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# Spatial Heterogeneity of Rice Production Responses to ENSO Anomalies in Banten Province, Indonesia

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**Abstract.** *El Niño–Southern Oscillation (ENSO) anomalies are significant drivers of climate variability affecting agricultural production, although their impacts exhibit high spatial and temporal complexity. This study investigates rice production responses to ENSO phases in four districts of Banten Province, Indonesia—Pandeglang, Serang, Lebak, and Tangerang—during the 2000–2024 period. Utilizing descriptive statistics, OLS regression, and comparative time-series models (linear, quadratic, exponential, and moving average), the study evaluates how climatic signals are translated into production outcomes. Results reveal significant spatial heterogeneity. Although El Niño generally suppressed yields, regression analysis identifies Tangerang as the only district with a statistically significant vulnerability to drought-induced losses (β= -33,371 t/year). Conversely, the study identifies a "Triple-Dip" La Niña anomaly (2020–2023) where excessive rainfall reduced production in flood-prone districts such as Pandeglang, challenging the assumption that La Niña universally benefits rice yields. Methodologically, second- and third-order moving average models (MA(2) and MA(3)) consistently outperformed alternative specifications in capturing stochastic fluctuations. These findings underscore the localized nature of ENSO impacts and the inadequacy of generalized policies. The study therefore advocates spatially differentiated adaptation strategies, including localized early warning systems and improved drainage infrastructure, to mitigate drought and flood risks in Banten's rice systems.*
***Keywords:*** *Climate anomaly; ENSO; rice production; Banten Province; time-series analysis.*

**Type of the Paper:** Regular Article.

## 1. Introduction

The increasing frequency and severity of anomalous events such as El Niño and La Niña, emblematic of climate change, pose substantial risks to worldwide crop output and food security. Such climatic anomalies reshape seasonal weather regimes, provoke irregular temperature dynamics, and precipitate extreme events—including droughts and floods—that depress agricultural productivity [1–3]. Because agriculture depends on stable climatic conditions, any perturbation substantially threatens food production, particularly in tropical and subtropical zones where climate variability is already pronounced [4,5].

El Niño and La Niña—antithetical phases of the El Niño–Southern Oscillation (ENSO)—exert profound effects on agricultural output, particularly rice cultivation in Southeast Asia, home to major rice producers such as Indonesia, Thailand, and Vietnam [6,7]. Evidence from the



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Mekong River Delta shows that La Niña advances seasonal rains and slightly improves rice yields, whereas El Niño delays precipitation and significantly diminishes productivity [8]. Thailand similarly records notable yield contractions during El Niño events due to reduced precipitation—especially across inland rice-growing regions—while La Niña conditions generally enhance yields [9,10]. Evidence from crop models—particularly WOFOST—confirms this pattern, revealing persistently below-average rice production during El Niño and above-average yields during La Niña [11]. Across the region, ENSO phases substantially alter rainfall distribution: La Niña typically enhances rice productivity through increased precipitation, whereas El Niño-induced droughts lead to yield losses [12,13]. In contrast, evidence from China shows more complex, crop- and region-specific responses. Wheat and rice benefit differently across climatic zones, corn consistently suffers during El Niño phases, and pest outbreaks intensify during El Niño but decline during La Niña [14].

Agriculture remains a cornerstone of Indonesia's national economy and a linchpin of food security and rural livelihoods. Accordingly, ENSO-driven climate anomalies substantially impact farm productivity, particularly in rice-centered agriculture. Substantial yield declines in rainfed areas were recorded during El Niño, especially in Java and South Sulawesi during the extreme 2015 episode [3,15,16]. Yield losses during intense El Niño events can reach 40%, emphasizing the pressing need for adaptive actions—including improved water-resource management, drought-tolerant cultivars, and risk-transfer mechanisms such as crop insurance [17–19]. Beyond rice, studies in Sulawesi demonstrated that ENSO phases explain up to 75% of interannual yield variation in cacao production, with management responses such as fertilizer use being predictable from ENSO indices alone. This underscores ENSO's value as a predictive tool for climate-informed crop management and highlights the importance of site-specific data for adaptation strategies [20].

Banten Province—located at the western extremity of Java Island—is a significant rice-producing area in Indonesia yet exhibits rising vulnerability to ENSO-related climate variability and extremes. The province lies within the Southeast Asian monsoon system, characterized by distinct wet and dry seasons shaped by large-scale ocean-atmosphere interactions, including the Asian-Australian monsoon and the El Niño–Southern Oscillation [21,22]. In this region, climatic anomalies disrupt traditional planting calendars, reduce yields, and threaten local and national food security.

The magnitude of these effects is evident in production statistics from years with and without climatic anomalies. Statistics Indonesia [23] reported that rice production declined from 53.98 million tons in 2023 to 52.66 million tons in 2024, primarily due to prolonged dry spells associated with El Niño. At the district level, instability is more pronounced. For instance, in Pandeglang, Banten's central rice-producing district, production peaked at approximately 789,310 tons in 2017 under favorable La Niña conditions but declined to about 414,580 tons in 2024 due to strong El Niño conditions. In 2024, Banten contributed approximately 1.55 million tons from 299.09 thousand hectares of harvested area, accounting for about 2.9% of national output [23]. These differences illustrate the heightened instability of rice production during extreme climatic events compared with normal conditions and underscore the province's strategic role in safeguarding national food security amid escalating climate risks.

Numerous adaptation and mitigation strategies have been advanced to counter the adverse consequences of ENSO-induced climatic variability. Crop insurance programs, particularly Indonesia's Rice Farming Insurance (AUTP), provide financial protection against climate uncertainty and harvest failure [2,3]. Investments in irrigation and water-storage infrastructure substantially diminish drought vulnerability during El Niño periods [24,25]. Strengthening agrarian resilience necessitates climate-smart approaches, including adjusted cropping calendar, introducing drought-tolerant varieties, and improved nutrient regimes [26,27]. These measures are supplemented by governmental policies, fertilizer subsidies, extension outreach, and programs for both intensifying and expanding cultivated land, which collectively support productivity under increasing climatic challenges [17,25]. Beyond input subsidies and extension programs, evidence from Uganda demonstrates that participatory policy design, capacity building, and substantial research–policy collaboration are vital to ensure that governmental measures effectively enhance resilience to climatic challenges [28].

Although the influence of ENSO on agricultural output has been thoroughly examined at national and regional levels, localised evaluations that consider spatial variability remain limited. Much current research depends on aggregate data or fundamental correlation analysis, which often overlook sub-regional responses influenced by local agroecological variables. This study fills this gap by utilising a comparative time-series forecasting methodology, including linear, quadratic, exponential, and moving average (MA) models to distinguish long-term production patterns from fluctuations caused by anomalies meticulously.

This study presents an innovative analytical approach for measuring vulnerabilities in four districts of Banten Province: Pandeglang, Serang, Lebak, and Tangerang. By integrating sophisticated forecasting models with the Oceanic Niño Index (ONI), it facilitates a more accurate assessment of production variances during particular ENSO phases. This method elucidates the extent of yield losses or increases and offers detailed evidence to endorse spatially tailored adaptation solutions, rather than the generic "one-size-fits-all" policies typically generated from extensive national research. Therefore, broad national assessments may mask these localized vulnerabilities. This study aims to quantify these district-specific responses in Banten Province to inform spatially targeted adaptation strategies.

## 2. Materials and Methods

### *2.1. Study Area*

The research was conducted in Banten Province, Indonesia, focusing on four key rice-producing districts: Pandeglang, Serang, Lebak, and Tangerang (Fig. 1). These districts were selected for their substantial contributions to provincial rice output and agroecological diversity, including irrigated and rainfed systems. Banten experiences a tropical monsoon climate, with annual rainfall ranging from approximately 2,000 to 3,500 mm and a distinct wet (November–April) and dry season (May–October). Such conditions render the province highly sensitive to climate variability, particularly El Niño and La Niña events that alter rainfall distribution and water availability for agriculture [29].

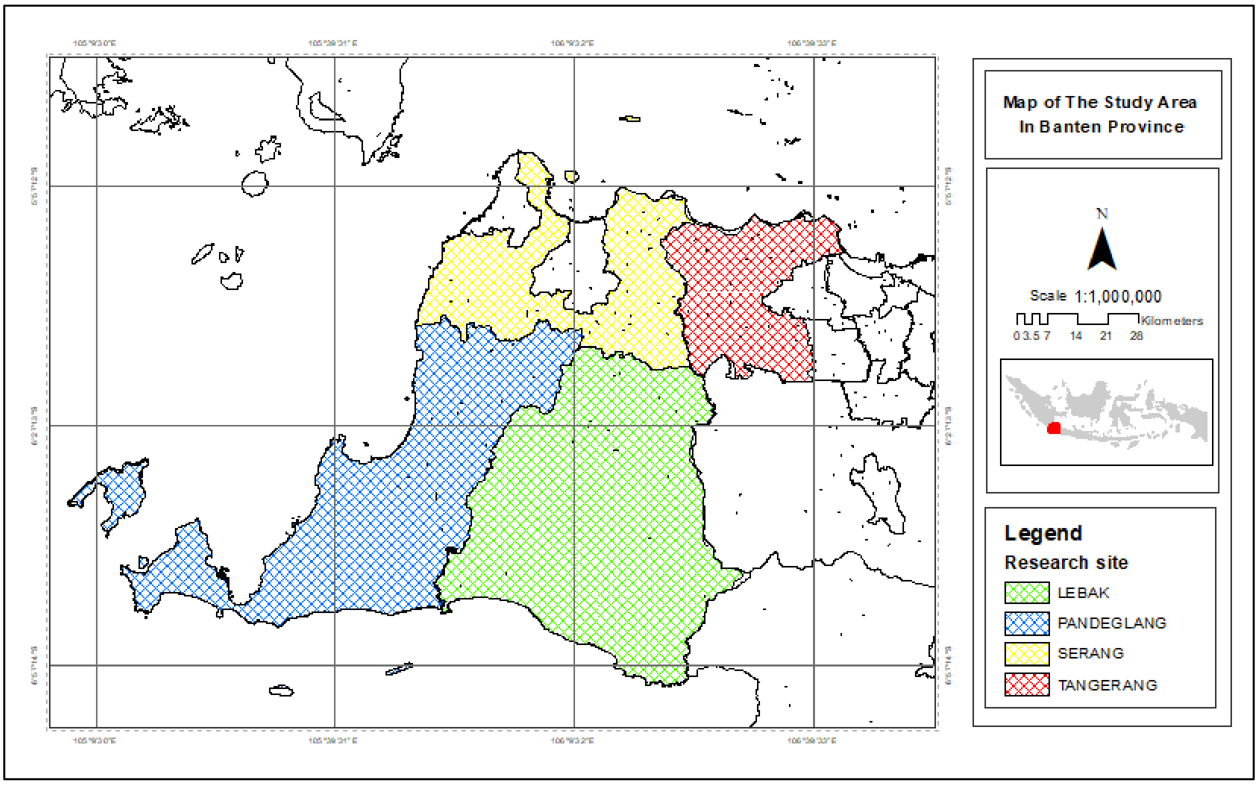



**Fig. 1**. Map of the study area in Banten Province, Indonesia.

### *2.2. Data Collection and Preparation*

District-level rice production data for 2000–2024 were obtained from Banten's Central Bureau of Statistics (BPS). Climatic anomaly data were sourced from the United States National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center, with the Oceanic Niño Index (ONI) used to classify El Niño and La Niña events. The datasets were cleaned and organized by district, and production records were aligned with corresponding ENSO phases to enable comparative analysis across years and locations.

This study utilizes total rice production (in tons) as the primary dependent variable rather than productivity (yield per hectare). The approach is justified because climate anomalies, particularly ENSO events, impact agricultural output through two distinct pathways: reducing crop yield (physiological stress) and shrinking the harvested area (due to delayed planting, unplanted fields due to water scarcity, or total crop failure). Focusing solely on productivity would underestimate the total impact of climate shocks, as it does not capture land entirely removed from production.

### *2.3. Trend Analysis and Model Selection*

Multiple time-series models were assessed to analyze rice production trends, including linear, quadratic, exponential, and moving average (MA) specifications. The linear model assumes a constant rate of change, whereas the quadratic form considers curvilinear dynamics. The exponential model reflects constant growth or decay rates, and the MA model smooths short-term fluctuations by averaging production values across two- and three-year windows (MA(2) and MA(3)).

Model performance was assessed using $R^2$, mean absolute percentage error (MAPE), mean squared deviation (MSD), and root mean squared error (RMSE). The best-fitting model was defined as the one with the highest $R^2$ and the lowest error metrics across these metrics.

### *2.4. Impact Assessment*

The effects of climate anomalies were quantified by comparing production outcomes during El Niño and La Niña years against neutral periods, based on deviations from model-predicted trends. Model-predicted values were utilized as the baseline rather than raw historical data to effectively isolate climate-induced variability from long-term structural drivers, such as technological advancements and irrigation expansion. This approach aligns with established methodologies in climate-crop modeling, which emphasize detrending historical data to remove non-climatic signals [30]. Consequently, the analysis focuses on the residuals, the difference between actual and predicted production, as the primary indicator of climate sensitivity.

### *2.5. Visualization and Limitations*

All analyses and visualizations were conducted in R using the ggplot2 package to illustrate production trends and anomaly effects. As the study relied on secondary data, limitations include the absence of farm-level heterogeneity and potential influences from other climatic indices not incorporated in this analysis.

## 3. Results and Discussion

### *3.1. Descriptive statistics*

Descriptive statistics reveal marked variation in rice production across the four districts of Banten Province during 2000–2024 (Table 1). Pandeglang consistently recorded the highest average production, followed by Lebak and Serang, while Tangerang reported the lowest. The relatively large standard deviation in Pandeglang reflects substantial interannual fluctuations, in contrast to Tangerang, which exhibited more stable output. These differences likely reflect variations in cultivated area, irrigation infrastructure, and agronomic practices.

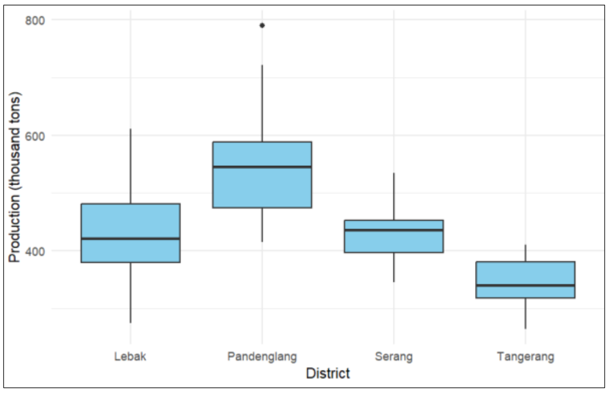
Further examination of extreme values highlights the temporal heterogeneity. Pandeglang peaked in 2017, while Lebak and Serang achieved maximum output in 2016. By contrast, production lows occurred in different years across districts, underscoring the asynchronous nature of rice yields in response to local conditions. Such spatial and temporal variability emphasizes the role of climate variability and district-level adaptive capacity.

**Table 1.** Descriptive Statistics of Rice Production by District (2000–2024)

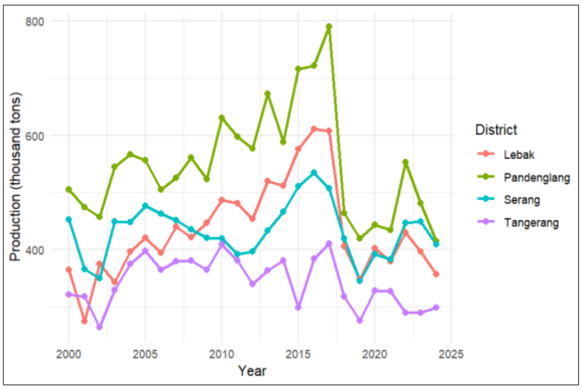
| District | Mean (000 ton) | Min (000 ton) | Year Min | Max (000 ton) | Year Max | Std. Dev. |
|---|---|---|---|---|---|---|
| Lebak | 433.86 | 274.76 | 2001 | 611.05 | 2016 | 82.99 |
| Pandeglang | 548.84 | 414.58 | 2024 | 789.31 | 2017 | 98.43 |
| Serang | 432.75 | 345.16 | 2019 | 534.48 | 2016 | 47.64 |
| Tangerang | 343.93 | 264.5 | 2002 | 410.54 | 2017 | 42.97 |

Source: Statistics Indonesia (BPS), processed 2025

Visual inspection using box plots and time-series charts confirms these disparities (Fig. 2). Pandeglang shows the widest distribution of production values, reflecting its higher variability, while Tangerang displays a narrower spread, indicating greater stability. The time-series trends also reveal synchronized peaks in 2016–2017, followed by a noticeable decline in 2019–2024, which may correspond to climate anomalies or policy-driven interventions.




(a)




(b)

**Fig. 2** Boxplot (a) and Annual Trend (b) of Rice Production by District in Banten (2000-2024), Note: The post-2017 break results from the BPS KSA methodological revision, not an actual production decline, Source: Statistics Indonesia (BPS), processed 2025

A notable deviation from theoretical expectations occurred during 2020–2023. While La Niña phases are typically correlated with increased rice production due to ample water availability, our data indicate a production decline across the study districts during this 'Triple-Dip' La Niña event. This counterintuitive finding is explained by the detrimental impact of excessive rainfall, which caused widespread flooding rather than beneficial irrigation.

Official data from Statistics of Banten Province (BPS) confirms this phenomenon. In 2021, despite wet conditions, rice production in Banten decreased by 1.54% (from 1.66 million tons in

2020 to 1.63 million tons in 2021), driven by a 1.78% contraction in harvested area (from 325.33 thousand ha to 319.56 thousand ha) [31]. This reduction largely resulted from high-intensity rainfall that inundated paddy fields in low-lying alluvial plains, causing crop failure instead of higher yields.

Furthermore, this period coincided with socio-economic stressors, including the COVID-19 pandemic and the 2022 global fertilizer crisis, which constrained farmers' ability to mitigate these hydro-meteorological shocks. Thus, the 2020–2023 decline underscores that while La Niña offers potential water resources, excessive rainfall may become a primary constraint on production in Banten's flood-prone zones.

Overall, the descriptive analysis underscores the heterogeneous dynamics of rice production in Banten, suggesting that climatic shocks, particularly ENSO-related anomalies, interact with district-level characteristics to shape yield outcomes. These preliminary patterns provide the basis for subsequent model-based assessments of climate impacts.

**Table 2.** ONI-based classification of ENSO phases (2000–2024)

| Year | DJF | JFM | FMA | MAM | AMJ | MJJ | JJA | JAS | ASO | SON | OND | NDJ | Climate Anomaly |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2000 | -1.7 | -1.4 | -1.1 | -0.8 | -0.7 | -0.6 | -0.6 | -0.5 | -0.5 | -0.6 | -0.7 | -0.7 | La Niña |
| 2001 | -0.7 | -0.5 | -0.4 | -0.3 | -0.3 | -0.1 | -0.1 | -0.1 | -0.2 | -0.3 | -0.3 | -0.3 | Neutral |
| 2002 | -0.1 | 0.0 | 0.1 | 0.2 | 0.4 | 0.7 | 0.8 | 0.9 | 1.0 | 1.2 | 1.3 | 1.1 | El Niño |
| 2003 | 0.9 | 0.6 | 0.4 | 0.0 | -0.3 | -0.2 | 0.1 | 0.2 | 0.3 | 0.3 | 0.4 | 0.4 | Neutral |
| 2004 | 0.4 | 0.3 | 0.2 | 0.2 | 0.2 | 0.3 | 0.5 | 0.6 | 0.7 | 0.7 | 0.7 | 0.7 | El Niño |
| 2005 | 0.6 | 0.6 | 0.4 | 0.4 | 0.3 | 0.1 | -0.1 | -0.1 | -0.1 | -0.3 | -0.6 | -0.8 | Neutral |
| 2006 | -0.9 | -0.8 | -0.6 | -0.4 | -0.1 | 0.0 | 0.1 | 0.3 | 0.5 | 0.8 | 0.9 | 0.9 | Neutral |
| 2007 | 0.7 | 0.2 | -0.1 | -0.3 | -0.4 | -0.5 | -0.6 | -0.8 | -1.1 | -1.3 | -1.5 | -1.6 | La Niña |
| 2008 | -1.6 | -1.5 | -1.3 | -1.0 | -0.8 | -0.6 | -0.4 | -0.2 | -0.2 | -0.4 | -0.6 | -0.7 | La Niña |
| 2009 | -0.8 | -0.8 | -0.6 | -0.3 | 0.0 | 0.3 | 0.5 | 0.6 | 0.7 | 1.0 | 1.4 | 1.6 | El Niño |
| 2010 | 1.5 | 1.2 | 0.8 | 0.4 | -0.2 | -0.7 | -1.0 | -1.3 | -1.6 | -1.6 | -1.6 | -1.6 | La Niña |
| 2011 | -1.4 | -1.2 | -0.9 | -0.7 | -0.6 | -0.4 | -0.5 | -0.6 | -0.8 | -1.0 | -1.1 | -1.0 | La Niña |
| 2012 | -0.9 | -0.7 | -0.6 | -0.5 | -0.3 | 0.0 | 0.2 | 0.4 | 0.4 | 0.3 | 0.1 | -0.2 | Neutral |
| 2013 | -0.4 | -0.4 | -0.3 | -0.3 | -0.4 | -0.4 | -0.4 | -0.3 | -0.3 | -0.2 | -0.2 | -0.3 | Neutral |
| 2014 | -0.4 | -0.5 | -0.3 | 0.0 | 0.2 | 0.2 | 0.0 | 0.1 | 0.2 | 0.5 | 0.6 | 0.7 | Neutral |
| 2015 | 0.5 | 0.5 | 0.5 | 0.7 | 0.9 | 1.2 | 1.5 | 1.9 | 2.2 | 2.4 | 2.6 | 2.6 | El Niño |
| 2016 | 2.5 | 2.1 | 1.6 | 0.9 | 0.4 | -0.1 | -0.4 | -0.5 | -0.6 | -0.7 | -0.7 | -0.6 | La Niña |
| 2017 | -0.3 | -0.2 | 0.1 | 0.2 | 0.3 | 0.3 | 0.1 | -0.1 | -0.4 | -0.7 | -0.8 | -1.0 | Neutral |
| 2018 | -0.9 | -0.9 | -0.7 | -0.5 | -0.2 | 0.0 | 0.1 | 0.2 | 0.5 | 0.8 | 0.9 | 0.8 | La Niña |
| 2019 | 0.7 | 0.7 | 0.7 | 0.7 | 0.5 | 0.5 | 0.3 | 0.1 | 0.2 | 0.3 | 0.5 | 0.5 | El Niño |
| 2020 | 0.5 | 0.5 | 0.4 | 0.2 | -0.1 | -0.3 | -0.4 | -0.6 | -0.9 | -1.2 | -1.3 | -1.2 | La Niña |
| 2021 | -1.0 | -0.9 | -0.8 | -0.7 | -0.5 | -0.4 | -0.4 | -0.5 | -0.7 | -0.8 | -1.0 | -1.0 | La Niña |
| 2022 | -1.0 | -0.9 | -1.0 | -1.1 | -1.0 | -0.9 | -0.8 | -0.9 | -1.0 | -1.0 | -0.9 | -0.8 | La Niña |
| 2023 | -0.7 | -0.4 | -0.1 | 0.2 | 0.5 | 0.8 | 1.1 | 1.3 | 1.6 | 1.8 | 1.9 | 2.0 | El Niño |
| 2024 | 1.8 | 1.5 | 1.1 | 0.7 | 0.4 | 0.2 | 0 | -0.1 | -0.2 | -0.3 | -0.4 | -0.5 | El Niño |

Note: DJF (December–January–February), JFM (January–February–March), FMA (February–March–April), MAM (March–April–May), AMJ (April–May–June), MJJ (May–June–July), JJA (June–July–August), JAS (July–August–September), ASO (August–September–October), SON (September–October–November), OND (October–November–December), NDJ (November–December–January). ENSO anomalies are classified based on ONI threshold values: El Niño (≥ +0.5°C), La Niña (≤ -0.5°C), and Neutral (-0.5°C < ONI < +0.5°C). Data source: NOAA (2024).

### *3.2. Determining Climate Anomaly Phases (2000–2024)*

The Oceanic Niño Index (ONI), published by NOAA's Climate Prediction Center, was used to classify El Niño, La Niña, and neutral phases over the 2000–2024 period (Table 2). Using a ±0.5 °C threshold, ten years were categorized as La Niña, seven as El Niño, and the remainder as neutral. Extreme events occurred in 2015–2016 and 2023–2024, when ONI values exceeded +2.0 °C, indicating strong El Niño episodes. In contrast, strong La Niña events were evident in 2000, 2008, 2010, and 2022. This classification provides a robust basis for assessing ENSO-related production anomalies in Banten Province.

### *3.3. Model Selection and Predictive Accuracy*

Comparative evaluation of linear, quadratic, exponential, and moving average (MA) models revealed that MA specifications consistently provided the best fit across districts (Table 3). The MA(2) and MA(3) models yielded higher $R^2$ values and lower RMSE, MAPE, and MSD than alternative specifications. For instance, MA(3) achieved the highest accuracy in Lebak and Serang, while MA(2) was optimal for Pandeglang and Tangerang. In contrast, linear and exponential models frequently exhibited near-zero or negative $R^2$ values, reflecting poor alignment with observed production patterns.

**Table 3.** Model Accuracy Evaluation for Rice Production Forecasting in Banten Districts (2000–2024)

| District | Model | $R^2$ | RMSE (ton) | MAPE (%) | MSD (ton$^2$) |
|---|---|---|---|---|---|
| Lebak | Linear | 0.068 | 78,515 | 14.74 | $6.16\times10^9$ |
| | Quadratic | 0.545 | 54,832 | 9.51 | $3.01\times10^9$ |
| | Exponential | 0.053 | 79,157 | 14.55 | $6.27\times10^9$ |
| | MA(2) | 0.856 | 30,879 | 5.63 | $9.54\times10^8$ |
| | MA(3) | 0.861 | 30,468 | 6.23 | $9.28\times10^8$ |
| Pandeglang | Linear | 0.002 | 96,359 | 13.77 | $9.28\times10^9$ |
| | Quadratic | 0.361 | 77,097 | 10.94 | $5.94\times10^9$ |
| | Exponential | -0.008 | 96,829 | 13.50 | $9.38\times10^9$ |
| | MA(2) | 0.769 | 45,382 | 5.51 | $2.06\times10^9$ |
| | MA(3) | 0.752 | 47,720 | 6.40 | $2.28\times10^9$ |
| Serang | Linear | 0.001 | 46,657 | 8.82 | $2.18\times10^9$ |
| | Quadratic | 0.075 | 44,899 | 8.98 | $2.02\times10^9$ |
| | Exponential | -0.002 | 46,726 | 8.83 | $2.18\times10^9$ |
| | MA(2) | 0.784 | 22,017 | 3.97 | $4.85\times10^8$ |
| | MA(3) | 0.857 | 18,273 | 3.48 | $3.34\times10^8$ |
| Tangerang | Linear | 0.068 | 40,654 | 10.33 | $1.65\times10^9$ |
| | Quadratic | 0.467 | 30,736 | 7.04 | $9.45\times10^8$ |
| | Exponential | 0.059 | 40,835 | 10.24 | $1.67\times10^9$ |
| | MA(2) | 0.728 | 21,843 | 5.14 | $4.77\times10^8$ |
| | MA(3) | 0.708 | 22,985 | 5.60 | $5.28\times10^8$ |

Source: Author's calculations, 2025.

The superiority of MA models underscores their ability to capture short-term fluctuations and recent production dynamics under climate variability. By smoothing noise while retaining sensitivity to anomalies, MA(2) and MA(3) provide reliable tools for operational forecasting in Banten's rice sector. These results suggest that adaptive forecasting systems should integrate such models to improve preparedness for ENSO-driven production shocks.

### *3.4. District-Level Rice Production Dynamics under ENSO Events*

#### *3.4.1. Lebak District – Production Dynamics under ENSO (MA(3) Model)*

The MA(3) model closely fits rice production in Lebak, effectively capturing both the long-term upward trend and short-term interannual fluctuations (Fig. 3). Historically, production in this district rose steadily from 2001, reaching peak in 2017 due to agricultural intensification, before experiencing notable structural declines in recent years. Analysis of deviations between actual and expected production (Table 4) reveals a distinct and somewhat counterintuitive vulnerability profile for Lebak, particularly in its response to different hydrological extremes.

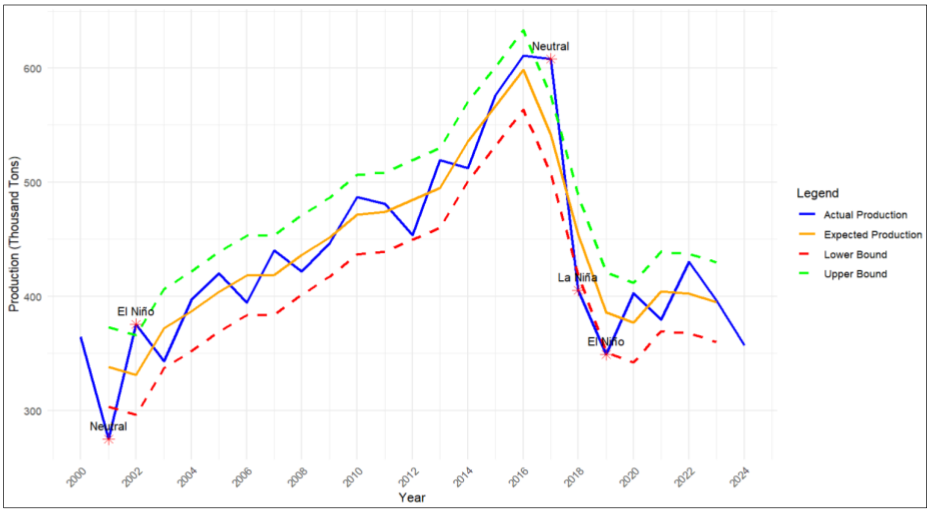



**Fig. 3**. Lebak: Observed vs. MA(3) expected production with 95% CI.

Interestingly, the district exhibited unexpected resilience during the mild El Niño of 2002, recording a production surplus of 44,283 tons, corresponding to a +13.38% positive deviation from the baseline. This suggests that, in Lebak's specific topographic context, likely characterized by low-lying, flood-prone alluvial areas, mild rainfall deficits may be beneficial by mitigating inundation risks during the vegetative phase and facilitating better grain drying at harvest. Conversely, the La Niña event of 2018 resulted in a significant deficit of 48,644 tons (-10.71%), challenging the assumption that wetter conditions universally boost national production. This indicates that excessive rainfall associated with La Niña likely overwhelmed local drainage capacities, causing crop failure from prolonged submergence or humidity-related pest outbreaks.

**Table 4.** Impact of climate anomalies on rice production in Lebak (MA(3) model)

| Year | Climate Anomaly | Actual Production (ton) | Expected Production (ton) | Lower 95% CI (ton) | Upper 95% CI (ton) | Climate Effect Δ (Actual−Expected) (ton) | Deviation (%) | Impact Δ (ton) |
|---|---|---|---|---|---|---|---|---|
| 2001 | Neutral | 274759 | 338184 | 303394 | 372975 | -63425 | -18.75% | -28635 |
| 2002 | El Niño | 375268 | 330985 | 296195 | 365776 | 44283 | 13.38% | 9492 |
| 2017 | Neutral | 608036 | 541525 | 506735 | 576316 | 66511 | 12.28% | 31721 |
| 2018 | La Niña | 405487 | 454131 | 419340 | 488921 | -48644 | -10.71% | -13853 |
| 2019 | El Niño | 348869 | 385742 | 350952 | 420533 | -36873 | -9.56% | -2083 |

Note: Δ_effect = Actual − Expected; Impact Δ = Actual − Lower 95% CI if Δ_effect is negative, otherwise Actual − Upper 95% CI; CI = 95% confidence interval. Source: Author's calculations (2025)

Furthermore, the deficit observed during the subsequent 2019 El Niño (-9.56%) confirms that while Lebak can tolerate mild dryness, severe or prolonged moisture deficits still pose substantial risks, particularly in rainfed zones lacking irrigation infrastructure. Collectively, these results imply that Lebak's rice production is highly sensitive to excessive water. Unlike regions primarily threatened by drought, Lebak suffers significant losses during wet extremes; therefore, adaptation strategies must prioritize flood management and drainage improvement alongside traditional drought mitigation efforts.

*3.4.2. Pandeglang District – Production Dynamics under ENSO (MA(2) Model)*

In Pandeglang, the largest rice-producing district in Banten, the MA(2) model highlights a pattern of steady production growth until 2016–2017, followed by a pronounced downturn after 2017 (Fig. 4). Analysis of production deviations (Table 5) reveals that this district is highly sensitive to both hydrological extremes, challenging the assumption that production risks are solely associated with drought. For instance, the El Niño event of 2009 caused a production deficit of 9.25% (-53,364 tons) below expected levels, confirming the district's vulnerability to meteorological drought and water scarcity in its rainfed zones.

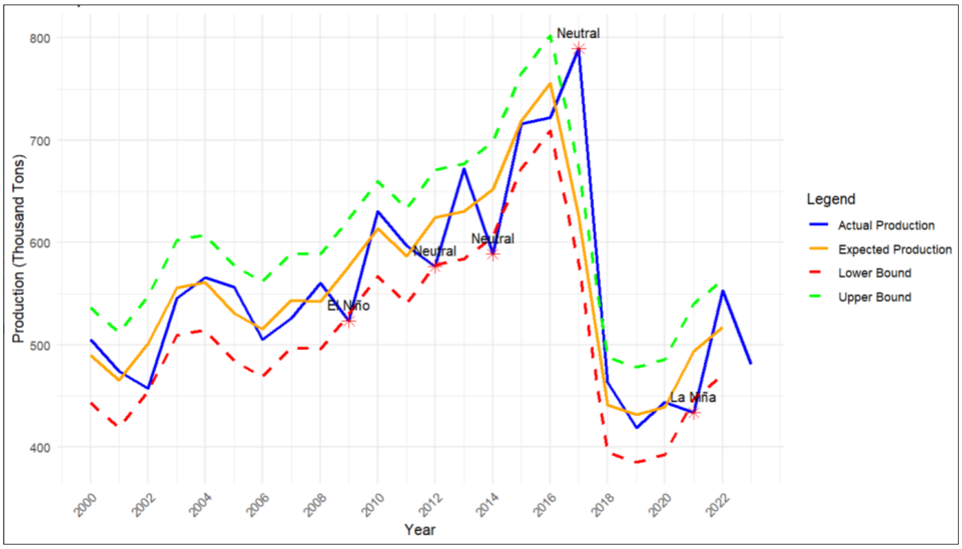



**Fig. 4.** Pandeglang: Observed vs. MA(2) expected production with 95% CI.

However, a critical finding emerges when examining the impact of wet anomalies. As shown in Table 5, the La Niña event of 2021 caused an even deeper deficit of 12.06% (-59,558 tons), surpassing the losses observed during the 2009 El Niño. This substantial reduction resulted from excessive rainfall, which triggered widespread flooding (banjir) and inundated paddy fields across Pandeglang's low-lying plains. This finding corroborates observation from the "Triple-Dip" La Niña, highlighting that in Pandeglang, the risk of crop failure from inundation is as critical, or even more critical, than the risk of drought.

Interestingly, 2017—classified as a Neutral year—stands out as an exceptional anomaly, with a massive production surplus of 26.00% (+162,874 tons) above model expectations (Table

5). This peak represents the optimal convergence of climatic stability and favorable agronomic inputs. Unlike other neutral years, such as 2012 and 2014, which recorded slight deficits due to localized constraints, 2017 demonstrates the true potential of Pandeglang's agriculture when freed from extreme ENSO interference.

**Table 5.** Impact of climate anomalies on rice production in Pandeglang (MA(2) model)

| Year | Climate Anomaly | Actual Production (ton) | Expected Production (ton) | Lower 95% CI (ton) | Upper 95% CI (ton) | Climate Effect Δ (Actual−Expected) (ton) | Deviation (%) | Impact Δ (ton) |
|---|---|---|---|---|---|---|---|---|
| 2009 | El Niño | 523460 | 576824 | 530418 | 623230 | -53364 | -9.25% | -6958 |
| 2012 | Neutral | 576662 | 624611 | 578204 | 671017 | -47949 | -7.68% | -1542 |
| 2014 | Neutral | 588539 | 652160 | 605753 | 698566 | -63621 | -9.76% | -17214 |
| 2017 | Neutral | 789311 | 626438 | 580031 | 672844 | 162874 | 26.00% | 116467 |
| 2021 | La Niña | 434088 | 493646 | 447239 | 540052 | -59558 | -12.06% | -13151 |

Note: Δ_effect = Actual − Expected; Impact Δ = Actual − Lower 95% CI if Δ_effect is negative, otherwise Actual − Upper 95% CI; CI = 95% confidence interval. Source: Author's calculations (2025).

*3.4.3. Serang District – Production Dynamics under ENSO (MA(3) Model)*

The MA(3) specification for Serang demonstrates resilience under most neutral and La Niña years, with yields often meeting or exceeding expectations (Fig. 5).

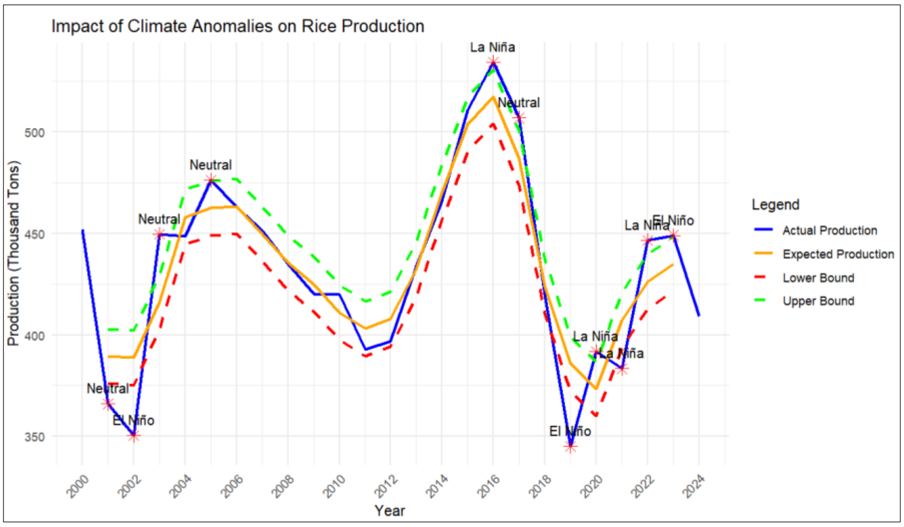



**Fig. 5.** Serang: Observed vs. MA(3) expected production with 95% CI.

In Serang District, the MA(3) model reveals a distinctly more resilient production system compared to the southern districts of Banten (Table 6). While deviations occur, they are generally smaller in magnitude, suggesting a higher capacity to buffer climatic shocks. For instance, the 2002 El Niño caused a 9.83% reduction in production, and the intense 2019 El Niño caused a 10.52% deficit. Remarkably, the 2023 El Niño event showed a slight surplus of 3.24% (+14,110 tons). This resilience during a drought year highlights the critical role of technical irrigation infrastructure, such as the Pamarayan Weir, which stabilizes water supply in Serang even under below-average rainfall conditions.

Serang's response to La Niña is mixed but predominantly positive. Unlike Lebak and Pandeglang, which suffered heavy flood losses, Serang recorded production surpluses during the

La Niña years of 2016 (+3.31%), 2020 (+4.95%), and 2022 (+4.76%). This indicates that Serang's drainage and water management systems effectively capitalize on excess rainfall. However, the exception was 2021, where production dipped by 5.89% (-23,974 tons). This aligns with the "Triple-Dip" anomaly discussed earlier, where the sheer intensity of rainfall in 2021 overwhelmed even well-irrigated zones, causing unavoidable flood-induced crop failures. Nevertheless, the overall pattern suggests that Serang benefits from comparatively robust infrastructure that mitigates the severity of ENSO impacts relative to its neighbors.

**Table 6.** Impact of climate anomalies on rice production in Serang (MA(3) model)

| Year | Climate Anomaly | Actual Production (ton) | Expected Production (ton) | Lower 95% CI (ton) | Upper 95% CI (ton) | Climate Effect Δ (Actual−Expected) (ton) | Deviation (%) | Impact Δ (ton) |
|---|---|---|---|---|---|---|---|---|
| 2001 | Neutral | 366004 | 389518 | 376055 | 402981 | -23514 | -6.04% | -10051 |
| 2002 | El Niño | 350468 | 388675 | 375213 | 402138 | -38207 | -9.83% | -24745 |
| 2003 | Neutral | 449554 | 416177 | 402714 | 429640 | 33377 | 8.02% | 19914 |
| 2005 | Neutral | 476274 | 462525 | 449062 | 475988 | 13749 | 2.97% | 286 |
| 2016 | La Niña | 534475 | 517372 | 503909 | 530835 | 17103 | 3.31% | 3640 |
| 2017 | Neutral | 506892 | 487138 | 473675 | 500601 | 19754 | 4.06% | 6291 |
| 2019 | El Niño | 345163 | 385728 | 372265 | 399191 | -40565 | -10.52% | -27102 |
| 2020 | La Niña | 391973 | 373496 | 360034 | 386959 | 18477 | 4.95% | 5014 |
| 2021 | La Niña | 383353 | 407327 | 393864 | 420790 | -23974 | -5.89% | -10511 |
| 2022 | La Niña | 446654 | 426358 | 412895 | 439821 | 20296 | 4.76% | 6833 |
| 2023 | El Niño | 449067 | 434957 | 421494 | 448420 | 14110 | 3.24% | 647 |

Note: Δ_effect = Actual − Expected; Impact Δ = Actual − Lower 95% CI if Δ_effect is negative, otherwise Actual − Upper 95% CI; CI = 95% confidence interval. Source: Author's calculations (2025).

### *3.4.4. Tangerang District – Production Dynamics under ENSO (MA(2) Model)*

The MA(2) model shows high interannual variability in Tangerang (Fig. 6). El Niño events (2002, 2015, 2019) consistently suppressed yields, with 2015 registering the most severe losses.

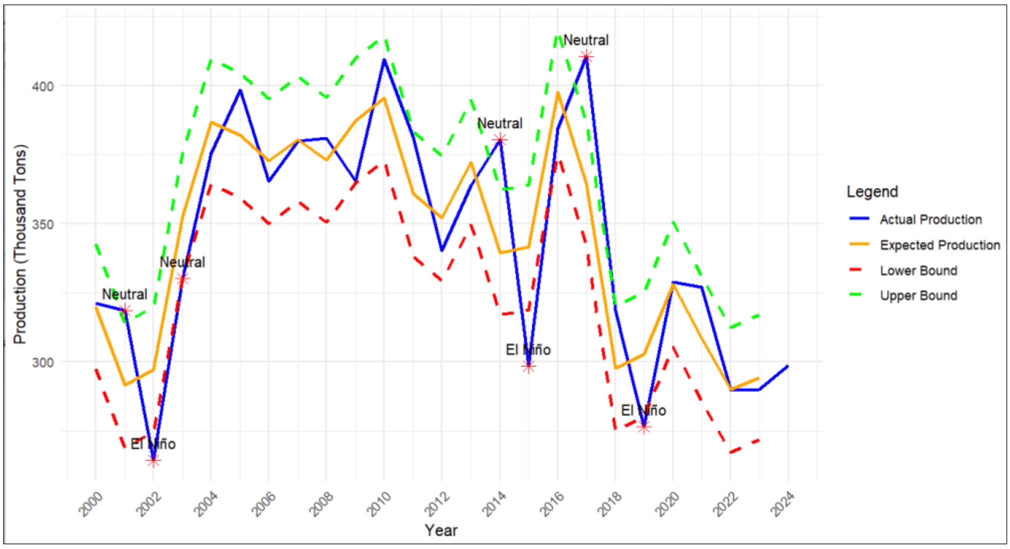



**Fig. 6.** Tangerang: Observed vs. MA(2) expected production with 95% CI

Tangerang District, characterized by its peri-urban landscape and rapid industrialization, exhibits high sensitivity to hydrological deficits (Table 7). The MA(2) model highlights a consistent pattern of sharp production declines during El Niño events. Notably, the mild El Niño of 2002 caused a production contraction of 11.04%, while the strong El Niño of 2015 produced the most severe deficit of 12.58% (-42,971 tons). This acute vulnerability to drought is likely exacerbated by land-use competition, as agricultural zones often face water scarcity when resources are diverted for industrial and domestic use during dry periods.

Interestingly, similar to Pandeglang, Tangerang experienced a significant production peak in the neutral year of 2017, with a surplus of 12.61% (+45,976 tons). This suggests that, in the absence of climatic stressors, the remaining agricultural areas in Tangerang are highly productive. However, the subsequent decline in 2019 (-8.62%) during another El Niño phase reaffirms that climate variability remains a potent threat to food security in this rapidly urbanizing district. Unlike Serang, which benefits from extensive irrigation, Tangerang's production stability relies heavily on consistent rainfall, making it prone to significant volatility during dry anomalies.

**Table 7.** Impact of climate anomalies on rice production in Tangerang (MA(2) model)

| Year | Climate Anomaly | Actual Production (ton) | Expected Production (ton) | Lower 95% CI (ton) | Upper 95% CI (ton) | Climate Effect Δ (Actual−Expected) (ton) | Deviation (%) | Impact Δ (ton) |
|---|---|---|---|---|---|---|---|---|
| 2001 | Neutral | 318574 | 291537 | 268992 | 314081 | 27038 | 9.27% | 4493 |
| 2002 | El Niño | 264499 | 297311 | 274766 | 319856 | -32812 | -11.04% | -10267 |
| 2003 | Neutral | 330123 | 352725 | 330180 | 375269 | -22602 | -6.41% | -57 |
| 2014 | Neutral | 380476 | 339509 | 316964 | 362053 | 40968 | 12.07% | 18423 |
| 2015 | El Niño | 298541 | 341512 | 318967 | 364057 | -42971 | -12.58% | -20426 |
| 2017 | Neutral | 410535 | 364559 | 342014 | 387104 | 45976 | 12.61% | 23431 |
| 2019 | El Niño | 276627 | 302726 | 280181 | 325271 | -26099 | -8.62% | -3554 |

Note: Δ_effect = Actual − Expected; Impact Δ = Actual − Lower 95% CI if Δ_effect is negative, otherwise Actual − Upper 95% CI; CI = 95% confidence interval. Source: Author's calculations (2025).

### *3.5. District-Level Variation in ENSO Impacts on Rice Production*

Analysis of the average impacts of ENSO-related climate anomalies across Banten's four central rice-producing districts reveals apparent spatial disparities in sensitivity (Table 8). La Niña episodes generally supported rice production, generating average annual gains in all districts. The largest positive effect was observed in Tangerang (+7,058 tons/year), followed by Serang (+3,039 tons/year), Lebak (+2,566 tons/year), and Pandeglang (+1,366 tons/year). These disparities likely reflect variations in hydrological infrastructure, soil water retention capacities, and district-specific management practices in utilizing excess rainfall.

In contrast, El Niño years were primarily associated with average annual yield declines. Tangerang (−23,301 tons/year), Pandeglang (−12,438 tons/year), and Serang (−11,990 tons/year) experienced the largest losses. However, Lebak exhibited an unexpected positive average impact (+3,965 tons/year). As noted previously (2.1.1), this suggests localized resilience, where the benefits of reduced flooding during mild El Niño events statistically outweigh the losses from severe droughts, producing a net positive average for this specific district.

**Table 8.** Average impacts of El Niño and La Niña across districts

| District | Climate anomalies | Mean Impact (ton/year) | Total Year Occurrence |
|---|---|---|---|
| Lebak | La Niña | 2566 | 10 |
| | El Niño | 3965 | 7 |
| Pandeglang | La Niña | 1366 | 10 |
| | El Niño | -12438 | 7 |
| Serang | La Niña | 3039 | 10 |
| | El Niño | -11990 | 7 |
| Tangerang | La Niña | 7058 | 10 |
| | El Niño | -23301 | 7 |

*Source: Author's calculations (2025).*

Overall, these findings confirm the asymmetric effects of ENSO: La Niña generally enhances yields, albeit unevenly, whereas El Niño imposes significant risks—especially in Tangerang and Pandeglang. This underscores the need for district-specific adaptation strategies to address differentiated vulnerabilities. These results align with findings from India, where ENSO impacts on rice production varied significantly across districts; while El Niño often reduces monsoon rainfall, rice yields respond heterogeneously, with some districts experiencing severe losses (−39.7%) while others recorded gains (+42.1%) [31,32]. Similarly, our study confirms that the "climate signal" is modulated by local agro-ecological conditions, necessitating localized rather than generalized adaptation policies.

### *3.6. District-Level Regression Analysis of ENSO Impacts on Rice Production*

Table 9 presents the OLS regression estimates of ENSO anomalies on rice production deviations. The coefficients represent the expected change in production in tons per year (t/year) relative to neutral conditions.

**Table 9.** OLS regression results of ENSO anomalies on production deviations by district

| District | Variable | Coefficient | Std. Error | t-value | p-value | Sig. |
|---|---|---|---|---|---|---|
| Tangerang | Intercept | 10,069 | 6,401 | 1.573 | 0.1307 | |
| | La Niña | −3,011 | 8,588 | −0.351 | 0.7294 | |
| | El Niño | −33,371 | 9,778 | −3.413 | 0.0026 | *** |
| Pandeglang | Intercept | 13,297 | 16,738 | 0.794 | 0.4360 | |
| | La Niña | −11,931 | 22,457 | −0.531 | 0.6010 | |
| | El Niño | −25,735 | 25,568 | −1.007 | 0.3260 | |
| Lebak | Intercept | −7,952 | 11,372 | −0.699 | 0.4920 | |
| | La Niña | 10,518 | 15,629 | 0.673 | 0.5090 | |
| | El Niño | 11,917 | 17,371 | 0.686 | 0.5010 | |
| Serang | Intercept | 3,649.8 | 6,436.2 | 0.567 | 0.5770 | |
| | La Niña | −610.4 | 8,845.7 | −0.069 | 0.9460 | |
| | El Niño | −15,639.7 | 9,831.4 | −1.591 | 0.1270 | |

*Note: Dependent variable is production deviation (tons). Coefficients represent the change in production in tons per year (t/year). Sig: *** $p < 0.01$. Source: Author's calculations (2025)*

In Tangerang, the analysis reveals a substantial and statistically significant adverse effect of El Niño ($\beta$ = -33,371 t/year; $p < 0.01$). This confirms the district's acute vulnerability to hydrological deficits, likely exacerbated by its peri-urban characteristics, where agricultural water demand competes with industrial use. Conversely, La Niña shows a negative but statistically insignificant coefficient ($p > 0.05$), indicating no consistent production benefit from wetter conditions in this area.

In Pandeglang, the model estimates large average losses during both El Niño (-25,735 t/year) and La Niña (-11,931 t/year), but these coefficients are not statistically significant ($p > 0.05$). This suggests that although climate anomalies generally suppress yields, high inter-annual variability precludes a definitive statistical conclusion from this dataset alone. Similarly, Serang exhibits a considerable but statistically insignificant production loss during El Niño events (-15,640 t/year; $p = 0.13$), with minimal and non-significant impacts observed during La Niña phases. Interestingly, Lebak displays positive coefficients for both El Niño (+11,917 t/year) and La Niña (+10,518 t/year), although neither is statistically significant. While inconclusive, this pattern aligns with the descriptive findings (Section 2.1.1), hinting at a unique buffering capacity where moderate climate deviations do not systematically disrupt production in this district.

Overall, the regression results underscore the heterogeneity impacts of ENSO across districts. Tangerang emerges as the only district with a statistically robust sensitivity to El Niño drought stress. The lack of statistical significance in other districts, despite large coefficient values, implies that production outcomes are influenced by complex local interactions—such as irrigation efficacy and pest dynamics—that mitigate or obscure the direct signal of global climate anomalies. This highlights the necessity for spatially tailored adaptation strategies, with urgent priority for drought mitigation in Tangerang.

## 4. Conclusions

This study demonstrates that rice production responses to ENSO anomalies in Banten Province are spatially heterogeneous. Statistical analysis identifies Tangerang as a critical hotspot with a significant production decline during El Niño ($\beta$=-33,371 t/year), while the 2020–2023 "Triple-Dip" La Niña revealed that excessive rainfall can trigger detrimental flood-induced losses, particularly in Pandeglang. Methodologically, second- and third-order moving average models (MA(2) and MA(3)) consistently outperformed linear, quadratic, and exponential alternatives, proving their efficacy in capturing stochastic fluctuations for short-term climate risk assessment.

From a policy perspective, these findings affirm that generalized adaptation strategies are insufficient. Effective resilience-building must be spatially differentiated, prioritizing drought mitigation in Tangerang and drainage infrastructure in flood-prone districts such as Pandeglang. Although limited by a univariate approach, this research provides a foundation for future multivariate studies and sub-district level analysis to refine site-specific early warning systems and safeguard regional food security.

## Abbreviations

Not applicable.

## Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

## CRediT Authorship Contribution Statement

**Tian Mulyaqin**: Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Rita Nurmalina**: Conceptualization, Validation, Supervision. **Nunung Kusnadi**: Conceptualization, Validation, Supervision. **Bambang Hendro Trisasongko**: Conceptualization, Validation, Supervision.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Declaration of Use of AI in the Writing Process

Nothing to disclose.

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