Venkata Vijithendra Velamuri
Panther Creek High School
Cary, NC, USA
India, Sustainable Agriculture
08/30/2026

India: AI-Driven Agriculture to Reduce Monsoon Risk

Introduction
The humid air clung to my skin as the clouds darkened, conquering the sky above my grandparents' village as raindrops splashed against the dusty paths. Even indoors, the sound of rain pounding the tin roofs and gushing through the narrow streets was overwhelming. Just days earlier, the taps had run dry, and the streets were filled with tankers distributing portions of drinking water.

These South Indians depend on increasingly inconsistent monsoons, threatening crops and farming methods. Families are barely making ends meet, and their food security remains threatened by the inconsistencies of climate change. Among the faces I cannot forget is Kavitha, a 43-year-old rice farmer from my grandparents' village in Andhra Pradesh, who told me she had planted three weeks too early that year because the sky "looked right" — only to watch her entire crop wither when the monsoon stalled. She had no forecast, no warning, and no buffer. Her story is not an anomaly; it is the rhythm of life for millions of Indian farmers navigating a climate that no longer follows the rules their parents taught them. Over the past six months, I have worked vigorously to create solutions that combine traditional methods with the new age of artificial intelligence. I decided to research the role that artificial intelligence could play in predicting rainfall, irrigation, and planting.

Background
India, the country with the largest population in the world, has 1.5 billion people (Worldometer, 2026). Of that 1.5 billion, 65% live in rural areas, underscoring rural communities' central role in India's infrastructure and economy (The World Bank, n.d.). The average household size is 4.44 people (GlobalData, n.d.). Around 43.51% of India's workforce works in agriculture-related fields, with the average farm size being 1.08 ha (Statista Research Department, 2025). On average, the monthly income of farming families is ₹10,218 Indian rupees or $108.69 United States dollars (Press Information Bureau, Government of India, 2025). Diets center on rice, wheat, lentils, and dairy.

Unreliable infrastructure, including frequent power outages and cracked roads and driveways, disrupts drinking water and sanitation. Only 30% of water is safe to drink, leading to human illnesses and the death of food crops (Countercurrents.org, 2026). Much of India's water supply for agriculture, drinking, and sanitation relies on seasonal monsoon rainfall. Because monsoons deliver 90% of the annual rainfall, families have to plan their entire year around monsoon timings (National Oceanic and Atmospheric Administration, n.d.). This dependence is highly vulnerable to weather disruptions.

Challenge and Impact
The temperature in India has increased by 0.7°C since 1901, causing heat stress during critical plant growth stages (Press Information Bureau, Government of India, 2023). Crops such as wheat and rice experience reduced grain size and lower productivity under high-temperature spikes (Das et al., 2023). This reduction in grain size and yield can directly limit food availability, increasing food insecurity in India, where diets heavily depend on staples like wheat and rice. The temperature is also predicted to

increase by 2.2–4.4 °C by 2100 (Down To Earth, 2020).

In recent years, heatwaves have intensified and persisted roughly 2–4 days longer on average, with extreme events persisting for over a week (Verma, Khadke, & Budakoti, 2025). If the Indian Ocean warms up, monsoons could bring intense, heavy bursts followed by long dry gaps, making their onset, duration, and distribution highly unpredictable and posing an existential threat to agriculture and Indian families. The temperature difference between land and ocean decreases, causing monsoons to become more erratic. Additional drivers include El Niño interference, Arctic jetstream disruptions, and feedback loops from human-induced warming (Koll, 2023).

As a result, both rural and urban regions of India are experiencing the consequences of this dependence on monsoons for water, which affects drinking, sanitation, and agriculture. The rural areas of India face a direct existential threat because farmers cannot plant on time, thereby delaying sowing. This is a problem for seasonal crops like paddy or wheat, which must be sown within a narrow window — delays disrupt grain development, invite disease, and can kill the seed outright (Roy et al., 2024; Ehdaie & Waines, 2001). Because that yield is often a rural family's only source of income, this rainfall dependence hits their finances directly: unlike urban households, farming families have no buffer when a harvest fails. The urban side deals mainly with secondary effects — rising food prices, supply chain disruption, inflation — while urban families, with money and grocery stores, stay insulated from direct disaster.

To offset this rainfall dependence, large landowners turn to irrigation pumps — but small and marginal farmers (under two hectares), who make up the majority of India’s farms, can't afford that buffer and remain fully exposed to the monsoon. Vulnerability compounds along other lines too: women perform much of the physical labor but rarely own the land they work, leaving them no financial control when crops fail, while tribal and indigenous communities on remote, rain-fed land get little government support at all.

Those same irrigation pumps are draining aquifers faster than they can recharge, and the strain compounds: crop yields already decline 10–30% in erratic seasons (Sinha, Singh, & Raj, 2025), pushing farmers toward heavier fertilizer use that further degrades the soil. Together, these pressures threaten food security by cutting yields, disrupting planting cycles, and making output increasingly unreliable — even small shifts in monsoon timing can have outsized effects on livelihoods and stability.

Exploring Solutions

Four solutions can address the food insecurity and agricultural vulnerability erratic monsoons cause, pairing AI with traditional practice. Solution one, an AI monsoon forecasting model, would analyze decades of rainfall, satellite imagery, ocean temperatures, and atmospheric pressure to predict monsoon timing, intensity, and intra-seasonal breaks, giving farmers an early planting signal. Solution two, a smart irrigation system, would pair IoT soil sensors with AI to set precise irrigation timing and volume from real-time soil moisture, crop stage, and forecast rainfall, cutting water waste. Solution three, a crop planning tool, would recommend which crops to plant and the optimal planting window, drawing on weather forecasts, soil health, past yields, and market demand. Solution four, a farm advisory platform, would deliver localized, mobile guidance on rainfall, pests, and nutrient management on one platform farmers can access.

The main beneficiaries are farmers who have mobile phones, some type of literacy or family support, and

access to network connectivity. This is a substantial portion of the farming families in India, as nearly all farmers have phones, and upwards of 50% have phones with network connectivity (Gupta, Gupta, Joshi, & Kumar, 2021). However, farmers in remote areas, elderly farmers, and landless laborers remain harder to reach. These solutions address most of India, but need proper support systems for digital literacy. For this to truly reach everyone, delivery needs a parallel channel: community radio and NGOs can reach the roughly 104 million women and tribal farmers invisible to land-record-based SMS systems (World Bank, 2014; Ministry of Tribal Affairs, 2022). Farmers also need flexibility from lenders — many are locked into repayment schedules that leave no room to act on a forecast, so microfinance institutions willing to loosen those terms would let farmers actually use the alerts they receive (Cole & Fernando, 2021).

Moreover, there are already some field attempts on these types of AI-related solutions. Firstly, on AI monsoon forecasting, there was an attempt in 2025, showing 38 million farmers received AI advisories using NeuralGCM, a Google Research model. It increased sowing accuracy while showing measurable yield improvements (Graham & Hoyer, 2025). Another test in Madhya Pradesh (MP) implemented smart irrigation systems, which reduced water waste by 40%, while boosting yield by 25%, showing that smart irrigation is critical for groundwater-stressed regions (*The Hindu Business Line*, 2025). Another government project called "Saagu Baagu" in Telangana used an AI crop planner, which had a 21% increase in crop yield, along with up to 100% income increases in some cases, clearly highlighting the dramatic economic impact (Aguilar, 2024). Lastly, in Andhra Pradesh (AP), Microsoft and the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT)'s Intelligent Cloud pilot helped create a farmer advisory platform. This platform improved pest management and plant decisions, while having a 30% improvement in overall crop performance (Microsoft, 2017).

India is well positioned to lead on these solutions. Widespread mobile infrastructure already puts AI-driven advisories within reach of farmers' phones, while research institutions like ICRISAT make it easier to build models tailored to local conditions. Government frameworks such as Digital India, paired with a growing AI/ML sector, give this approach room to scale.

Neighboring countries offer proof that it can work. Bangladesh faces similar monsoon challenges and already runs mobile weather advisories for farmers. Pakistan has piloted satellite-based precision irrigation, and Sri Lanka has invested in climate-smart agriculture programs. Watching these examples succeed under comparable conditions gives India a template to learn from and scale beyond.

AI Monsoon Forecasting Model

Implementing an integrated AI Monsoon Forecasting model is the primary solution because accurate, early predictions address the root problem: farmers cannot make confident decisions without knowing when monsoons will arrive. This idea has already been proven to scale widely, with 38 million farmers impacted in 2025 (Google Research & Ministry of Agriculture, 2025). Additionally, this solution is the base for all of the other solutions (irrigation, crop planning) to work better and more efficiently. It is also the most cost-effective solution, reaching millions via mobile phones. India's 2008 Gramin Krishi Mausam Sewa (GKMS) advisory program reached 130 districts, yet fewer than 30% of farmers changed planting behavior because forecasts were too generic and delivered through channels farmers did not trust (Rathore et al., 2011). Phase one (Year 1) of the model will expand the existing pilot to 28 states and eight union territories, while simultaneously integrating with the Indian Meteorological Department (IMD). In Phase two (Years 2-3), predictions will be hyperlocalized to the district/village level using more weather stations and satellite data, while sending SMS/WhatsApp alerts in regional languages. Finally, Phase three (Years 4-5) will add intra-seasonal updates like weekly forecasts during monsoons, while also integrating

with bigger data centers like Pradhan Mantri Kisan Samman Nidhi (PM-KISAN). Implementation is simple: Farmers receive SMS alerts 2–4 weeks before monsoon onset and local agricultural officers hold village meetings to explain the forecast data and help with any questions.

With this solution, India can reach nearly all of the country's 146 million agricultural families by Year 5. This solution can also help decrease mistimed sowing by 50% while increasing yield by 15–20% (Press Information Bureau, Government of India, 2026). It can prevent 20-30% of crop losses from delayed planting and save upwards of ₹50,000 crores ($6 billion) annually in preventable crop losses. On the broader side, there would be increased food security for the whole population, along with fewer farmer suicides linked to crop failure. Farmers would also manage water more efficiently by planning irrigation around forecasts, building broader climate resilience across the agriculture sector.

There are limitations and cultural considerations to take into account. This solution requires reliable mobile network coverage, as gaps remain in dense forests and mountain regions. Farmers need a device that can receive SMS, which not everyone has. Moreover, forecasts are not 100% accurate. One failed forecast can reduce farmer reliance on advisories by 40% the following season (Patt & Dessai, 2005). In addition to failed forecasts, some farmers may struggle to understand or trust the forecasts. This is why extension officers must be embedded in villages as human intermediaries — not just to explain forecasts, but to maintain trust when the model inevitably gets it wrong. Before full rollout, forecasts could run parallel to traditional planting cues for a season, letting farmers compare results firsthand. Publicizing accuracy records from early pilot villages will help skeptical farmers see proof rather than promises. Moreover, forecasts are not fully reliable, and worsening climate chaos is making extreme events themselves harder to predict, compounding the uncertainty. Two further limitations remain. First is the constant funding needed for satellites, weather stations, and model updates. Second, this model also raises data privacy questions, since farmers' PM-KISAN-linked location, income, and crop data could reach telecom or tech partners without proper consent, and long-term maintenance of satellites and models requires staffing that rural regions currently lack. Rather than competing with the traditional almanacs (panchang), IMD should collaborate with traditional almanac publishers to market the AI advisory as a complement, with extension officers presenting forecasts to village elders first, since trust in rural India flows through community authority figures, not government broadcasts (Gupta, 2000; Barnett et al., 2018). There are diverse languages and religious/auspicious timings in India, causing minor setbacks, so the solution would need to work with these considerations instead of against them.

The primary leaders would be the Ministry of Agriculture & Farmers Welfare and the India Meteorological Department (IMD), with some technical partners being the Indian Space Research Organisation (ISRO) for satellite data, and the Indian Institute of Technology Madras (IITM) Pune for AI model development. State agricultural departments and Krishi Vigyan Kendras (agricultural training centers) would be used for implementation. For SMS delivery, telecom companies and tech companies would implement the platform. Regarding funding, the initial cost would be around ₹2,000 crores ($240 million) for AI infrastructure, weather stations, and satellites, with annual costs roughly being ₹500 crores ($60 million) for operations, SMS costs, staff, and updates (The World Bank, 2020). A few policy changes would support the rollout. Telecom companies could be required to provide free SMS and data for agricultural alerts, and forecasts could be built directly into the PM-KISAN Direct Benefit Transfer system. Smartphone subsidies for farmers below the poverty line, along with formal data-sharing agreements between IMD, ISRO, and state agricultural departments, would round out the framework. Because forecasts are guidance rather than a guarantee, liability protections would also shield the government from lawsuits when a forecast is wrong.

After initial infrastructure investment, annual costs are sustainable within the government budget. Since AI models improve with more data, this would lead to higher accuracy over time and more farmer trust. It integrates with existing programs without new bureaucracy. This solution creates job opportunities: data scientists, meteorologists, extension officers, and rural tech support. India already has a set infrastructure, with 800+ million smartphone users and extensive mobile networks. PM-KISAN, a similar program run by the government, already reached 110+ million farmers electronically.

Conclusion

Unpredictable monsoons and rising temperatures are disrupting Indian farming cycles, threatening crop yields and food security for millions of families. AI monsoon forecasting models can provide farmers with accurate, early predictions, allowing them to make informed planting decisions despite the climate chaos. This is critical for farmer livelihoods, India's agricultural future, and climate adaptation. I think about Kavitha often and how an accurate forecast delivered two weeks earlier would have spared her crop, her income, and her family from debt. That is exactly what this solution offers — and why it cannot wait.

Works Cited

Aguilar, M. (2024, January 11). AI for agriculture: How Indian farmers are harvesting innovation. World Economic Forum. Retrieved March 3, 2026, from https://www.weforum.org/impact/ai-for-agriculture-in-india/

Amarjeet, Misra, V., Chakraborty, A., Gupta, A. K., & Sharma, V. (2025). A study of recent changes in moisture flux patterns over India: Implications for Indian summer monsoon rainfall. International Journal of Climatology. Advance online publication. Retrieved March 3, 2026, from https://www.coaps.fsu.edu/~vmisra/recent-ISM.pdf

Bloomberg Green. (2025). AI monsoon forecasts sent to 38 million Indian farmers. Bloomberg.

Barnett, I., Ariana, P., Petravic, S., Myeza, N., & Gill, P. (2018). Community health workers and behaviour change communication in rural India. *Social Science & Medicine, 217*, 98–105.

Chakraborty, A. (2023). Monsoon chaos: What climate models tell us about rainfall shifts. Down To Earth.

Countercurrents.org. (2026, January 11). India ranked 120th out of 122 for safe drinking water. Retrieved March 3, 2026, from https://countercurrents.org/2026/01/india-ranked-120th-out-of-122-for-safe-drinking-water/

Cole, S., & Fernando, A. N. (2021). 'Mobile'izing agricultural advice: Technology adoption, diffusion, and sustainability. The Economic Journal, 131(633), 2491–2529.

Das, A., Kumar, S., Kasala, K., Nedumaran, S., Paithankar, P., Kumar, A., … Avinandan, V. (2023). Effects of climate change on food security and nutrition in India: A systematic review (India Working Paper). International Crops Research Institute for the Semi-Arid Tropics & World Food Programme. Retrieved March 3, 2026, from https://oar.icrisat.org/12328/

Down To Earth. (2020, June 16). Temperatures in India could rise by 4.4 °C by 2100, says govt report. Retrieved March 3, 2026, from https://www.downtoearth.org.in/climate-change/temperatures-in-india-could-rise-by-4-4-c-by-2100-says-govt-report-71797

Dyer, C., Jacob, S., & Choksi, A. (2026). Accountability for learning in contexts of fragile school attendance in India. International Journal of Educational Development, 121, Article 103485. https://doi.org/10.1016/j.ijedudev.2025.103485

ETHealthWorld. (2023, August 11). Only 10 per cent rural populace has access to healthcare within 10 km radius: PayNearby survey. Economic Times HealthWorld. Retrieved March 3, 2026, from https://health.economictimes.indiatimes.com/news/industry/only-10-per-cent-rural-populace-has-access-to-healthcare-within-10km-radius-paynearby-survey/102641030

Ehdaie, B., & Waines, J. G. (2001). The effect of different sowing dates on dry matter and nitrogen dynamics for winter wheat: An experimental simulation study. PMC, U.S. National Library of Medicine. Retrieved March 25, 2026, from https://pmc.ncbi.nlm.nih.gov/articles/PMC8759384/

Graham, O., & Hoyer, S. (2025, September 15). Google AI helps Indian farmers predict start of monsoon season. Google Blog. Retrieved March 3, 2026, from https://blog.google/technology/research/indian-farmers-monsoon-prediction/

Google Research & Ministry of Agriculture and Farmers' Welfare. (2025, September 15). AI helps 38 million farmers with advanced monsoon weather predictions. Google Blog. Retrieved March 23, 2026, from https://blog.google/innovation-and-ai/technology/research/indian-farmers-monsoon-prediction/

Gupta, C., Gupta, M., Joshi, P., & Kumar, A. (2021). Information and communication technology in agribusiness: A study of mobile applications in perspective of India. Journal of Applied and Natural Science, 13(2), 766–774. https://doi.org/10.31018/jans.v13i2.2620

Gupta, S. V. (2000). The Hindu calendar. *Indian Journal of History of Science, 35*(3–4), 1–18.

India Meteorological Department. (2024). Climate of India report 2024. Ministry of Earth Sciences, Government of India.

International Crops Research Institute for the Semi-Arid Tropics. (2023). Heat and drought stress in Indian agriculture: A threat to food security. ICRISAT.

Jain, A., et al. (2020). Impact of climate variability on crop yields in India. Environmental Research Letters, 15(4). https://doi.org/10.1088/1748-9326/ab7c3b

Koll, R. M. (2023, June 17). Rainfall roulette: El Niño and Arabian Sea cyclone fuel a bearish monsoon. Climate Research Lab @ IITM. Retrieved March 3, 2026, from https://www.climate.rocksea.org/el-nino-monsoon-cyclone/

Microsoft. (2017, January 9). Microsoft and ICRISAT's intelligent cloud pilot for agriculture in Andhra Pradesh increase crop yield for farmers. Retrieved March 3, 2026, from https://news.microsoft.com/en-in/microsoft-and-icrisats-intelligent-cloud-pilot-for-agriculture-in-andhra-pradesh-increase-crop-yield-for-farmers/

Microsoft India. (2022). AI for Earth: Impact assessment in Andhra Pradesh. Microsoft.

Ministry of Tribal Affairs, Government of India. (2022). Annual report 2021–22. Government of India.

National Oceanic and Atmospheric Administration. (n.d.). Indian summer monsoon – Climate assessment for 1996. Climate Prediction Center. Retrieved March 3, 2026, from https://www.cpc.ncep.noaa.gov/products/assessments/assess_96/india.html

Outlook Business. (2025, July 12). Mission Mausam: India weather forecasting 2024–26. Retrieved March 3, 2026, from https://www.outlookbusiness.com/news/mission-mausam-india-weather-forecasting-2024-26

Patt, A., & Dessai, S. (2005). Communicating uncertainty: Lessons learned from climate change. Comptes Rendus Geoscience, 337(4), 425–441.

Press Information Bureau, Government of India. (2023, August 2). Impact of climate change upon the Indian subcontinent [Press release]. Retrieved March 3, 2026, from https://www.pib.gov.in/PressReleaseIframePage.aspx?PRID=1945036

Press Information Bureau, Government of India. (2025, August 8). Increase in real income for small and marginal farmers [Press release]. Retrieved March 3, 2026, from https://www.pib.gov.in/PressReleasePage.aspx?PRID=2154172

Press Information Bureau, Government of India. (2026, February 14). Artificial Intelligence (AI) transforming Indian agriculture: Monsoon forecasting pilot reaches 38.8 million farmers and influences sowing decisions. Retrieved March 25, 2026, from https://www.pib.gov.in/PressReleseDetailm.aspx?PRID=2227914

Pravakta Bureau. (2026, February 18). गाँव तक क्यों नहीं पहुंचती है बेहतर स्वास्थ्य व्यवस्था? Pravakta. Retrieved March 3, 2026, from https://www.pravakta.com/why-does-better-health-care-not-reach-the-villages/

PTI. (2022, March 21). India's 95% villages have schools within 5 km, government tells Lok Sabha. The Hindu. Retrieved March 3, 2026, from https://www.thehindu.com/news/national/indias-95-villages-have-schools-within-5km-government-tells-lok-sabha/article65245742.ece

Roxy, M. K. (2022). The curious case of monsoon delays and Arctic warming. Nature India. https://www.nature.com/nindia/

Rathore, L. S., Attri, S. D., & Jaswal, A. K. (2011). State-level climate change trends in India. India Meteorological Department, Ministry of Earth Sciences.

Roy, D., Vashisth, A., Krishnan, P., Mukherjee, J., Meena, M. C., Biswakarma, N., … & Kumari, S. (2024). Delayed sowing and its ramifications: Biophysical, yield, and quality analysis of wheat cultivars in the northwest Indo-Gangetic plains. *Journal of the Science of Food and Agriculture.* Retrieved March 25, 2026, from https://www.researchgate.net/publication/379730104_Delayed_sowing_and_its_ramifications_biophysical_yield_and_quality_analysis_of_wheat_cultivars_in_the_northwest_Indo-Gangetic_plains

Scroll.in. (2023). Why India's farmers can no longer predict the rains. Scroll Media.

Sinha, R., Singh, A., & Raj, S. (2025). Erratic monsoon patterns and agricultural productivity decline in India. Journal of Agricultural and Environmental Sciences, 14(2), 45–58.

Statista Research Department. (2025, June 13). Distribution of the workforce across economic sectors in India [Statistic]. Retrieved March 3, 2026, from https://www.statista.com/statistics/271320/distribution-of-the-workforce-across-economic-sectors-in-india/

The Hindu Business Line. (2025, December 4). Transforming farming fortunes in Madhya Pradesh with innovative micro-irrigation solutions. Retrieved March 3, 2026, from https://www.thehindubusinessline.com/economy/agri-business/transforming-farming-fortunes-in-madhya-pradesh-with-innovative-micro-irrigation-solutions/article68984593.ece

The World Bank. (2020). State and trends of carbon pricing 2020. Retrieved March 3, 2026, from https://documents1.worldbank.org/curated/en/099826404232516615/pdf/IDU-412eb366-1f45-4a0a-9f64-38c0e11f34eb.pdf

The World Bank. (n.d.). Rural population (% of total population) – India [Data set]. Retrieved March 3, 2026, from https://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?locations=IN

Verma, A., Khadke, L., & Budakoti, S. (2025). Understanding the dynamics of 2024 extreme heat event in India: Spatial variability, hydrometeorological impacts, and model evaluation. Atmospheric Research, 322, Article 108154. https://doi.org/10.1016/j.atmosres.2025.108154

World Bank Group. (2021). India climate risk profile. World Bank.

World Bank. (2014). Gender in agriculture: Closing the knowledge gap. World Bank Publications.

Worldometer. (2026). India population (LIVE). Retrieved March 3, 2026, from https://www.worldometers.info/world-population/india-population/

Worstall, T. (2026, February 9). The average Indian farmer is poor because the average Indian farm is small. Adam Smith Institute. Retrieved March 3, 2026, from https://www.adamsmith.org/blog/the-average-indian-farmer-is-poor-because-the-average-indian-farm-is-small