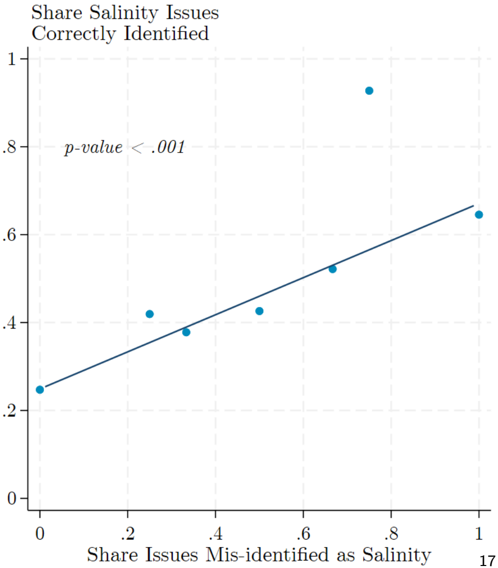
Lab-in-the-Field Evidence of Identification Problem

"What might make the plant look like this?"

Example: **Blast Fungus**

Example: **Salinity**

Note: Picture-by-order and survey round fixed effects, standard errors clustered by household



Learning From Past Environmental Experiences

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- Consider two types of environmental signals characteristic of global warming:

1. **Subtle shocks:** e.g. rising sea levels introduce salt into irrigation water underground
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1. Exogenous increase in true salinity

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1. Exogenous increase in true salinity
2. **Small** increase in initial beliefs

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Subtle Salinity Shock

1. Exogenous increase in true salinity
2. **Small** increase in initial beliefs
3. Relatively more likely to interpret low yield as sign of a **non-salinity threat**

Salient Salinity Shock

1. Exogenous increase in true salinity
2. **Large** increase in initial beliefs
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Subtle vs. Salient Shocks in Soil Salinity

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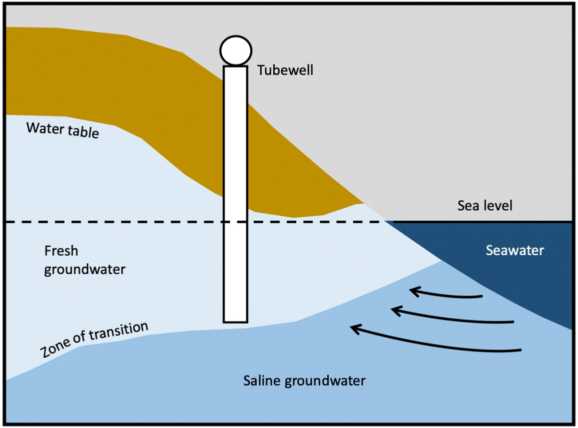
Subtle Shocks: Irrigation Water Intrusion

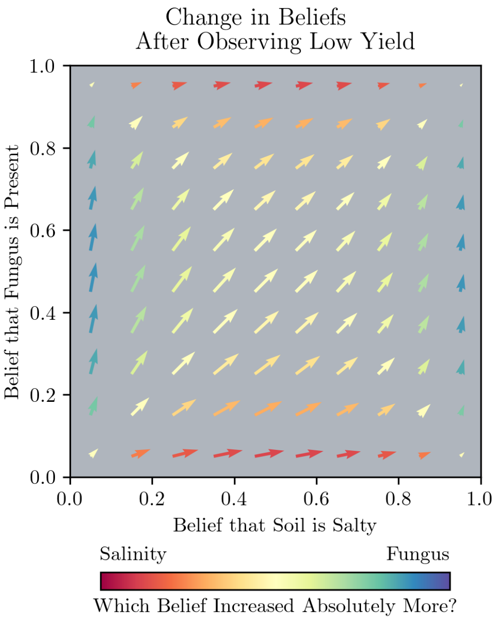


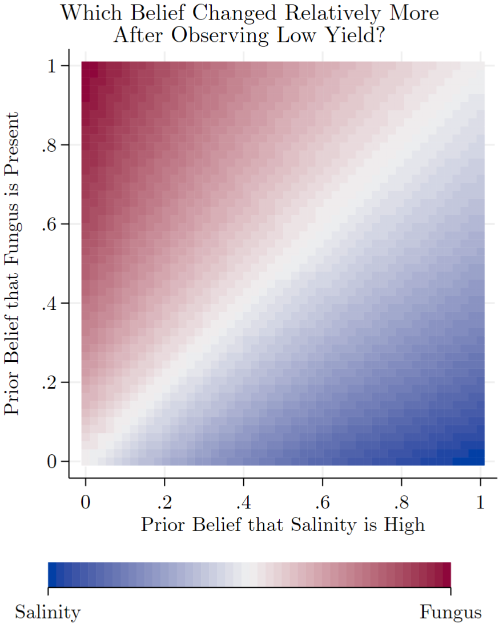
Source: US Environmental Protection Agency, 2016

Salient Shocks: Salty Floods

- Floods with saline water can deposit salt on plots
- Attention-grabbing event:
  - Ask farmers to recall things that impacted the amount of salt on their soil

  $\Rightarrow$ 38.53% of 436 events were floods—most common answer


Change in Beliefs
After Observing Low Yield
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Belief that Fungus is Present
Belief that Soil is Salty
Salinity
Fungus
Which Belief Increased Absolutely More?


Which Belief Changed Relatively More
After Observing Low Yield?
1
.8
.6
.4
.2
0
0
.2
.4
.6
.8
1
Prior Belief that Fungus is Present
Prior Belief that Salinity is High
Salinity
Fungus

Estimating the Causal Impact of Subtle vs. Salient Shocks

Subtle Shocks: Irrigation Water Intrusion

Difference-in-differences design:

1. Villages exposed to higher vs. lower sea levels in Fall 2022 relative to their historical average (*satellite data*)
2. Villages exposed to higher vs. lower ocean salinity in Fall 2022 relative to their historical average (*satellite data*)
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- Cluster standard errors by village (nearly identical results with Conley S.E.s) More

⇒ 250 villages in sample spread across 15% of Bangladesh Map

Quick Aside: Measuring Floods from Space

Develop a new way to detect floods combining methods from machine learning and geophysics in the analysis of satellite data—more in (Patel 2024)

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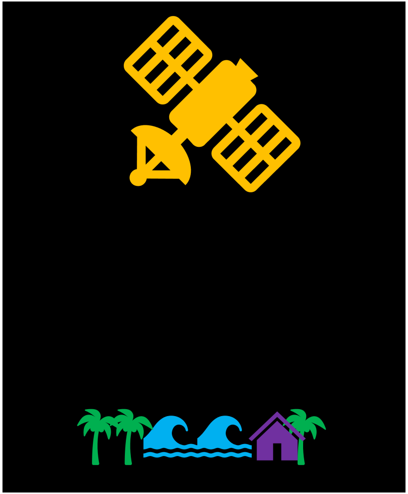

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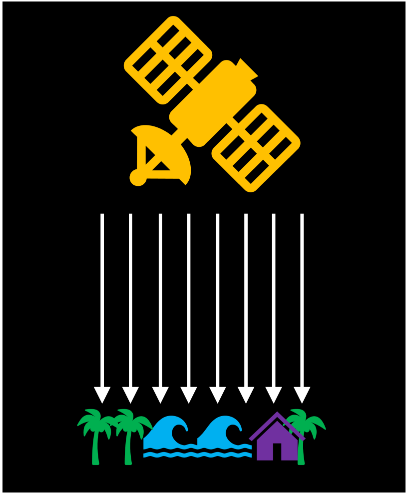

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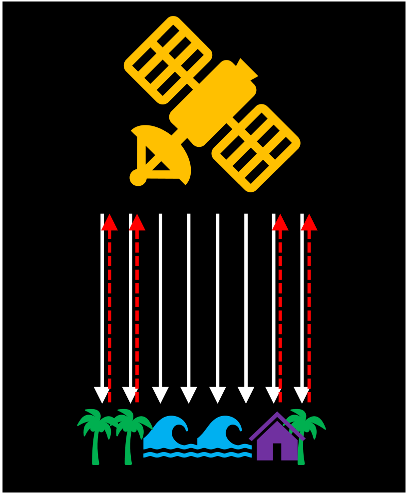

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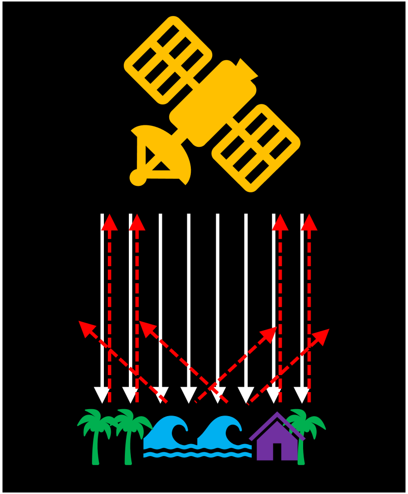

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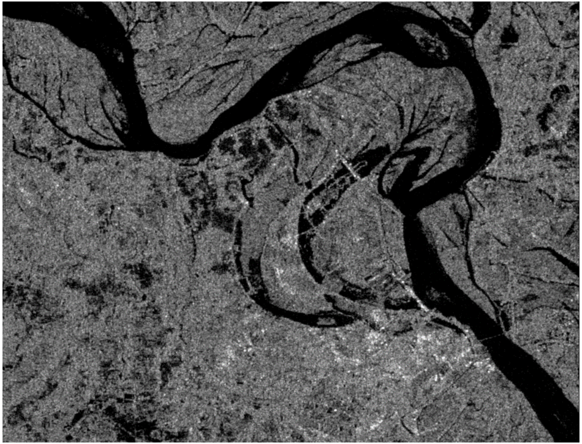

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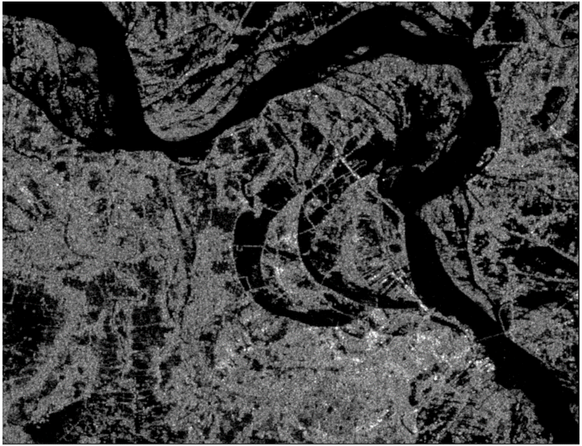

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2. Optical satellites
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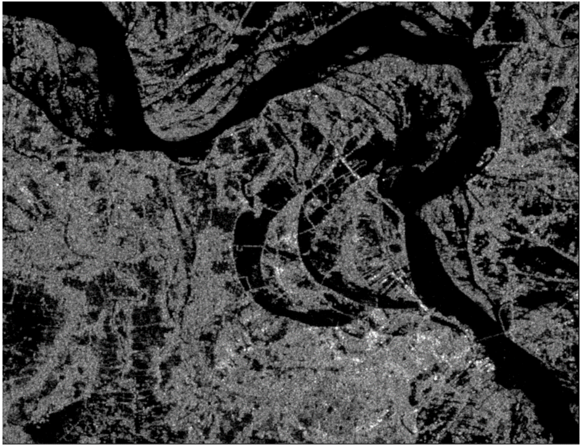
   - Orbits frequently, but photos obscured by clouds



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2. Optical satellites
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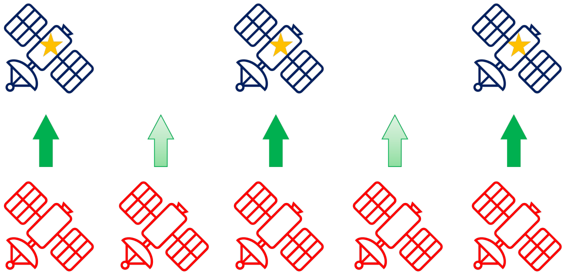
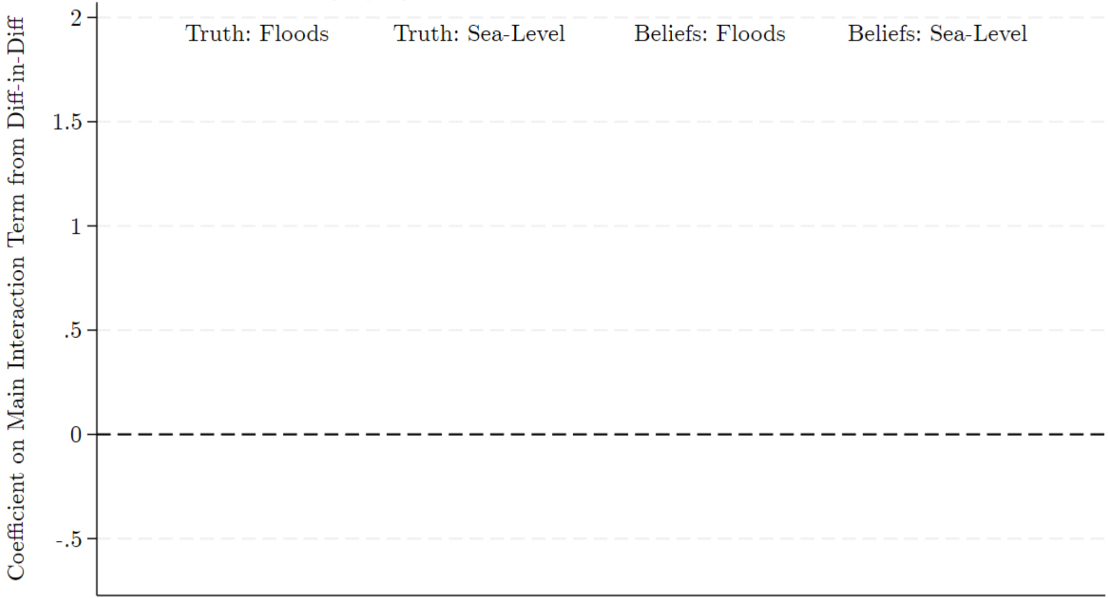
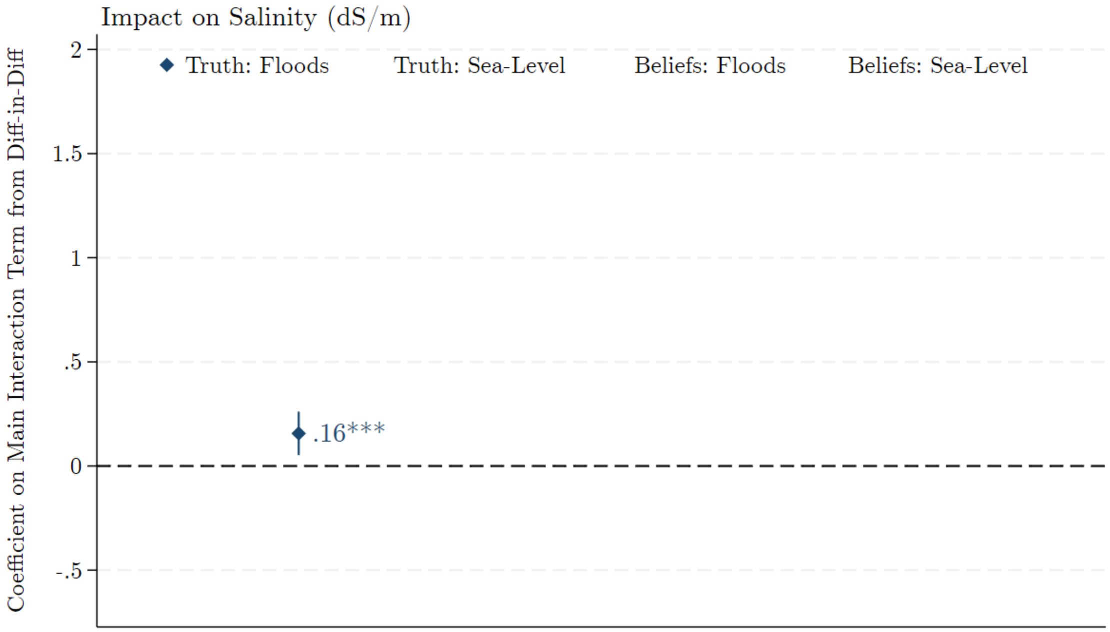
   - Orbits frequently, but photos obscured by clouds

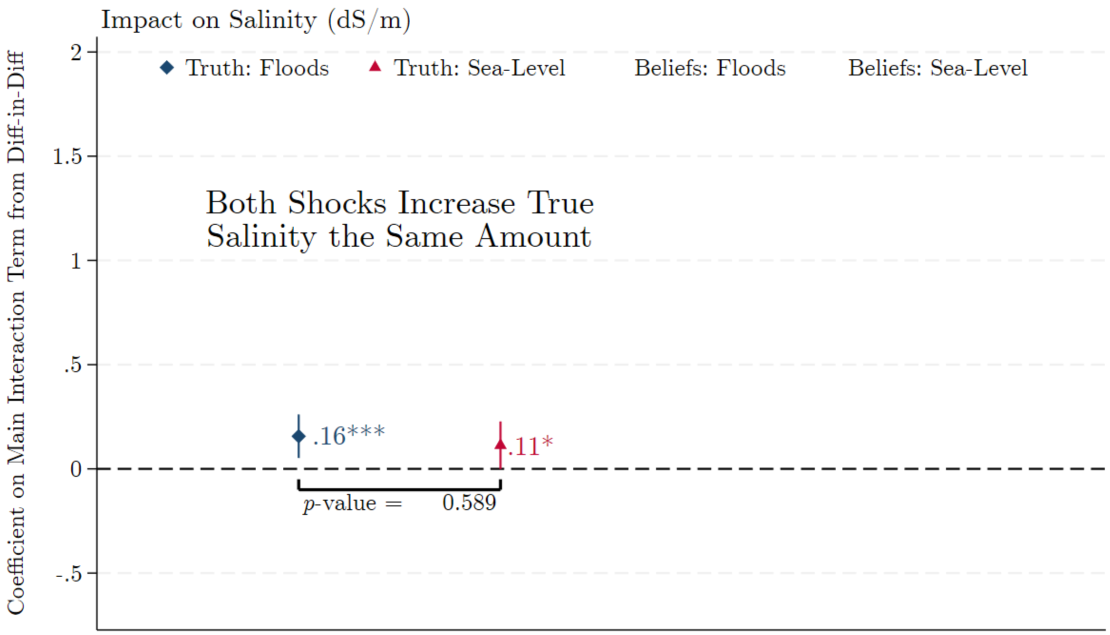
- Use machine learning to extract signal from optical wavelengths
- Measure local daily floods for 20 years
- *On-going work:* expand to the whole world

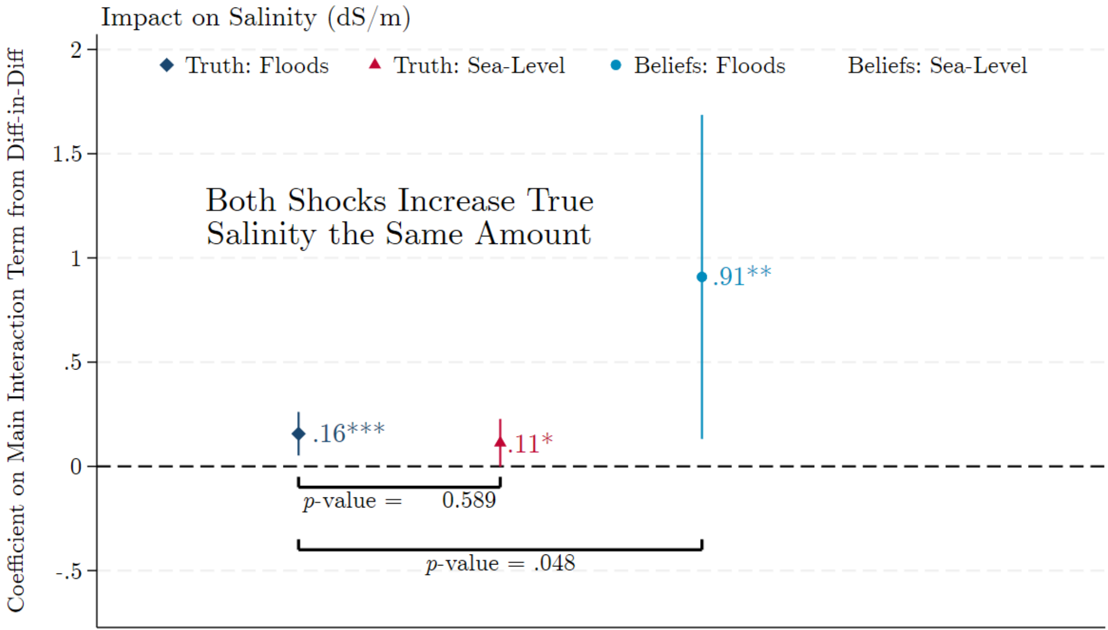


Impact on Salinity (dS/m)

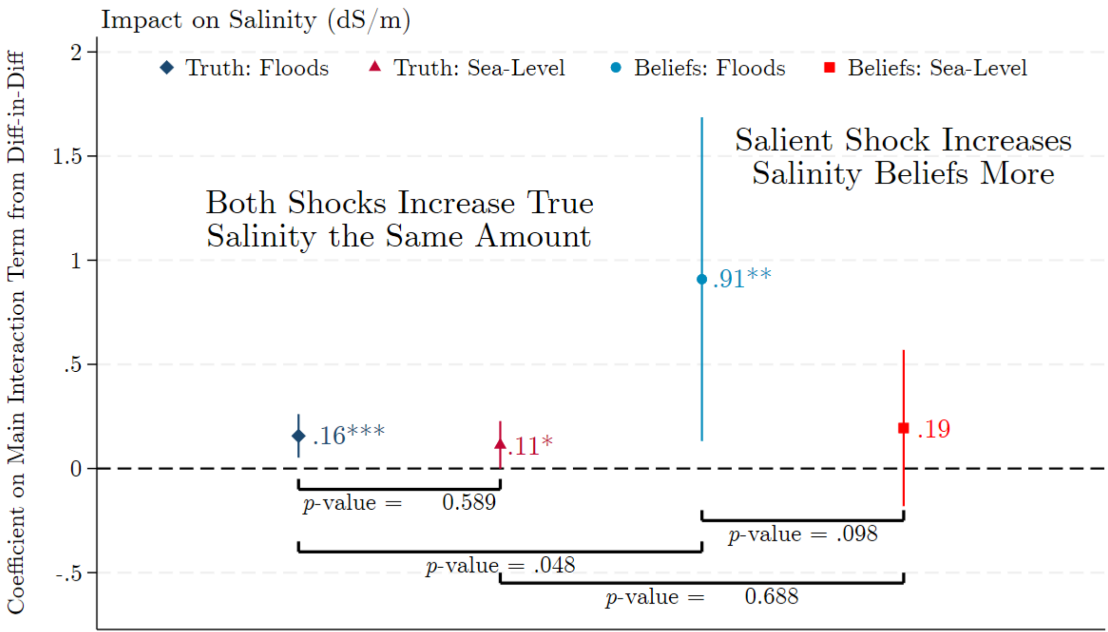



Impact on Salinity (dS/m)
Coefficient on Main Interaction Term from Diff-in-Diff
2
1.5
1
.5
0
-.5
Truth: Floods
Truth: Sea-Level
Beliefs: Floods
Beliefs: Sea-Level
.16***

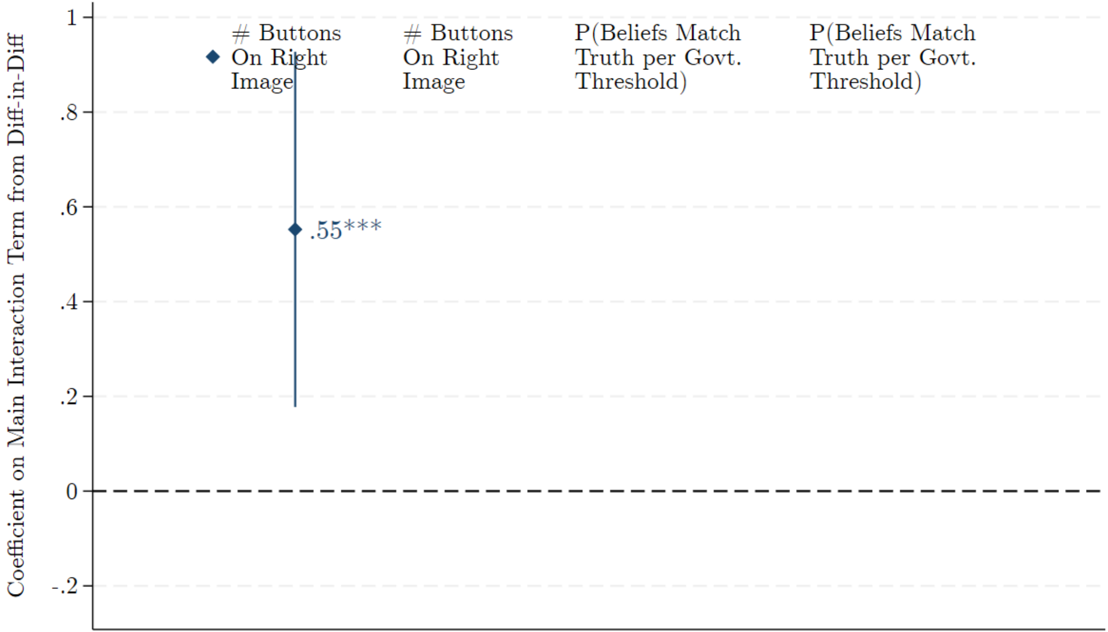

Impact on Salinity (dS/m)
Truth: Floods
Truth: Sea-Level
Beliefs: Floods
Beliefs: Sea-Level
Both Shocks Increase True Salinity the Same Amount
.16***
.11*
p-value = 0.589
Coefficient on Main Interaction Term from Diff-in-Diff
2
1.5
1
.5
0
-.5

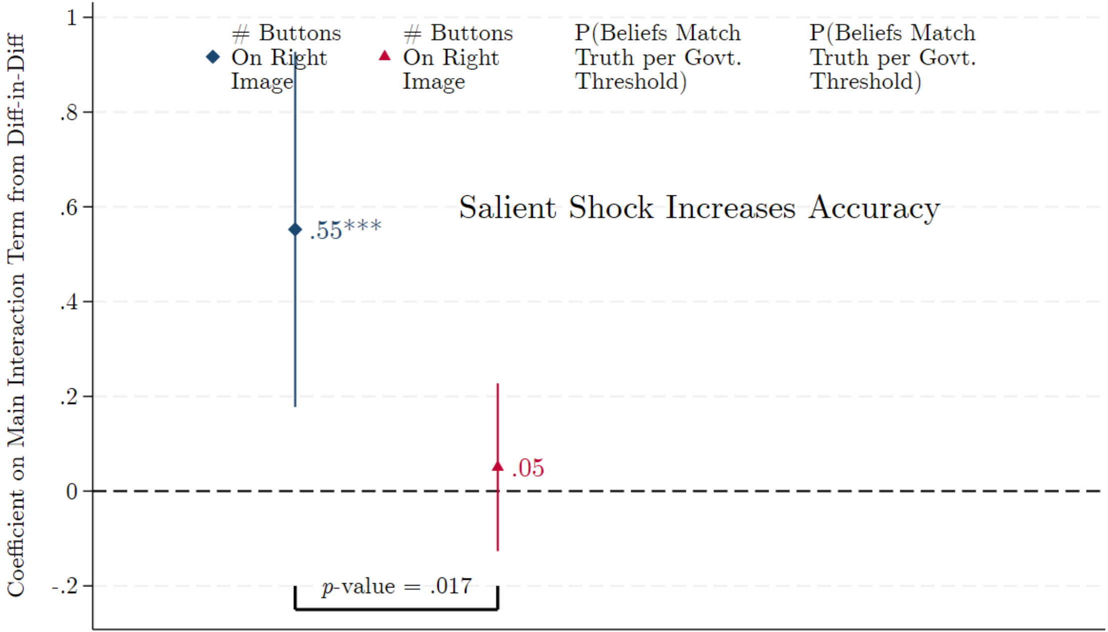


Impact on Salinity (dS/m)
Coefficient on Main Interaction Term from Diff-in-Diff
2
1.5
1
.5
0
-.5
Truth: Floods
Truth: Sea-Level
Beliefs: Floods
Beliefs: Sea-Level
Both Shocks Increase True Salinity the Same Amount
.91**
.16***
.11*
p-value = 0.589
p-value = .048



Impact on Salinity (dS/m)
Truth: Floods
Truth: Sea-Level
Beliefs: Floods
Beliefs: Sea-Level
Coefficient on Main Interaction Term from Diff-in-Diff
2
1.5
1
.5
0
-.5
Salient Shock Increases Salinity Beliefs More
Both Shocks Increase True Salinity the Same Amount
.91**
.16***
.11*
.19
p-value = 0.589
p-value = .098
p-value = .048
p-value = 0.688


Coefficient on Main Interaction Term from Diff-in-Diff
1
.8
.6
.4
.2
0
-.2
# Buttons On Right Image
# Buttons On Right Image
P(Beliefs Match Truth per Govt. Threshold)
P(Beliefs Match Truth per Govt. Threshold)
.55***



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1
.8
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-.2
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P(Beliefs Match Truth per Govt. Threshold)
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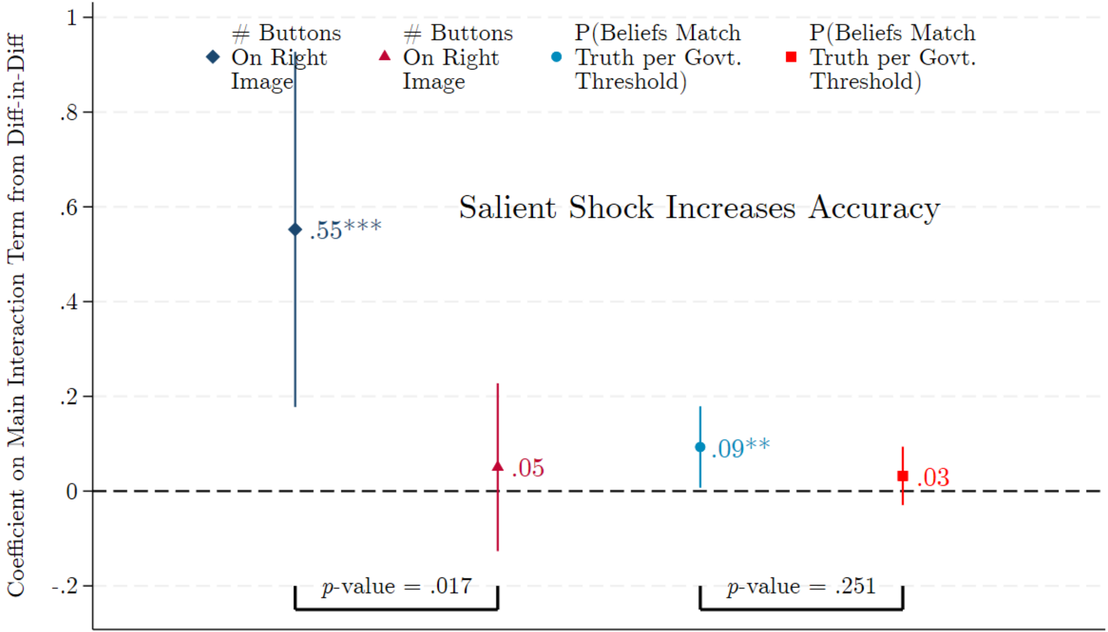
Salient Shock Increases Accuracy
.55***
.05
p-value = .017



Coefficient on Main Interaction Term from Diff-in-Diff
1
.8
.6
.4
.2
0
-.2
# Buttons On Right Image
# Buttons On Right Image
P(Beliefs Match Truth per Govt. Threshold)
P(Beliefs Match Truth per Govt. Threshold)
Salient Shock Increases Accuracy
.55***
.05
.09**
.03
p-value = .017
p-value = .251

Interpretation of Low Yield as Salinity

- *Prediction:* Nature of past experience changes how likely farmers are to attribute low yield to high soil salinity
    - *Survey Question:* What signs do you use to figure out the amount of salt in the soil?
- Outcome is an indicator for whether the farmer mentions low yield

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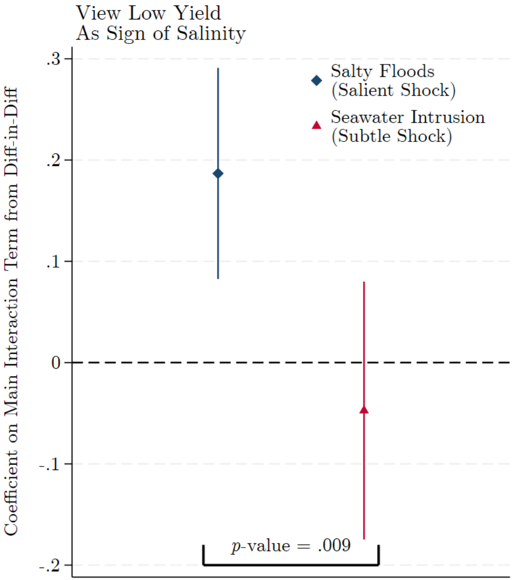
- Outcome is an indicator for whether the farmer mentions low yield
- **Salient** shock relatively concentrates interpretation of new data as sign of salinity



Interpretation of Salinity Signals as Other Threats

- *Prediction:* Nature of past experience changes the diagnosticity of salinity signals
  - *Survey Question Part #1:* If you had too much salt in your soil, how do you think that would impact what your rice plants look like?
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Interpretation of Salinity Signals as Other Threats

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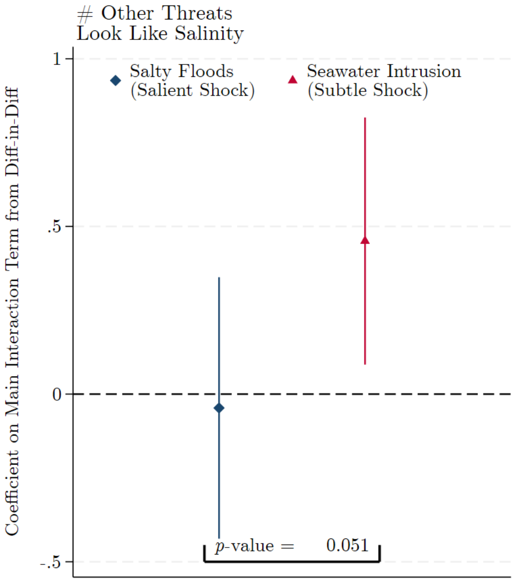
- Outcome is the number of other environmental threats listed
- **Subtle** shock makes salinity signals relatively less diagnostic



Paper Summary

R.Q. #1: How accurate are environmental beliefs?

- New data show that half of farmers misclassify their soil salinity based on govt. threshold
- Farmers with smaller identification problem ($\uparrow$ land, $\uparrow$ experience) $\Rightarrow \uparrow$ accuracy

R.Q. #2: How do farmers form environmental beliefs?

- Initial shocks to beliefs $\Rightarrow$ change interpretation of new data $\Rightarrow$ persistent errors
- Suggestive evidence that salient shocks made beliefs "catch up"

R.Q. #3: How do beliefs shape climate adaptation?

- Beliefs have large impact on agricultural profits through seed choice
- Info is cheap & most impactful for least accurate hhds, and we know *where* to target

Conclusion

- Climate technology alone is insufficient for adaptation
  - Information is a *complement* to innovation
  - Correct beliefs increase the social returns to R&D
- The extent to which an environmental shock grabs attention matters
  - Subtle shocks engendered by global warming may be the most dangerous
- Climate change is upending many aspects of agricultural production at once
  - Multi-dimensional changes of global warming exacerbate identification problem
  - Information interventions have spillovers on *non*-targeted dimensions

Thank You!

devpatel@fas.harvard.edu

The Missing Market for Environmental Data

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- Environmental conditions are inherently *spatial*
  - Within-village salinity correlation $> .9$

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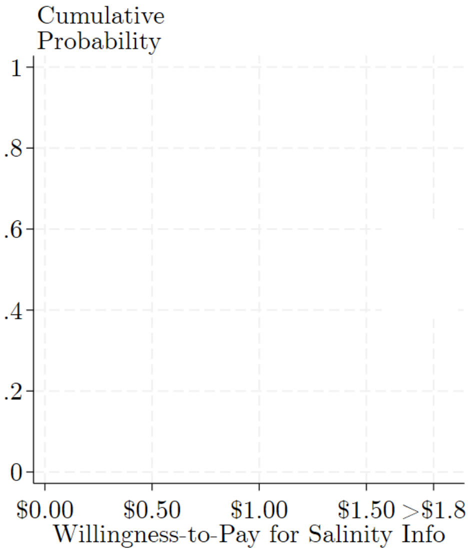

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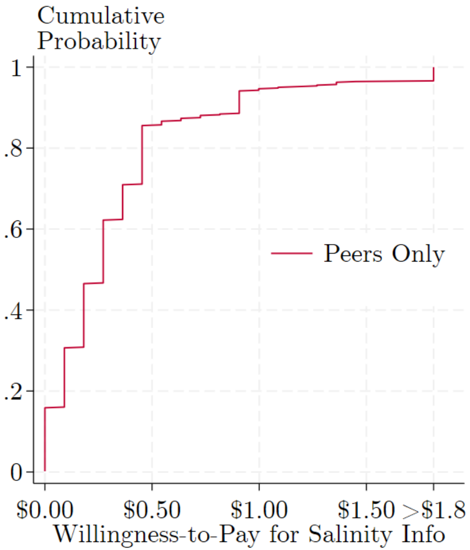

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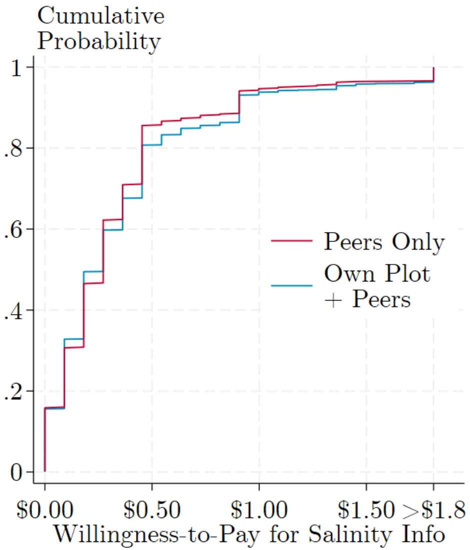
  - **Arm #2:** additionally give own-plot readings



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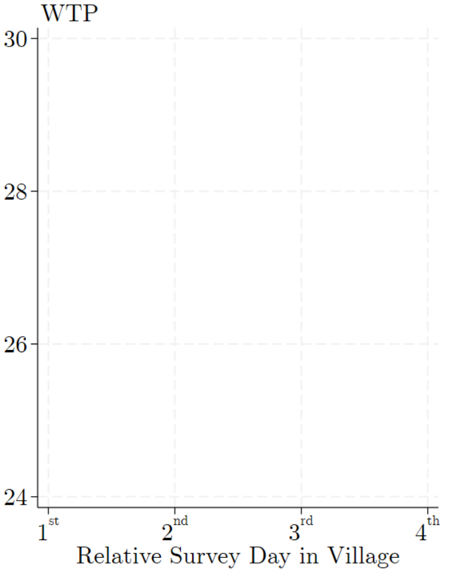

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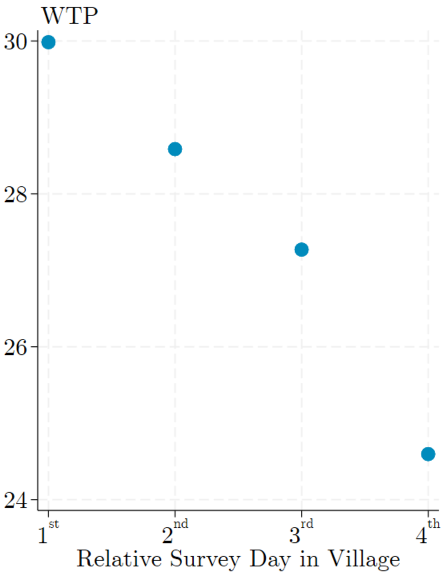
- **Missing Market RCT #1:** Do farmers recognize spatial covariance?
- **Natural Experiment:** Does free-riding occur in the wild?
  - Extra day $\downarrow$ WTP 5% with Farmer + Village $\times$ Round F.E.s (p-val $= .06$)

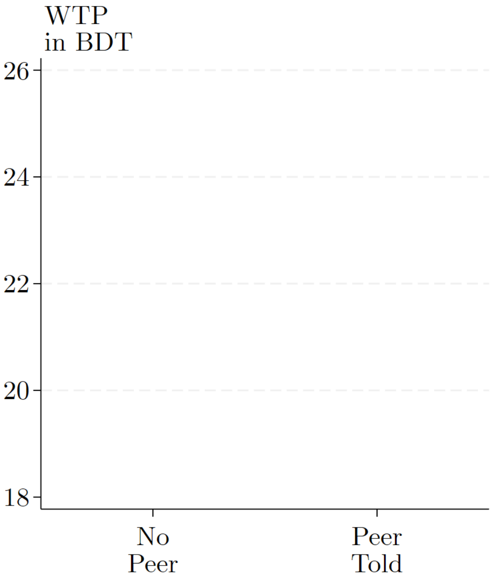


The Missing Market for Environmental Data

- "If one of your neighbors purchased soil salinity information, would you ask them to share that information with you?"
  84% say yes
  - 86% say would share if asked

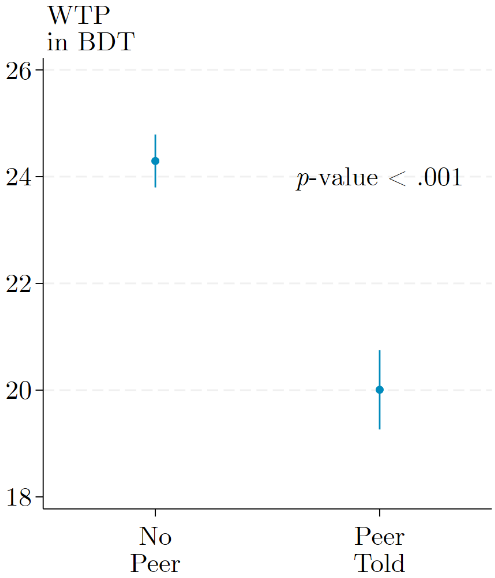
The Missing Market for Environmental Data

- "If one of your neighbors purchased soil salinity information, would you ask them to share that information with you?" **84% say yes**
  - 86% say would share if asked
- **Missing Market RCT #2:** Does demand fall when one's neighbor has information?
  - **No Peer Arm:** elicit WTP for salinity information
  - **Peer Told Arm:** additionally tell respondent that *specific* neighbor will definitely be told



The Missing Market for Environmental Data

- "If one of your neighbors purchased soil salinity information, would you ask them to share that information with you?"
  84% say yes
  - 86% say would share if asked
- **Missing Market RCT #2:** Does demand fall when one's neighbor has information?
  - **No Peer Arm:** elicit WTP for salinity information
  - **Peer Told Arm:** additionally tell respondent that *specific* neighbor will definitely be told



The Missing Market for Environmental Data

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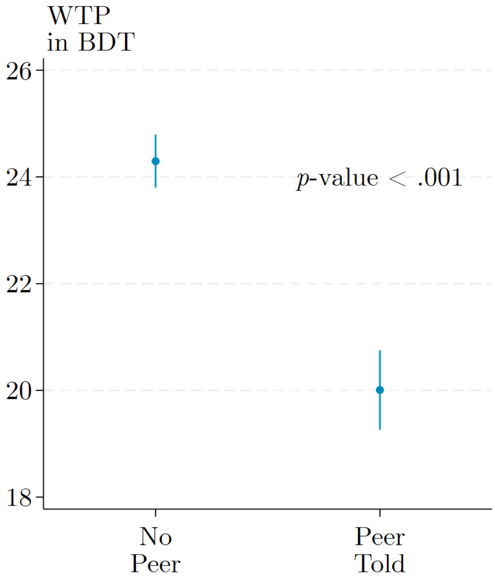
- **Missing Market RCT #2:** Does demand fall when one’s neighbor has information?
  - **No Peer Arm:** elicit WTP for salinity information
  - **Peer Told Arm:** additionally tell respondent that *specific* neighbor will definitely be told
- Among those with lower WTP in peer arm, 75% say reason is “I can ask the other person for the information so I don’t need to buy it myself”



Roadmap

1. How accurate are environmental beliefs?

2. How do people learn about their environment?

3. **How do environmental beliefs shape adaptation to climate change?**

Environmental Beliefs $\Rightarrow$ **Climate Adaptation Decision** $\Rightarrow$ **Profits**

- **RCT #1**: Information Experiment
- **RCT #2:** Salinity Tolerant Seed Experiment
- Structural Model of Seed Demand

$\underbrace{\text{Environmental Beliefs} \Rightarrow \text{Climate Adaptation}}_{\text{Salinity Information Experiment}} \Rightarrow \text{Profits}$

Soil Salinity Measurement (Nov. – Dec. 2022) → Planting (Dec. 2022 – Jan. 2023) → Soil Salinity Measurement (Feb. – Mar. 2023) → Harvesting (Apr. – May 2023) → Info RCT (Jun. – Jul. 2023) → Phone Survey (Dec. 2023)

- **Treatment:** provide farmers with information on the soil salinity they faced
- 2022-23 salinity ultimately was unexpectedly **very low**: most farmers overestimated *More*

Salinity Info Changes Beliefs

- I use the Becker-DeGroot-Marschak method to elicit willingness-to-pay (WTP) for salinity information

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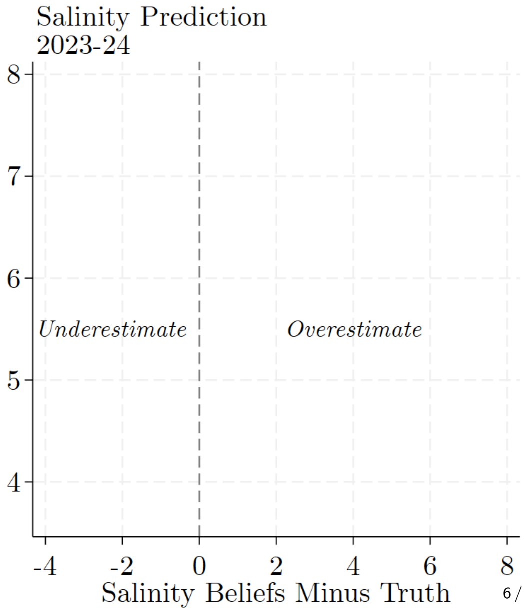

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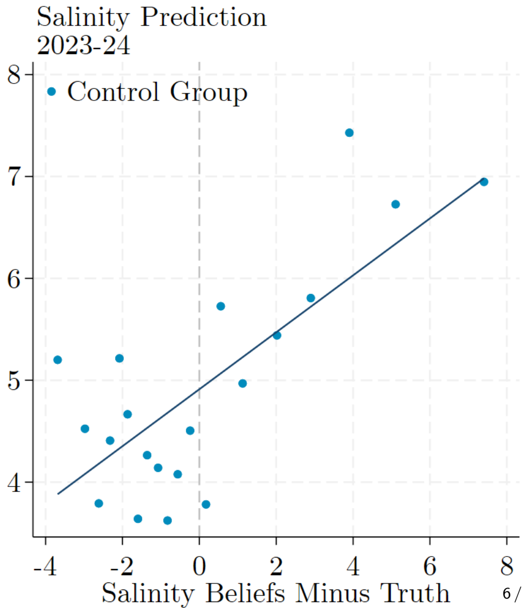
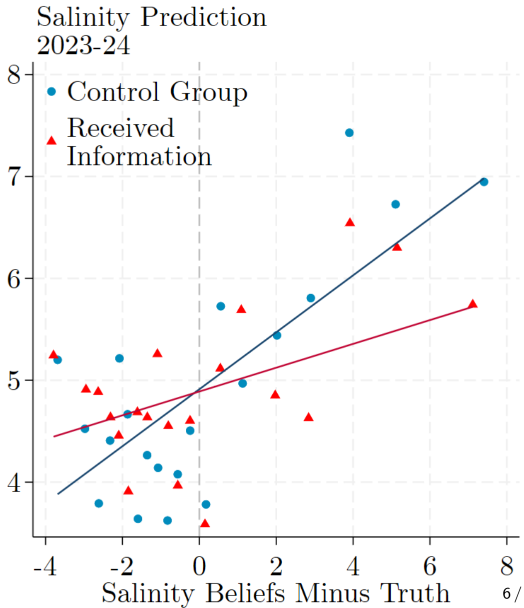


Salinity Info Changes Beliefs

- I use the Becker-DeGroot-Marschak method to elicit willingness-to-pay (WTP) for salinity information
  - 85% of farmers have WTP > 0
- **RCT:** Draw price from skewed distribution $\Rightarrow$ random half of farmers given information for free
- **Strong first-stage:** treatment impacted farmers' beliefs about next year's salinity
  - Effects persist in phone survey 6 months later



Info Experiment Results

- Focus on main salinity tolerant seed recommended by government

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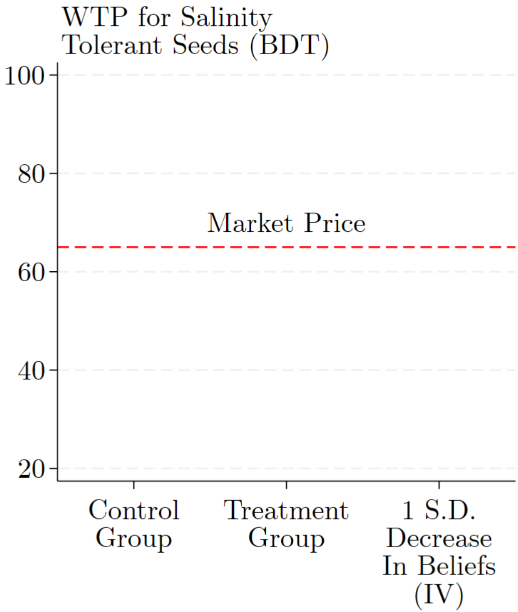
- Focus on main salinity tolerant seed recommended by government
- Measure WTP for these seeds using same BDM method



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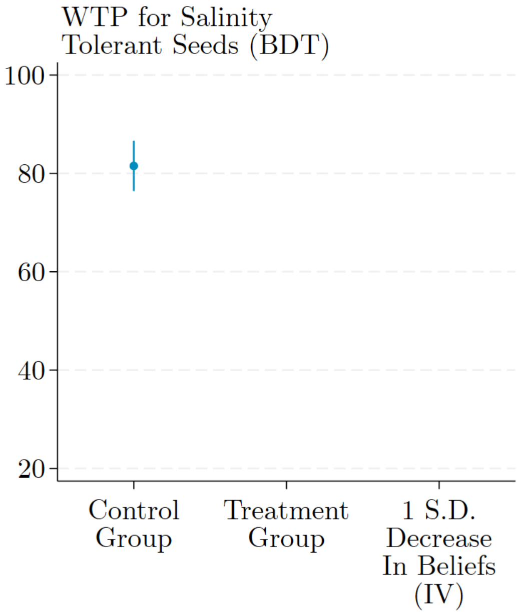

Note: All regressions include heteroskedasticity robust standard errors.

Info Experiment Results

- Focus on main salinity tolerant seed recommended by government
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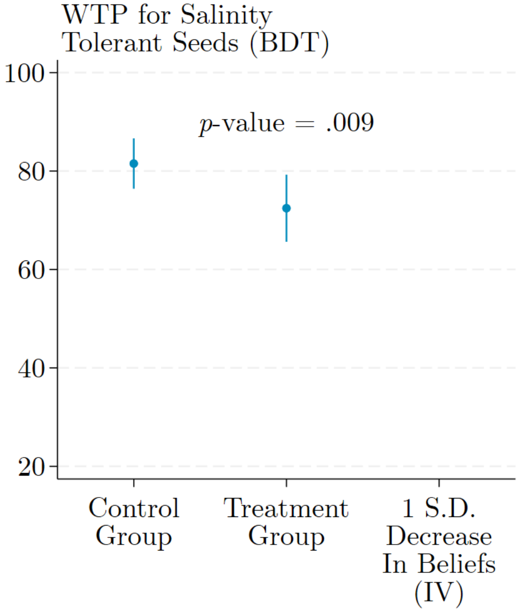
- Reduced form:

$$WTP_i = \alpha + \beta \textit{Free Info}_i + \varepsilon_i$$



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Info Experiment Results

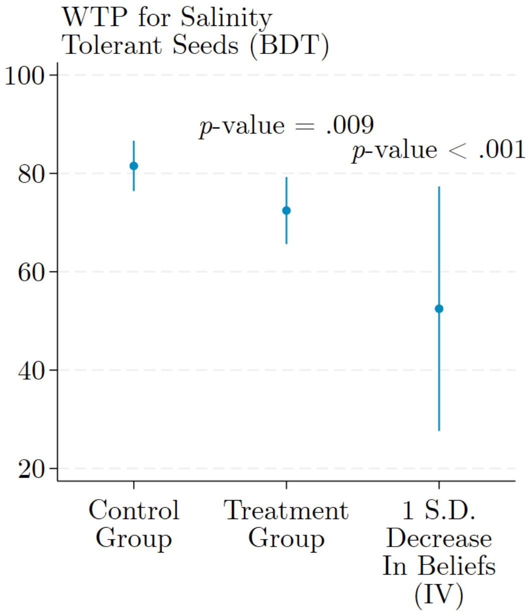
- Focus on main salinity tolerant seed recommended by government
- Measure WTP for these seeds using same BDM method
- Reduced form:

$$WTP_i = \alpha + \beta \textit{Free Info}_i + \varepsilon_i$$

- IV specification:

$$WTP_i = \alpha + \beta \widehat{\textit{2023-24 Salinity Beliefs}} + \varepsilon_i$$

One S.D. decrease in beliefs lowers demand 43% of market price



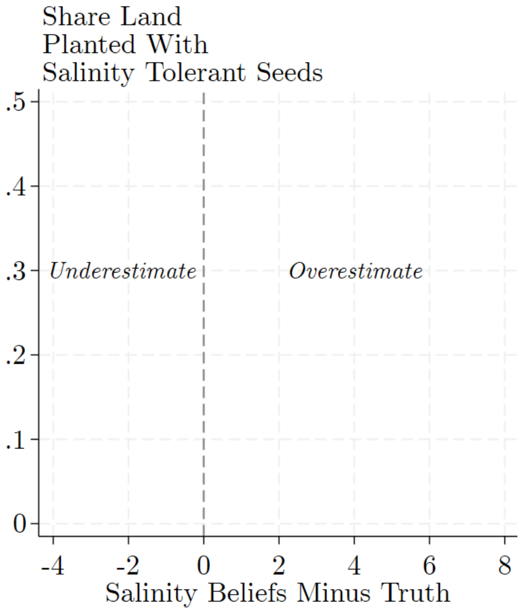
Note: All regressions include heteroskedasticity robust standard errors. The first stage of the IV specification regresses 2023-24 predictions on treatment interacted with belief error and beliefs.

$$\textbf{Environmental Beliefs} \Rightarrow \underbrace{\textbf{Climate Adaptation} \Rightarrow \textbf{Profits}}_{\textbf{Seed Experiment}}$$

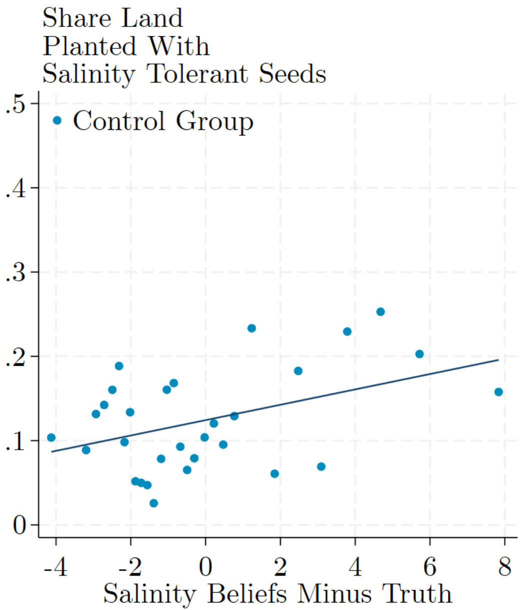
- Use same BDM approach to measure WTP for salinity-tolerant seeds during baseline survey, prior to planting for 2022-23 season
- Draw seed price from skewed distribution
  - Random half of farmers received seed for free

Seed RCT (Nov. – Dec. 2022) → Planting (Dec. 2022 – Jan. 2023) → Harvesting (Apr. – May 2023) → Endline Survey (Jun. – Jul. 2023)

Seed Experiment Results

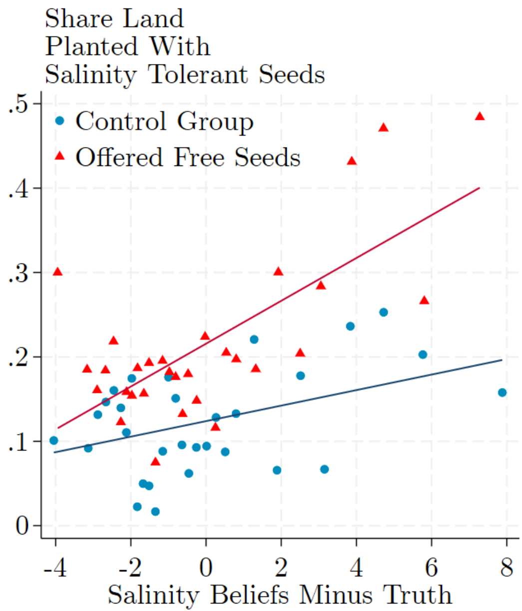


Seed Experiment Results



Seed Experiment Results

- **First-stage:** Being offered 1 kg free seeds causes a 75% increase in share of land with salinity tolerant seeds (12.7 p.p. $\rightarrow$ 22.2 p.p.)
    - Larger increase among farmers who overestimated salinity



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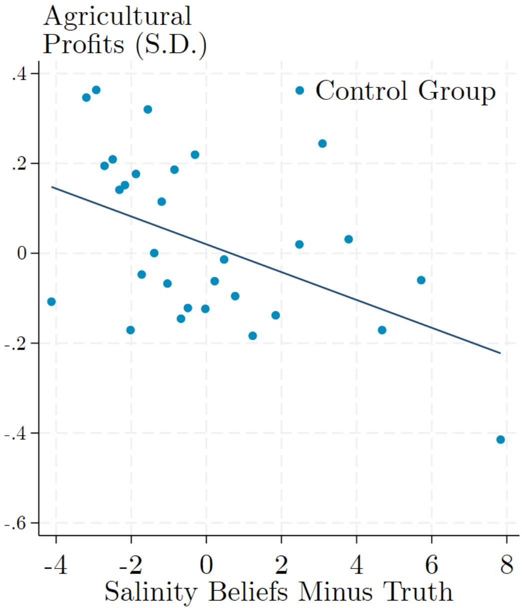
- What happened to profits?
  - Because salinity was so low, underestimation was *good*



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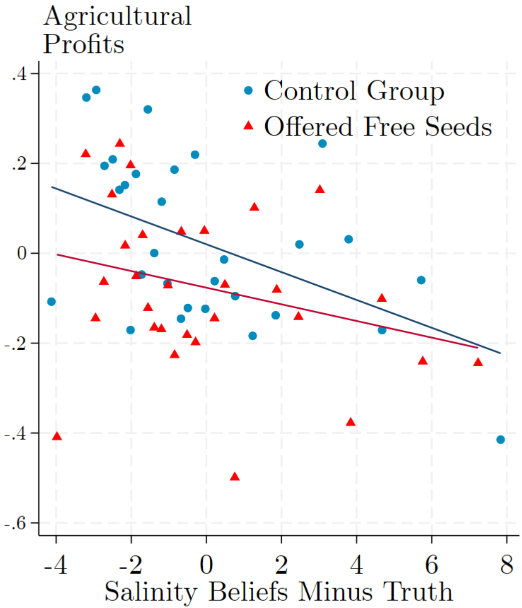
    - Larger increase among farmers who overestimated salinity
- What happened to profits?
    - Because salinity was so low, underestimation was *good*
    - Profits lower for hhds with access to salinity tolerant seeds

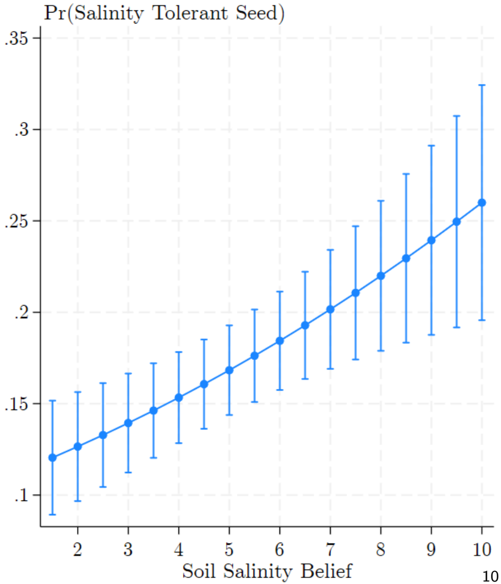


Structural Model of Demand for Seeds

- Estimate a random coefficients logit model using maximum simulated likelihood (McFadden, 1974; Train, 2009)
  Math *Validation*

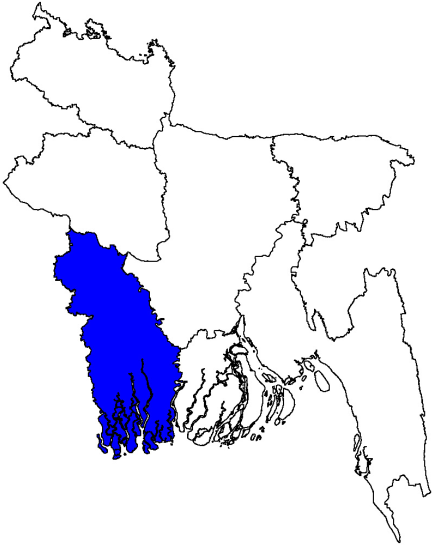
1. Assign farmers counterfactual beliefs
2. Simulate seed decisions
3. Use seed RCT results to estimate profits

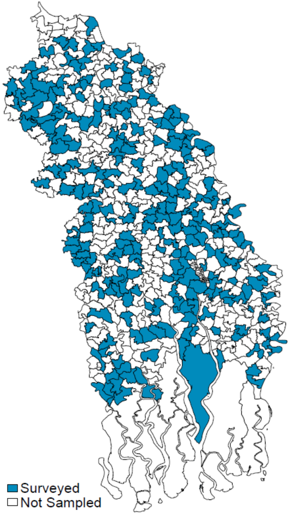
- **Back-of-the-envelope:** perfect beliefs increase agricultural profits **16%**
- *Overstates* impacts because perfect forecast is impossible
- *Understates* impacts because underpowered for high salinity soil in RCT



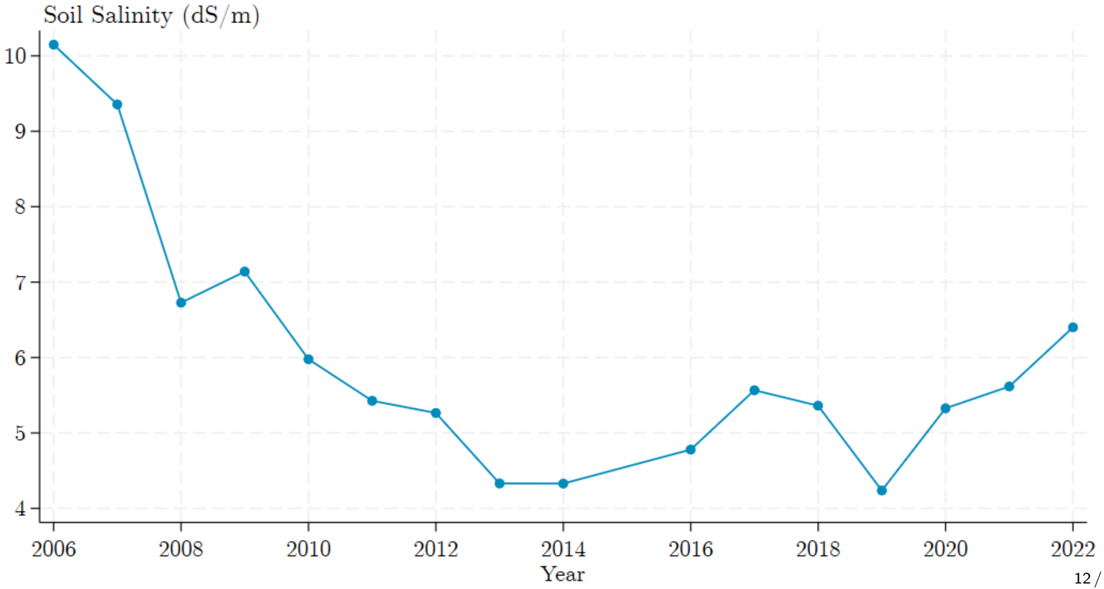
Map of Surveyed Villages

R.Q. Back Meas. Truth Back



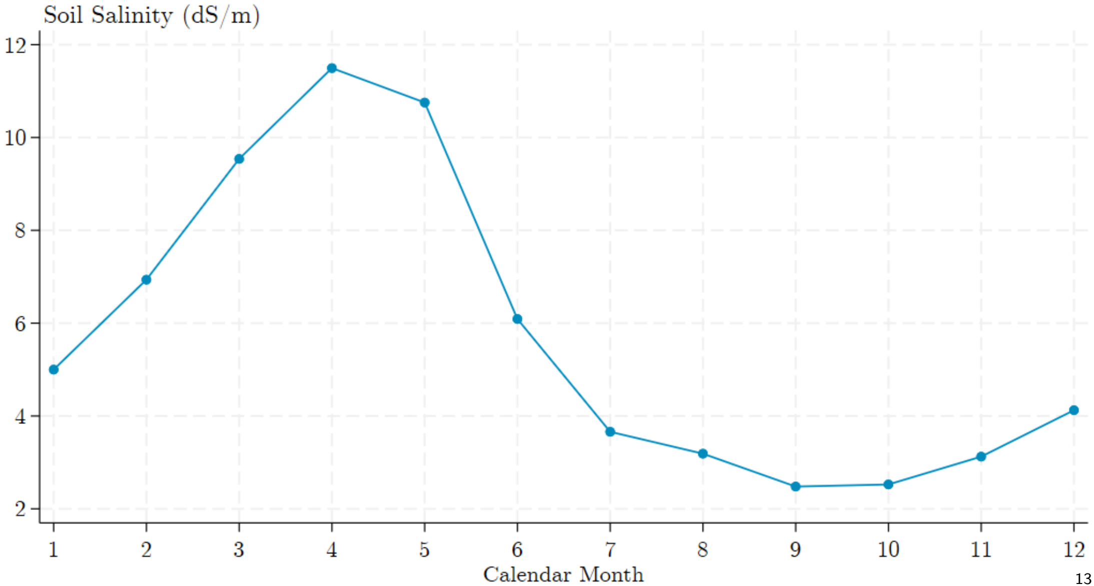


Trends in Annual Salinity Back



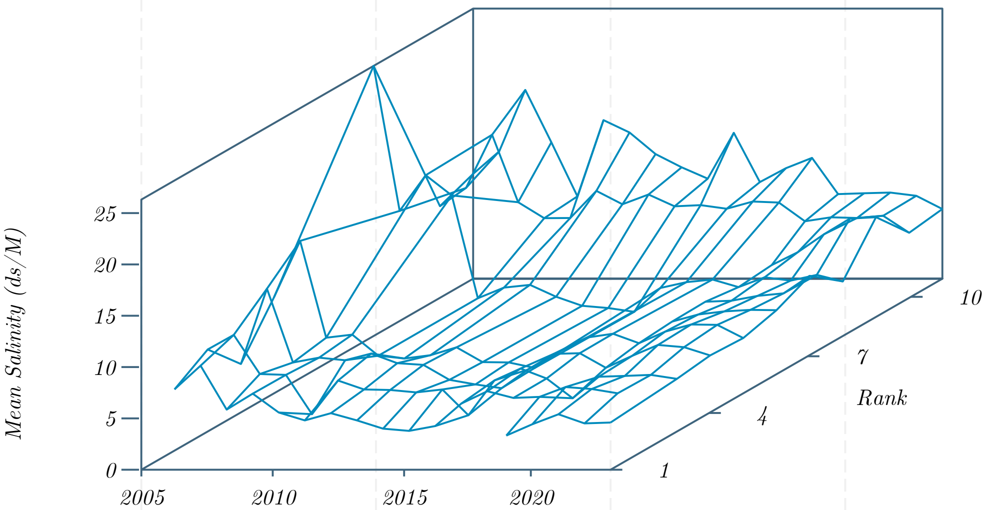
Seasonal Salinity Patterns

Back



SRDI Soil Station Data

Back



Salinity Measurement Details

Back

- Convert salinity measurements into average seasonal exposure using data I obtained from government's soil monitoring sites

- Two cross-sections in the months I measure strongly predicts overall salinity during growing season: $R^2 = .90$

- For a small number of households, enumerators could not collect salinity measurements during one of the two visits: 164 during the baseline (largely due to flooding making the plot inaccessible) and 31 during the midline (typically because of migration or other household unavailability)

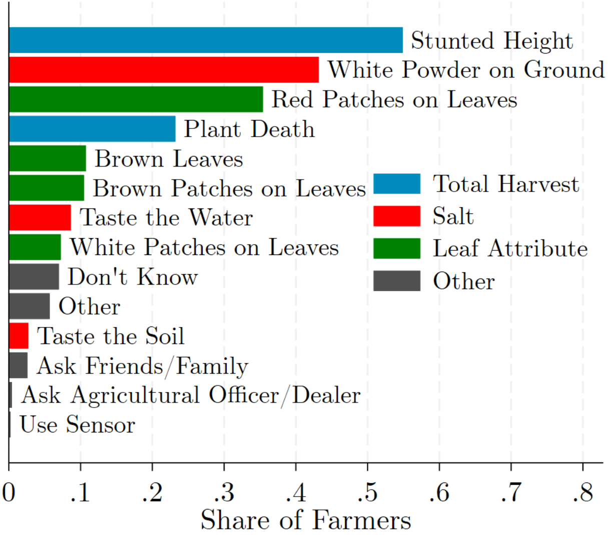
- I replace the missing measurement with the mean village value prior to predicting seasonal salinity exposure; if the entire village lacks the measurement, then I use the mean for the upazila.

Salinity Measurement Lab Validation

Back

- Gold-standard method requires taking soil samples to a lab—prohibitively expensive at scale
- I conduct lab tests with my handheld sensors and compare them to other more expensive sensors
- I know the ground truth by mixing 250 milliliters of distilled water with grams of NaCl ranging from 0 to 1.5 in increments of .1
- I find no statistically significant evidence that the cheaper sensors I use perform differently than the more expensive ones, and gaps from the truth are small

What Signs Do Farmers Use to Learn About Salinity?



Meas. Bel. Back

Visual Belief Eliciation Comprehension

Back

- Just 3.82% of respondents answered comprehension questions incorrectly
- Just 11.63% found belief elicitation “a lot” or “very” confusing
- Pre-registered cuts by this dimension

Text of Salinity Belief Elicitation

Back

This image shows pictures of rice plants at the end of the season, once they are fully grown. They are arranged from the best growing to the worst growing. The smallest ones grew the worst. The biggest plants grew the best. Plant number 1 is the least healthy, and plant number 7 is the most healthy.

First, think about last year. Which of these pictures best matches the plants that grew on **plot X** last year?

I would now like to know how you think your own crops will fare this year. Think about the end of the season. What are your guesses about what your grown plant will look like on **plot X**? Place the highest number of buttons on the image that best matches your guess. Remember, plant 7 is the healthiest and plant 1 is the least healthy.

This is not a picture of your own plant, it is taken from a previous study. Researchers have grown rice seedlings under different conditions. This rice variety is not specially adapted for saline soils.

Instructions: Point to picture that has the biggest plant.

This picture shows the seed grown in soil with the least amount of salt.

Instructions: Point to picture that has the smallest plant.

This picture shows the seed grown in soil with the most amount of salt.

Instructions: Point to the pictures in the middle.

These pictures show seeds grown in increasing amounts of salt, from largest to smallest.

Do you have any questions about these plants?

This photo comes from researchers who planted rice that is not saline tolerant in different soils with different amounts of salt. If they used your soil from plot X, which of these pictures do you think would look most like the plant at the end of the season? We are asking this question because we are trying to understand how much salt you think is in your soil. You should assume that the researchers copy all aspects of your soil, such as the water and fertilizers you use over the season and the weather on your plot. Please place more buttons on the pictures that you think are more likely.

Comparing Salinity Beliefs vs. Truths

Back

	(1) Salinity Belief	(2) Salinity Belief
Salinity Truth	0.786^{***}	0.805^{***}
	(0.121)	(0.111)
Constant	0.999^{*}	0.913^{*}
	(0.547)	(0.504)
Include Comp. Check Failures	No	Yes
Outcome Mean	4.617	4.633
Observations	2,068	2,271
R^2	0.034	0.038
p-value: β True Salinity $= 1$	0.078	0.080
p-value: β Constant $= 0$	0.068	0.070

Whose Beliefs Are Less Accurate?

More accurate farmers...

Whose Beliefs Are Less Accurate?

More accurate farmers...

- have more data

	(1)	(2)
	1 More Acre	10 Years Older
$\mid$ Beliefs - Truth $\mid$	-0.133***	-0.0856***
	(0.0320)	(0.0125)
Observations	2008	2068
Ind. Variable Mean	0.706	4.641

Note: Outcome is standardized absolute value of mean belief minus true soil reading. Sample includes the farmers passing comprehension checks, controlling linearly for underlying salinity where I allow the slope to change by ventile, with heteroskedasticity-robust standard errors.

Whose Beliefs Are Less Accurate?

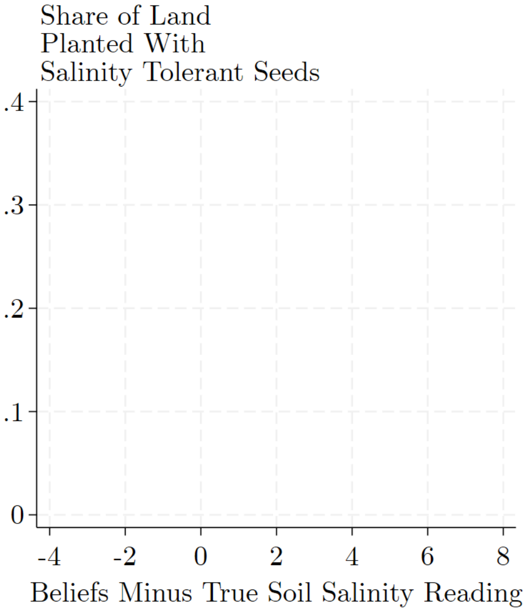
More accurate farmers...

- have more data
- are viewed as more skilled by their peers

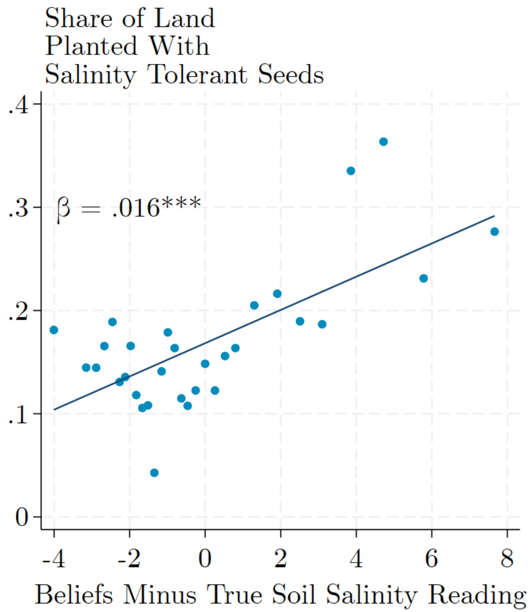
⇒ *Back*

	(1) Viewed As Extremely Knowledgeable	(2) Neighbors Would Follow Seed Advice
| Beliefs - Truth |	-0.246***	-0.672***
	(0.0921)	(0.0705)
Observations	2035	2035
Ind. Variable Mean	0.120	0.771

Note: Outcome is standardized absolute value of mean belief minus true soil reading. Sample includes the farmers passing comprehension checks, controlling linearly for underlying salinity where I allow the slope to change by ventile, with heteroskedasticity-robust standard errors.



Gaps Predict Behavior



Gaps Predict Behavior

- Gap between beliefs and true soil readings strongly predicts farmers' behavior
  - 1 S.D. increase in overestimation of the truth associated with a 4.5 p.p. increase in share land planted with salinity tolerant seeds (26%) Back

"When the leaves of paddy plants turn red in the land, it is easy to understand that there is salinity in the land. And when rice plants are not growing well, it becomes difficult to know whether the problem is due to salinity, soil or fertilizer."

"After planting rice plants in the land, when the rice plants turn brown, it is easy to understand that the salinity of the land has increased. And when the paddy plant gets a little bigger and then if the paddy plant does not grow, it seems difficult to know whether the problem is due to salinity or some other reason."

"If white substance like salt is seen in the soil then it is easy to understand that salinity level is high. And when the paddy plant dies, it becomes difficult."

"After planting rice in the land, when the rice plants do not grow and are small in size, it is easy to understand that there is salinity in the land. But when the paddy leaves turn red, I find it difficult whether the problem is due to salinity or some other reason."

"When the rice turns red it is easy to understand that it is due to salinity. When after planting paddy in the land and applying proper fertilizers it is found that the crop is not growing well and the crop is not being nourished then it is difficult to understand whether it is actually due to salinity or some other reason."

"If a white substance like salt appears in the soil when the soil is dry, it is easy to understand that the salinity level is high. And if a disease occurs after planting paddy in the land, it is difficult to understand whether the problem is due to salinity or for some other reason."

"If after planting paddy in the land, if the paddy does not grow and the paddy plants are stunted, then it is easy to understand that the land has salinity. But when rice plants turn yellow due to insect attack, it is not easy to understand whether the problem is due to salinity or insect attack." *Back*

- Let $\widehat{s_t^i}$ and $\widehat{b_t^i}$ denote binary beliefs held by farmer i in period t about salinity S and fungus B respectively, and let y_t^i denote the binary yield observed by farmer i in period t
- **Definition:** An environmental factor $E \in \{S, B\}$ is the *default* hypothesis in period t when the corresponding belief $\widehat{e}_t = \max(\widehat{s}_t, \widehat{b}_t)$.
- **Remark:** If two farmers i and j have different default hypotheses $(\max(\widehat{s_1^i}, \widehat{b_1^i}) \neq \max(\widehat{s_1^j}, \widehat{b_1^j}))$, then even if their priors are arbitrarily close $(|\widehat{s_1^i} - \widehat{s_1^j}| < \varepsilon)$ and $(|\widehat{b_1^i} - \widehat{b_1^j}| < \varepsilon)$, after observing identical data $(y_1^i = y_1^j)$, their posterior beliefs will exhibit the same difference in default hypotheses $(\max(\widehat{s_2^i}, \widehat{b_2^i}) \neq \max(\widehat{s_2^j}, \widehat{b_2^j}))$.

Back

- Farmer grows rice in two periods, $t \in \{1, 2\}$
- Output in period t is given by the binary indicator $y_t \in \{0, 1\}$, where $y_t = 0$ denotes low harvest, and $y_t = 1$ denotes high harvest
- Harvest is subject to a random productivity shock ξ that can be either negative ($\xi = -1$), positive ($\xi = 1$), or neutral ($\xi = 0$)
- I assume productivity shocks are distributed symmetrically with mean zero such that the positive and negative shocks occur with equal, positive probability denoted by $\rho > 0$ and that neutral shocks occur with positive probability such that $\rho < .5$
- In the first period, farmers make no decisions about inputs and plant the standard seed
- In the second period, salinity tolerant seeds are introduced, and farmers decide whether to plant salinity tolerant seed or plant the standard seed. This decision is given by the binary indicator $d_t \in \{0, 1\}$. Planting a standard seed is given by $d_t = 0$, where $d_1 = 0$ by default because salinity tolerant seeds are not available in the first period. In the second period, farmers may plant a salinity tolerant seed, denoted by $d_2 = 1$.
- Seed choice costs $c(d_t)$, where I normalize such that planting a non-salinity tolerant seed is free $c(d_t = 0) = 0$. I assume planting a salinity tolerant seed costs $c(d_t = 1) > 0$, where $c(d_t = 1)$ is positive yet small to capture the notion that salinity tolerant seeds perform relatively better in high salt environments yet relatively worse than standard seeds amid low salinity

Back

- Two independent and unchanging environmental conditions denoted by the set $\{S, B\}$ can impact harvest, where S is the soil salinity and B is blast, an important fungus threatening rice
- I use lower case letters to denote the true, binary environmental states in these respective domains, given by $s \in \{0,1\}$, where $s = 0$ denotes low salt levels and $s = 1$ denotes high salt levels, and by $b \in \{0,1\}$, where $b = 0$ denotes no blast and $b = 1$ denotes the presence of blast
- I assume the agricultural production function follows a particular, simple functional form given by Equation 1. The maximization and minimization expressions ensure the binary support of output $y_t \in \{0,1\}$. Planting salinity tolerant seeds $d_t = 1$ mitigates the damage from soil with high salt content $(s = 1)$.

$$y_t(s, b, d_t) = \max\left(\min\left(1 - (s - d_t)^2 - b + \xi, 1\right), 0\right) \tag{1}$$

- I assume farmers cannot directly observe the environmental states. As a result, farmers are uncertain about how their decision d_2 impacts their output y_2 entering the second period. This uncertainty is captured by their prior over the states of soil salinity and blast. I use $\widehat{\cdot}$ and lower case letters to denote beliefs, such that $\widehat{s}_t$ denotes a farmer's belief entering period t about the probability that true salinity levels are high $\widehat{s}_t = P(s = 1)$, and $\widehat{b}_t$ denotes a farmer's belief in period t about the probability that blast is present $\widehat{b}_t = P(b = 1)$.
- I assume that farmers use Bayes' rule to learn about these unobserved environmental conditions by updating using the harvest in period 1.
- Risk-neutral farmers choose seeds to maximize output in period 2 given their beliefs

$$U = \max_{d_2} \mathbb{E}\left[y_2(\widehat{s}_2, \widehat{b}_2, d_2) - c(d_2)\right] \tag{2}$$

- The *default* domain is $E \in \{S, B\}$ corresponding to the most likely threat $\widehat{e} = \max(\widehat{s}, \widehat{b})$ Back

- First, consider the case shown in Equation 3 of updating about the likelihood of high salinity after observing a bad harvest.

$$\widehat{s}_2 = P(s=1|y_1=0) = \frac{P(s_1)P(y_1=0|s=1)}{P(y_1=0)} \tag{3}$$

$$\widehat{s}_2 = \frac{\widehat{s}_1\widehat{b}_1 + \widehat{s}_1(1-\widehat{b}_1)(1-\rho)}{\widehat{b}_1\widehat{s}_1 + \widehat{s}_1(1-\widehat{b}_1)(1-\rho) + \widehat{b}_1(1-\widehat{s}_1)(1-\rho) + (1-\widehat{b}_1)(1-\widehat{s}_1)\rho} \tag{4}$$

- The difference between posterior and prior beliefs about salinity is then given by Equation 5.

$$\widehat{s}_2 - \widehat{s}_1 = \frac{\widehat{s}_1 - 2\rho\widehat{s}_1 - \widehat{b}_1\widehat{s}_1 + 3\rho\widehat{b}_1\widehat{s}_1 - (\widehat{s}_1)^2 + 2\rho(\widehat{s}_1)^2 + \widehat{b}_1(\widehat{s}_1)^2 - 3\rho\widehat{b}_1(\widehat{s}_1)^2}{\widehat{b}_1 + \widehat{s}_1 + \rho + 3\rho\widehat{b}_1\widehat{s}_1 - \widehat{b}_1\widehat{s}_1 - 2\rho\widehat{b}_1 - 2\rho\widehat{s}_1} \tag{5}$$

- The expression for the difference between posterior and prior beliefs about blast is given by the symmetric expression, substituting $\widehat{b}_1$ for $\widehat{s}_1$ and vice versa. Note that the denominators are identical and always positive since it is simply $P(y_1 = 0)$, so I focus exclusively on the numerator.
- To account for mechanical bound effects,I divide by $|1 - y_t - \widehat{s}_1|$.

$$\frac{\widehat{s}_2 - \widehat{s}_1}{|1 - y_1 - \widehat{s}_1|} \propto \widehat{s}_1 - 2\rho\widehat{s}_1 - \widehat{b}_1\widehat{s}_1 - 3\rho\widehat{s}_1\widehat{b}_1 \tag{6}$$

Back

- Since the expression for blast is symmetric, the expression for the relative difference between posterior and prior beliefs along the two unobserved environmental dimensions is therefore given by Equation 7.

$$\frac{\left(\widehat{b}_2 - \widehat{b}_1\right)}{|1 - y_1 - \widehat{b}_1|} - \frac{(\widehat{s}_2 - \widehat{s}_1)}{|1 - y_1 - \widehat{s}_1|} \propto (\widehat{b}_1 - \widehat{s}_1)(1 - 2\rho) \tag{7}$$

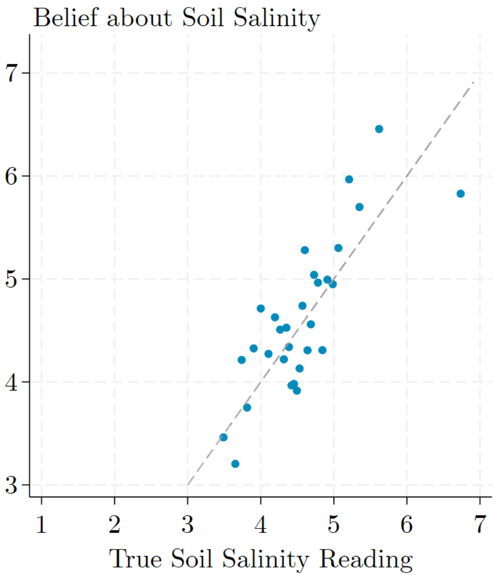
- Since $\rho < .5$ by assumption, the sign depends on the term $(\widehat{b}_1 - \widehat{s}_1)$. When prior beliefs about the likelihood of high salinity exceed initial beliefs about the chance of blast, then observing low yield leads the farmer to disproportionately increase their beliefs about salinity relative to blast.
- Repeating process for positive yield gives the relative change is given by Equation 8.

$$\frac{(\widehat{b}_2 - \widehat{b}_1)}{|1 - y_1 - \widehat{b}_1|} - \frac{(\widehat{s}_2 - \widehat{s}_1)}{|1 - y_1 - \widehat{s}_1|} \propto (\widehat{b}_1 - \widehat{s}_1)3\rho \tag{8}$$

- Combining the results from Equations 7 and 8 illustrates that after observing either low yield or high yield, the rank ordering of beliefs is preserved. In other words, the default domain exhibits path dependence and will always be the default domain. *Back*

Reasons for Salience vs. Subtle Gap in Beliefs

1. **Pure Bayesian:** Salient shock carries different statistical content: increases beliefs about salt risk more
2. **Bayesian with limited info:** Even if statistical info is same, subtle shifts may be invisible/difficult to notice $\rightarrow$ salinity beliefs increase less than salient case
3. **Limited attention:** Even if info is the same and farmers notice, salient shocks increase chance that salinity comes to mind when interpreting new data *Back*

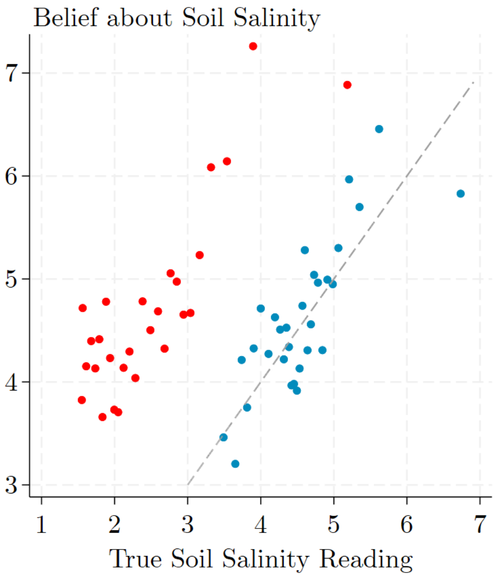


Note: Binned scatter plot of beliefs measured before planting and measured salinity over the course of the 2022-23 season, restricted to sample passing beliefs comprehension checks. $N = 2,068$. Blue dots use the *ex ante* agronomic prediction.

2022-23 Salinity Was Very Low

- Farmers' predictions about 2022-23 soil salinity on average accurate based on best *ex ante* agronomic prediction

2022-23 Salinity Was Very Low



Note: Binned scatter plot of beliefs measured before planting and measured salinity over the course of the 2022-23 season, restricted to sample passing beliefs comprehension checks. $N = 2,068$. Blue dots use the *ex ante* agronomic prediction. Red dots use the realized salinity level.

- Farmers' predictions about 2022-23 soil salinity on average accurate based on best *ex ante* agronomic prediction
- For reasons difficult to predict with observables, 2022-23 ultimately had **unusually low** salinity
- Both farmers and I overestimated realized salinity
- In endline, 25% of farmers said salinity ended up lower than they had expected, 15% said higher *Back*

A Simple Structural Model of Seed Demand

Equation 9 captures the indirect utility of farmer i choosing seed j, where $\mathbf{x}_{ij}$ is a vector of seed-specific characteristics, β_i are random coefficients that vary over farmers in the population, $\mathbf{w}_{ij}$ is a vector of seed-specific characteristics, $\mathbf{z}_i$ is a vector of farmer-specific characteristics, c_j are intercepts, and ε_{ij} are unobserved random taste shocks, which I model as independent type I (Gumbel-type) extreme-value random variables.

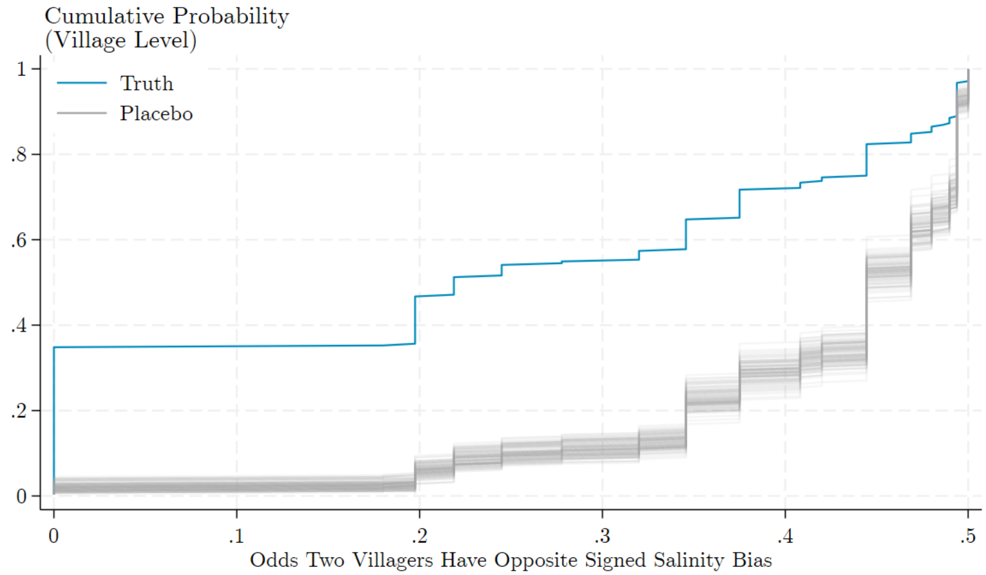
$$U_{ij} = V_{ij} + \varepsilon_{ij} = \mathbf{x}_{ij}\beta_i + \mathbf{w}_{ij}\alpha + \mathbf{z_i}\delta_j + c_j + \varepsilon_{ij} \tag{9}$$

Given this utility function, the probability of the ith farmer choosing seed j is given by equations 10 and 11. Because the integral in Equation 11 has no closed-form solution, I compute it using maximum simulated likelihood. Back

$$P_{ij}(\beta) = \frac{e^{V_{ij}}}{\sum_{k \in \mathcal{J}_v} e^{V_{ik}}} \tag{10}$$

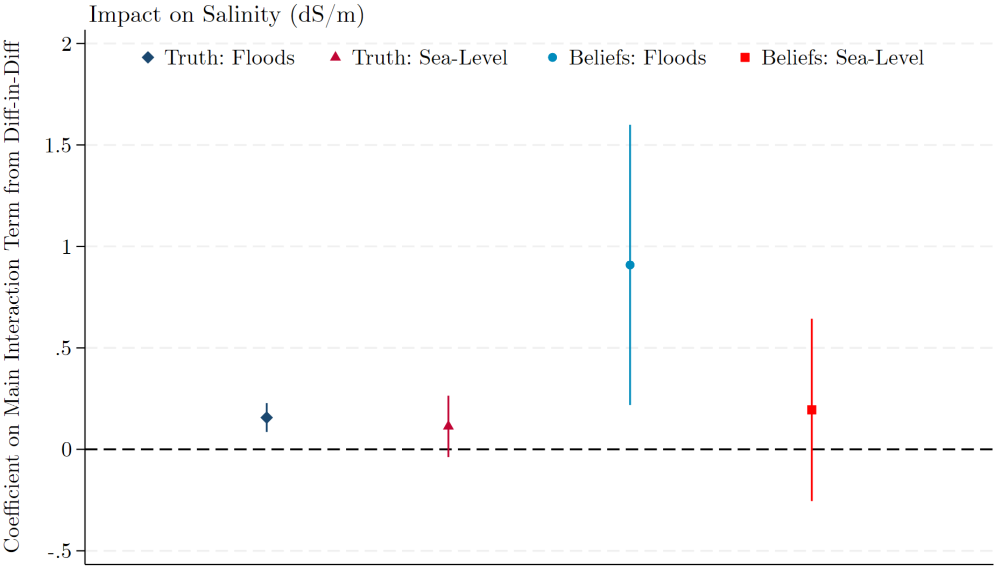
$$P_{ij} = \int P_{ij}(\beta) f(\beta) d\beta \tag{11}$$

The Spatial Covariance of Salinity Beliefs *Back*



Out-of-Sample Test of Simple Demand Model

	(1) Control (Out-of-Sample)	(2) Treatment (In-Sample)
Model Prediction	0.981***	1.034***
	(0.0359)	(0.0364)
Constant	0.00310	-0.00547
	(0.00579)	(0.00592)
Observations	4678	4455
Farmers	754	725



Impact on Salinity (dS/m)
Coefficient on Main Interaction Term from Diff-in-Diff
2
1.5
1
.5
0
-.5
Truth: Floods
Truth: Sea-Level
Beliefs: Floods
Beliefs: Sea-Level

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