

Early warning of Pacific food-supply risks

ENSO, shipping, fertilizer and opportunities for further analysis

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ENSO implications for crops

Under our central scenario for the 2026–27 El Niño, we estimate a 17 percent reduction in Australian wheat production, about 5 million tonnes. We estimate U.S. maize gains of 4.9 percent, about 18 million tonnes. U.S. soybean gains reach 3.6 percent, about 4 million tonnes. These estimates describe the fitted ENSO contribution relative to production trends for harvests between September 2026 and August 2027. Actual harvests also depend on planted area, local weather, irrigation and farm inputs.

We estimate global increases of about 20 million tonnes of maize and 5 million tonnes of wheat. Soybean production increases by about 4 million tonnes, while paddy rice declines by a similar amount. Gains elsewhere therefore offset much of the regional losses in world totals. For Pacific buyers, the consequences depend on which crops are available from particular suppliers and when shipments arrive. Additional maize or soybean cannot replace rice in every use, and a wheat gain elsewhere may entail different delivery costs for buyers accustomed to Australian supplies.

We derive these estimates by matching historical crop responses to ENSO conditions over each growing season. The yield compilation contains 1.79 million observations across 193 countries. We combine subnational and national records with planting and harvest calendars, then estimate how yields have varied with seasonal ENSO exposure after removing local means and trends. We apply the fitted responses to the stored September 2026 ENSO outlook. Production weights hold planted area fixed, so the estimates do not yet incorporate farmers' responses to current prices or input availability.

We use low, central and high ENSO scenarios to assess how the harvest estimates depend on the event's development. The scenarios retain observed conditions through August 2026 and use the monthly evolution of 2015–16 to extend the September outlook through the coming seasons. We also examine the 1997–98 event as an alternative seasonal shape. Figures 1 and 2 show the index paths and selected crop responses. The resulting quantities are conditional estimates based on a dated outlook. The present analysis has not yet established their performance as an operational harvest forecast, and shared errors among producing regions require further assessment.

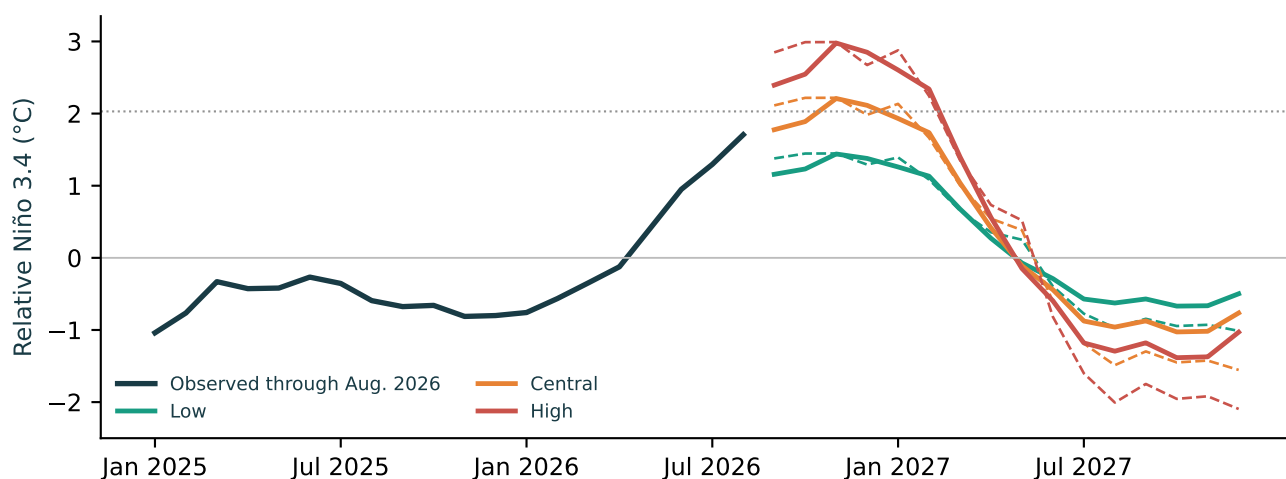


Figure 1: ENSO paths underlying the crop scenarios, adapted from Figure 1 of the manuscript. Observations end in August 2026. Solid colored lines follow the 2015–16 monthly shape scaled to the September outlook; dashed lines use 1997–98. The dotted horizontal line marks the largest growing-season exposure in the fitted record. These are dated scenario paths, not observations of the months ahead.

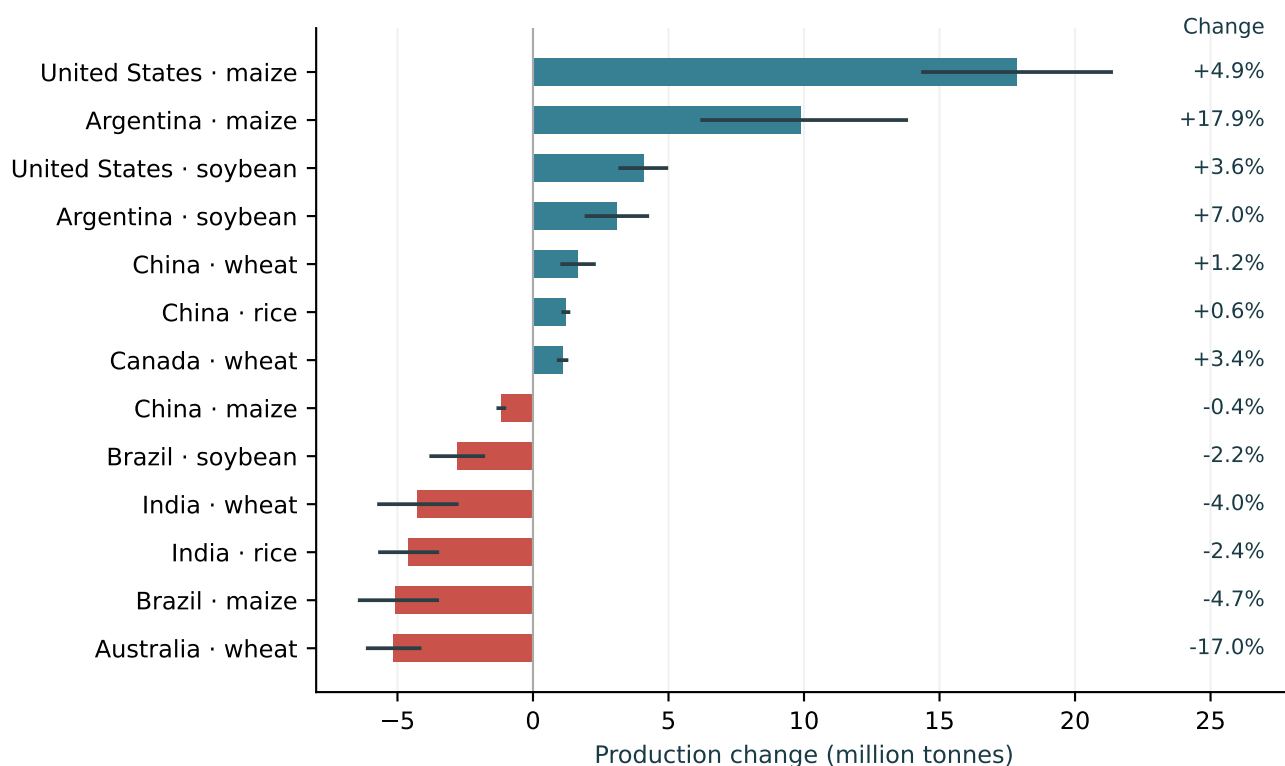


Figure 2: Selected crop-production changes among Pacific producers and suppliers, adapted from Figure 3 of the manuscript. Bars show the central ENSO scenario; horizontal lines span the low and high index scenarios with fitted crop responses held fixed. Labels give percentage changes. The lines are scenario ranges, not confidence intervals. Quantities cover harvests from September 2026 through August 2027; rice is paddy.

Tracking ENSO and rainfall

We track ENSO using monthly Niño 3.4 temperatures relative to tropical-mean warming, matched to each crop's growing season. The scenarios use the September outlook (Climate Prediction Center, 2026). Our September tracker extends rainfall observations through 25 September 2026 and compares matching partial growing seasons across years. Figure 3 places current rainfall against the historical ENSO relationship.

Indonesia's rice-area rainfall is about 50 percent below its reference, close to the fitted expectation. India's kharif maize areas are about 29 percent below their reference, a larger deficit than expected. Australian wheat and U.S. maize areas fall on the opposite side of normal from their fitted expectations. These departures show why the crop scenarios need local weather updates; rainfall alone does not establish the yield change.

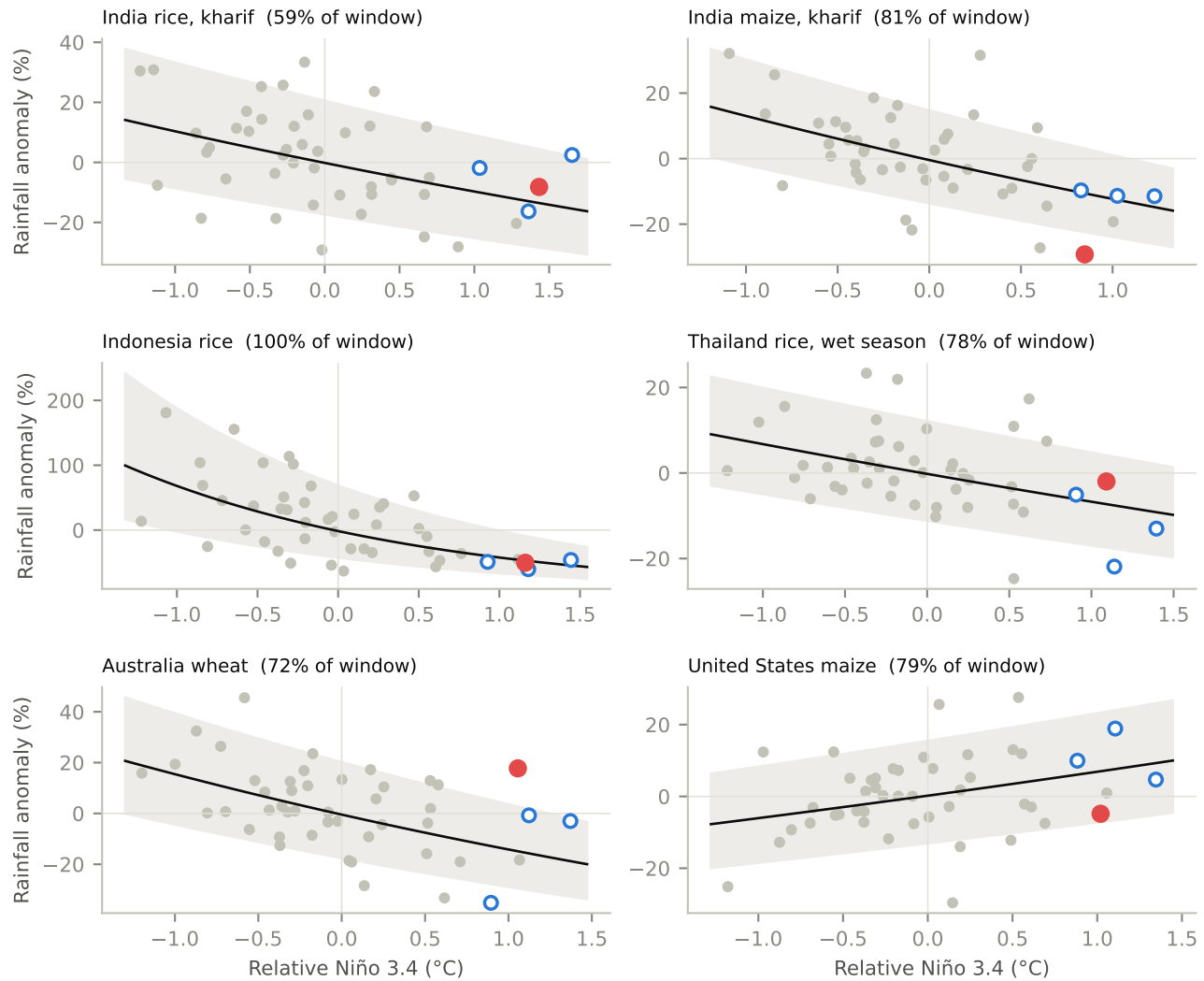


Figure 3: Rainfall tracking through 25 September 2026 for six selected crop regions. Red points show 2026; blue circles mark strong historical El Niño events; gray points show the remaining years. Fits use 1981–2025 log-rainfall anomalies and are displayed as percentage departures from the reference. Shading spans ± 1.28 residual standard deviations, not uncertainty in the fitted mean. Each panel uses the elapsed portion of its own growing season. September rainfall is preliminary CHIRPS.

Shipping, fertilizer and crop exposure

We assess shipping exposure by tracing where importing countries have sourced their crops. U.S. supplies account for about 58 percent of Japan's and 41 percent of the Philippines' combined maize, soybean and wheat imports in our compilation. Those shares identify dependence on U.S. suppliers, but departure ports and shipment routes determine exposure to Panama. We therefore treat the trade shares as historical sourcing measures. They do not establish that a particular share of imports is currently delayed or passes through the canal.

To follow deliveries, we would connect sourcing measures to port activity, shipment timing and freight costs. IMF PortWatch provides vessel-based trade estimates for comparison with customs and commodity records (International Monetary Fund, 2026). Distinguishing U.S. Gulf from Pacific departures would help assess Panama exposure. Figure 4 places sourcing dependence beside the crop scenarios and fertilizer estimates.

We estimate that Gulf suppliers account for about 46 percent of Australian and 41 percent of Thai nitrogen use. We combine the Gulf share of nitrogenous-fertilizer import weight in 2022–2024 with FAOSTAT nitrogen import and use balances (FAO, 2026; United Nations, 2026). These estimates identify where interruptions to fertilizer supply could affect production. Product weights approximate nutrient sourcing, and Gulf origin includes routes outside Hormuz. Refining the estimates requires nutrient-content information and fuller accounting for domestic production.

Tracking fertilizer risk would add current deliveries, inventories and prices to historical dependence measures. Shortage timing relative to planting and fertilizer application would determine which harvests are exposed. The crop scenarios do not yet quantify additional yield losses from fertilizer disruption; those losses require observations of input availability and farmers' responses.

	Crop production ENSO scenario (% of fitted output)	Fertilizer Gulf nitrogen (% of nitrogen use)	Transport exposure U.S. sourcing (% of staple imports)
Australia	-17%	46%	—
Brazil	-3%	23%	—
Argentina	+10%	3%	—
United States	+4%	9%	—
Mexico	-1%	41%	—
China	0%	0%	34%
Japan	-1%*	6%	58%
South Korea	+1%	24%	22%
Philippines	+1%	8%	41%
Indonesia	+1%	0%	18%
Thailand	0%	41%	16%
India	-4%	13%	—

Figure 4: Crop, fertilizer and transport-related exposure for selected Pacific economies and suppliers. Crop values are central-scenario changes in fitted staple output. Fertilizer values estimate Gulf nitrogen as a share of nitrogen use. U.S. sourcing gives the U.S. share of combined maize, soybean and wheat imports, not the share routed through Panama. A dash means the comparable sourcing measure is not assigned; it does not mean zero transport risk. An asterisk marks crop coverage below half of cereal output. Values are rounded; column denominators differ.

Expanding the analysis

We could expand the detailed analysis and seasonal monitoring to additional countries. The yield database already spans 193 countries, providing a starting point for selecting further producing regions and importing markets. Country-level extensions would require checking local crop calendars, updating weather and trade records, and evaluating forecast performance.

We could expand the ENSO scenarios into forecasts that combine seasonal climate outlooks with observations of weather, planting and crop development. As the season advances, observed rainfall, temperature and crop condition would replace assumptions about elapsed months. Satellite observations and national crop reports could update planted area and development stage. We would distinguish multiple rice and maize seasons in Asia and test whether weighting weather toward flowering and grain filling improves harvest estimates.

We could account for changing teleconnections—the links between ENSO and regional weather—using our work with Eran Vos and Eli Tziperman (Vos et al., 2026). We used covariance fingerprinting and multilinear regression to identify changes in monthly temperature teleconnections associated with anthropogenic forcing. We could adapt those methods to estimate how ENSO-related growing-season temperatures change as the climate warms, then carry the changes through crop-response calculations. Extending the approach to rainfall and crop yields would require separate evaluation.

We could estimate how irrigation, soil moisture and fertilizer availability alter crop responses to seasonal weather. A nitrogen shortage may have different consequences in a dry season than in a season with adequate water. Records of farm inputs and management, combined with weather and yields, would allow us to test those interactions. Separately estimating area and yield would also allow harvest forecasts to reflect planting responses to prices and water availability.

We could translate harvest estimates into export availability and import requirements using opening stocks, domestic food and feed use, processing demand and existing trade commitments. Crop-specific balances would help assess substitution between wheat and maize in animal feed and identify overlapping shortfalls among suppliers. Shipping, freight and exchange-rate information would then connect available quantities to delivered costs. Conflict, export restrictions and exceptional shipping closures would enter as explicit scenarios where reliable probabilities are unavailable.

We would evaluate each expansion on historical seasons using only information available at the forecast date. Withholding entire years and ENSO events would test performance across regions affected by the same event. Benchmarks would include recent production trends, simple ENSO estimates, APCC–NARO forecasts and GEOGLAM assessments (APEC Climate Center, 2026; GEOGLAM Crop Monitor, 2026). We would measure harvest errors, probability calibration, missed shortfalls and false alarms, then archive prospective forecasts for evaluation as outcomes become known.

We would develop the forecast measures with regional agencies and market participants around planting, procurement and shipment decisions. A shared record of crop statistics, calendars, weather and trade would document the observations available for each outlook. Partners could identify the lead times needed to assess reserves, sourcing alternatives and input assistance. Fisheries, horticulture and household food access would require additional evidence; assessing access would also require local prices, incomes and assistance coverage.

Appendix: data and analysis

Yield records and crop calendars

We assemble 1.79 million yield observations in 73,158 series across 193 countries. We give precedence to HarvestStat Asia's 708 stable administrative groups, followed by the subnational panels released by Hultgren et al. (2025), then national FAOSTAT series (Foley et al., 2026; FAO, 2025). HarvestStat covers nine Asian countries and reaches 2022–2025. The Hultgren panels cover 14,064 units in 52 countries, mostly ending in 2009–2015; we extend U.S. county yields with NASS records. FAOSTAT provides national coverage from 1961 to 2024. Precedence flags prevent duplicate counting. We exclude 19,364 observations flagged during source harmonization and quality checks.

We assign growing seasons from nine ranked calendar sources, including USDA and national crop records, RiceAtlas, FAO calendars, GEOGLAM, dates in the yield panels and GGCMI grids. Of the yield series, 62,128 have a season assignment and 45,821 have a planting day. Planting and harvest months, together with year offsets, connect each reported harvest to its growing-season weather. We compare annual yield anomalies with FAOSTAT and neighbouring units at alternative year shifts to check alignment. National and main-season calendars can poorly represent local crops, particularly where farmers plant multiple crops each year.

ENSO exposure and yield regressions

We calculate monthly Niño 3.4 anomalies from ERSSTv5 against 1991–2020 and subtract the tropical-mean anomaly between 20°S and 20°N (Huang et al., 2017; van Oldenborgh et al., 2021). We average this relative index over each planting-to-harvest window. The rescaling ratio between the Relative Oceanic Niño Index (RONI) and our index is 1.178. The stored September 2026 outlook quantiles of 1.48, 2.27 and 3.06 °C RONI become 1.26, 1.93 and 2.60 °C in our index (Climate Prediction Center, 2026). We retain observations through August 2026 and scale the monthly shape of 2015–16 to each December–February target; 1997–98 provides an alternative shape. These are the dated scenarios used for the brief's harvest estimates.

Within each country, crop and season panel, we estimate

$$\log Y_{it} = \alpha_i + \lambda_i t + \beta_p E_{it} + \varepsilon_{it},$$

where Y_{it} is unit i 's yield in harvest year t , E_{it} its growing-season ENSO exposure and β_p the panel response. We remove unit means and linear trends from yield and exposure before fitting the slope. Standard errors are clustered by harvest year. Panels require 15 harvest years and three units; individual series require ten years. We fit 282 country panels and 625 national series, using a linear trend and Newey–West errors for national fits. We control the false discovery rate across panel tests following Benjamini and Hochberg (1995).

We also fit 2,997 state panels and partially pool slopes within each country, crop and season using the Paule–Mandel estimate of between-state variance (Paule and Mandel, 1982). We use state responses in the supply calculation, followed by country-panel and national estimates where available. Pooling increases precision while reducing variation retained among nearby units.

Production changes and uncertainty

We calculate each series' production change as $P_i[\exp(\beta_i E_i) - 1]$ and sum over fitted series with harvests between September 2026 and August 2027. We distribute FAOSTAT 2019–2023 national production using HarvestStat 2018–2022 production shares or the Hultgren package's cropped-area shares. Countries without subnational coverage use national production and responses. We cover about 96 percent of world maize, rice and wheat production and 99 percent of soybean. Series without fitted responses contribute no estimated change. Rice quantities are paddy. The production weights hold area fixed and do not represent an updated forecast of planted area.

Low and high scenarios vary the index path with response slopes fixed. The manuscript's 2,000 Monte Carlo draws sample slope errors independently across series, including series sharing a state response. Shared estimation errors are therefore omitted and aggregate intervals can be too narrow; we omit those numerical intervals here. In the strongest scenario, exposures exceed the observed range for about 43 percent of covered maize production, 38 percent of rice, 30 percent of wheat and 80 percent of soybean. Joint uncertainty and performance beyond historical exposures require further assessment. The conditional ENSO contributions should not be added directly to crop forecasts already incorporating ENSO.

Weather, trade and continued updates

For the September tracker, we extend CHIRPS rainfall through 25 September 2026, using final data through August and preliminary September data. We compare production-weighted, detrended log-rainfall anomalies over matching partial growing seasons with the relative ENSO index over elapsed months. Figure 3 reproduces six panels from the existing tracker analysis. The weather-to-yield forecasting extension still requires independent validation.

We build daily weather series for 14,750 units using Berkeley Earth maximum and minimum temperature at 1°, CHIRPS v2.0 rainfall at 0.25°, and ERA5 rainfall for 97 units north of CHIRPS coverage (Funk et al., 2015; Hersbach et al., 2020). Temperature reaches 2024 and rainfall reaches 2025. SPAM 2010 harvested-area weights locate weather over cropland (Yu et al., 2020). Six growing-season metrics describe rainfall total, wet days, longest dry spell, mean maximum temperature, days above the local 95th percentile and degree days above 30 °C. Products of ENSO-to-weather and weather-to-yield regression slopes describe associated responses; correlated metrics and omitted influences limit causal interpretation.

We estimate Gulf nitrogen dependence as the Gulf share of HS 3102 import weight in 2022–2024 multiplied by the FAOSTAT nitrogen-import-to-use ratio, capped at one (FAO, 2026; United Nations, 2026). Product weights approximate nutrient sourcing, and Gulf origin includes routes outside Hormuz. U.S. origin shares use the combined import weight of maize, soybean and wheat. These sourcing measures describe historical dependence; shipment records are needed to determine current routes and deliveries.

Continued updates would require extending weather and yield records, revising crop calendars and preserving data versions. The Climate Hazards Center plans to end CHIRPS v2 production after December 2026 (Climate Hazards Center, 2026). We would assess the transition to CHIRPS v3 using overlapping records, particularly for wet-day and dry-spell metrics affected by daily rainfall estimation. Forecast development would then combine observed and predicted growing-season conditions, with historical evaluation at fixed issue dates and prospective records of each released outlook.

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