Dry Years, Irrigation and Rice Productivity in ASEAN: Evidence from Major Crop-Exporting Countries

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ABSTRACT

Southeast Asia includes several of the world's leading rice exporters, and rice yields have grown unevenly across the region over the past three decades. This study estimates how dry, hot and wet years affect agricultural productivity in the 8 ASEAN rice-producing countries, whether these short-run losses differ from those in other major crop exporters, and whether irrigation and public spending on agriculture are associated with smaller losses. We use a panel of 50 major crop-exporting countries from 1990 to 2023 that combines FAOSTAT, World Development Indicators and United States Department of Agriculture productivity data with shock years measured from gridded climate records. The models relate annual productivity growth to shock years with country and year fixed effects. As only eight countries identify every ASEAN contrast, inference rests on randomisation tests, a wild cluster bootstrap and t tests with seven degrees of freedom. A dynamic spatial panel provides a second estimate for rice. In ASEAN a dry year is associated with a 3.4 per cent fall in rice production ($p = 0.014$), although its split between yield and area is imprecise, and a 2.5 per cent fall in rice yields that is only marginally significant ($p = 0.051$). The point estimates suggest larger rice losses in ASEAN than elsewhere, but no ASEAN contrast is statistically significant and the design could detect only differences of 2.8 to 6.5 percentage points, so greater ASEAN vulnerability is not established. The spatial model gives a rice yield loss of 1.7 per cent but fails a placebo test in one of two implementations. A larger irrigated share is associated with smaller dry-year losses in value added per worker and cereal yields, not in rice yields, and these associations do not survive a multiple-testing correction. A higher budget priority for agriculture shows no cushioning for productivity.

Keywords: rice productivity, ASEAN, drought, irrigation, agricultural finance

INTRODUCTION

Rice is the staple food of Southeast Asia and a central source of farm income across the region. Thailand, Vietnam, Cambodia and Myanmar sell rice on the world market, while Indonesia, the Philippines and Malaysia also import it to meet domestic demand. Productivity has not risen evenly across these countries. Figure 1 traces rice yields from 1991 to 2023. Vietnam doubled its yield from 3.1 to 6.1 tonnes per hectare and Cambodia went from 1.4 to 3.6. Thailand, a leading exporter throughout the period, moved only from 2.2 to 3.0, and Malaysia from 2.8 to 3.5. The average for the other rice producers in our sample rose from 3.6 to 4.9.

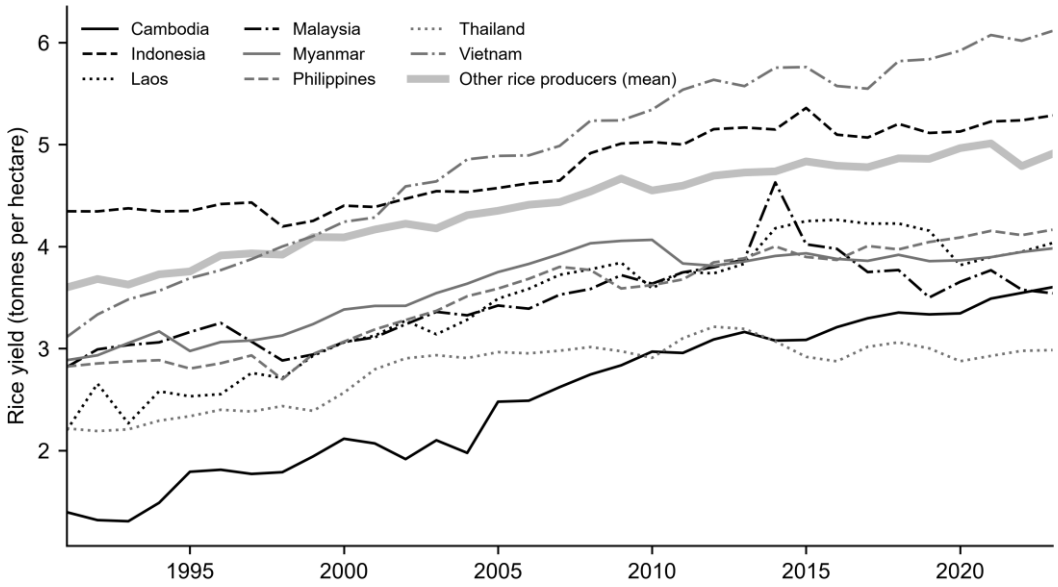


Figure 1. Rice yields in the ASEAN rice producers and the average of other major rice producers, 1991 to 2023 (FAOSTAT)

Long-run yield growth depends on technology, investment and policy, and this paper does not try to explain it. Its concern is the year-to-year risk around that path. Southeast Asian rice depends heavily on the monsoon. Late monsoon onset during El Niño years cuts Indonesian rice output [1, 2], and higher night temperatures reduce rice yields at experimental and farm sites in tropical Asia [3, 4]. The irrigated share of cropland in our data averages 19.5 per cent in ASEAN against 23.3 per cent in the rest of the sample, so a larger part of the region's cropland depends on rainfall in a given season.

Weather risk matters for policy because ASEAN governments support rice through input subsidies, guaranteed prices, irrigation and subsidised credit, and because rice markets react sharply when trade is disrupted. During the 2007 to 2008 food price crisis, export restrictions spread quickly through the rice market [5]. Whether public support reduces the damage from bad weather is an empirical question that the cross-country literature has rarely asked for this region. Global studies find that weather shocks reduce agricultural output and productivity [6, 7, 8] and that droughts cut national cereal production sharply [9], but they pool the world and say little about whether Southeast Asia responds differently.

This paper has three objectives. It estimates how dry, hot and wet years affect rice yields, agricultural value added per worker, cereal yields and total factor productivity (TFP) in the ASEAN rice producers. It tests whether those short-run effects differ from the effects in other major crop exporters, including 25 other rice producers such as India, China, Bangladesh and Pakistan. It then examines whether irrigation and public spending on agriculture are associated with smaller losses in dry years.

The paper contributes a regional estimate of weather damage to ASEAN rice that uses the same shock definition, outcomes and estimator as for the comparison countries, so that differences are not artefacts of different data. It also treats the small number of ASEAN countries as a central feature of the inference problem. We report randomisation tests, a wild cluster bootstrap, corrections for multiple testing and the smallest difference each test could detect. A statement that ASEAN is no different from other exporters would be easy to make and hard to defend, and the paper shows what the data can and cannot rule out.

LITERATURE REVIEW

A large literature uses year-to-year variation in weather to estimate how climate affects production. Once a location's normal climate is removed, weather in a given year is close to random, which makes it a credible

source of variation [10, 11]. Temperature shocks reduce economic growth in poor countries, with large effects on agricultural output [6], and the response of output to temperature is strongly non-linear [12, 13]. Crop studies find sharp yield losses above temperature thresholds [14] and attribute part of the slowdown in global maize and wheat yield growth since 1980 to warming [7]. Climate variation explains about a third of the year-to-year variation in global crop yields [15], and anthropogenic warming has reduced global agricultural TFP growth [8]. Extreme droughts lower national cereal production by roughly a tenth in the year they occur [9].

Rice responds to weather in ways that differ from the dryland cereals. Paddy rice is grown in standing water, so rainfall deficits matter through irrigation supply and the timing of transplanting. Evidence from an experimental farm in the Philippines links higher night temperatures to lower rice yields [3], and farm data from tropical and subtropical Asia show that higher minimum temperatures lowered yields while higher maximum temperatures raised them over the observed range [4]. Combining four independent methods, Zhao and co-authors estimate that each degree of warming lowers global rice yields by about three per cent [16]. In Indonesia the El Niño cycle delays the monsoon and the main rice planting, which lowers output in the following season [1, 2].

Two kinds of buffer could soften these losses. Irrigation is the direct one, since it replaces missing rainfall, although weather also shapes how much land farmers crop and how often [17], so a dry year can change area as well as yield. Seed technology is a second physical buffer. Flood-tolerant rice in India reduced downside risk enough that farmers increased other investments [18]. Finance is the indirect buffer. Credit and public spending could, in principle, let farmers replant, buy inputs after a bad season and smooth consumption [19]. The evidence that finance cushions weather shocks is weak, however. When credit and insurance constraints were relaxed at random in Ghana, it was the removal of risk, not of credit, that changed farm investment [20], and index insurance has struggled to reach scale [21]. Public agricultural spending is split between price support, input subsidies, irrigation and research, so its average effect on shock resilience is not obvious.

The cross-country literature leaves a regional gap. Studies pool all countries and estimate one average response, or they study one country in detail. Few ask whether a region with distinctive cropping systems and policies responds differently on comparable data, and those that split the sample seldom deal with the fact that a region of eight countries gives very few independent units for inference. Conventional clustered standard errors, and even some bootstrap methods, can mislead badly when only a handful of units are treated [22, 23, 24, 25]. This paper addresses that gap for ASEAN rice.

METHODOLOGY

Data and sample

The sample covers 50 major crop-exporting countries from 1990 to 2023, drawn from the doctoral study on which this paper is based. The countries are the leading exporters of wheat (21 countries), rice (22) and palm oil (10), ranked by exports. Pakistan, the United States and Thailand appear on two lists, which leaves 50 countries. All 8 ASEAN members in the sample, namely Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Thailand and Vietnam, are major rice producers, defined as a mean rice harvested area of at least 100,000 hectares. Brunei and Singapore produce almost no rice and are not in the sample. For the rice outcomes the comparison group is the 25 other major rice producers. For value added per worker, cereal yields and TFP it is the 42 non-ASEAN countries, which share world markets and common shocks with the ASEAN producers.

Rice yield, harvested area and production come from FAOSTAT. Agricultural value added per worker (constant 2015 United States dollars) and cereal yield come from the World Development Indicators. Agricultural TFP comes from the International Agricultural Productivity accounts of the United States Department of Agriculture, release of January 2026 [26]. TFP is the broadest measure, since it nets out changes in land, labour, capital and materials, while rice yield is the most direct measure for the crop at the centre of this paper. Every outcome enters as its annual growth rate, the first difference of its logarithm.

Weather shocks are built from CRU TS 4.08 monthly temperature and precipitation [27], averaged over each country's area. For each country we remove a linear trend fitted over 1961 to 2023 and express the residual in

standard deviations. In plain terms, a dry year is a year in which rainfall falls well below what is normal for that country, by more than one standard deviation. A wet year is the reverse, and a hot year is one with a temperature more than one standard deviation above trend. Since the shocks are measured against each country's own history, slow climate change and differences in normal climate do not drive the estimates, and every country experiences such years at a broadly similar frequency.

Two country characteristics serve as potential buffers. Irrigation is the share of cropland equipped for irrigation, from the same USDA accounts. Public spending on agriculture is the Agriculture Orientation Index of government expenditure (Sustainable Development Goal indicator 2.a.1), which compares agriculture's share of public spending with its share of GDP. The index measures budget priority, not investment. It does not separate spending on irrigation, research and extension, which can raise productivity, from price support, input subsidies and transfers, which mainly support incomes, and it is reported only from 2001. A high value therefore shows that a government gives agriculture weight in its budget, not that it invests in the activities most likely to reduce weather losses. The index is available for 49 countries, including all eight ASEAN members. The parallel index for credit covers 41 countries but not Laos or Myanmar, so it serves only as a robustness check. Both buffers enter as the standardised country mean, which measures a country's typical level.

Fixed effects model

The baseline model relates productivity growth in country i and year t to the shock indicators in the current and previous year, and lets the effects differ for ASEAN, as set out in equation (1).

$$\Delta \ln y_{it} = \alpha_i + \lambda_t + \Sigma_{k=0}^{1} (\beta_k' S_{i,t-k} + \theta_k' S_{i,t-k} \times A_i) + \varepsilon_{it} \qquad (1)$$

where Δln y is the growth of the outcome, S is the vector of dry, hot and wet indicators, A is one for ASEAN members, α and λ are country and year fixed effects, and ε is the error. The coefficient β measures the effect of a shock outside ASEAN, β + θ the effect inside ASEAN, and θ the difference. Country effects absorb each country's average growth rate, and year effects absorb shocks common to all countries, such as world price spikes. To test the buffers we add interactions of the dry-year indicator with irrigation and with spending. To make these interactions easier to read, we also report the implied dry-year effect for a country at the 10th, 50th and 90th percentiles of each buffer and at the ASEAN mean, with 95 per cent intervals. We also report how much of the loss accumulates over one and two years.

Inference with eight countries

Every ASEAN contrast is identified by eight countries, and that number shapes the inference. Standard errors are clustered by country, but cluster-robust tests are unreliable when clusters are few or when few of them carry the treatment [28, 29]. We therefore report three further tests. The wild cluster bootstrap uses 999 replications with the six-point weights recommended for small numbers of clusters [30]. The randomisation test reassigns the ASEAN label to eight countries drawn at random from the non-ASEAN sample 999 times and compares the actual studentised statistic with that distribution [24, 25]. Randomly drawn placebo groups do not share the regional climate pattern of Southeast Asia, so this test may be somewhat too generous. Effects within ASEAN are tested against a t distribution with seven degrees of freedom. Since we test twelve primary contrasts (four outcomes and three kinds of shock), we also apply the Holm correction for multiple testing [31]. The buffer analysis adds eight further tests (four outcomes and two buffers), and we apply the same correction to their bootstrap p-values as a separate family. For each contrast we report the minimum detectable effect, the difference the design would detect with 80 per cent power at the 5 per cent level using a t distribution with seven degrees of freedom. Driscoll and Kraay standard errors, which allow for correlation across countries within a year [32], are reported alongside.

Dynamic spatial panel

Weather and productivity are correlated across neighbouring countries, and regional prices and technologies move together. The fixed effects model handles common shocks through year effects but assumes every country responds to them in the same way. As a second estimator for rice yields we use the dynamic spatial panel of Cui,

Sarafidis and Yamagata [33], which adds the growth of neighbouring countries (ρ), the country's own lagged growth (ψ) and unobserved common factors with country-specific loadings [34, 35]. The spatial weights are inverse great-circle distances between countries [36], with five nearest neighbours as an alternative. The model is estimated on a balanced block of 32 rice producers from 1991 to 2023, in Python and, as a cross-check, with the Stata command spxtivdfreg [37]. Its p-values rest on large-sample normal approximations, which are optimistic with eight ASEAN countries.

RESULTS

Descriptive patterns

Table 1 compares the ASEAN members with the other rice producers and with the rest of the sample. ASEAN rice yields are lower on average, the irrigated share is lower, and value added per agricultural worker is a fraction of the level in the rest of the sample. Relative to the sector's weight in the economy, ASEAN governments also spend less on agriculture, with an expenditure orientation index of 0.27 against 0.46.

Table 1. Descriptive statistics

Variable	ASEAN	Other rice producers	All non-ASEAN
Rice yield (t/ha)	3.60 (0.97)	4.36 (2.30)	4.38 (2.28)
Value added per worker (2015 USD)	3321 (4140)	7634 (10261)	13300 (19867)
USDA TFP index (2015 = 100)	84.1 (18.3)	91.2 (15.9)	92.4 (18.1)
Irrigated share of cropland	0.20 (0.12)	0.28 (0.27)	0.23 (0.25)
Expenditure AOI	0.27 (0.19)	0.44 (0.54)	0.46 (0.48)
Credit AOI	0.36 (0.20)	0.78 (0.74)	1.38 (1.58)
Share of dry years	0.188	n.a.	0.135
Share of hot years	0.162	n.a.	0.143
Share of wet years	0.180	n.a.	0.143
Countries	8	25	42

Note. Means with standard deviations in parentheses, 1990 to 2023. Other rice producers are the non-ASEAN countries with a mean rice harvested area of at least 100,000 ha. AOI is the Agriculture Orientation Index (SDG 2.a.1). Shock shares are the share of country-years with a detrended rainfall or temperature residual beyond one standard deviation.

Dry-year effects in ASEAN and elsewhere

Table 2 reports the effect of a dry year on each outcome, separately for the rest of the sample and for ASEAN. In ASEAN a dry year lowers rice production growth by 3.4 per cent ($p = 0.014$) and rice yield growth by 2.5 per cent ($p = 0.051$). The yield estimate is marginally significant at the 10 per cent level, not at the conventional 5 per cent level. The point estimate for harvested area is a fall of 0.9 per cent, about 26 per cent of the production loss, but it is imprecise, and its 95 per cent interval runs to a fall of 4.0 per cent, so we cannot separate the yield and area channels with confidence. The production estimate is therefore best read as a loss of output whose division between yield and area remains uncertain. For the other rice producers the yield estimate is 1.0 per cent

with a standard error of 1.3, which is imprecise. For cereal yields the ASEAN loss is 3.0 per cent (p = 0.049), against 5.0 per cent elsewhere.

Table 2. Effect of a dry year on productivity growth (per cent)

Outcome	Rest of sample	ASEAN	Difference	RI p	MDE	N
Rice yield	−0.99(1.33)	−2.54*(1.08)	−1.55(1.71)	0.49	5.6	1087
Rice production	−2.56(2.13)	−3.44**(1.06)	−0.88(2.09)	n.a.	6.8	1087
Rice area	−1.57(1.66)	−0.89(1.30)	0.67(1.85)	n.a.	6.0	1087
Cereal yield	−4.96***(1.49)	−3.03**(1.27)	1.94(2.00)	0.42	6.5	1644
Value added per worker	−2.25***(0.79)	−1.58(1.88)	0.67(1.98)	0.73	6.4	1487
TFP	−1.23**(0.59)	−0.49(0.60)	0.74(0.87)	0.43	2.8	1650

Note. Coefficients times 100 with clustered standard errors in parentheses. Models include hot, dry and wet indicators and their first lags, each interacted with ASEAN, plus country and year fixed effects. Rice outcomes use the 33 major rice producers. Stars for the rest of the sample use clustered t tests, for ASEAN a t distribution with 7 degrees of freedom, and for the difference the randomisation p-value (RI p) where computed. MDE is the minimum detectable difference in percentage points (80 per cent power at the 5 per cent level, t with 7 degrees of freedom). *** p < 0.01, ** p < 0.05, * p < 0.10.

Figure 2 places the two sets of estimates side by side. On the point estimates, ASEAN rice losses are larger than those elsewhere, and losses in value added per worker, cereal yields and TFP are smaller, but every confidence interval overlaps. None of the ASEAN differences is significant. For rice yield the difference is 1.6 percentage points with a randomisation p-value of 0.49, and the smallest randomisation p-value across the four dry-year contrasts is 0.42. The minimum detectable differences range from 2.8 to 6.5 percentage points, between 1.4 and 3.8 times the size of the pooled dry-year losses. The data therefore cannot tell whether ASEAN suffers more or less than other exporters, and the larger ASEAN rice losses are a pattern in the point estimates, not a statistically established difference.

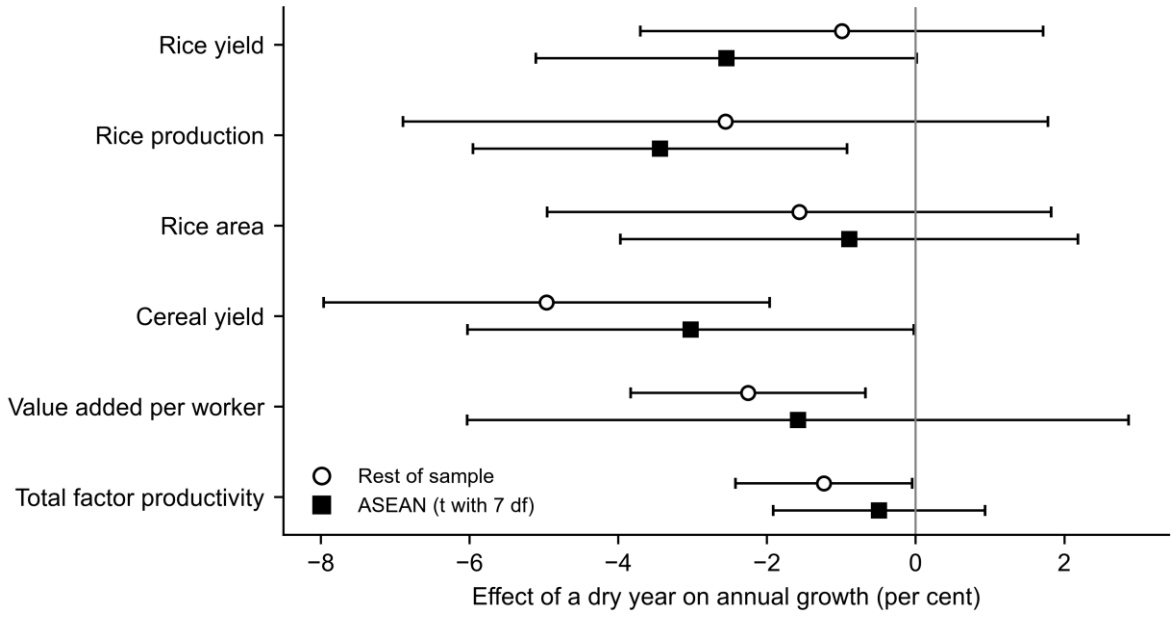


Figure 2. Effect of a dry year on productivity growth, ASEAN and the rest of the sample, with 95 per cent intervals

On the point estimates, about 45 per cent of the ASEAN rice yield loss is regained in the following year. The cumulative loss is 1.4 per cent after one year (p = 0.17) and 1.6 per cent after two (p = 0.19), so we cannot say with confidence whether the remainder is recovered. Over two years the ASEAN rice yield loss exceeds the loss elsewhere by 2.8 points (p = 0.084), the closest any dry-year contrast comes to significance.

Hot and wet years, and multiple testing

Table 3 extends the comparison to hot and wet years and reports every test for the twelve primary contrasts. Two contrasts reach conventional significance on some tests. In hot years ASEAN TFP growth falls 1.4 percentage points more than elsewhere, with a randomisation p-value of 0.041. This result is fragile. The Driscoll and Kraay p-value is 0.087, the effect reverses in the following year by 1.0 points, the two-year difference is only 0.4 points (p = 0.75), and after the Holm correction its p-value is 0.49. It looks like a shift in timing, not a lasting loss. The second case concerns wet years and value added per worker, where the ASEAN gap of 4.2 points passes the bootstrap (p = 0.018) but not the randomisation test (p = 0.10), and the Holm adjustment raises it to 1.00. No Holm-adjusted p-value falls below 0.49. A two-year hot-year rice yield difference of 4.8 points (p = 0.018) was not among the planned tests and should be treated as exploratory.

Table 3. ASEAN differences for all shocks and outcomes

Contrast	Difference	Cluster p	DK p	Bootstrap p	RI p	Holm p
Rice yield, dry year	−1.55 (1.71)	0.37	0.09	0.39	0.49	1.00
Rice yield, hot year	−2.59 (1.40)	0.07	0.09	0.09	0.09	0.99
Rice yield, wet year	0.66 (1.09)	0.55	0.47	0.52	0.55	1.00
Cereal yield, dry year	1.94 (2.00)	0.34	0.15	0.37	0.42	1.00
Cereal yield, hot year	0.27 (1.43)	0.85	0.77	0.86	0.87	1.00
Cereal yield, wet year	−1.79 (1.39)	0.21	0.11	0.21	0.26	1.00
Value added per worker, dry year	0.67 (1.98)	0.74	0.62	0.80	0.73	1.00
Value added per worker, hot year	1.89 (1.52)	0.22	0.27	0.25	0.26	1.00
Value added per worker, wet year	−4.21 (2.12)	0.05	0.06	0.02	0.10	1.00
TFP, dry year	0.74 (0.87)	0.40	0.48	0.40	0.43	1.00
TFP, hot year	−1.39 (0.58)	0.02	0.09	0.02	0.04	0.49
TFP, wet year	−0.37 (0.78)	0.63	0.57	0.64	0.68	1.00

Note. Difference between the ASEAN and non-ASEAN effect of each shock, times 100, standard error in parentheses. DK is Driscoll and Kraay. The wild cluster bootstrap uses 999 replications with Webb weights. RI p is the studentised

randomisation p-value from 999 placebo groups of eight non-ASEAN countries. Holm p adjusts the RI p-values for the twelve contrasts in the table.

Irrigation and public spending

Table 4 tests the two buffers. A country whose irrigated share is one standard deviation above the sample mean loses 1.1 percentage points less value added per worker in a dry year (bootstrap p = 0.047) and 1.8 points less cereal yield (p = 0.046). Both p-values sit just under 5 per cent. After the Holm correction across the eight buffer tests both rise to 0.37, so neither survives a correction for multiple testing. For cereal yields the gain is largely reversed the next year, by 1.7 points (p = 0.095), which suggests a shift in timing. The interaction is not significant for rice yields (p = 0.64) or TFP (p = 0.98), so these data do not show that irrigation explains how ASEAN rice responds to dry years. Irrigation is a country characteristic that moves with income, so these estimates describe where losses are smaller, not the effect of building a new scheme.

Table 4. Irrigation, government spending and the dry-year loss

Outcome	Dry × irrigation	Bootstrap p	Dry × spending	Bootstrap p	Max. offset (%)	Dry × spending × ASEAN	Bootstrap p
Rice yield	0.58 (0.97)	0.64	1.43 (0.81)	0.15	255	0.57 (1.46)	0.73
Cereal yield	1.84** (0.91)	0.05	−0.63 (1.37)	0.65	49	2.73 (2.52)	0.37
Value added per worker	1.11** (0.51)	0.05	−1.14 (0.93)	0.25	47	−4.14 (2.43)	0.32
TFP	−0.01 (0.43)	0.98	−1.10* (0.59)	0.08	8	1.93 (1.13)	0.13

Note. Interaction of the dry-year indicator with the standardised country mean of the irrigated share (left) and of the expenditure Agriculture Orientation Index (right), times 100. A positive value means a smaller dry-year loss. Stars use the wild cluster bootstrap p-value. Max. offset is the largest share of the dry-year loss that one standard deviation of spending could offset at the upper end of its 95 per cent interval. Values above 100 mean the data cannot rule out a full offset. The last two columns give the additional ASEAN interaction from a model that also interacts every shock with ASEAN.

For TFP, spending shows no cushioning. The interaction is negative, 1.1 points (bootstrap p = 0.077), and the upper end of its confidence interval implies that spending one standard deviation above the mean could offset at most 8 per cent of the dry-year TFP loss. For rice yields the picture is different. The interaction is positive, 1.4 points, with a bootstrap p-value of 0.15 and a Driscoll and Kraay p-value of 0.022, and its interval cannot rule out a full offset of the rice loss. For value added per worker and cereal yields the intervals are also wide. Because the orientation index measures budget priority rather than what the money buys, these results show that countries giving agriculture a larger budget share do not lose less TFP, not that investment in irrigation or research fails to protect productivity. We find no reliable evidence that spending or credit works differently in ASEAN. The smallest bootstrap p-value among the ASEAN finance interactions, contemporaneous or lagged, is 0.072.

Table 5 converts the Table 4 interactions into implied dry-year effects at representative levels of each buffer. For a non-ASEAN country at the 10th percentile of irrigation, where 1.7 per cent of cropland is irrigated, a dry year is associated with a fall of 3.6 per cent in value added per worker (95 per cent interval −5.8 to −1.3) and 7.2 per cent in cereal yields (−11.6 to −2.8). At the 90th percentile, 55 per cent irrigated, the implied falls are 1.0 per cent (−2.4 to 0.4) and 2.9 per cent (−5.2 to −0.7). For rice yields the implied loss is 1.8 per cent at the 10th percentile and 0.4 per cent at the 90th, both with intervals that include zero, and the slope that separates them is far from significant (bootstrap p = 0.64). In ASEAN, at its mean irrigated share of 19.5 per cent, the implied rice yield loss is 2.6 per cent (−5.1 to −0.1), close to the ASEAN estimate in Table 2. For spending, the implied TFP

effect moves from 0.2 per cent at the 10th percentile of the orientation index (−1.2 to 1.6) to −2.2 per cent at the 90th (−3.9 to −0.5), a pattern opposite to cushioning that is not significant after correction (Holm p = 0.46). The implied rice yield loss is 2.9 per cent at the 10th percentile and close to zero at the 90th, but the slope behind this difference has a bootstrap p-value of 0.15 and a Holm-adjusted p-value of 0.75. After the Holm correction the smallest p-value among the eight buffer slopes is 0.37.

Table 5. Implied dry-year effect at representative levels of irrigation and spending (per cent)

Outcome	10th percentile	Median	90th percentile	ASEAN mean	Holm p
A. Irrigated share (level)	1.7%	14.9%	55.2%	19.5%	
Rice yield	−1.8 [−6.5, 3.0]	−1.4 [−5.2, 2.3]	−0.4 [−2.4, 1.6]	−2.6 [−5.1, −0.1]	1.00
Cereal yield	−7.2 [−11.6, −2.8]	−6.2 [−9.7, −2.6]	−2.9 [−5.2, −0.7]	−3.1 [−6.1, −0.2]	0.37
Value added per worker	−3.6 [−5.8, −1.3]	−3.0 [−4.8, −1.1]	−1.0 [−2.4, 0.4]	−1.7 [−6.4, 3.0]	0.37
TFP	−1.3 [−3.0, 0.5]	−1.3 [−2.6, 0.1]	−1.3 [−2.6, 0.1]	−0.6 [−2.0, 0.8]	1.00
B. Expenditure AOI (level)	0.10	0.32	0.70	0.21	
Rice yield	−2.9 [−5.4, −0.4]	−1.1 [−3.1, 1.0]	0.1 [−2.7, 3.0]	−1.7 [−3.7, 0.3]	0.75
Cereal yield	−4.1 [−6.8, −1.4]	−4.9 [−7.6, −2.2]	−5.4 [−10.0, −0.9]	−4.6 [−6.8, −2.5]	1.00
Value added per worker	−0.6 [−2.7, 1.6]	−2.0 [−3.5, −0.5]	−3.0 [−5.7, −0.3]	−1.5 [−2.8, −0.2]	1.00
TFP	0.2 [−1.2, 1.6]	−1.2 [−2.2, −0.2]	−2.2 [−3.9, −0.5]	−0.8 [−1.7, 0.1]	0.46

Note. Implied effect of a dry year on growth, times 100, at the stated level of the buffer, with 95 per cent cluster-robust intervals in brackets. Levels are percentiles of the country means across the sample and the ASEAN average. For the AOI they are geometric means of each country's annual index, and years with a zero index are excluded by the log. Panel A uses the Table 4 irrigation model. Its percentile columns are for a non-ASEAN country, with t intervals on G − 1 degrees of freedom, and its ASEAN column is the ASEAN effect at the ASEAN mean irrigated share, with t intervals on 7 degrees of freedom. Panel B uses the Table 4 spending model, which has no ASEAN terms, so every column assumes a common slope and its ASEAN column is not the ASEAN-specific estimate of Table 2. These intervals are less conservative than the wild cluster bootstrap used for the Table 4 slopes. Holm p adjusts the Table 4 bootstrap p-values of the buffer interactions for the eight buffer tests.

Robustness

Table 6 checks the ASEAN dry-year results against alternative specifications. The ASEAN rice yield loss stays between 2.4 and 2.6 per cent under crop-year timing, without 2020 to 2023, against Asian countries only and with region-by-year effects, with t(7) p-values from 0.040 to 0.099. It shrinks to 1.6 per cent (p = 0.21) when estimated in levels with country trends and to 0.3 per cent (p = 0.82) with reported droughts. The ASEAN difference for rice stays negative in every variant, and dropping one ASEAN country at a time leaves it between 0.9 and 2.1 points below zero. Next year's dry indicator does not predict this year's growth, which is the placebo check that the shock is not picking up trends. The smallest p-value on the lead is 0.13 and on its ASEAN interaction 0.26.

Table 6. Robustness of the ASEAN dry-year difference

Specification	ASEAN rice effect	Rice yield	Cereal yield	Value added per worker	TFP
Baseline	−2.54* (1.08)	−1.55 (1.71)	1.94 (2.00)	0.67 (1.98)	0.74 (0.87)
Crop-year timing	−2.60** (1.09)	−1.17 (1.76)	1.12 (2.04)	1.74 (2.12)	1.46 (0.90)
EM-DAT reported drought	−0.27 (1.17)	−0.79 (1.38)	−2.99* (1.56)	−2.30 (1.50)	−2.94** (1.12)
Excluding 2020 to 2023	−2.58** (1.02)	−1.66 (1.83)	2.05 (2.06)	1.34 (2.19)	0.62 (0.89)
Asian countries only	−2.63** (1.10)	−2.74 (1.63)	1.45 (4.40)	−0.91 (2.33)	0.83 (0.96)
Region-by-year effects	−2.39* (1.26)	−1.19 (1.69)	3.39 (2.18)	0.60 (2.69)	0.13 (0.87)
Levels with country trends	−1.65 (1.18)	−0.49 (1.58)	−0.40 (2.05)	4.87 (3.07)	0.71 (1.32)
Leave one ASEAN country out (range)	−1.89 to −3.07	−2.08 to −0.92	1.27 to 2.80	0.15 to 2.55	0.31 to 1.11

Note. The first column is the ASEAN dry-year effect on rice yield growth (stars from t with 7 degrees of freedom). The other columns are the difference between the ASEAN and non-ASEAN dry-year effect, times 100, clustered standard error in parentheses and clustered-test stars. The EM-DAT row replaces the rainfall-based dry year with a year of reported drought and the wet year with a year of reported flooding.

The reported-disaster check deserves comment. When drought is measured by reported disasters from the EM-DAT database instead of rainfall, the ASEAN contrast for TFP becomes −2.9 points ($p = 0.011$) and for cereal yields −3.0 points ($p = 0.061$), reversing the sign. Reported disasters depend on reporting capacity and on how much damage occurred, and disaster impacts themselves vary with a country's level of development [38], so they measure impact as much as weather. We read the gap as a difference between the two measures and keep rainfall as the baseline because it is not affected by the outcome.

Dynamic spatial panel

Table 7 reports the spatial estimates for rice yields. In the baseline model the spatial coefficient is 0.78 and the own-lag coefficient is negative (0.18 in absolute value), so a good year tends to be followed by a weaker one. The sum of their absolute values is 0.96, just inside the usual stability bound of one. In this model ASEAN rice yields grow 1.7 per cent less in a dry year ($p = 0.039$), and outside ASEAN the effect is close to zero. The difference of 1.7 points has a p-value of 0.079, and the overidentification test does not reject ($p = 0.86$). With five nearest neighbours the ASEAN loss is 2.1 per cent and the difference has $p = 0.013$. Specifications with other numbers of factors give larger and more significant differences, but their absolute coefficient sums of 1.12 to 1.18 lie outside the stability bound, so we do not rely on them.

Table 7. Dynamic spatial panel estimates for rice yield growth

Model	Python, inverse distance	Python, 5 nearest	Stata, inverse distance	Stata, 5 nearest	Stata, factors chosen by test
Spatial lag ρ	0.782*** (0.166)	0.180 (0.122)	0.851*** (0.160)	0.524*** (0.124)	0.881*** (0.139)

Own lag ψ	−0.181** (0.075)	−0.303** (0.119)	−0.160 (0.111)	0.012 (0.096)	−0.213** (0.102)
|ρ| + |ψ|	0.96	0.48	1.01	0.54	1.09
Dry year, rest	−0.04 (0.47)	0.21 (0.58)	−0.41 (0.64)	−0.24 (0.58)	−0.36 (0.47)
Dry year, ASEAN	−1.73** (0.84)	−2.12*** (0.63)	−2.03** (0.93)	−2.76*** (0.84)	−1.69* (0.89)
Difference	−1.69* (0.96)	−2.33** (0.94)	−1.62 (1.14)	−2.51** (1.18)	−1.33 (0.93)
Hansen J p	0.86	0.54	0.83	0.43	0.75
Lead placebo p	0.61	n.a.	0.02	n.a.	n.a.

Note. Two-stage instrumental variable estimator of Cui, Sarafidis and Yamagata on a balanced block of 32 major rice producers, 1991 to 2023. Dry-year rows are times 100. Two factors are extracted from the instruments and one from the residuals, except in the last column, where Stata chooses the numbers with its eigenvalue-ratio test. Values of $|\rho| + |\psi|$ below one are inside the usual stability bound. p-values are asymptotic. The lead placebo p is for the ASEAN interaction of next year's dry indicator. Hot and wet indicators and their ASEAN interactions are included but not shown.

The Stata cross-check agrees in sign and size. Its baseline ASEAN loss is 2.0 per cent ($p = 0.029$), with a difference p-value of 0.15, although its absolute coefficient sum of 1.01 sits at the stability bound, and when Stata chooses the number of factors itself the loss is 1.7 per cent ($p = 0.058$). With no factors the two programs give 2.65 and 2.63 per cent, which confirms that they estimate the same model. They differ in how they extract the factors, which shows in the five-neighbour spatial coefficient (0.52 in Stata against 0.18 in Python) and in the lead placebo. In Python the lead of the ASEAN dry indicator is insignificant ($p = 0.61$), but in Stata it is significant ($p = 0.016$). We therefore treat the spatial estimates as supporting evidence that ASEAN rice yields fall in dry years, not as evidence that they fall more than elsewhere. For TFP and value added per worker the spatial model is unstable, with the sum of the spatial and own-lag coefficients at 1.21 and 1.30, and for TFP the ASEAN lead placebo fails ($p < 0.001$). We do not interpret those models.

DISCUSSION

The findings suggest where ASEAN agriculture may be most exposed, although the comparative evidence is not conclusive. Dry years are associated with a fall in rice output in the region of about three per cent in the year they occur, and the fixed effects and spatial estimates of the yield loss point the same way. On the point estimates most of this comes through yield, which is what one would expect where much of the rice depends on seasonal rainfall, but the yield estimate is only marginally significant and the area response is too imprecise to rule out.

Whether ASEAN is more vulnerable than other exporters remains open. The point estimates for rice suggest it may be, and the two-year difference comes close to significance, but with eight countries the design cannot separate a difference of a few percentage points from chance. A regional assessment that claimed ASEAN suffers no more than others, on the strength of an insignificant test, would understate a risk the data cannot exclude. Equally, the larger ASEAN rice losses are a pattern in the point estimates that calls for further testing with more units or finer data, not evidence that the region is more vulnerable.

For policy in ASEAN, and in Malaysia in particular, the results do not identify irrigation as the explanation for how ASEAN rice responds to dry years. Countries with more irrigation lose less value added per worker and less cereal yield in dry years, and ASEAN has less irrigation than the rest of the sample, but these associations do not survive the Holm correction and describe differences between countries, not the effect of new schemes. We do not find the same association for rice yields, where the implied losses at low and high irrigation do not

differ significantly, so the case for irrigation as a protection for rice specifically rests on agronomy more than on these estimates. Malaysia's rice yields have stalled at about 3.5 tonnes per hectare, well below Vietnam's 6.1. Maintaining existing schemes and spreading stress-tolerant varieties remain reasonable instruments on agronomic grounds, and the experience with flood-tolerant rice in India shows that such varieties can reduce downside risk [18].

General spending on agriculture is a less certain lever. Countries that give agriculture a larger share of their budget do not lose less TFP in dry years, and the estimate rules out more than a small offset. The Agriculture Orientation Index measures this budget priority, not the amount invested in irrigation, research or extension, so the result concerns the size of the agricultural budget relative to the sector, not the return to any particular investment. For rice yields the estimate is positive but too imprecise to support or reject a cushioning role. Much agricultural spending pays for price support and input subsidies, which raise incomes in normal years but do little to keep water on the field in a dry one, so its composition is likely to matter more than its size. Expenditure data split by function, such as irrigation, research and input subsidies, would allow that to be tested directly.

The study has limits. Eight countries are few, and the minimum detectable differences are large. The paper also runs twelve primary contrasts and eight buffer tests, so an isolated significant result can arise by chance, and none survives the Holm correction. National averages hide the difference between irrigated deltas and rainfed uplands within each country. Irrigation and spending are measured as country averages, and the spending index is available only from 2001, so their interactions describe associations, not the effect of a policy change. The reported-disaster measure gives a different answer from the rainfall measure for TFP and cereal yields, and the spatial model passes its lead placebo in one program and fails it in the other. Sub-national data on rice areas, irrigation and planting dates would allow sharper tests, and are the natural next step.

CONCLUSION

Across 50 exporting countries and more than three decades, the point estimates suggest that rice is where ASEAN agriculture is most exposed to dry years, although the data do not establish this statistically. A dry year is associated with a 3.4 per cent fall in ASEAN rice production and a 2.5 per cent fall in rice yields that is only marginally significant at the 10 per cent level. How the production loss divides between yield and area cannot be measured precisely, and on the point estimates close to half of the yield loss returns in the next season. Whether the region suffers more than other exporters cannot be settled with eight countries, since the design could detect only differences of 2.8 to 6.5 percentage points. Irrigation is associated with smaller dry-year losses in broader productivity measures but not, in these data, in rice yields, and these associations do not survive a correction for multiple testing. Countries that give agriculture a higher budget priority do not lose less TFP. Better data within countries, and on how agricultural budgets are spent, are needed before the region's rice policy can be tied firmly to weather resilience.

Ethical Approval

Not applicable. The study uses publicly available country-level secondary data and involves no human participants or animals.

Conflict Of Interest

The authors declare no conflict of interest.

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Data Availability

All data are publicly available from FAOSTAT, the World Development Indicators, the USDA Economic Research Service International Agricultural Productivity accounts, the CRU TS 4.08 dataset and EM-DAT. The assembled panel and the estimation code are available from the corresponding author on request.

Declaration Of Generative Ai Use

The authors used Claude (Anthropic) to assist with data processing code, figure generation and language editing. The authors reviewed and edited all content and take full responsibility for the publication.

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