Harnessing Artificial Intelligence to Empower Farmers with Weather Information

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Executive summary

Artificial intelligence (AI) is enabling a revolution in weather forecasting, creating the potential to empower farmers with information for agricultural decisions. Multiple technology firms and research institutions have developed global AI weather models and made them open access. It is relatively straightforward to check how well these models predict particular weather variables that are important for agricultural decision-making in particular times and places. The best models for any particular purpose can then be disseminated to farmers, either through mass media or digitally.

Multiple randomized trials find farmers adjust their behavior in response to accurate weather forecasts. Farmers share information with each other, generating benefits of up to $141 USD per farmer.

India digitally distributed AI-based weather forecasts to 38 million farmers in 2025, with dissemination costs less than $0.005 USD per farmer. Forecast messages were developed through focus groups and A/B tests to boost farmer comprehension. The forecast successfully predicted an unusual monsoon year, including a pause in the northward progression of the monsoon. Farmers had not received any other forecasts of the pause in monsoon progression.

Multilateral development banks have committed funds to support other countries who wish to scale weather forecast dissemination. A variety of organizations have provided training in AI weather forecasting, benchmarking of open-access weather models to test how well they predict agriculturally-relevant phenomena in particular contexts, and technical assistance in developing and testing digital messages for conveying forecast information.

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1. Context

Climate change is exacerbating weather uncertainty, making farming decisions more difficult and increasing the importance of timely weather information (Pendergrass et al. 2017; Bathiany et al. 2018). For example, one major decision for farmers in regions with rainfed agriculture is when to plant. Planting just after the start of the rainy season typically leads to a longer growing season and higher yields, but if farmers plant too early (before continuous rains arrive) or if there is a dry period after planting, seeds may not germinate and inputs may be lost, causing substantial financial losses.

2. Innovations in AI weather forecasting

Innovations in artificial intelligence (AI) are driving a revolution in weather forecasting. For example, GraphCast (Google DeepMind's AI weather forecasting model) outperforms the accuracy of physics-based forecasts on 90% of 1,380 metrics (Lam et al. 2023). Many global AI weather models have now been made available on an open-source basis, including multiple models from Google, FourCastNet from Nvidia, AIFS from the European Center for Medium-Range Weather Forecasting, FuXi from researchers at Fudan University, and others.

AI-based forecasts can be produced much more quickly and cheaply than traditional physics-based forecasts. Traditional weather models may require hundreds of millions of dollars in infrastructure. Some AI models, in contrast, can be run on a desktop computer. Nvidia's FourCastNet can generate forecasts 80,000 times faster than traditional forecast-generation processes (Kurth et al. 2023). This allows development of forecasts tailored to farmers' needs.

3. Farmer response to forecasts

Farmers adjust their behavior and investment decisions in response to weather forecasts.[2] Five out of six rigorous randomized controlled trials find that farmers change their behavior in response to forecasts. In Pakistan, farmers who received forecasts were less likely to apply pesticides or to irrigate when heavy rain was forecasted, improving water resource efficiency and reducing runoff (Rudder and Viviano, 2024). In Telangana, India, farmers who were randomly assigned to receive a seasonal monsoon forecast substantially altered their planting and investment decisions to better align with the forecasted seasonal timing. Farmers who expected a shorter season than what was forecast increased their land under cultivation, added new crops, and invested 34 percent more in all pre-harvest expenditures. Farmers who expected a longer monsoon season than predicted adjusted toward the forecast in the opposite direction (Burlig et al. 2025). In Colombia, farmers who received weather forecasts and price information by SMS reduced their labor costs by over $103 USD per farmer, although this result is imprecisely estimated (Camacho and Conover 2019). In Maharashtra, India, farmers who received SMS updates with both weather and market information showed no behavioral

[2] Note that here, as elsewhere in this report, we focus on results from randomized trials or other well-identified studies which can plausibly isolate a causal relationship.

change—possibly due to low salience of the weather forecasts, as farmers received up to a hundred messages each month that also included price and market updates, as well as crop advisories (Fafchamps and Minten, 2012).

Five randomized trials estimate the monetary benefits of weather forecasts in terms of agricultural profits or cost savings. Four of these studies find gains ranging from $5–$141 per farmer (2023 USD).[3] The fifth study evaluates a monsoon onset forecast, finding a 7 percent increase in food consumption and an increase in an aggregate welfare index (Burlig et al., 2025).

Most of these studies did not include agro-meteorological advice. It seems likely that benefits could be even larger with agro-meteorological advice. A weather-based pest alert system for potato farmers in Bangladesh helped reduce the risk of crop loss and led farmers to increase their investment in fertilizer by 8 percent, which led to a 7 percent increase in yields (Barnett-Howell 2021). In Odisha, India, digital agromet advisory services increased profits by $30-$47 per farmer in areas affected by excess rainfall and by $4.5-$13 on average across all farmers (Cole et al. 2025). These examples point to the potential from combining weather information with agro-meteorological advisory services for farmers. Testing how to integrate agro-meteorological advice alongside weather forecast dissemination is an important area for future work.

Farmers share weather information with their neighbors, and this produces community-wide benefits, even when digital forecasts are shared only with some farmers. In Pakistan, farmers in areas where a larger share of peers received forecasts were more likely to discuss the weather and adjust their behavior accordingly, even if they did not receive the forecasts themselves (Rudder and Viviano, 2024). In Ghana, farmers in communities that received forecasts via SMS timed planting and fertilizer and pesticide application on days with forecasted light rain, which facilitates seed germination and effective absorption of inputs (Fosu et al. 2018). In Benin, farmers in communities that received forecasts via SMS reduced their labor costs and increased their yields (Yegbemey et al. 2023).

Farmers learn over time which weather forecasts are useful, and then react to those that they find useful. High-quality non-experimental research finds that in parts of India where total monsoon rainfall forecasts have a higher degree of accuracy, farmers increase planting-stage investments in response to favorable weather forecasts (Rosenzweig and Udry 2019).

Forecasts can also increase resilience to disasters. For instance, 1-10 day flood forecasts in Bangladesh led to timely evacuations, minimizing financial losses (Webster et al. 2010). In Bihar, India, flood forecasts 2-4 days in advance increased preparedness and improved health outcomes, ultimately reducing medical costs by 30% (Jagnani and Pande, 2024).

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[3] Camacho and Conover (2019); Cole et al. (2025); Rudder and Viviano (2024); Yegbemey et al. (2019).

4. India's AI-based weather forecasting program

In 2025, India's Ministry of Agriculture and Farmers Welfare (MoA&FW) disseminated AI-based monsoon onset forecasts to approximately 38 million farmers. Since the Ministry had lists of farmer phone numbers, it could use digital dissemination via phones. Tens of millions of farmers across India depend on monsoon rainfall for their main source of income and livelihood. This forecast was available up to four weeks ahead of the rain. AI-based models made it possible to design forecasts specifically for farmers' needs by forecasting an agriculturally-relevant definition of the monsoon, accounting for the risk of dry spells (MoA&FW, 2025). The state of Odisha also disseminated these forecasts to about 1 million farmers using recorded voice messages.

These forecasts successfully identified an unusual pause in the monsoon's progression across India in 2025 three weeks ahead. In 2025, the monsoon reached Kerala (the first part of mainland India) by May 24, significantly earlier than usual. Many assume that the monsoon advances northward at the same rate each year after Kerala onset. Media coverage indicated an early monsoon. However, the northward progression of the monsoon paused. The AI forecasts correctly predicted this stall. No other forecasts gave farmers guidance on this unusual pause.

The SMS and Whatsapp costs of disseminating monsoon forecasts were under $0.005 USD per farmer, or less than half a cent. Telecommunication costs are larger in many countries and some countries do not have lists of farmer phone numbers, but radio is typically inexpensive per farmer reached. The total cost for monsoon forecasts in India in 2025 was about $0.027 per farmer, including forecast generation, message testing, and dissemination. Many of these costs were one-time costs or are expected to fall as forecast generation becomes cheaper.

The Indian government's approach—grounded in the needs of farmers—offers a compelling blueprint for the future. Forecasts were selected based on a systematic benchmarking exercise to assess the performance of various open-access AI models at forecasting an agriculturally-relevant definition of the continuous rainy season. The exercise, which used India Meteorological Department (IMD)'s 60 years of rain-gauge data for validation, showed that a blend of multiple AI models and IMD's rainfall data outperformed the baseline (climatology based on historical information) at forecasting monsoon onset up to 30 days ahead. The generation of forecasts using inputs from the government of India, Google, the European Centre for Medium-Range Weather Forecasts, and university-based researchers demonstrates the potential for public–private–academic collaborations to empower farmers with information.[4]

Focus groups and A/B tests helped to improve message design. To ensure forecast communication was relevant, accessible, and actionable message design was assessed through focus group discussions with farmers and refining the messages through iterative testing.

[4] Precision Development (PxD), the Development Innovation Lab, the Human Centered Weather Forecast Initiative at the University of Chicago, University of California-Berkeley, and the University of Chicago Trust in India provided technical assistance with support from the Gates Foundation, AIM for Scale, and the University of Chicago.

In 2025, the government of India relied on SMS combined with WhatsApp, but more generally a range of media can be used for disseminating forecasts. Forecasts could be delivered at scale through mass media channels such as newspaper, radio (a low-cost channel through which governments often obtain free airtime), and TV as well as through digital channels such as voice messages, SMS, and WhatsApp. Digital delivery may not be necessary for all geographies and forecast types. However, it could provide additional value by allowing customization to individual farmers' needs and providing forecasts at greater geographic specificity and frequency. This could be especially useful for forecasts that vary across small geographic distances and have shorter time horizons. AI also has the potential to transform how these forecasts are communicated to farmers, as large language models could help deliver tailored advice in ways that are accessible and easy to understand.

Box 1: The economics of weather forecasting

Weather forecasts are a public good, which provides a rationale for public and philanthropic entities to provide them for free at scale. Weather forecasts are non-rival (and largely non-excludable) public goods. Once the fixed costs of producing this information are paid, because of its nonrival nature, information can be used by additional farmers at minimal cost. Farmers can share information received, making the services not fully excludable. Each farmer is therefore unwilling to pay the full value of the information, which reduces the profit incentive for the private sector to sell forecasts directly to farmers. This means it is typically efficient to provide forecasts for free at scale. Free delivery for end-users leads to higher take-up, which leads to much greater cost-effectiveness, given the fixed cost of developing forecasts.

Governments often have a strong comparative advantage in disseminating messages at scale at low costs. In many cases, governments have lists of farmer phone numbers and delivery systems (including SMS) which can reach farmers very broadly. For example, the government of India has a registry of over 100 million farmer phone numbers, and state governments also have registries with additional farmer phone numbers. The state of Odisha set up a comprehensive digital agriculture voice-based platform including weather advisories. As the platform scaled from 1.4 million to 5 million farmers, the annual cost per farmer dropped from $0.76 to less than $0.20 (Cole et al. 2025).

Partnerships with private sector entities, such as telecommunications companies, social media companies, and mass media may help facilitate free, large-scale dissemination of forecasts. In some cases governments can further reduce dissemination costs at scale by negotiating with telecom operators. Telecommunications companies are subject to regulation, and rural cell phone towers are typically underused, so these companies may be willing to deliver at least some weather messages with the most important news (for example about rainy season onset, emergencies, or heat warnings) for free. Social media companies may disseminate forecasts for free for customer acquisition, to generate positive public relations, or due to social good motivations. Mass media traditionally includes weather forecasts because they appeal to listeners.

Governments can choose whether to produce their own forecasts or purchase them from private providers. It is hard for private firms to earn revenue using a subscription model of selling forecasts because farmers share forecasts with each other. Some firms sell forecasts to businesses, such as agribusiness, or to governments. However, private sector firms often repackage and distribute forecasts in user-friendly ways, supporting those efforts with advertising. Governments can weigh the advantages of purchasing these forecasts versus taking advantage of open access AI models based on their ability to predict agriculturally relevant variables.

5. Several institutions are providing financing and technical assistance to support governments to deliver weather forecasts

Multilateral development banks (MDBs) and national governments have announced major commitments to invest in weather forecasts at COP29. The Asian Development Bank (ADB) committed $300 million USD to support advanced weather forecasts for farmers in Asia and the Pacific as part of its 2025-2027 food security operations and the Inter-American Development Bank (IADB) announced an expectation to integrate weather forecasts in a portfolio of $280 million USD in loans related to agriculture, including in Bolivia, Chile, Colombia, and Peru (WMO, 2024). During the 16th Session of the Conference of the Parties to the United Nations Convention to Combat Desertification, the Arab Gulf Programme for Development (AGFUND) and the Arab Bank for Economic Development in Africa (BADEA) announced support to reach 10 million farmers with digital agriculture and weather forecasts in Ethiopia.

The Agricultural Innovation Mechanism for Scale (AIM for Scale), a global initiative supported by the Gates Foundation and the International Affairs Office of the Presidential Court of the UAE, was launched at COP28 to scale cost-effective innovations in low- and middle-income countries and adopted weather services for farmers as its first area of focus. AIM for Scale provided financial support for monsoon onset benchmarking and forecasting in India, and was involved in the inception of the project through its Technical Panel on Weather Forecasts. AIM for Scale is separately training officials from meteorological departments and ministries of agriculture on AI weather forecasting, and is working with multilateral development banks (MDBs) and governments to effectively deliver weather forecasts at scale.

Other organizations are well-positioned to support the development, adaptation, and dissemination of AI weather forecasts. These include the African Centre of Meteorological Applications for Development (ACMAD), which supports meteorological services across Africa, and the Human-Centered Weather Forecasts (HCF) Initiative at the University of Chicago, which develops, tests, and benchmarks AI weather models and partners with governments to support forecast dissemination. Academic institutions and non-governmental organizations, like Precision Development, can also provide technical assistance in message design, testing, and dissemination to optimize the delivery of forecasts so that they are easy for people to understand and act upon.

6. Potential for further improvements

A standardized system for human-centered benchmarking of forecast accuracy would enhance transparency, strengthen incentives for forecast producers, and facilitate the procurement of better forecasts for end users. Such a benchmarking system would need to focus on users' needs, including what information is agriculturally relevant, not just meteorological metrics. Additional research to identify where and under which conditions existing forecasts are already performing well could build on the existing work of the International Research Institute for Climate and Society (IRI) and the European Centre for Medium-Range Weather Forecasts (ECMWF) (IRI; ECMWF). The results would identify "forecasts of opportunity" where existing forecasts can be used immediately, as well as establish the standards for external validation of forecasts. This system could be housed within the World Meteorological Organization (WMO) or another similar organization. If made publicly available, the results of this validation and research could be used by governments and other stakeholders, thereby informing decisions about which forecasts to procure and deliver in their geographies. The results could also help improve transparency and incentivize forecast producers to improve their products.

AI weather models will continue to improve across geographies and time scales. AI models are already undergoing rapid improvements, which may lead to higher-resolution, more accurate, and earlier weather forecasts. Of particular interest is the advances at the subseasonal-to-seasonal (S2S) lead times. Another area of interest is AI models that better represent tropical dynamics and the effects of land and ocean feedback on weather. Regularly benchmarking these models to identify which produce the most accurate forecasts for specific agricultural needs ensures that improvements in model performance translate directly into greater benefits.

AI weather models can be further refined via benchmarking exercises and targeted R&D. Future AI weather models could be adapted and trained for specific weather events and contexts. Benchmarking exercises could be conducted to evaluate the accuracy of various AI weather models in different geographic and climatic contexts, particularly tropical areas. Further R&D could improve the accuracy and usefulness of AI models or extend prediction lead times.

AI weather forecasting models could also be modified to include or target other variables relevant to agricultural decisions, such as pest outbreaks, soil moisture levels, and heat stress. A weather-based pest advisory for potato farmers in Bangladesh helped reduce the risk of crop loss (Barnett-Howell 2021). Soil moisture models are already benefiting farmers in high-income countries and could potentially do so in lower-income countries. Heat wave forecasts could also incorporate humidity to forecast unperceivable heat—a combination of high temperature and humidity. Forecasting such conditions days or even weeks in advance incorporates not only peak daytime temperatures and humidities, but also nighttime temperatures which can be epidemiologically relevant. Heat advisories coupled with guidance (such as how to recognize the symptoms of heat stroke) could help farmers better time their work during the day, and reduce exposure for vulnerable family members, such as the elderly.

Making weather data and forecasts publicly available can advance weather forecasting, generating a global public good. Since many weather systems span national borders, data from one country can improve forecast accuracy in another. However, barriers to coordination and data sharing prevent this information from being shared, limiting progress. Building on the successful model of the WMO, investments that release data and forecasts into the public domain are likely to have spillover benefits for other forecasts, in addition to their direct benefits. International efforts to invest in weather stations could be coupled with agreements to share data. Federated data-sharing frameworks, which leverage decentralized learning, could enable national and regional partners to contribute observations for model training and validation without exposing data to unauthorized use.

An online forecast generation and localization platform could facilitate greater coordination and improve forecasts. For example, the WMO's global Climate Services Information System (CSIS) could further tailor its information towards end users in low- and middle-income countries. Such a platform could act as a public portal for users, including forecast providers, researchers, and "boundary organizations" that bridge between forecast providers and end users. This platform could host past, present, and future weather data to allow users to produce, deliver, and validate improved forecasts (GFCS). It could be used to generate real-time operational forecasts from various models (e.g., for further blending), and could help with tailoring forecast models with local data and metrics.

Beyond generating forecasts, AI also has tremendous potential in communicating weather information with farmers. LLMs could enhance the communication of forecasts and other agricultural information to farmers by enabling farmers to interact with information in a more natural language way.

Human-centered design and A/B testing can help ensure that weather information provided is comprehensible, useful, and actionable for farmers. Convening focus groups with farmers to better understand what information and delivery mechanisms are most useful and conducting A/B testing can improve and refine the dissemination of forecasts. For instance, focus group discussion in India found that farmers found it easier to understand forecasts when percentages were paired with ratios (out of 100).

7. Conclusion

AI-informed forecasts have the potential to empower farmers around the world to make more informed decisions. Multiple randomized trials find monetary benefits ranging from $5-141 USD. India's 2025 program providing 38 million farmers with monsoon onset forecasts, at a total cost of less than $0.03 USD per farmer, provides a model. National governments and multilateral development banks can play key roles in supporting such efforts, and philanthropy can play an important role in helping researchers in universities, meteorological departments, research institutes, and the private sector benchmark models and adapt them to the needs of farmers in low- and middle-income countries. Costs and benefits of different programs in different contexts will vary, but there are likely many investments with benefit cost ratios exceeding 100:1.

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