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Crop Forecasting in the Shadow of El Nino

*Ayush Sharma, Dr. Kanik Kumar Bansal and Sandeep Kaur
Faculty of Agriculture, Guru Kashi University, Sardulgarh Road,
Talwandi Sabo, Bathinda, Punjab, India
*Corresponding Author's email: upretiayush7@gmail.com

El Nino has returned in 2026, and its consequences for global agriculture are already unfolding. Erratic rainfall, rising temperatures, and prolonged dry spells are threatening staple crop production across South Asia, Southeast Asia, and sub-Saharan Africa. This article explores how El Nino-driven climate variability affects crop yields, examines the limitations of current forecasting systems, and highlights modern tools including satellite monitoring and machine learning that can strengthen early warning capabilities. Improving forecast accuracy and ensuring that information reaches farmers in time remains the most urgent challenge facing agricultural systems today.

Keywords: El Nino, crop forecasting, food security, ENSO, climate variability.

Introduction

Agriculture has always carried weather risk. Farmers have read the sky, tracked the rains, and planned their seasons around the rhythms of local climate for thousands of years. But the scale and reach of El Nino the periodic warming of the tropical Pacific that reshapes weather patterns across entire continents sits in a different category altogether. When El Nino takes hold, its consequences appear simultaneously on rainfall gauges in Punjab, river levels in the Mekong Delta, and harvest records in the African Sahel et al., no other climate phenomenon touches global food production as broadly or as forcefully. In 2026, El Nino has returned. Anomalous sea surface temperature warming across the equatorial Pacific the defining physical signature of the phenomenon has been confirmed by the World Meteorological Organization and corroborated by oceanic monitoring networks worldwide. The agricultural implications are already unfolding. Weakened monsoon systems across South and Southeast Asia are reducing soil moisture during critical sowing windows. Below-normal rainfall across parts of sub-Saharan Africa is squeezing the narrow margins that smallholder farmers depend on. Flooding in portions of South America is damaging standing crops and delaying planting across productive agricultural zones. None of this is without precedent. Strong El Nino events have repeatedly exposed the vulnerability of staple crop systems to ENSO-driven climate variability. Rice, wheat, and maize the three cereals that collectively provide the majority of global caloric intake show documented production declines of 10–25% during severe El Nino years . Drought across Asia and Australia combined with erratic precipitation in the Americas has historically generated supply shocks that reverberate through global food markets long after the seasonal rains eventually normalize. What distinguishes 2026 is the moment in which El Nino arrives. Global food systems are already under pressure strained by post-pandemic supply chain disruptions, geopolitical conflicts affecting grain trade, and the cumulative baseline shifts that long-term climate change continues to impose. The margin for absorbing another production shock is thinner than it has been in years.

Crop forecasting is the primary scientific tool available to anticipate and manage that shock. By integrating meteorological observations, satellite-derived vegetation monitoring, and process-based crop simulation models, forecasting systems can estimate yield outcomes weeks or months before harvest giving governments, aid agencies, and traders the lead time needed to act before shortfalls escalate into crises. The spatial heterogeneity of El Nino's impacts, persistent data gaps in vulnerable regions, and the coarse resolution of seasonal climate models all limit what current forecasting systems can reliably deliver (Hansen et al., 2011). Recent advances in machine learning, high-resolution satellite monitoring, and ensemble climate modeling have improved forecast skill considerably (Ray et al., 2015) but translating technical progress into timely, actionable information for farmers remains the defining challenge.

Impact of El Nino on Agriculture

El Nino reaches into nearly every farming system on earth, though its effects are uneven and often cruel in their selectivity hitting hardest where farmers have the least capacity to absorb a bad season. Precipitation is where the damage begins. Across South Asia, Southeast Asia, and Australia, El Nino years bring persistently below-normal rainfall during critical growing periods, leaving rainfed crops starved of soil moisture at germination and early vegetative growth. The opposite problem unfolds in parts of South America, where excess rainfall causes waterlogging and soil erosion that are equally destructive to yield potential. The same climate event that dries one continent drowns another. Temperature rise compounds these effects. Warmer conditions accelerate crop development, squeezing the flowering and grain-filling stages into shorter, more stressful windows. Heat stress during pollination increases sterility in rice and wheat, producing lighter grains and smaller harvests even in seasons where rainfall holds up reasonably well. When heat and drought arrive together as they frequently do during strong El Nino years the losses in rice, wheat, and maize production are substantial and well documented. The consequences extend well beyond crop fields. Shrinking pastures and drying water sources weaken livestock productivity. Pest pressure intensifies as locust populations expand in drier zones and fungal pathogens spread where humidity rises (FAO, 2016). Smallholder farmers absorb the steepest losses they lack irrigation backup, crop insurance, and financial reserves to survive a failed season. In India, ENSO-driven monsoon deficits have repeatedly reduced output of rice, pulses, and oilseeds that rural households depend on for both income and food (Gadgil et al., 2004).

Challenges in Crop Forecasting during El Nino

Forecasting crop production during El Nino is genuinely difficult not because scientific tools are lacking, but because uncertainty runs through every layer of the problem, from the ocean surface to the farm gate. The difficulty starts with El Nino itself. Even the most advanced ocean-atmosphere models cannot reliably predict the precise timing, intensity, or geographic reach of an ENSO event beyond a few months (Barnston et al., 2012; Meng et al., 2019). A crop forecast built on that uncertain climate foundation inherits the same limitations from the outset. Spatial variability adds another layer of complexity. El Nino does not arrive uniformly drought strikes one region while a neighboring area floods. Broad-scale forecasting models struggle to capture these sharp local contrasts, making continental-level conclusions potentially misleading at the district or village level (FAO, 2023). Translating coarse seasonal climate outputs into field-level predictions a process known as downscaling remains one of agricultural meteorology's most persistent unsolved problems.

Climate signals alone cannot determine yields. Soil fertility, seed variety, irrigation availability, and individual farm management decisions all shape how a weather pattern becomes an actual harvest (Iizumi et al., 2014; Ray et al., 2015). Forecasting models that overlook these agronomic realities produce outputs that are climatologically sound but practically unreliable. Data scarcity makes every challenge worse. Across South Asia and sub-Saharan Africa regions most severely exposed to El Nino observational networks are thin, yield records are short, and real-time monitoring is limited (Hansen et al., 2011). Climate change further weakens historical ENSO-yield relationships as rising temperatures and shifting rainfall patterns push conditions outside the range that existing models were built to handle. Sudden extremes brief heatwaves, unseasonal frost fall entirely outside historical norms yet can destroy a harvest within days (Lesk et al., 2016).

El Nino-Induced Climate Variability and Its Impact on Agricultural Productivity in Punjab, India

Punjab, India's primary wheat and rice producing state, faces serious agricultural stress during El Nino years. Weakened southwest monsoon rainfall reduces soil moisture during kharif season, directly affecting paddy yields (Gadgil et al., 2004). Warmer winters compress wheat's grain-filling period, lowering output across millions of hectares. Smallholder farmers bear the heaviest burden through rising input costs, pest pressure, and groundwater depletion, threatening both farm incomes and regional food security (FAO, 2023).

Strategies to Improve Crop Forecasting Accuracy

Accurate crop forecasting during El Nino requires more than better models it demands better data, stronger institutions, and clearer communication between scientists and farmers. Combining satellite imagery, ground-based weather stations, and soil databases into unified forecasting systems significantly reduces prediction uncertainty. When multiple data sources are fused together, gaps in one stream are compensated by others (Lobell et al., 2015; Dorigo et al., 2007). Coupling these inputs with process-based crop models like DSSAT and APSIM driven by ENSO-conditioned seasonal forecasts allows yield risks to be identified months before harvest (Hansen et al., 2011). Machine learning algorithms have added further capability, capturing complex, non-linear relationships between climate variables and yield outcomes that conventional statistics cannot resolve (Jeong et al., 2016; Kamilaris and Prenafeta-Boldú, 2018). Incorporating large-scale climate indicators such as ENSO, IOD, and NAO into forecasting frameworks sharpens seasonal prediction skill and improves anticipation of droughts and floods. GIS-based spatial monitoring supports district-level decision-making by mapping crop conditions and soil variability across regions (Basso et al., 2013). Ultimately, even the most precise forecast loses its value if farmers cannot access or act on it (Hansen et al., 2011).

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