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Research Article

Rainfall variability and coconut production dynamics in Eastern Visayas, Philippines: A spatiotemporal analysis using panel data (2010-2025)

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Abstract

This study examined spatiotemporal patterns of coconut production and their association with rainfall across six provinces of Eastern Visayas, Philippines, from 2010 to 2025. A balanced provincial panel (6 provinces × 16 years; N=96) was analyzed using Mann–Kendall trend tests with Sen's slope, a province fixed-effects regression of yield on bearing-tree density and one-year-lagged annual rainfall, and an area–yield–interaction decomposition. Production declined in five of six provinces, but no production trend remained significant after correction for serial autocorrelation. Annual rainfall showed no monotonic trend in any province, which does not show that rainfall was stable. Bearing-tree density and province accounted for 84.3% of the variance in yield, mostly between provinces. One-year-lagged rainfall added 0.008 to R^2 ($p = .034$) but was only narrowly significant under a wild cluster bootstrap ($p = .043$), and density was not ($p = .193$); residuals were serially correlated, so conventional p-values are likely too small. Yield change was the larger component of production change in four of six provinces. These are associations from a short observational panel, not causal effects; finer rainfall indicators and typhoon, replanting and management data are needed.

Keywords: Rainfall, Coconut, Yield, Eastern Visayas, Panel data, Mann–Kendall test

Introduction

Coconut (*Cocos nucifera* L.) is an important tropical perennial crop that provides food, employment and income in many producing countries, including the Philippines. Its production, however, is constrained by biological, technological, environmental and socioeconomic factors. Beveridge *et al.* (2022) reported that about 50–70% of the coconut palms currently under cultivation are well past their peak production age and are considered senile and unproductive, with fruit production declining after about 35 years of age; they also identified abiotic and biotic stresses and the limited availability of suitable planting material as key constraints. A systematic review of the coconut value chain by Zainol *et al.* (2023) likewise identified technological, political, socioeconomic and environmental factors associated with low production and supply-chain constraints. Together, these studies indicate that coconut production is shaped by multiple interacting production-related and industry-related conditions.

In the Philippines, coconut is one of the most widely cultivated agricultural commodities. The Philippine Statistics Authority (PSA) reported that coconut covered approximately 3.67 million hectares and produced 14.89 million metric tons of nuts in 2023, with a yield of 43.16 kg per bearing tree, and accounted for 5.3% of the total value of agriculture and fisheries production (Philippine Statistics Authority, 2024). In Leyte, Ruales *et al.* (2020) noted that small-scale farmers face challenges from frequent weather disturbances and changing climatic conditions, and examined coconut–banana intercropping and improved coconut varieties as options for climate-smart agriculture. Bentayao *et al.* (2025) found that coconut farmers in Davao Oriental perceived climate change to have a severe effect on coconut quality, yield, seasonal patterns, soil fertility and labor demands, whereas extreme weather, water scarcity and heat stress were perceived to have a moderate effect.

Rainfall and other meteorological conditions are relevant to coconut production because climate is linked to differences in palm growth, development and productivity. Rani *et al.* (2021), analyzing coconut production and productivity in India, reported that rainfall accounted for a larger share of yield variation than temperature. Agoh *et al.* (2023), studying coconut hybrids in Côte d'Ivoire from 2009 to 2018, found that climate variability, particularly drought, reduced production. In the eastern Amazon, Nery *et al.* (2025), using data from 2015 to 2023, reported that extreme precipitation events and excess water surplus were associated with higher productivity, whereas low precipitation during the less rainy period reduced productivity. These studies suggest that the amount, seasonal distribution and extremes of rainfall influence coconut productivity across production environments.

In the Philippines, studies have examined coconut production constraints, climate-related challenges and farmers' responses, whereas international studies have examined the effects of rainfall, drought and other climatic conditions on coconut productivity. However, few studies have related rainfall to coconut production using provincial panel data from several provinces within a single region over an extended period. This study therefore examines spatiotemporal patterns of coconut production, yield, area harvested, number of bearing trees, farmgate price and annual rainfall in Biliran, Eastern Samar, Leyte, Northern Samar, Samar and Southern Leyte from 2010 to 2025, and evaluates the association between rainfall and coconut yield while accounting for bearing-tree density and provincial

differences. Because annual rainfall totals can mask seasonal timing, dry periods and extreme events, the study discusses the limits of annual aggregation.

This study aimed to examine the spatiotemporal dynamics of coconut production in Eastern Visayas, Philippines, during 2010–2025 and its association with rainfall using provincial panel data. Specifically, it assessed trends and spatial patterns in coconut production, yield, harvested area, bearing-tree density, farmgate price and rainfall variability; evaluated the effects of one-year-lagged rainfall, bearing-tree density and provincial location on coconut yield; and quantified the contributions of harvested area and yield to changes in total coconut production.

Materials and methods

Research design and study area

This study used a quantitative, non-experimental design based on secondary provincial panel data to examine spatiotemporal patterns of rainfall and coconut production in Eastern Visayas, Philippines. The study covered six provinces (Biliran, Eastern Samar, Leyte, Northern Samar, Samar and Southern Leyte; Figure 1) over 16 years (2010–2025), giving a balanced panel of 96 province-year observations. Geographically, the study area covers the major coconut-producing provinces of Eastern Visayas and extends across the eastern portion of the Visayas region, approximately within 9°–13° N latitude and 124°–126° E longitude. The spatial component of the study was used to compare provincial differences in rainfall, coconut production, area harvested, yield, farmgate price, and number of bearing trees, while the temporal component examined changes in these variables over the 2010–2025 period.

Data Sources

Two secondary, publicly available datasets were used. Coconut production (metric tons, MT), area harvested (ha), yield (MT/ha), number of bearing trees (number of trees/hills/vines) and farmgate price (PHP/kg) were obtained from the Philippine Statistics Authority (PSA) OpenStat database (Economic and Financial Statistics, Agriculture, Forestry and Fisheries). Provincial rainfall was obtained from the Rainfall Indicators at Subnational Level dataset in the Philippine Rice Research Institute (PhilRice) Ricelytics Data Catalog, which reports rainfall in decadal (10-day) intervals for each province. Annual rainfall (mm/year) was computed by summing the decadal values within each calendar year. PSA OpenStat provides province-level coconut data only from 2010 onward, which determined the start of the study period.

Data preparation

Bearing-tree density (trees/ha) was computed for each province-year as the number of bearing trees/hills/vines divided by the area harvested. Because the denominator is harvested area rather than planted area, this variable describes the density of bearing trees per harvested hectare, not planting density or spacing, and is hereafter referred to as bearing-tree density. Because yield (production per harvested hectare) uses the same denominator, the two variables are partly mechanically related (yield per hectare = yield per bearing tree × bearing trees per hectare); this is taken into account when interpreting the regression results. Farmgate price series were incomplete for some provinces, which appears to reflect incomplete reporting in the source database rather than random missingness. Farmgate price was available for all 16 years in Biliran, Leyte and Northern Samar, 14 years in Eastern Samar (missing 2021–2022),

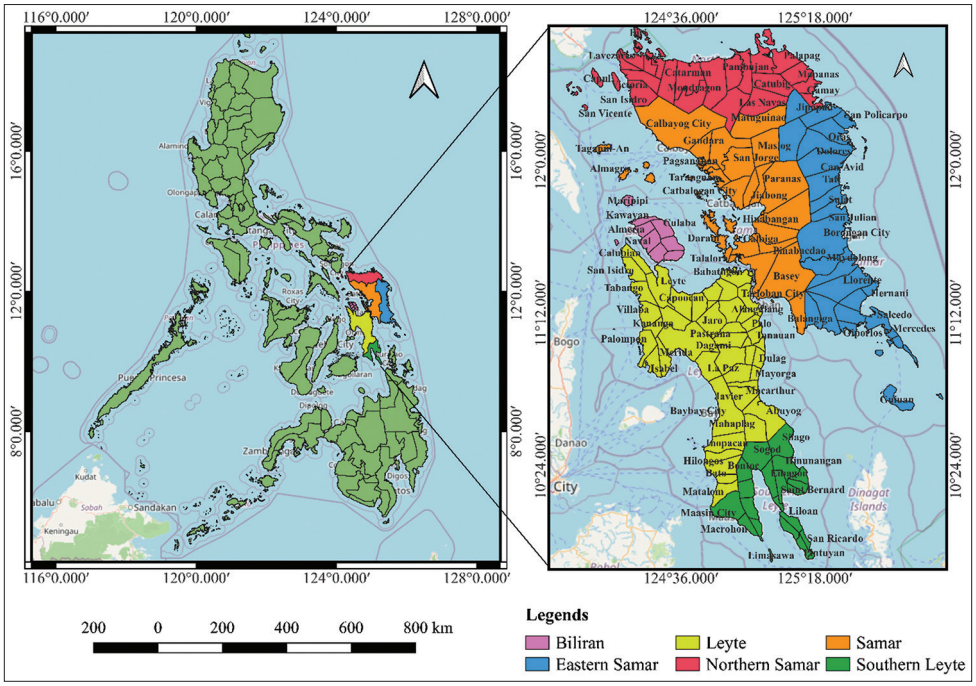


Figure 1: Map of Eastern Visayas showing the six provinces

5 years in Samar (2021–2025) and 2 years in Southern Leyte (2024–2025). Including price would have reduced the panel from 96 to 69 province-years (a 28% loss) and left only 5 and 2 observations for Samar and Southern Leyte. Farmgate price was therefore excluded from the regression.

One-year-lagged rainfall ($Rainfall_{t-1}$) was defined for each province-year as the annual rainfall total of the preceding calendar year. Because the primary dataset begins in 2010, the 2009 rainfall of each province was obtained from the same PhilRice dataset and aggregated in the same way (sum of decadal values, mm/year), so that all 96 observations were retained in both regression models.

Statistical software and tools

All statistical analyses were conducted in Jamovi (version 2.7), with underlying computations performed in R (version 4.5). The hierarchical multiple regression and its basic diagnostics (variance inflation factors, the Shapiro–Wilk test of residuals and the Durbin–Watson test for residual autocorrelation) were run using Jamovi's linear regression module. Because Jamovi's core modules do not include the following procedures, they were implemented in custom base R scripts, without additional packages, and run through Jamovi's Rj Editor module: (1) the Mann–Kendall trend test and Sen's slope estimator, with a tie correction to the variance of the Mann–Kendall statistic and the Hamed–Rao (Hamed & Rao, 1998) variance correction for serial autocorrelation (Appendix E); (2) the Pettitt change-point test (Appendix F); and (3) the panel-regression diagnostics and robust inference, namely the within-province Durbin–Watson statistic, the Wooldridge test for serial correlation, the Breusch–Pagan test, Driscoll–Kraay standard errors, the wild cluster bootstrap by province and the within-province R^2 (Appendix G). Spatial mapping was performed in QGIS (version 4.2).

Data analysis

To summarize the central tendency and variability of production, area, harvested, yield, farmgate price, number of bearing trees, and annual rainfall across the six provinces in Eastern Visayas, the mean and standard deviation are computed as:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

Where x_i is the observed value of the variable in year i, $\bar{x}$ is the mean, s is the standard deviation, and then n is the number of years (n = 16, from 2010 to 2025) in each province.

Trend analysis: Mann–Kendall Test, Sen's Slope and Change-Point Test

To determine whether each variable showed a statistically significant monotonic trend over 2010–2025, the non-parametric Mann–Kendall test was applied separately to each province and variable (Mann, 1945; Kendall, 1975). The test statistic S is:

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sgn\left(x_j - x_i\right)$$

where x_i and x_j are the observed values in years i and j (j > i), and sgn(·) equals +1 if $x_j > x_i$, −1 if $x_j < x_i$ and 0 if $x_j = x_i$ (a tie). Kendall's tau (τ), which expresses the direction and strength of the monotonic trend, was calculated as:

$$\tau = \frac{S}{\frac{n(n-1)}{2}}$$

where τ ranges from −1 (perfectly decreasing) to +1 (perfectly increasing) and values near 0 indicate no consistent trend. The null hypothesis of no monotonic trend was tested with the standardized statistic Z (with continuity correction) at $\alpha = 0.05$. The magnitude of change was estimated with Sen's slope (Sen, 1968), the median of all pairwise rates of change:

$$Sen's\ slope = median\left(\frac{x_j - x_i}{j - i}\right), for\ all\ i < j$$

Ties

Tied observations reduce the variance of S. The variance was therefore computed with the tie correction, $Var(S) = [n(n-1)(2n+5) - \Sigma\, t_p(t_p-1)(2t_p+5)]/18$, where t_p is the number of observations in the p-th group of tied values (Kendall, 1975; Gilbert, 1987). The script used for the originally reported results did not include this correction; it has been updated (Appendix E), and Tables 1 and 2 were re-run with the corrected script. The correction changed only the p-values of the area harvested and bearing-tree series, by no more than.025, and no conclusion at α =.05 changed. Series with fewer than four non-missing observations were not tested. Series with fewer than four non-missing observations were not tested.

Serial autocorrelation

Positive serial correlation inflates the false-positive rate of the Mann-Kendall test (Yue *et al.,* 2002), and series of only 16 values have limited power to detect it. The lag-1 autocorrelation of each series, after removing the Sen's slope trend, was therefore examined, and a lag-1 coefficient was considered significant when $|r_1| > 1.96/\sqrt{n}$. The Hamed-Rao (Hamed & Rao, 1998) variance-corrected Mann-Kendall test was then applied to all series as a sensitivity analysis. Lag-1 autocorrelation was significant in 18 of the 35 series tested (r_1 = 0.51 to 0.78), all of them production, area, yield or bearing-tree series. It was not significant in any rainfall series (r_1 = −0.11 to 0.00) or any farmgate price series. The correction inflated the variance of S by a factor of 1.78 to 2.14 in 17 series and left it unchanged in the rest. Of the eight trends significant at α =.05 under the tie-corrected test, two were no longer significant after correction (Northern Samar production and yield, p =.0133 to.0783); the other

Table 1: Mann–Kendall trend test and Sen's slope estimates by province and variable, 2010–2025

Province	Variable	Tau (τ)	P-value (tie-corrected)	P-value (Hamed-Rao)	Sen's Slope
Biliran	Production (MT)	−0.367	0.0529	0.0529	−496.56
	Area harvested (ha)	0.150	0.4431	0.5748	10.99
	Yield (MT/ha)	−0.333	0.0791	0.2004	−0.03
	Farmgate price	0.133	0.4995	0.4995	0.03
	Bearing trees	−0.367	0.0508	0.0508	−1,605.25
	Annual rainfall (mm/year)	0.000	1.0000	1.0000	0.64
Eastern Samar	Production (MT)	−0.283	0.1373	0.3097	−4,987.30
	Area harvested (ha)	−0.058	0.7787	0.8437	0.00
	Yield (MT/ha)	−0.567	0.0026**	0.0026**	−0.09
	Farmgate price	0.516	0.0118*	0.0118*	0.42
	Bearing trees	−0.117	0.5527	0.6632	−19,296.67
	Annual rainfall (mm/year)	0.050	0.8219	0.8219	10.86
Leyte	Production (MT)	0.017	0.9641	0.9746	342.99
	Area harvested (ha)	−0.050	0.8128	0.8635	0.00
	Yield (MT/ha)	0.017	0.9641	0.9746	0.00
	Farmgate Price	−0.067	0.7526	0.7526	−0.09
	Bearing Trees	−0.625	0.0006***	0.0006***	−16,300.90
	Annual Rainfall (mm/year)	0.017	0.9641	0.9641	1.65
Northern Samar	Production (MT)	−0.467	0.0133*	0.0783	−4,666.26
	Area harvested (ha)	−0.217	0.2351	0.4051	−45.17
	Yield (MT/ha)	−0.467	0.0133*	0.0783	−0.05
	Farmgate price	0.383	0.0428*	0.0428*	0.34
	Bearing trees	−0.283	0.1323	0.2912	−3,459.77
	Annual rainfall (mm/year)	0.067	0.7526	0.7526	14.39
Samar	Production (MT)	0.350	0.0649	0.1661	3,404.75
	Area harvested (ha)	0.283	0.1299	0.2923	50.00
	Yield (MT/ha)	−0.200	0.3004	0.3004	−0.02
	Farmgate price†	0.800	0.0864	0.0864	1.92
	Bearing trees	0.250	0.1908	0.3683	65,079.29
	Annual rainfall (mm/year)	0.050	0.8219	0.8219	24.09
Southern Leyte	Production (MT)	−0.067	0.7526	0.8150	−51.39
	Area harvested (ha)	−0.467	0.0121*	0.0121*	−193.35
	Yield (MT/ha)	0.817	<.0001***	<.0001***	0.03
	Bearing trees	−0.325	0.0861	0.2058	−22,747.77
	Annual rainfall (mm/year)	0.050	0.8219	0.8219	15.21

Kendall's τ is the direction and strength of the monotonic pattern; positive values mean an increasing trend and negative values a decreasing one. The p-value tests the null hypothesis of no monotonic trend. The first p-value column uses the tie-corrected variance of S; the second additionally applies the Hamed-Rao (1998) correction for serial autocorrelation. Sen's slope is the estimated median annual rate of change in the original units of each variable. Significance: ***p<.001, **p<.01, * p<.05. Based on only 5 observations (2021–2025); interpret with caution. Farmgate price for Southern Leyte (2 observations) was not tested. Eastern Samar's price series is missing 2021–2022, and its slope was computed using the actual years

Table 2: Annual rainfall variability and Mann–Kendall results by province, 2010–2025

Province	Mean (mm/year)	SD (mm/year)	Min. (mm/year)	Max. (mm/year)	CV (%)	Tau (τ)	Sen's Slope	P-value
Biliran	3,477	866	2,002	5,365	24.9	0.000	0.64	1.0000
Eastern Samar	4,273	1,176	2,377	6,781	27.5	0.050	10.86	0.8219
Leyte	3,470	913	2,028	5,504	26.3	0.017	1.65	0.9641
Northern Samar	4,286	1,069	2,421	6,488	24.9	0.067	14.39	0.7526
Samar	4,031	1,051	2,296	6,299	26.1	0.050	24.09	0.8219
Southern Leyte	3,579	968	2,157	5,669	27.1	0.050	15.21	0.8219

CV=coefficient of variation. CV <20% indicates low variability, 20–30% moderate and >0% high variability (Bogale, 2023). The p-value tests the null hypothesis of no monotonic trend

six remained significant, and no previously non-significant trend became significant. Because the corrected test can only widen the variance, it can remove false positives but cannot create new ones.

Abrupt change

Because the Mann–Kendall test detects only monotonic trends and is insensitive to step changes, each annual rainfall, production, yield, area harvested, and bearing-tree series was also tested for a single abrupt change point with the Pettitt test (Pettitt, 1979). The change year is reported as the first year of the new regime, and p-values were obtained from the standard approximation $p \approx 2 \cdot \exp[-6K^2/(n^3 + n^2)]$, where K is the maximum absolute value of the Pettitt statistic. Farmgate price was not tested because of missing years and short series. With n = 16, the test cannot reach p <.05 when four or fewer observations lie on one side of the break, so it has little power to detect early or late shifts. Non-significant Mann–Kendall and Pettitt results are interpreted as the absence of a detectable monotonic trend or single step change in annual totals, not as evidence that rainfall was stable.

Spatial distribution mapping

For the choropleth maps in Figures 2 and 3, a three-class scheme (low, moderate, high) was used instead of a five-class scheme. Fewer classes are recommended when mapping a

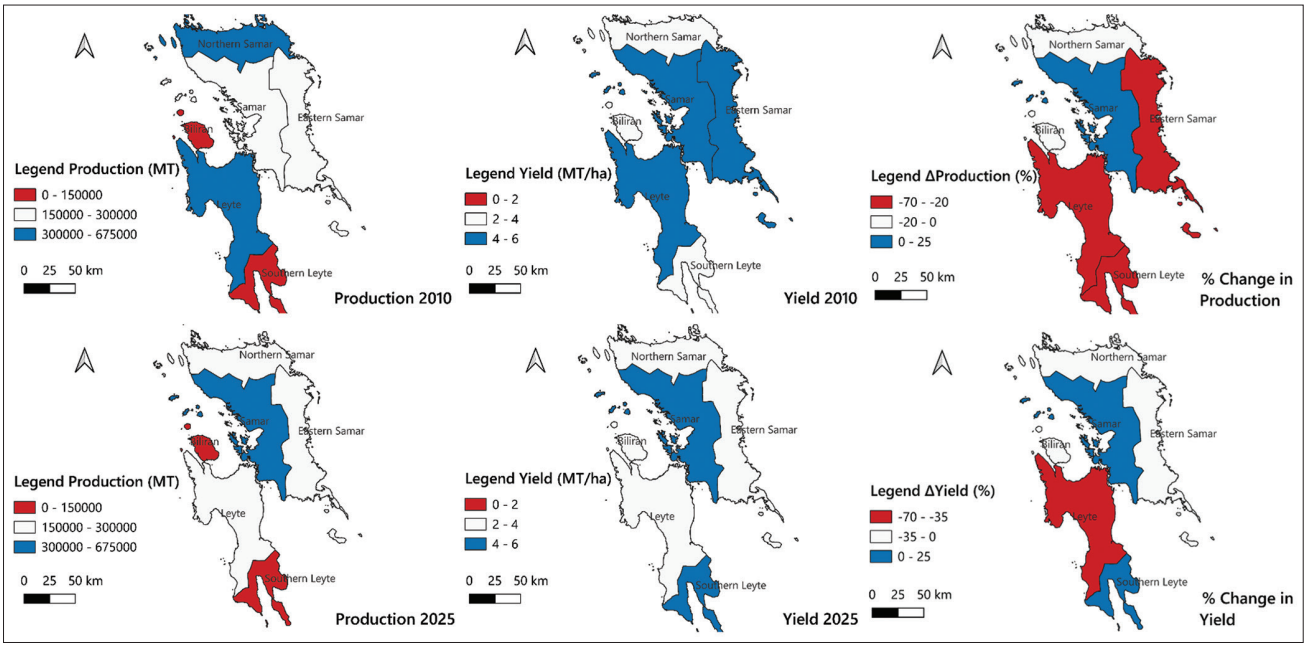


Figure 2: Spatial distribution of coconut production and yield across the Provinces of Eastern Visayas, Philippines in 2010 and 2025

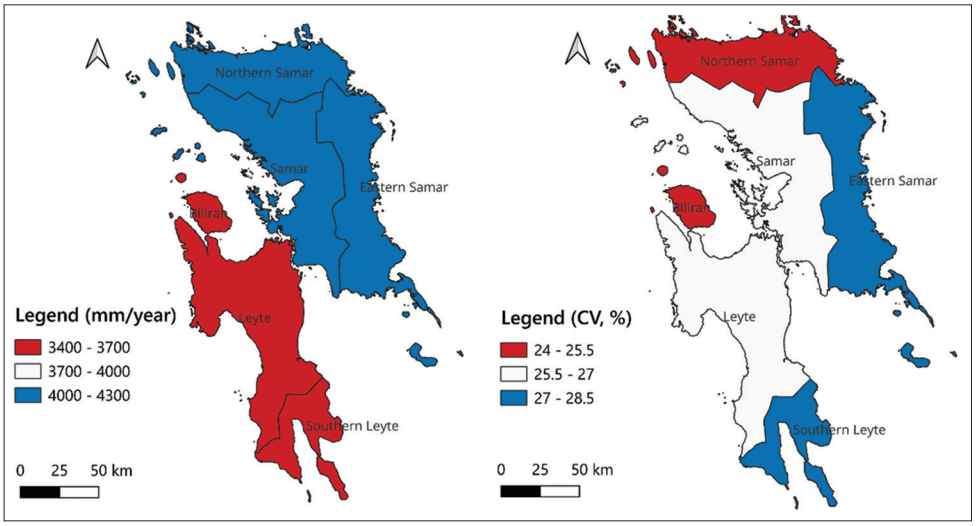


Figure 3: Spatial distribution of mean annual rainfall and rainfall variability across Provinces in Eastern Visayas

small number of spatial units (Evans, 1977); with only six provinces, five classes would place one or two provinces in each class and obscure rather than reveal spatial patterns.

Percentage change in production and yield

To describe change between the start and end of the study period, the percentage change in production and yield was computed for each province as:

$$\Delta Production\,\% = \frac{Production_{2025} - Production_{2010}}{Production_{2010}} \times 100$$

$$\Delta Yield\,\% = \frac{Yield_{2025} - Yield_{2010}}{Yield_{2010}} \times 100$$

Where $Production_{2010}$ and $Production_{2025}$ (and also $Yield_{2010}$ and $Yield_{2025}$) refers to coconut production and yield for each province at the beginning and end of the study period, respectively.

Coefficient of cariation

To compare rainfall variability among provinces independent of mean rainfall, the coefficient of variation (CV) of annual rainfall was computed as:

$$CV\,\% = \frac{s}{\bar{x}} \times 100$$

Where s is the standard deviation and $\bar{x}$ is the mean annual rainfall for each province. Results were interpreted based on Bogale (2023) ranges where CV < 20% was interpreted as low variability, 20% - 30% as moderate variability, and CV > 30% as high variability.

Regression analysis of yield (MT/ha)

The association of yield with bearing-tree density, provincial location and lagged rainfall was examined with

a province fixed-effects panel regression, estimated by ordinary least squares with province dummy variables (the least-squares dummy-variable estimator) and entered hierarchically in two steps. Hierarchical entry is not a separate estimator; it is used only to quantify the incremental explanatory power (ΔR^2) of lagged rainfall once bearing-tree density and province are controlled. This specification suits a balanced panel of six provinces observed over 16 years because the province terms absorb all time-invariant differences among provinces (for example soils, agro-ecological conditions, long-run management and typical variety mix), so that the density and rainfall coefficients are identified from within-province, year-to-year variation. Treating the 96 observations as independent, however, ignores that repeated observations within a province are likely to be serially correlated; this was assessed and addressed as described below.

Model 1 included bearing-tree density and province as predictors:

$$Yield_{ij} = \beta_0 + \beta_1 (Trees / ha)_{ij} + \sum_{k=2}^{6} \beta_k (Province_k)_{ij} + \varepsilon_{ij}$$

Model 2 added one-year-lagged rainfall:

$$Yield_{ij} = \beta_0 + \beta_1 (Trees / ha)_{ij} + \sum_{k=2}^{6} \beta_k (Province_k)_{ij} + \beta_7 (Rainfall_{t-1})_{ij} + \varepsilon_{ij}$$

where $Yield_{ij}$ is coconut yield (MT/ha) in province i and year j; β_0 is the intercept; $(Trees/ha)_{ij}$ is the number of bearing trees per harvested hectare (trees/ha); $(Province_k)_{ij}$ are dummy variables for the five provinces other than Biliran, the reference category (k = 2,…, 6: Eastern Samar, Leyte, Northern Samar, Samar and Southern Leyte); $(Rainfall_{t-1})_{ij}$ is the annual rainfall of the preceding year (mm/year); β_1 to β_7 are unstandardized regression coefficients; and ε_{ij} is the error term. The improvement from Model 1 to Model 2 was evaluated with the change in R^2 and its F-test:

$$\Delta R^2 = R^2_{Model\,2} - R^2_{Model\,1}$$

$$F_{\Delta} = \frac{\frac{\Delta R^2}{k_2 - k_1}}{\frac{1 - R^2_{Model\,2}}{N - k_2 - 1}}$$

Where $R^2_{Model\,1}$ and $R^2_{Model\,2}$ are the coefficients of determination for Models 1 and 2, respectively; k_1 and k_2 are the number of predictors in Model 1 and 2; and N is the total sample size.

Rationale for the one-year lag

The lag was specified a priori from coconut phenology, with the statistical comparison serving as a check. A palm produces one inflorescence per leaf axil; the nut harvested in a given year develops from a spathe that opened roughly 12 months earlier, and the inflorescence primordium forms about 32 months before spathe opening, giving about 44 months from initiation to mature nut (Child, 1974; Kumar *et al.,* 2022). Fruit set and early nut development, the stages most sensitive to water availability, therefore take place largely in the year before harvest (Peiris *et al.,* 1995). Rainfall of the previous calendar year thus overlaps with these stages for nuts harvested in the current year, which supports $Rainfall_{t-1}$ as the primary specification, whereas rainfall of the harvest year mostly affects later stages. A parallel model with same-year rainfall was estimated for comparison (Appendices B and C). Only lags of 0 and 1 year were examined; longer lags, relevant to inflorescence initiation, cannot be estimated reliably from 16 years of data.

Serial correlation and inference

Residuals of both models were checked for within-province serial correlation with the Wooldridge test for panel data (Wooldridge, 2010) and the Durbin–Watson statistic, and for heteroskedasticity with the Breusch–Pagan test; results are reported in the Results. Conventional OLS standard errors assume independent errors and would be too small if residuals are serially correlated. Inference for Model 2 was therefore repeated with Driscoll–Kraay standard errors (Driscoll & Kraay, 1998; Bartlett kernel, maximum lag of 2, with 3 as a sensitivity check) and, because six provinces are too few clusters for conventional cluster-robust standard errors, with a wild cluster bootstrap by province (Cameron *et al.,* 2008; restricted residuals, Webb six-point weights, cluster-robust t statistics, 9,999 replications). Bootstrap results for lagged rainfall were stable across three random seeds (p =.041–.043). These procedures were applied to the two time-varying predictors, bearing-tree density and lagged rainfall, because the province coefficients are not identified from within-province variation. A within-province R^2 (the R^2 after subtracting each province's mean from yield and the predictors) is also reported because the R^2 of a model with province dummies is dominated by between-province differences. Year fixed effects were not included because rainfall may co-vary among provinces in a given year, and year effects would absorb that variation. All routines were implemented in base R (Appendix G).

Multicollinearity was low (variance inflation factors ≤ 2.54 in all models). Residuals departed from normality (Shapiro–Wilk W = 0.904, p <.001 for Model 1; W = 0.920, p <.001 for Model 2). With N = 96, coefficient estimates remain consistent and large-sample inference is approximately valid without normal residuals (Wooldridge, 2015), but this is acknowledged as a limitation, and a log-transformed or robust-regression model is suggested for future work.

Area-yield-interaction decomposition

To determine the relative contribution of area expansion and yield change to production change, an additive area–yield–interaction decomposition (Minhas & Vaidyanathan,

1965) was applied to each province. Because PSA OpenStat provides province-level production, area harvested and yield only from 2010 onward, the analysis used the 15 annual transitions between 2010 and 2025. For each transition, the change in production was decomposed as:

$$\Delta Production_t = Area\ Effect_t + Yield\ Effect_t + Interaction\ Effect_t$$

$$Area\ Effect_t = \left(Area_t - Area_{t-1}\right) \times Yield_{t-1}$$

$$Yield\ Effect_t = \left(Yield_t - Yield_{t-1}\right) \times Area_{t-1}$$

$$Interaction\ Effect_t = \left(Area_t - Area_{t-1}\right) \times \left(Yield_t - Yield_{t-1}\right)$$

where $Area_t$ and $Yield_t$ are the area harvested (ha) and yield (MT/ha) in year t, and $Area_{t-1}$ and $Yield_{t-1}$ are the corresponding values in the preceding year. The annual components were summed across the 15 transitions to obtain each province's total effects:

$$Total\ Area\ Effect = \sum_{t=2011}^{2025} Area\ Effect_t,$$

$$Total\ Yield\ Effect = \sum_{t=2011}^{2025} Yield\ Effect_t,$$

$$Total\ Interaction\ Effect = \sum_{t=2011}^{2025} Interaction\ Effect_t$$

Each component was then expressed as a percentage share of the province's actual total production change between 2010 and 2025:

$$Actual\ Total\ Change = Production_{2025} - Production_{2010}$$

$$Area\ Share\ \% = \frac{Total\ Area\ Effect}{Actual\ Total\ Change} \times 100$$

$$Yield\ Share\ \% = \frac{Total\ Yield\ Effect}{Actual\ Total\ Change} \times 100$$

$$Interaction\ Share\ \% = \frac{Total\ Interaction\ Effect}{Actual\ Total\ Change} \times 100$$

The three components sum exactly to the actual change in production, so the three shares sum to 100% for each province. Because shares are expressed relative to the net change, they can exceed 100% or be negative when a component acts opposite to the net change or when the net change is small relative to year-to-year fluctuations.

Results and discussion

Temporal trends of coconut production, yield, area harvested, bearing trees, farmgate price and rainfall

Mean production differed widely among provinces (Table 3), from about 52,000 MT in Biliran to about 319,000 MT in Leyte, which also had the greatest variability, largely because production fell from about 516,000 MT in 2013 to about 190,000 MT in 2014. Mann–Kendall tests (Table 1) detected few significant trends, and these were province specific. Yield declined in Eastern Samar and increased in Southern Leyte, harvested area declined in Southern Leyte, bearing trees declined in Leyte, and farmgate price increased in Eastern Samar and Northern Samar. The declines in production and yield in Northern Samar were significant only before correction for serial autocorrelation (production p=.013 versus.078 after the Hamed–Rao correction) and should be regarded as suggestive; no province showed a significant production trend after correction.

A non-significant Mann–Kendall result does not mean there was no change. Leyte's production fell sharply in 2014 and recovered only partly, a step-and-recovery pattern that a monotonic test is not designed to detect, and with only 16 observations per series the tests have limited power. The decline in Leyte's bearing trees occurred almost entirely between 2013 and 2014 (from about 19.2 to 10.8 million trees), so the Sen's slope should not be read as a gradual annual loss. Annual rainfall is considered separately below.

The Pettitt test, which is sensitive to step changes that the Mann–Kendall test can miss, detected single change points in yield in Eastern Samar, in production and yield in Northern Samar (both from 2017), in production in Samar (from 2021), in yield in Southern Leyte (from 2019) and in bearing trees in Leyte (from 2015; 17.4 → 10.8 million). Area harvested and bearing trees in Northern Samar also showed breaks, but the shifts were under 2%. The sharp declines around 2014–2015 in Leyte (production 629,363 → 214,899 MT) and Eastern Samar did not reach significance (p =.073–.084), which reflects the limited power of the test for breaks near the start of a 16-year series, not the absence of change. Because about 30 change-point tests were run, one or two significant results could arise by chance at α =.05. The predominance of declining or non-increasing production is consistent with reports of declining

Table 3: Province-level mean±standard deviation of coconut indicators and annual rainfall, 2010–2025

Province	Production (MT)	Area harvested (ha)	Yield (MT/ha)	Farmgate price (PHP/kg)	Bearing trees (no.)	Annual rainfall (mm)
Biliran	52,295±4,165	20,561±657	2.55±0.21	8.32±1.73	1.88×10^6±15,287	3,477±866
Eastern Samar	196,430±47,012	51,909±8,095	3.76±0.50	7.38±3.45	5.10×10^6±840,001	4,273±1,176
Leyte	318,515±188,940	112,835±32,369	2.64±0.72	6.05±2.96	1.29×10^7±3.70×10^6	3,470±913
Northern Samar	295,373±42,402	84,741±727	3.48±0.47	12.1±2.82	9.49×10^6±125,518	4,286±1,069
Samar	290,412±25,850	54,100±7,208	5.40±0.37	10.8±3.33	6.42×10^6±742,258	4,031±1,051
Southern Leyte	117,358±17,309	28,564±6,961	4.25±0.64	11.6±1.97	2.48×10^6±484,949	3,579±968

Values are mean±SD over 16 years per province. Farmgate price series are incomplete for some provinces (see Data Preparation)

Philippine coconut production (Moreno *et al.,* 2020) and of negative yield growth despite positive area growth in later periods (Narmadha & Karunakaran, 2022). Crisostomo *et al.* (2023) reported that Northern Samar had the largest yield gap (68%), associated with inadequate soil nutrient management, which is a possible but untested contributor to the yield pattern observed there. The present data cannot identify the causes of the increases or decreases.

Typhoons are a recurring hazard for coconut farming in Eastern Visayas. A study of small-scale farmers on Leyte Island reported that Typhoon Yolanda (Haiyan) in 2013 significantly reduced coconut income and that replanted coconut trees typically take seven to nine years to return to full production (Seriño *et al.,* 2020). An assessment of post-Yolanda programs in Burauen, Leyte (coconut replanting, fertilization, debris management and intercropping) found no significant effect on beneficiaries' livelihoods (Pormon *et al.,* 2021). In the present data, harvested area and production in both Leyte and Eastern Samar dropped between 2013 and 2014, the year after Yolanda, a timing consistent with this hazard. Such evidence suggests that extreme-weather exposure, farm management and prolonged recovery could contribute to provincial differences in coconut-sector performance. Typhoon damage, replanting and management were not included in the present dataset, however, so these explanations are hypotheses that this study cannot test.

Spatial distribution and spatiotemporal changes in coconut production and yield across provinces in Eastern Visayas

Figure 2 and Table 4 show the spatial distribution of, and change in, production and yield. In 2010, Leyte (674,388 MT) and Northern Samar (325,936 MT) had the highest production, followed by Samar (293,305 MT), whereas Biliran and Southern Leyte had the lowest (below 150,000 MT). Yields in 2010 ranged from 2.78 to 4.39 MT/ha. By 2025 the pattern had shifted: Samar had the highest production and yield, and Leyte had dropped out of the highest classes. Between 2010 and 2025, production declined in five of the six provinces (Table 4), most steeply in Leyte (−65.2%), followed by Southern Leyte (−37.7%), Eastern Samar (−27.2%), Northern Samar (−19.1%) and Biliran (−18.4%); Samar was the only province with higher production (+11.6%). Yield declined in four provinces, most steeply in Leyte (−38.9%), and rose in Southern Leyte (+23.8%) and Samar (+22.8%).

Endpoint comparisons depend on conditions in the two years chosen. The large change in Leyte, together with its non-significant Mann–Kendall result (Table 1), is consistent with a step-like change rather than a steady monotonic trend, which the Mann–Kendall test would not detect. The Pettitt test did not reach significance for Leyte production (p =.073–.084), which reflects limited power for breaks near the start of a 16-year series rather than the absence of change. PSA's 2024 provincial figures (Samar 336,883 MT; Northern Samar 265,188 MT; Leyte 238,894 MT; Southern Leyte 94,399 MT; Biliran 50,411 MT) (Philippine Statistics Authority–Regional Statistical Services Office VIII, 2025) show the same ranking among these provinces as the 2025 values in Table 4.

Several factors reported in the literature could contribute to the changes in Leyte and Southern Leyte, but none was analyzed here. Calungsod and Ramoneda (2020) found that coconut farmers in typhoon-affected areas of Hindang and Mayorga, Leyte, had fewer coconut trees per hectare and significantly lower coconut income than farmers in less-affected areas, and that most affected farmers had replanted, indicating a prolonged recovery. Super Typhoon Rai (Odette), which made landfall on 16 December 2021, damaged more than 10 million coconut trees nationwide, and the Philippine Coconut Authority reported ₱1.58 billion in damage to the coconut sector and mobilized fertilization and replanting programs (Philippine Coconut Authority, 2022). Reyes (2025) reported that about 3.9 million trees in Eastern Visayas were destroyed beyond recovery and that rehabilitation, including replanting with higher-yielding hybrid varieties, was estimated to take six to nine years. Replanting with hybrids may have contributed to the increase in Southern Leyte's yield despite lower production and harvested area, but replanting and variety data were not available to test this.

Variability and trends of annual rainfall across Provinces

Table 2 and Figures 3 and 4 summarize annual rainfall variability and trends. Mean annual rainfall ranged from 3,470 mm in Leyte to 4,286 mm in Northern Samar. The three Samar Island provinces (Northern Samar, Eastern Samar and Samar; 4,000–4,300 mm/year) were wetter than Biliran, Leyte and Southern Leyte (3,400–3,700 mm/year; Figure 3). Within each province, annual totals varied 2.6- to 2.9-fold between the driest and wettest years (minimum 2,002 mm in Biliran; maximum 6,781 mm in Eastern Samar).

Table 4: Provincial coconut production and yield in 2010 and 2025 with percentage change

Province	Production 2010 (MT)	Production 2025 (MT)	ΔProduction (%)	Yield 2010 (MT/ha)	Yield 2025 (MT/ha)	ΔYield (%)
Biliran	56,777	46,355	−18.4	2.78	2.40	−13.7
Eastern Samar	272,484	198,291	−27.2	4.37	3.50	−19.9
Leyte	674,388	234,730	−65.2	4.06	2.48	−38.9
Northern Samar	325,936	263,807	−19.1	3.81	3.13	−17.8
Samar	293,305	327,418	+11.6	4.39	5.38	+22.8
Southern Leyte	125,075	77,931	−37.7	3.79	4.69	+23.8

Δ denotes the change between 2010 and 2025

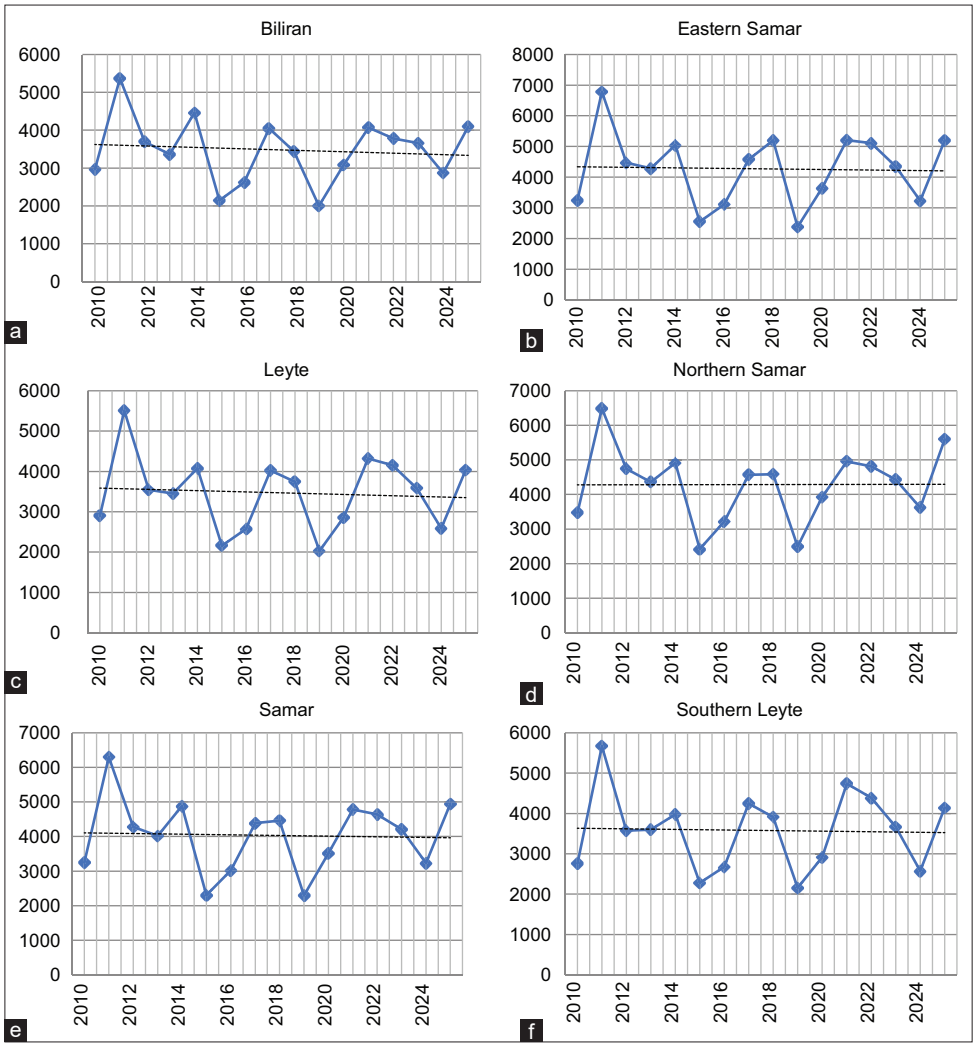


Figure 4: Annual rainfall (mm/year) across provinces in Eastern Visayas (2010-2025). a) Biliran, b) Eastern Samar, c) Leyte, d Northern Samar, e) Samar and f) Southern Leyte

The CV of annual rainfall was 24.9–27.5%, which is moderate variability (20–30%; Bogale, 2023) in every province, highest in Eastern Samar (27.5%) and lowest in Biliran and Northern Samar (24.9%; Figure 3). The narrow range (about 2.6 percentage points) indicates similar year-to-year variability in annual totals across provinces. A CV of annual totals does not, however, describe how rainfall is distributed within the year.

No province showed a significant monotonic trend in annual rainfall (all $p > .75$; Sen's slopes from 0.6 mm/year in Biliran to 24.1 mm/year in Samar; Table 2). These results indicate that no monotonic increase or decrease in annual totals was detected over 2010–2025 with 16 annual values. They do not establish that rainfall was stable: the Mann–Kendall test is insensitive to abrupt changes and to changes in seasonality, dry spells or extremes, and its power is limited in short series. The Pettitt test likewise detected no abrupt change in annual rainfall in any province (all $p \geq .96$; Appendix D), and the detrended lag-1 autocorrelation of the rainfall series was not significant ($r_1 = -0.11$ to 0.00), so serial correlation did not affect the interpretation of the trend tests. The conclusion therefore does not change: no monotonic trend or single step change was detected in annual rainfall totals. This still does not show that rainfall was stable, because 16 annual values give limited power and annual totals cannot reveal changes in seasonality, dry spells or extremes.

Annual rainfall in all provinces fluctuated from year to year without a sustained rise or fall (Figure 4), with relatively wet years around 2011 and 2021 and relatively dry years around 2015 and 2019.

Fluctuations of this kind in the Philippines have been linked to the El Niño–Southern Oscillation (ENSO) and to tropical cyclones. Sekhon *et al.* (2022), using 100 years of rainfall and river data from 29 rainfall stations and 61 river stations across Philippine climate types, found that rainfall declined in the period leading to El Niño events and recovered afterward, with the full effect sometimes lasting up to seven years. Petilla *et al.* (2023) reported that tropical cyclones crossing the central and southern Philippines generally weaken over land, but by amounts that vary from storm to storm, so the rainfall contribution of typhoons differs among years. ENSO phase and typhoon passage were not analyzed in this study; they are possible explanations for the year-to-year variation in Figure 4, not demonstrated ones.

Comparable results have been reported elsewhere. Aclan and Curay (2025), applying the Mann–Kendall

test, Sen's slope and CV to 1991–2020 rainfall in Baybay City, Leyte, found that total rainfall increased relative to earlier decades but that yearly and seasonal changes were not statistically significant. In Johor, Malaysia, Talib *et al.* (2024) found non-significant declining trends in annual and seasonal rainfall (p>.05), together with extreme wet and dry years linked to floods and to El Niño-related drought.

Association of bearing-tree density, province and lagged rainfall with coconut yield

Model 1 (bearing-tree density and province) was statistically significant and accounted for 84.3% of the variance in yield (R^2 = 0.843, RMSE = 0.433 MT/ha, $F(6, 89) = 79.60$, p <.001; Table 5). Bearing-tree density per harvested hectare was positively associated with yield (B = 0.047, SE = 0.009, p <.001 under conventional standard errors; within provinces), 10 additional bearing trees per hectare corresponded to about 0.47 MT/ha higher yield. Three cautions apply. First, yield and bearing-tree density share harvested area as the denominator, so part of this association is mechanical. Second, the province dummies absorb the large differences in mean yield among provinces, so most of the R^2 reflects between-province differences and should not be read as density and location "explaining" yield in a causal sense. Third, conventional standard errors are likely too small because residuals are serially correlated, and in Model 2 the density coefficient was not significant under a wild cluster bootstrap (see below). Trac and Thuy (2026) likewise observed differences in planting density and yield among coconut production systems in Vinh Long, Vietnam, although yield also depended on coconut type and other biological and environmental factors.

Relative to Biliran, yield was higher in Eastern Samar (B = 0.91 MT/ha, p <.001), Samar (B = 1.56, p <.001) and Southern Leyte (B = 1.85, p <.001) and lower in Leyte (B = −0.96, p <.001); Northern Samar did not differ significantly (B = −0.02, p =.924). Leyte's lower yield despite the largest production and harvested area shows that production scale does not necessarily correspond to productivity per hectare. The province terms summarize all stable provincial differences (soils, varieties, palm age, management and others); the model cannot identify which of them matter.

Model 2 added one-year-lagged annual rainfall, specified a priori from coconut phenology (see Methods). Its addition produced a small but statistically significant improvement in fit ($\Delta R^2 = 0.008$, $F(1, 88) = 4.65$, p =.034; R^2 = 0.851, RMSE = 0.422 MT/ha) under conventional standard errors. The coefficient was positive (B = 0.00010 MT/ha per mm, SE = 0.00005, p =.034), equivalent to about 0.10 MT/ha higher yield per additional 1,000 mm of previous-year rainfall, holding bearing-tree density and province constant. This association was weaker under robust inference (wild cluster bootstrap p =.043; see below). One standard deviation of annual rainfall (866–1,176 mm; Table 2) corresponds to roughly 0.09–0.12 MT/ha, or about 2–4% of provincial mean yield. The coefficients for bearing-tree density and province were stable after rainfall was added (Table 5). Silva and Matsui (2026) similarly found that previous-year rainfall was an important determinant of coconut yield in Sri Lanka (p =.032), estimating an increase of 1.3 nuts per hectare for each additional millimeter.

In the parallel model with same-year rainfall, the coefficient was not significant (B = 0.0000326, SE = 0.0000474, p =.493 under conventional standard errors) and model fit did not improve (ΔR^2 = 0.0008, $F(1, 88) = 0.473$, p =.493; Appendix B). This agrees with the phenological expectation that rainfall in the year before harvest is more relevant than harvest-year rainfall, but only lags of 0 and 1 year were compared, and the comparison does not show that a one-year lag is the only relevant lag.

Table 5: Hierarchical fixed-effects regression predicting yield (MT/ha)

Predictor	Model 1 *B* (SE)	*t*	*p*	Model 2 *B* (SE)	*t*	*p*	*Model 2 Driscoll–Kraay SE*	*Model 2 wild-cluster bootstrap p*
(Intercept)	-1.70 (0.82)	-2.06	0.042	-1.92 (0.81)	-2.36	0.021	—	—
Bearing-tree density (trees/ha)	0.047 (0.009)	5.20	< 0.001	0.045 (0.009)	5.12	< 0.001	0.0056	0.193
Province (ref. = Biliran)							—	—
Eastern Samar	0.91 (0.17)	5.32	< 0.001	0.84 (0.17)	4.92	< 0.001	—	—
Leyte	-0.96 (0.26)	-3.72	< 0.001	-0.93 (0.25)	-3.65	< 0.001	—	—
Northern Samar	-0.02 (0.24)	-0.10	0.924	-0.07 (0.24)	-0.29	0.769	—	—
Samar	1.56 (0.30)	5.30	< 0.001	1.55 (0.29)	5.36	< 0.001	—	—
Southern Leyte	1.85 (0.16)	11.45	< 0.001	1.83 (0.16)	11.58	< 0.001	—	—
Rainfall, t−1 (mm/year)	—	—	—	0.00010 (0.00005)	2.16	0.034	0.000025	0.043
Model Summary								
Model 1: R=0.918, R^2 = 0.843, within-province R^2 = 0.233, RMSE=0.433, F (6, 89) = 79.60, p<0.001								
Model 2: R=0.922, R^2 = 0.851, within-province R^2 = 0.272, RMSE=0.422, F (7, 88) = 71.70, p<0.001								
The addition of one-year-lagged rainfall significantly improved Model 2 under conventional standard errors, ΔR^2 = 0.008, F (1, 88) = 4.65, p=0.034 (wild-cluster bootstrap p=0.043 for the lagged-rainfall coefficient).								

N=96 province-year observations. Province dummies use Biliran as the reference category. B=unstandardized coefficient; SE=conventional OLS standard error; t=t statistic; RMSE=root mean square error. Driscoll–Kraay standard errors use a Bartlett kernel with maximum lag 2 (p<0.001 for both predictors); they are smaller than the conventional standard errors and are not used for inference (see text). Wild-cluster bootstrap p-values are by province (9,999 replications). Robust inference is not reported for the intercept and province coefficients, which are not identified from within-province variation

Table 6: Area–yield–interaction decomposition of the change in coconut production, 2010–2025

Province	Actual Change (2010→2025)	Area Share %	Yield Share %	Interaction %
Biliran	−10,422	27.8	70.1	2.1
Eastern Samar	−74,193	48.1	36.4	15.5
Leyte	−439,658	49.6	68.2	−17.8
Northern Samar	−62,129	10.0	93.1	−3.1
Samar	34,113	−30.4	221.5	−91.1
Southern Leyte	−47,144	138.4	−87.1	48.8

Shares are percentages of each province's net change in production between 2010 and 2025 and sum to 100% by construction. Shares above 100% or below 0% occur when a component acts opposite to the net change or when the net change is small relative to year-to-year fluctuations (Samar and Southern Leyte)

Residual diagnostics indicated serial correlation and heteroskedasticity in both models. The Wooldridge test rejected the null of no serial correlation (Model 1: $F(1, 82) = 6.40$, $p = .013$; Model 2: $F(1, 82) = 5.01$, $p = .028$), with Durbin–Watson statistics of 0.62 and 0.63 for pooled residuals and 0.40 and 0.44 when computed within provinces. The Breusch–Pagan test indicated heteroskedasticity (Model 1: $\chi^2(6) = 17.98$, $p = .006$; Model 2: $\chi^2(7) = 18.09$, $p = .012$). Conventional standard errors and p-values are therefore likely too small. Within provinces, bearing-tree density accounted for 23.3% of the variance in yield (Model 1), and adding lagged rainfall raised this to 27.2% (Model 2), an increase of about four percentage points compared with 0.8 points in the total R^2. Driscoll–Kraay standard errors were smaller, not larger, than the conventional ones (lagged rainfall: SE = 0.000025 versus 0.000047), the opposite of the expected correction; because this estimator is designed for long panels and only 16 years and six provinces were available, its p-values are shown in Table 5 but not used for inference. The wild cluster bootstrap by province, which is designed for few clusters, gave $p = .043$ for lagged rainfall (cluster-robust $t = 2.67$; $p = .041$–$.043$ across three seeds), so the association remained significant at $\alpha = .05$ but only narrowly. For bearing-tree density the bootstrap p-value was.193 ($t = 3.27$), so its within-province association with yield was not distinguishable from zero once serial correlation and the small number of provinces were taken into account.

Within this model, therefore, province differences accounted for most of the variance in yield; bearing-tree density was associated with yield under conventional standard errors but not under the wild cluster bootstrap, and one-year-lagged annual rainfall had a small association that was only narrowly significant under the bootstrap. These results should not be read as showing that rainfall is unimportant for coconut production. The model contains a single annual rainfall total, which cannot represent seasonal timing, dry spells, drought or extreme rainfall; most of the explained variance comes from between-province differences absorbed by the province terms; and any rainfall effect operating through typhoon damage, soil moisture or management is not represented. Nor do the results justify prioritizing one factor over another in policy, because bearing-tree density per harvested area is partly a by-product of how yield is measured, and potentially important drivers (typhoon damage, replanting, palm age, varieties, soil fertility and management) were not measured.

Relative contribution of area harvested and yield to differences in total coconut production across Provinces in Eastern Visayas (2010-2025)

Table 6 separates the net change in production into an area effect (change in harvested area), a yield effect (change in yield per hectare) and an interaction effect (their joint change).

Yield change was the largest component in Biliran (70.1%), Leyte (68.2%) and Northern Samar (93.1%), where production declined, and in Samar (221.5%), where production increased. In Eastern Samar, area (48.1%) and yield (36.4%) contributed similarly to the decline, with a smaller interaction component (15.5%). In Southern Leyte, the decline in production was due to reduced harvested area (138.4%), partly offset by higher yield (−87.1%, i.e., acting opposite to the net change). Yield change thus dominated in four of six provinces, consistent with Antia-Obong *et al.* (2024), who found for Nigeria (1961–2017) that yield contributed 61.4% and area 14.2% of coconut production growth.

Because the net changes in Samar (+34,113 MT) and Southern Leyte (−47,144 MT) were small relative to the gross annual changes in area and yield, their shares are extreme and should be interpreted cautiously. The decomposition is descriptive: it shows how production change divides between area and yield but not why either changed, and it does not show that bearing-tree density, province or rainfall affect total production.

Year-by-year analysis of the annual effects would help identify the years and events behind the large shifts in these provinces.

Conclusions

This study examined spatiotemporal patterns of coconut production and their association with rainfall in six Eastern Visayas provinces from 2010 to 2025 using a short observational provincial panel. Production declined in five of six provinces between 2010 and 2025, most steeply in Leyte (−65.2%), while Samar was the only province with an increase (+11.6%). However, no monotonic trend in production was significant after the Hamed–Rao correction for serial autocorrelation; the Northern Samar declines in production and yield ($p = .013$) were no longer significant ($p = .078$). Significant trends were few and province specific:

yield declined in Eastern Samar and increased in Southern Leyte, harvested area declined in Southern Leyte, and the number of bearing trees declined in Leyte. The Pettitt test detected step changes in several series, such as production and yield in Northern Samar from 2017 and bearing trees in Leyte from 2015, but the sharp declines around 2014–2015 in Leyte and Eastern Samar did not reach significance, which reflects limited power in a 16-year series rather than an absence of change. No monotonic trend or abrupt change in annual rainfall totals was detected in any province, and the coefficient of variation of annual rainfall was moderate (about 25–28%) and similar among provinces. Because these tests have limited power in 16 annual values and annual totals do not describe seasonality, dry spells or extremes, these results do not show that rainfall was stable.

In the fixed-effects regression, bearing-tree density per harvested area and province were strongly associated with yield ($R^2 = 0.843$), but most of this reflects differences among provinces; within provinces, density accounted for 23.3% of the variance in yield. One-year-lagged annual rainfall added a small association ($\Delta R^2 = 0.008$; within-province $R^2 = 0.272$), consistent with the phenology of nut development, whereas same-year rainfall did not. Residuals showed positive serial correlation (Durbin–Watson = 0.62 and 0.63 pooled; 0.40 and 0.44 within provinces; Wooldridge test p =.013 and.028) and heteroskedasticity, so conventional p-values are likely too small. Under a wild cluster bootstrap by province, the lagged-rainfall association remained significant only narrowly (p =.043), and the bearing-tree density association was not distinguishable from zero (p =.193). The lagged rainfall finding should therefore be regarded as suggestive rather than firm. These are statistical associations within the specified model; they do not demonstrate causal effects or that rainfall is unimportant, and part of the density–yield association is mechanical because both use harvested area as the denominator. The decomposition indicated that yield change was the larger component of production change in four of six provinces, but it describes how production changed, not why.

Typhoons, ENSO, replanting, varieties, soil fertility and farm management are plausible contributors to the provincial differences but were not analyzed. The conclusions are limited by the observational design, the short 16-year period with only six provinces, the annual aggregation of rainfall and the variables included in the models. Future work should combine finer-resolution rainfall indicators (daily or monthly) with typhoon-damage, replanting, variety, palm-age and management data, preferably at municipal or farm level, using longer series and more provinces so that panel methods that account for serial correlation can be applied with reliable inference.

Limitations

Design and inference

The data are observational, cover 16 years and only six provinces, and the results describe associations, not causal effects. Residuals of both regression models showed positive serial correlation: the Durbin–Watson statistics were 0.62 (Model 1) and 0.63 (Model 2) for pooled residuals and 0.40 and 0.44 when computed within provinces, all well below 2, and the Wooldridge test for panel data rejected the null of no serial correlation (Model 1: p =.013; Model 2: p =.028). Repeated yearly observations within a province are therefore not independent, and, together with the heteroskedasticity detected by the Breusch–Pagan test, the p-values based on conventional OLS standard errors are likely too small. Coefficient estimates remain consistent, but their significance should be interpreted with caution. The corrections applied have their own limits. Driscoll–Kraay standard errors were smaller than the conventional ones, the opposite of the expected correction, because the estimator is designed for long panels and only 16 years and six provinces were available, so they were not used for inference. The wild cluster bootstrap, which is designed for few clusters, left the lagged-rainfall association only narrowly significant (p =.043) and the bearing-tree density association not significant (p =.193), but six provinces are still too few for conventional cluster-robust inference, so robust and bootstrap-based inference mitigates but does not remove this limitation. Residuals departed from normality (Shapiro–Wilk $p < 0.001$); with N = 96 this is of limited concern for coefficient estimation, but p-values should be interpreted cautiously. Because yield and bearing-tree density share harvested area as the denominator, part of their association is arithmetic, and the density coefficient should not be read as a purely agronomic effect. The R^2 of models with province dummies is also dominated by between-province differences.

Rainfall measurement and lag

Annual rainfall totals do not adequately represent the rainfall conditions most relevant to coconut. Seasonal distribution, dry spells, drought periods and extreme rainfall may matter more for fruit set and nut development than the total amount, and calendar-year totals do not align exactly with the developmental stages of nuts harvested in a given year. Seasonal and extreme-rainfall indicators were not analyzed in this study, so the associations reported here pertain only to annual rainfall totals and do not rule out effects of rainfall timing or extremes. The decadal (10-day) resolution of the available rainfall data would permit seasonal, dry-decad and maximum-decadal indicators but precludes daily indices such as consecutive dry days, and these are recommended for future work. Only lags of 0 and 1 year were compared; effects at longer lags, relevant to inflorescence initiation about 32 months before spathe opening, could not be assessed with 16 years of data. Provincial rainfall values also average over coastal and upland areas that may have different rainfall regimes.

Omitted variables and the province term

Farmgate price was available for all 16 years only in Biliran, Leyte and Northern Samar; Eastern Samar lacked 2021–2022, Samar had 5 years (2021–2025) and Southern Leyte 2 years (2024–2025). Price was therefore

excluded from the regression, its possible influence on input use and management was not tested, price trends for Samar (5 values) are unreliable, and none was tested for Southern Leyte.

Trend tests and decomposition

With only 16 annual observations per series, the Mann–Kendall and Pettitt tests have limited power and lag-1 autocorrelation estimates are imprecise. Tie and autocorrelation corrections were applied, and two Northern Samar results (production and yield) lost significance after correction, but some trends may remain over- or understated. The Mann–Kendall test detects only monotonic trends, and the Pettitt test cannot reach $p < .05$ when four or fewer observations lie on one side of the break, so early or late changes, such as the sharp declines around 2014 in Leyte and Eastern Samar, mostly did not reach significance ($p = .073–.084$). Non-significant results are therefore not evidence of stability. About 30 Pettitt tests and 35 Mann–Kendall tests were run without adjustment for multiple comparisons, so a small number of significant results may be false positives. The script used for the originally reported results did not apply a tie correction. Endpoint comparisons (2010 versus 2025; Figure 2 and Table 4) can overstate or understate change because of conditions in those two years, for example recovery after Typhoon Yolanda in 2013. In the decomposition, percentage shares are relative to the net change and become extreme when the net change is small.

Aggregation and data quality

Some year-to-year changes may reflect reporting revisions as well as real change; for example, Samar's harvested area fell from [66,883 ha in 2010 to 50,125 ha in 2011] while production changed little, raising yield by about a third in one year, and such discontinuities cannot be separated from agronomic change with the present data. The study uses province-level administrative statistics rather than farm- or municipal-level data. Relationships observed at the provincial level may not hold at finer scales (ecological fallacy), and differences between coastal and upland municipalities in rainfall exposure, farming practices and soils are not captured. The accuracy of the PSA and PhilRice data was not independently verified.

Declaration of generative AI use

During the preparation of this manuscript, the authors used Claude (Anthropic) to improve grammar and clarity, to assist in writing and debugging the base R scripts used for the Mann–Kendall (tie and autocorrelation corrections), Sen's slope and Pettitt analyses, and to suggest wording for parts of the Methods, Results and Limitations sections. The research questions, study design, choice of data and analytical approach, interpretation of the findings and conclusions are those of the authors. The authors ran all scripts in Jamovi, checked the outputs against the data, reviewed and edited all AI-assisted text, and take full responsibility for the content of the manuscript.

Data availability and supplementary materials

The supplementary materials supporting this study are available in the following repository: https://doi.org/10.6084/m9.figshare.33475525. They include the raw dataset, the Jamovi statistical output, the R scripts and output for the Mann–Kendall, Sen's slope, Pettitt and panel-diagnostic analyses (also reproduced in Appendices D–H), and the complete manuscript. These materials are provided to promote transparency and to facilitate verification and further understanding of the analyses and results presented in this study.

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