

WEATHER PACKAGE

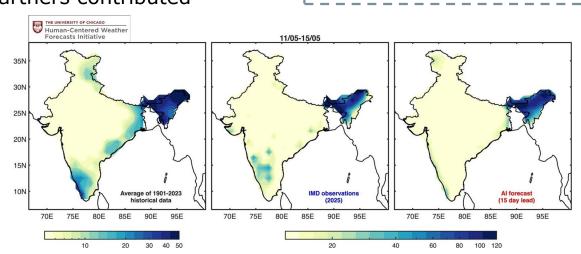
Blending AI Models for Indian Monsoon Onset - An Operational Example

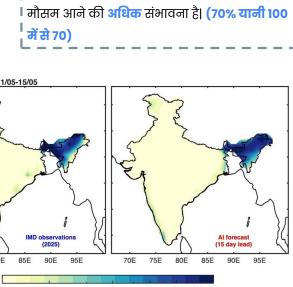
Pedram Hassanzadeh, Amir Jina, and Niriksha Shetty

38 Million Indian Farmers Benefited from Accurate 30-day AI Forecasts of Monsoon Onset in 2025

ECMWF's AIFS, Google's NeuralGCM, and open data (ERA5, IFS HRES, GEFS) played a critical role

- Project of the Indian Ministry of Agriculture & Farmers Welfare (MoA&FW)
- UChicago's Human-centered Weather Forecasts (HCF) Initiative led a team of *climate scientists*, AI experts, and economists to benchmark and generate AI forecasts and turn them into field-tested messages. PxD, Google, and many other partners contributed
- MoA&FW disseminated the messages weekly via SMS to 38 million farmers
- HCF was partially funded by AIM for Scale, a global initiative of the United Arab Emirates and the Gates Foundation



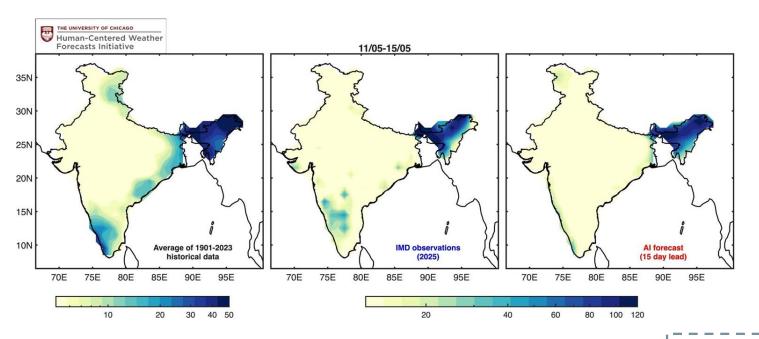


किसानों के लिए नई मौसम जानकारी: 11 जून 2025

आपके इलाके में, २४ जून के पहले, लगातार बारिश का

The Forecasts Were Accurate and Helped the Farmers Plan Better

The forecasts captured the 2-week pause in the monsoon progression



Message formats informed by 24 focus groups and 66 farmer interviews

New Weather Information I for Farmers: 11 June 2025

In your area, there is a higher likelihood of continuous rainy weather before 24 June—about 70% chance (that is, 70 out of 100).

- The AI-based forecasts were accurate, captured the unusual pause of the 2025 monsoon over India
- No other available forecast gave farmers guidance on this unusual monsoon progress, especially with 2-4 week lead times
- Surveys show that farmers benefited from these timely forecasts

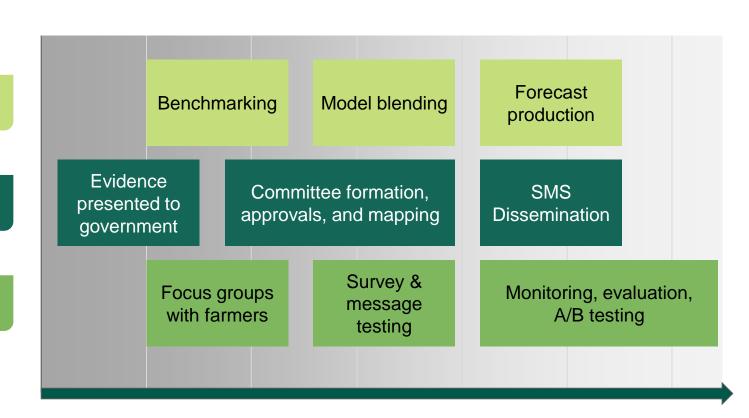
किसानों के लिए नई मौसम जानकारी: 11 जून 2025 आपके इलाके में, 24 जून के पहले, लगातार बारिश का मौसम आने की <mark>अधिक</mark> संभावना है| **(70% यानी 100**

AI Monsoon Onset Forecasts: Indian Ministry of Agriculture and Farmer Welfare

Forecasts

Policy

Impact



Decisions Affected by Weather Forecasts



Planting

Optimal planting times based on short-range forecasts can help farmers avoid adverse conditions

Crop choice based on longrange forecasts can help farmers optimize their crops for seasonal outcomes



Irrigation Planning

Schedule irrigation to maximize crop yield and use groundwater (and energy to run pumps) efficiently



Harvesting and Post-Harvest Management

Time harvests to avoid damage or food safety issues

Decide when to **move crops** to storage



Pest and Disease Management

Predict and prevent pest outbreaks

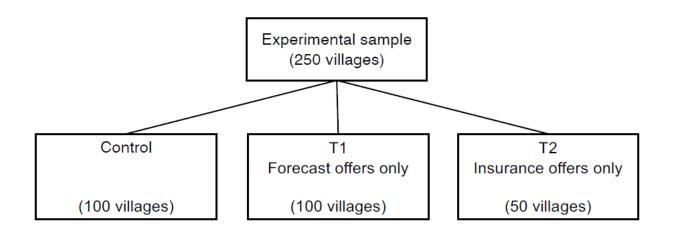
Ensure **pesticides are used effectively** and efficiently



Fertilizer and Input Timing

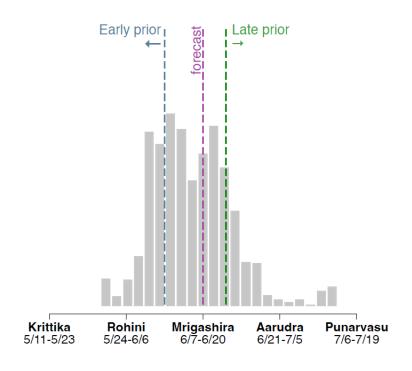
Optimize fertilizer application timing to coincide with optimal weather conditions

Evidence for monsoon onset forecast effectiveness

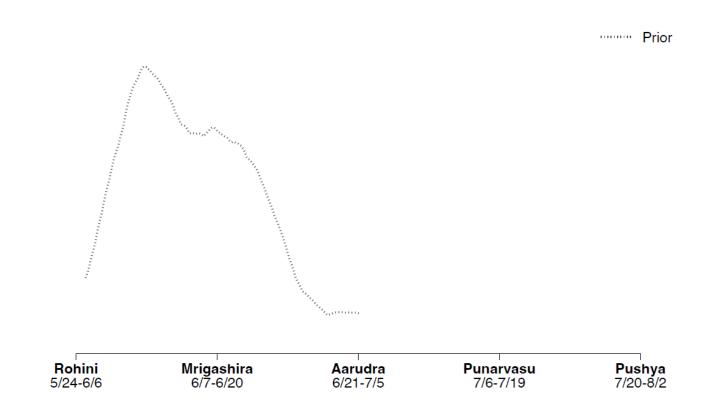


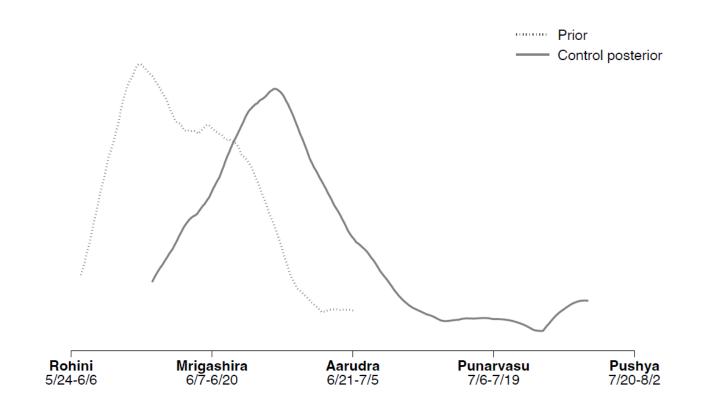
- Cluster-randomized control trial to evaluate the impact of onset forecasts in 2022
- Implemented with ICRISAT in Telangana, India
- Village-level randomization, sampling 10 farmers per village with low irrigation access

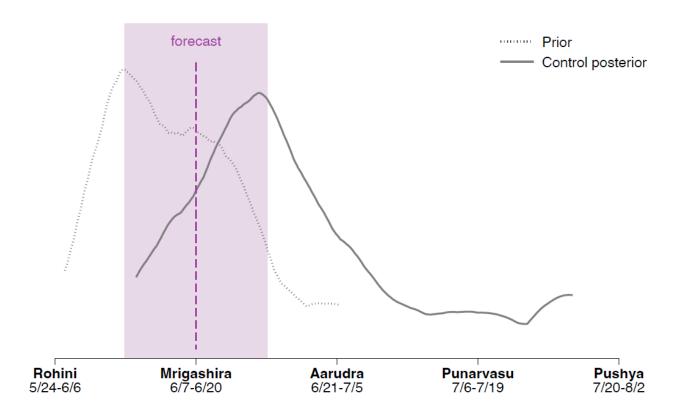
Evidence for monsoon onset forecast effectiveness

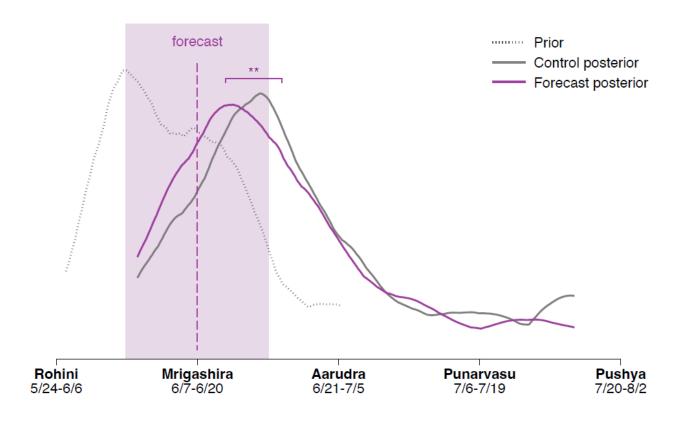


- Wide spread in when farmers believed onset would occur
- Expect different behaviour for farmers who believed onset would be earlier than forecast than farmers who believed onset would be later than forecast
- Onset in 2022 was in middle of farmers' distribution

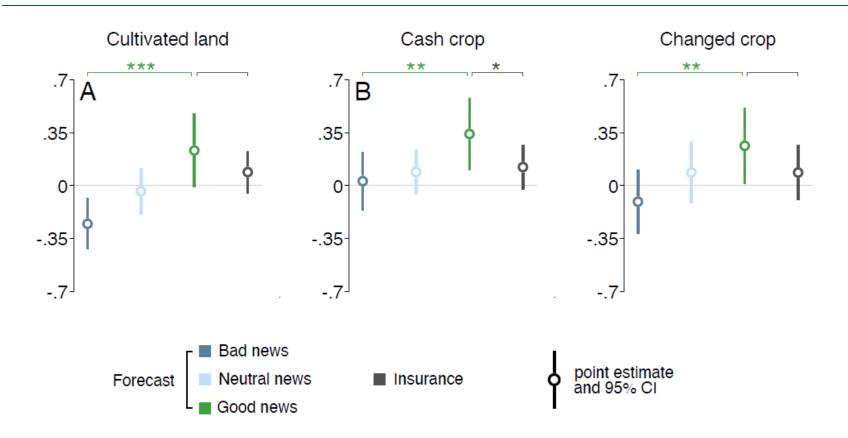




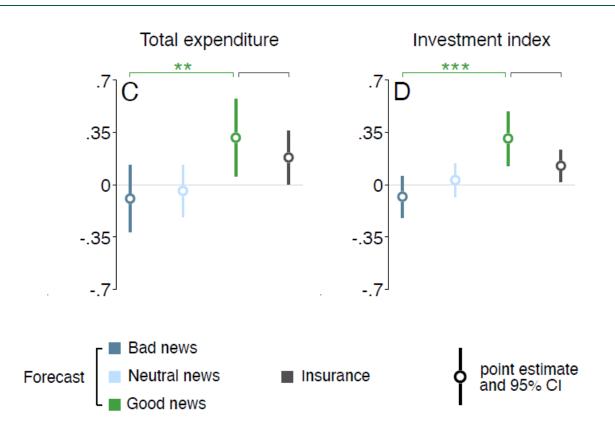




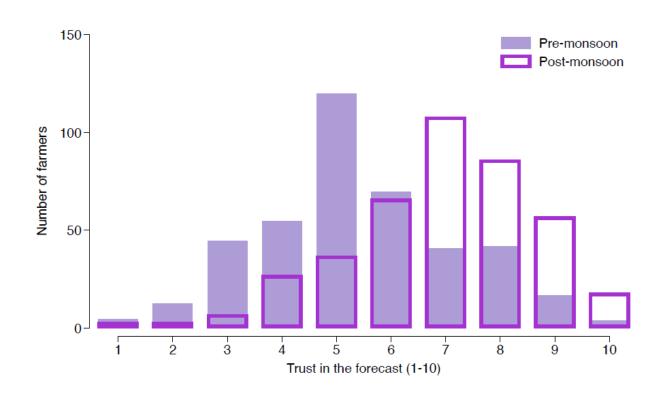
Impacts: Changes in land cultivated and crops planted



Impacts: Increases in expenditures



Impacts: Trust in forecast increases after 1 year

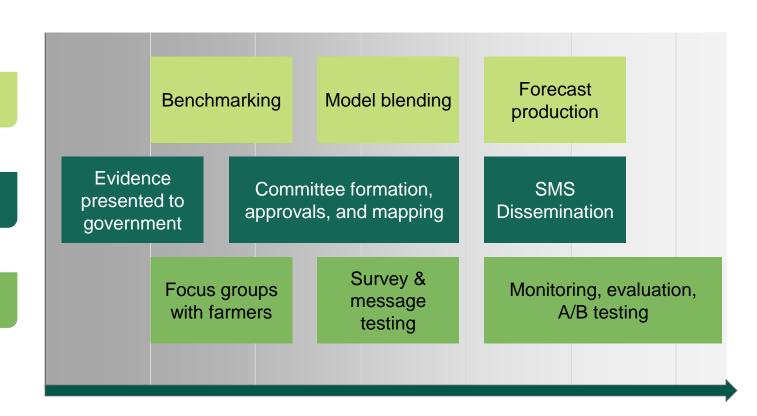


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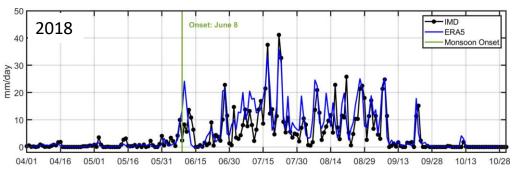
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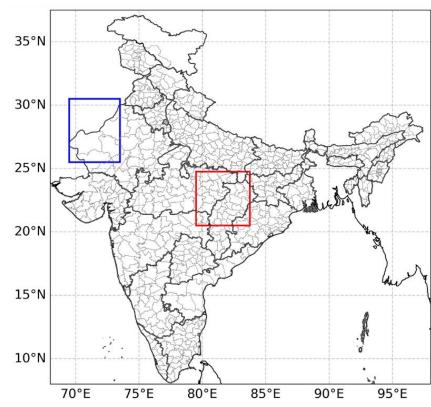
Based on Rigorous *Human-centered, Operational* Benchmarking that Integrates Climate, AI, and Social Science Criteria

The key attribute for benchmarking: The model had to accurately forecast not only the physics of the atmosphere but also the information the farmers needed and can act on

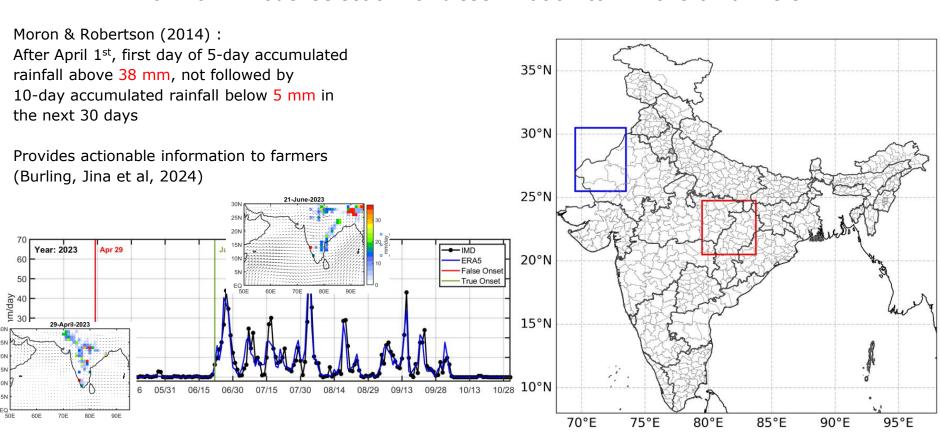
To inform model selection for dissemination to millions of farmers



Ground truth (Pai et al. 2014): High-quality IMD rain-gauge data, 1° gridded data from 1901-2024

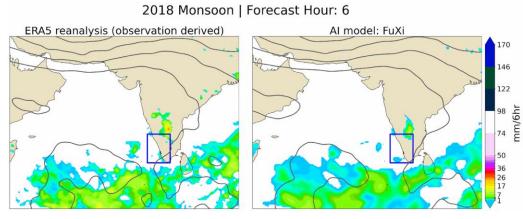


To inform model selection for dissemination to millions of farmers



Comparing AI, NWP, and Climatology

| Baseline & NWP | Years |
|-----------------------|-----------|
| Climatology (history) | 1901-2023 |
| IFS/IFS S2S (NWP) | 2004-2024 |



| Al models | Training | Fine-tuning |
|--------------------|-----------|-------------------------|
| AIFS | 1979-2020 | 2019-2020 (IFS HRES) |
| GenCast* | 1979-2018 | None |
| GraphCast | 1979–2017 | 2016–2021 (IFS HRES) |
| NeuralGCM (IMERG)* | 2001–2018 | None |
| FuXi | 1979–2015 | 2016–2017 |
| FuXi-S2S* | 1950-2016 | None |



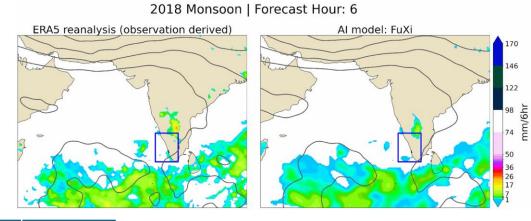
Al model: 3 min on 1 A40 GPU (\$3K)



IFS 9km: 1 hour on 12500 CPUs of Cray XC40 supercomputer (\$125M)

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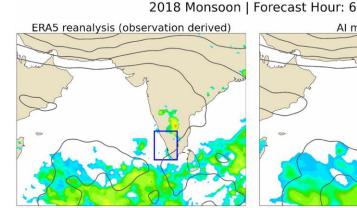
| AI models | Training | Fine-tuning | Testing | |
|--------------------|-----------|-------------------------|------------|--|
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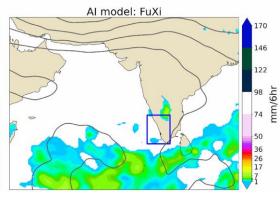




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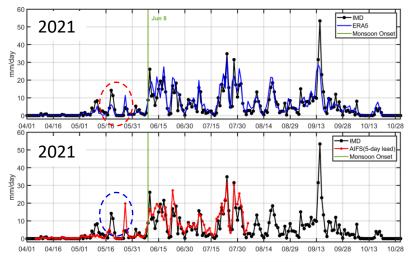




| Al models | Training | Fine-tuning | Testing |
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| AIFS | 1979-2020 | 2019-2020 (IFS HRES) | 2021–2023, pre 1979 |
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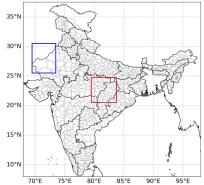
- Small test sample size is a major challenge for subseasonal-toseasonal (S2S) benchmarking
- Models vary in data they need for operation, cost, forecasted variables, etc. (e.g., soil moisture in only one model)

Indian Monsoon Onset Forecasts: 5- to 15-day lead times Al models can outperform NWP and climatology

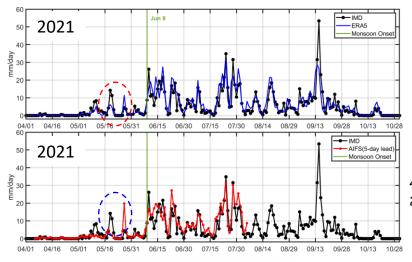


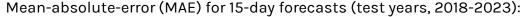
Mean-absolute-error (MAE) for 15-day forecasts (test years, 2018-2023):

| | Clim | IFS S2S | AIFS | GenCast | NGCM | Fuxi | GCast |
|------------|------|------------|------|---------|------|------|-------|
| MAE (days) | 7.0 | 3.3 | 0.56 | 2.5 | 2.0 | 1.33 | 2.5 |
| Miss rate | | 0% | 0% | 40% | 60% | 50% | 0% |



Indian Monsoon Onset Forecasts: 5- to 15-day lead times Al models can outperform NWP and climatology

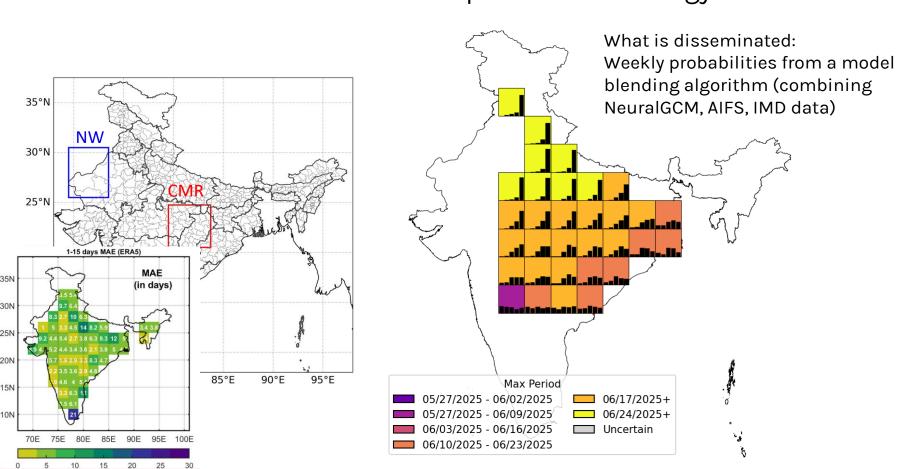




| | | Clim | IFS S2S | AIFS | GenCast | NGCM | Fuxi | GCast |
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| | Miss rate | | 0% | 0% | 40% | 6 b % | 50% | 0% |
| 4.5 days and 0% for 2.7 days and 0% if we include 1965-1978 too | | | | | | ays and 0% probabilist and 2018-2 | Z500 if we ic 1965- | st global ACC |

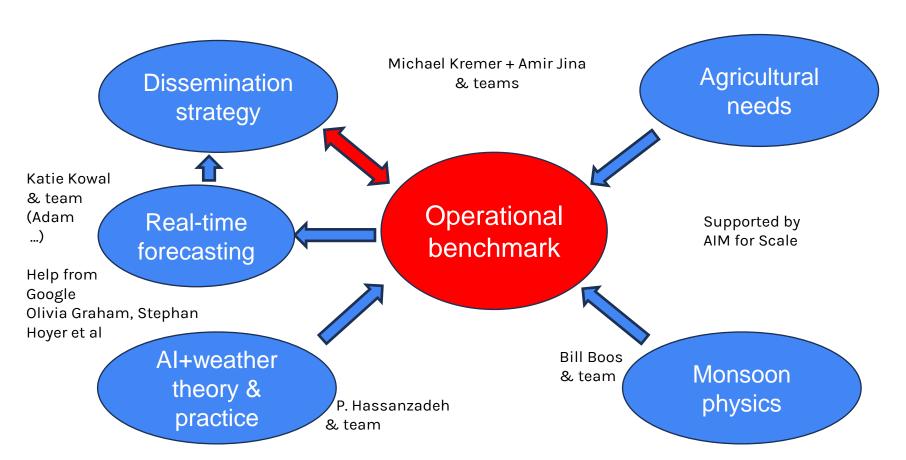
- There are various ways to measure the accuracy (metric, averaging area etc.)
- Top-performing models remain the same
- Technical details (would love feedback!) https://envfluids.github.io/monsoon-operational/index.html

Indian Monsoon Onset Forecasts: 30-day lead times Al models can outperform climatology



Benchmarking that Informs Decision-Making & Dissemination

Requires a multi-disciplinary team and a feedback loop



Benchmarking Indian Monsoon Onset Forecasts Lessons learned (so far)

- Even existing AI models are promising, including for tropical rainfall!
 - A lot more potential with localication and debiasing etc.
 - A lot lot more potential with S2S models and tailoring for tropical dynamics
- Interdisciplinary teams and feedback loops are essential
- Need special care:
 - Validation data
 - Real-time operational use
 - Designing indices and metrics most informative to farmers
 - Correct physics + maximum usefulness for farmers
 - Small test sample size
 - Benchmarking on pre-1979 data
 - Mechanistic analysis to ensure that the
 - "model is doing the thing for the right reason"

Broader Implications for India, Africa, and other Countries

This first-of-its-kind program is a model for how AI can help adapting to climate change

This is just the start: *Now we know it can be done!*

Blueprint for other countries: India's model, led by the government, grounded in farmer needs, and taking cutting-edge (*open*) science out into the real world

"Our idea is to follow India's lead and take this all over the world—not just to farmers, but to others as they encounter climate impacts. All is reframing how we think of weather forecasting and providing a critical tool as people make decisions about how to live with and adapt to climate change." Amir Jina

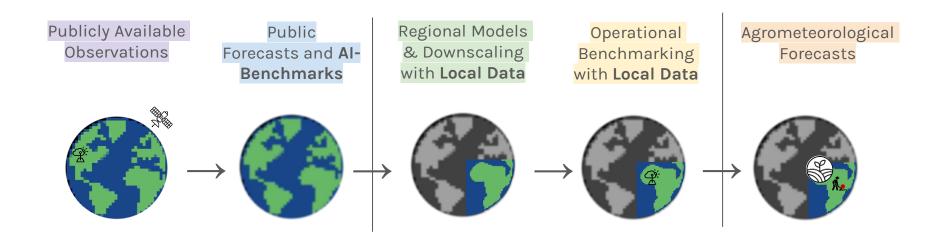
Start of every work? Rigorous, human-centered, operational benchmarking

Project Cirrus: Benchmarking of AI forecasts for Africa's rainy seasons (supported by Gates Foundation + Rhiza Research and others)

Benchmarking Overview:

5- to 30-day Forecasts of Indian Monsoon Onset

To inform model selection for dissemination to millions of farmers

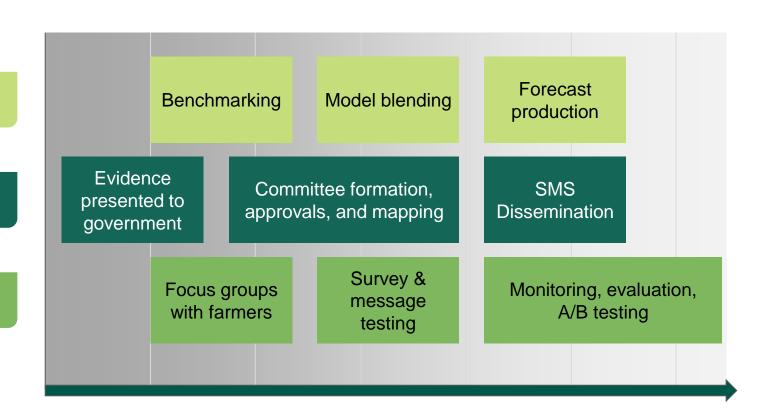


AI Monsoon Onset Forecasts: Indian Ministry of Agriculture and Farmer Welfare

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MoA&FW Committee formation

- Production of forecasts and agromet advisories is responsibility of Meteorological Department
- MoA&FW had access to and resources to support dissemination
- Committee formed with various government partners to advise and guide on monsoon onset forecast dissemination
- Scientific committee and implementation committee combined into single role
- Committee very active in 2024, more passive in 2025 in renewing program, despite increase in scale from 800,000 to 38 million farmers

Selecting dissemination areas

- Onset is large scale spatial process
- Variation at small scales is relatively low
- Forecast produced at 2x2 resolution
- Dissemination areas chosen by forecast skill
- Phone numbers at individual level
- Mapping required village level GPS for 10,000s of villages



SMS dissemination

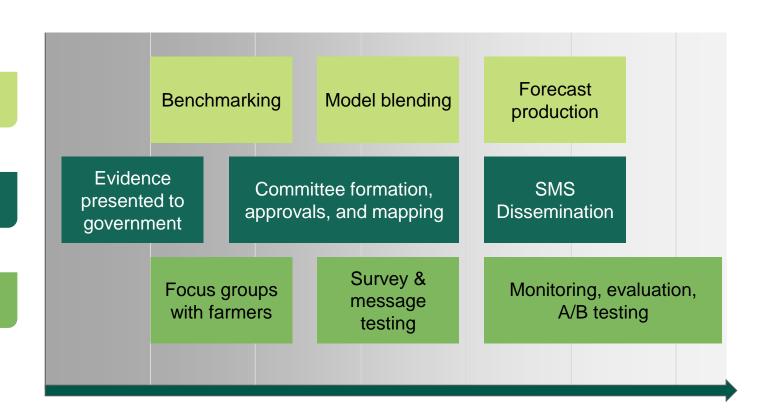
- Many dissemination methods were explored with MoA&FW.
 E.g., SMS, Whatsapp, TV, radio, ...
- MoA&FW maintains large database of farmer contact details for use in cash transfer and insurance programs
- Not previously used to disseminate actionable information or advisories
- Re-purposing database for forecast dissemination required careful discussions about limitation of platform

AI Monsoon Onset Forecasts: Indian Ministry of Agriculture and Farmer Welfare

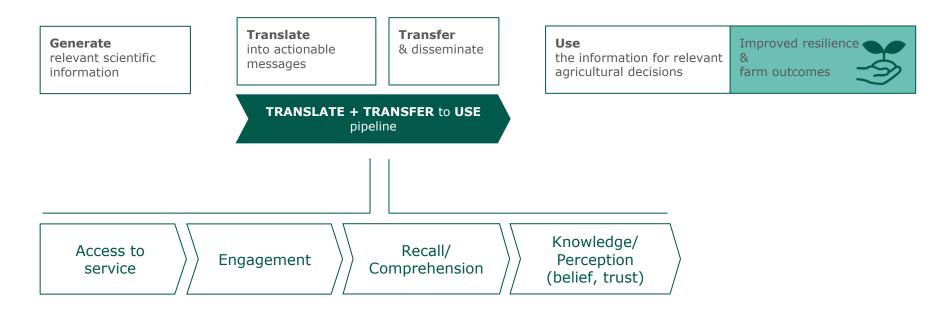
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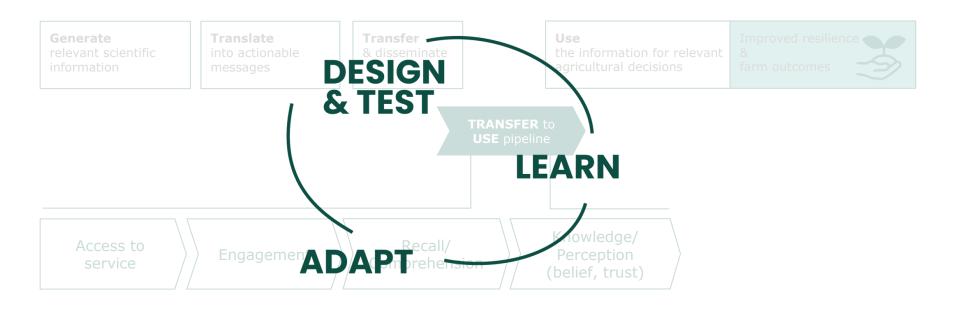
Impact



Theory of Change: From Translate + Transfer to Use



Theory of Change: Digital information services



Why design testing?

Agricultural or climate information can be difficult to communicate precisely

O2 | Small design tweaks matter

Farmer reactions are context-specific

The 2024 monsoon rainfall (Jun-Sept) in India is expected to be above normal (106% of average \pm 5% error).

Too technical

Latest forecast: The monsoon seasonal rainfall in India this Kharif season is expected to be 6% above normal.

Less information, but farmers can understand

Testing to transfer: The process

Field testing with 100+ farmers to get from forecast to message design:

- Message development (inductive)
 - Understand how farmers talk/think about expected weather and uncertainties - probabilities, forecasted events
 - Understand when farmers need forecasts and how they'd use it lead time, forecast windows
- Message feedback (deductive)
 - Present message templates and ask farmers to react, adapt messages
 - Co-design sessions with farmers to improve local relevance and comprehensibility of messages
- Small group testing in natural setting
 - Test shortlisted messages with a small group of farmers in a natural setting

Examples

Annotation

You will continue to receive SMS updates from this number about when the rainy season is likely to arrive in your locality this year. The arrival of the rainy season does not just mean the first rainfall; it means the state of continuous

27-44% could recall this

40-60% could recall this

New weather information for farmers: 4 June 2025

In your locality, after 17 June, the possibility of a continuous rainy season arriving is medium. (65%, meaning 65 in 100)

New weather information for farmers: 4 June 2025

In your locality, from 10 June to 24 June, the possibility of a continuous rainy season arriving is highest. (65%, meaning 65 in 100)

Before 10 June, the possibility of a continuous rainy season arriving is very low. (5%, meaning 5 in 100)

After 24 June, the possibility of a continuous rainy season arriving is low. (30%, meaning 30 in 100)

The policy/coordination side of testing + transfer

- Engagement with MoA&FW department and partners
 - **Extension division** to validate and secure approvals for (i) message templates, (ii) message dissemination schedule, (iii) monitoring and evaluation (M&E) plan
 - o IT division to align on (i) cost of dissemination and (ii) system set-up and vendor onboarding
- Coordination with the dissemination partner
 - SMS vendor to deliver the text messages
 - IVRS platform manager to deliver voice messages in 1 state
- Utilization of existing call center to monitor service and collect feedback
 - Securing permissions from Ag-Ministry Extension Division
 - Training call centre staff of monitoring survey tool
 - Quality control of monitoring activities