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Quantifying spatial and lagged effects of rainfall on rainfed rice production in East Nusa Tenggara, Indonesia

Marten Luter Lano[1*], Lesybeth Marlina Nubatonis[1], Jonathan Ebet Koehuan[1], Marthen Makaborang[1], Nikodemus P. P. E. Nainiti[1], Jemmy Jonson Sula Dethan[1]

[1] Faculty of Agricultural Technology, Artha Wacana Christian University, Oesapa, 85228 Kupang, Indonesia
* Corresponding author's e-mail: lano.marten@gmail.com

ABSTRACT

Rainfall variability is a critical factor shaping agricultural production in tropical dryland regions. This study analyzes the spatial distribution of rainfall and rice production, examines their relationship, and evaluates the temporal lag of rainfall on rice production in East Nusa Tenggara, Indonesia. Secondary data at the district level were analyzed using spatial mapping, correlation analysis, and lag analysis. The results show significant spatial disparities in rice production, with higher output concentrated in western regions (notably West Manggarai and Manggarai) and lower output in eastern and smaller island districts. Correlation analysis reveals a lag-dependent relationship between rainfall and rice production: the contemporaneous correlation is weak and non-significant ($r = -0.26$, $p = 0.074$), while correlations strengthen substantially at longer lags, peaking at lag 3 months ($r = 0.81$, $p < 0.001$). This indicates that cumulative rainfall during the growing season, rather than rainfall in the harvest month, is the dominant factor associated with rice production. These findings emphasize the importance of integrating temporal lag dynamics into climate–agriculture analyses and provide a quantitative basis for improving agricultural planning and climate adaptation strategies in rainfed monsoonal systems.

Keywords: rainfall variability, rice production, spatial analysis, correlation analysis, lag effect, East Nusa Tenggara.

INTRODUCTION

Rainfall variability is a key factor influencing agricultural productivity in tropical dryland regions (Ray et al., 2015). In areas dominated by rainfed systems, such as East Nusa Tenggara, Indonesia, fluctuations in rainfall patterns can significantly affect crop growth and yield stability. The region is characterized by a monsoonal climate with a short wet season and a prolonged dry period, making agricultural production highly dependent on the timing and distribution of rainfall (McKay et al., 2023).

The monsoonal climate plays a fundamental role in shaping agricultural systems, particularly through rainfall timing and seasonal distribution. The onset of the rainy season is especially critical, as early onset is generally associated with greater water availability, whereas delayed onset often leads to water deficits that constrain crop growth (Gudoshava et al., 2022). However, total annual rainfall alone is not a sufficient indicator of agricultural performance. In semi-arid environments, intraseasonal variability – such as prolonged dry spells during key crop growth stages – can significantly reduce productivity despite relatively high annual rainfall (Porkka et al., 2021). Similarly, the distribution of rainfall within the season, including the frequency and timing of rainfall events, strongly influences vegetation productivity (Zhang et al., 2018). Beyond biophysical effects, rainfall timing also has important economic implications, as intra-annual variability can exert a greater influence on agricultural income than total annual rainfall (Torres et al., 2019).

Rice is one of the main staple crops in East Nusa Tenggara, yet its production is constrained by irregular rainfall patterns and limited water availability. Rainfall variability influences water availability, planting schedules, crop development, and ultimately yield outcomes. Historical evidence shows that fluctuations in both annual and monthly rainfall can significantly affect rice production, with excessive rainfall during critical growth stages often resulting in yield reductions (Shrestha et al., 2022).

Recent studies further highlight the complexity of rainfall–crop interactions. Changes in seasonal rainfall patterns, such as reduced early-season precipitation, may delay planting but do not necessarily reduce yields if cropping calendars are successfully adjusted (Sujariya et al., 2020). However, future climate projections indicate increasing uncertainty, particularly in monsoonal regions like Indonesia, where delayed onset of the rainy season is expected to become more frequent, potentially intensifying the risk of crop failure and food insecurity (Naylor et al., 2007). To address these challenges, adaptive strategies such as optimizing sowing windows have been shown to improve resilience in rainfed systems by better aligning crop growth with rainfall availability (Agoungbome et al., 2023). Nevertheless, increasing rainfall variability under climate change conditions necessitates continuous adaptation and flexible management strategies.

In East Nusa Tenggara, rainfall distribution exhibits strong spatial heterogeneity due to variations in topography and island geography. Western regions generally receive higher rainfall compared to eastern and smaller islands, resulting in differences in agricultural potential across districts. Understanding these spatial patterns is essential for interpreting regional disparities in rice production.

Despite the recognized importance of rainfall variability, there remains limited integrated analysis that simultaneously examines spatial distribution, direct rainfall–production relationships, and temporal lag effects in this region. Such an approach is crucial for capturing the complex dynamics through which rainfall influences agricultural systems across both space and time.

Despite extensive research on rainfall–agriculture interactions globally, critical gaps remain in the integrated, district-scale analysis of rainfall–rice production dynamics in Indonesian monsoonal dryland regions. Existing studies tend to address either spatial variability or temporal lag effects in isolation, rarely combining both perspectives within a single analytical framework. Furthermore, the specific temporal window over which rainfall most strongly influences rice production in East Nusa Tenggara has not been quantified. This study hypothesizes that (a) rainfall distribution is a primary driver of spatial disparities in rice production across districts, and (b) rainfall influences rice production with a measurable temporal lag corresponding to the crop's biological growth cycle. Therefore, this study aims to: (1) characterize the spatial distribution of rainfall and rice production at the district level in East Nusa Tenggara; (2) quantify the statistical relationship between rainfall and rice production using Pearson correlation analysis; and (3) identify the dominant temporal lag through which rainfall variability influences rice production. By integrating spatial and temporal perspectives, this study fills a gap in district-scale climate–agriculture analysis and provides an evidence base for improving agricultural planning and adaptive strategies in rainfed monsoonal systems

MATERIALS AND METHODS

Study area

This study was conducted in East Nusa Tenggara (Nusa Tenggara Timur), Indonesia, a monsoonal dryland region characterized by strong interannual and intra-seasonal rainfall variability and a prolonged dry season. The region comprises the main islands of Timor, Flores, and Sumba, with heterogeneous topography including coastal plains, uplands, and mountainous areas. Administrative boundaries at the district level were obtained from the Badan Informasi Geospasial (BIG) PPBW shapefile dataset, distributed via LapakGIS.com (https://lapakgis.com; accessed 2024), comprising two layers: provincial boundaries (Batas_Provinsi_BIG_PPBW) and district/city boundaries (Batas_Kabupaten_BIG_PPBW_V1), in the geographic coordinate system WGS 1984 (EPSG:4326). All 22 districts in East Nusa Tenggara were included in the analysis, with no districts excluded (Figure 1).

The climate is governed by the Asian–Australian monsoon system, producing a distinct wet season (December–March) and dry season (June–September), with transitional periods in April–May and October–November. These seasonal dynamics strongly regulate agricultural activity, particularly rainfed rice systems.

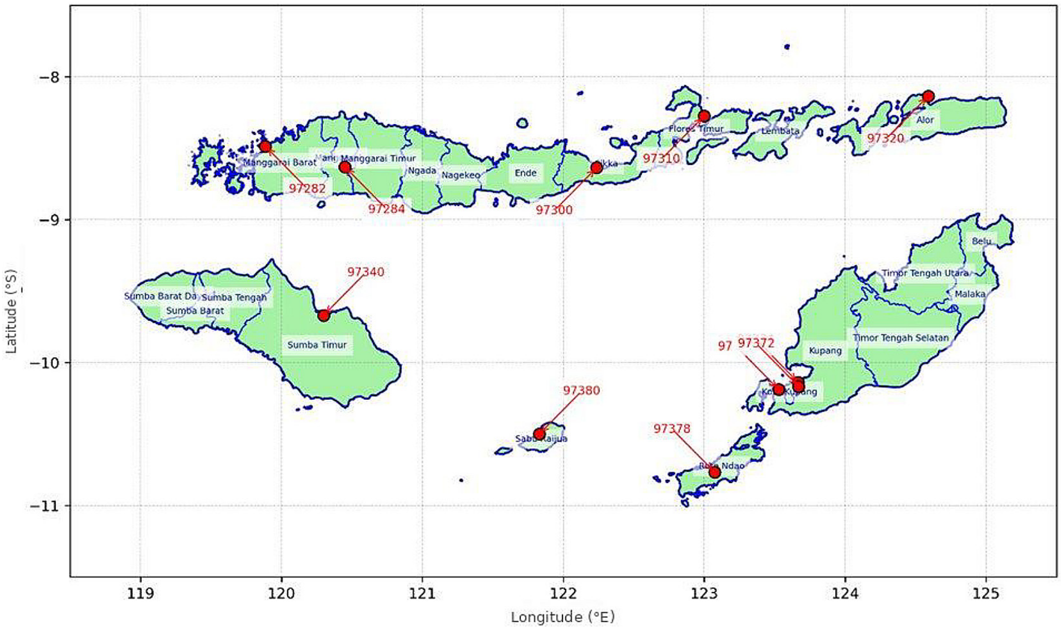


Figure 1. Study area map of East Nusa Tenggara Province, Indonesia, showing district administrative boundaries and the locations of 11 BMKG weather stations (red dots, identified by WMO station codes) used for CHIRPS rainfall data extraction. The study covers all 22 districts across the three main islands of Flores, Timor, and Sumba

Data sources

Rainfall data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS v2.0) dataset, which provides gridded precipitation estimates at a spatial resolution of 0.05° (~5 km). Daily rainfall data in NetCDF format (chirps-v2.0.YYYY.days_p05.nc) covering the period 1991–2023 were downloaded from the CHIRPS data repository (https://data.chc.ucsb.edu/products/CHIRPS-2.0/global_daily/netcdf/p05/; accessed 2025). Data extraction at 11 BMKG station locations was performed using point selection via the xarray library in Python 3.8, selecting the nearest grid cell to each station coordinate. Daily rainfall values were aggregated into monthly totals using temporal summation. The spatial distribution of these stations across the study area is illustrated in Figure 1.

Rice production data (in metric tons) were obtained from Badan Pusat Statistik (BPS – Statistics Indonesia) at the district level for the period 2020–2023. The dataset provides annual harvested rice production per district. To enable temporal analysis, annual production values were converted into monthly estimates using a cropping calendar-based allocation approach, following typical planting and harvesting periods in rainfed rice systems (Laborte et al., 2017). This approach assumes that production is concentrated around peak harvest months and distributed proportionally across the growing season.

This temporal disaggregation introduces uncertainty and results should therefore be interpreted with caution.

Data processing

All spatial and temporal processing steps were conducted to ensure consistency between rainfall and agricultural datasets.

Temporal alignment. Rainfall data were aggregated into monthly totals from daily CHIRPS values using temporal summation. Rice production data, originally available at an annual scale, were temporally disaggregated into monthly estimates using a cropping calendar-based allocation approach. This method distributes annual production across months based on typical planting and harvesting periods in rainfed rice systems, with production concentrated during peak harvest months. Both datasets were then aligned to a common monthly time series covering the overlapping study period (2020–2023), resulting in 48 observations (12 months × 4 years).

Spatial aggregation. Gridded CHIRPS rainfall data were aggregated to the district level using zonal statistics, calculating mean areal rainfall

($\bar{R}$_d,t) for each district polygon d at time t. The mean was computed across all CHIRPS grid cells whose centroids fall within each district boundary. Spatial joins were performed using the district boundary shapefile in QGIS 3.28.

For correlation and lag analysis, district-level rainfall and production data were further aggregated into a single regional monthly time series to capture overall system dynamics at the provincial scale.

Missing data handling. Observations with missing rainfall or production values were excluded using listwise deletion. The proportion of missing data was minimal and is not expected to significantly affect the results.

Data validation. All variables were checked for unit consistency, temporal alignment, and spatial correspondence prior to analysis. It should be noted that the temporal disaggregation of annual production into monthly estimates introduces uncertainty; therefore, results should be interpreted with appropriate caution.

Spatial analysis

Spatial patterns of rainfall and rice production were analyzed at the district level. For each district d, the long-term mean rainfall ($\bar{R}d$) and mean rice production ($\bar{P}d$) were computed over the available study period (2020–2023). Spatial distributions of both variables were visualized using choropleth mapping in QGIS 3.28 (QGIS Development Team, 2022). This step is descriptive in nature and characterizes spatial heterogeneity across the region; it does not include formal spatial autocorrelation tests such as Moran's I or Local Indicators of Spatial Association (LISA). Such tests are recommended as an optional extension for future work requiring statistical evidence of spatial clustering or dispersion.

Correlation and lag analysis

The relationship between rainfall and rice production was evaluated using Pearson's correlation coefficient, which measures the strength and direction of linear association between two variables. Statistical significance was assessed at the 95% confidence level ($p < 0.05$).

Correlation analysis was conducted using the regional monthly time series ($n = 48$). To capture delayed agricultural responses to rainfall variability, lagged correlations were computed by shifting the rainfall time series by k months relative to the production series, for $k = 0, 1, 2$, and 3. For each lag k, rainfall at time $t-k$ was correlated with production at time t. The lag producing the maximum absolute correlation was identified as the dominant response window.

The selected lag range (0–3 months) reflects the typical growth duration of rainfed rice systems (approximately 3–4 months), during which rainfall during planting, vegetative, and reproductive stages influences final yield outcomes (Laborte et al., 2017).

No seasonal detrending or differencing was applied prior to analysis. As both rainfall and production exhibit strong seasonal patterns, the resulting correlations may partially reflect shared seasonal cycles. Therefore, the results are interpreted as indicative of temporal association rather than causal relationships.

In addition, standard assumptions of Pearson correlation (linearity, normality, and independence) were not formally tested, representing a limitation of the study. Future research should address these assumptions to improve statistical robustness.

Analytical tools

All data processing and statistical analyses were conducted in Python, using the following libraries: pandas (data management and tabular operations), numpy (numerical computation), scipy (Pearson correlation and significance testing), xarray (NetCDF raster extraction for CHIRPS data), geopandas (spatial data processing and shapefile handling), matplotlib (map and figure visualization), scikit-learn (RMSE and MAE calculation for CHIRPS validation), and os (file and directory management). Spatial visualization and choropleth mapping were performed using QGIS 3.28 (QGIS Development Team, 2022). All analysis scripts are available upon request from the corresponding author.

RESULTS AND DISCUSSION

Rainfall variability in a monsoonal dryland system

Rainfall variability derived from CHIRPS data indicates that East Nusa Tenggara exhibits a strongly seasonal rainfall regime characteristic of monsoonal dryland environments. The temporal distribution of rainfall is marked by a short and concentrated wet season followed by a prolonged dry period, resulting in pronounced intra-annual variability.

Monthly rainfall patterns show that peak precipitation occurs during January–February, while the lowest rainfall is consistently observed between June and September, when rainfall approaches minimal levels in most districts (Figure 2). This strong seasonal contrast reflects the dominant influence of the Asian–Australian monsoon system, which controls moisture transport into the region. The rapid transition between wet and dry conditions further highlights the system's sensitivity to climatic fluctuations.

At the seasonal scale, the December–January–February (DJF) period represents the primary wet season and contributes the largest proportion of annual rainfall. In contrast, the June–July–August (JJA) period corresponds to peak dry conditions, with negligible rainfall recorded in several areas. Transitional seasons (March–April–May and September–October–November) exhibit intermediate rainfall levels, reflecting shifts between monsoon phases.

Spatially, rainfall distribution across East Nusa Tenggara is highly heterogeneous (Figure 3). Higher rainfall is observed in the western and central regions, particularly in Flores and central Timor, whereas significantly drier conditions prevail in southern and eastern areas such as Sumba and Rote.

The spatial variability of precipitation is strongly influenced by topographic and geographic factors. In mountainous regions, orographic uplift enhances rainfall as moist air masses are forced to rise, resulting in higher precipitation on the windward side, while the leeward side tends to experience reduced rainfall due to rain shadow effects (Alsafadi et al., 2023; Chen et al., 2023). In addition, areas located within rain shadow zones generally receive significantly lower precipitation due to the barrier effect of mountain ranges, which limits the transport of moist air (Chen et al., 2023)

Furthermore, geographic factors also play an important role in shaping rainfall patterns. The proximity of southern parts of East Nusa Tenggara to the Australian continent facilitates the intrusion of dry air masses, particularly during the dry season, thereby intensifying aridity (McKay et al., 2023). Variations in atmospheric circulation further contribute to spatial differences in rainfall distribution across the region (McKay et al., 2023).

Overall, the observed rainfall variability reflects the combined effects of large-scale monsoon dynamics and local geographic controls. Such variability plays a critical role in shaping

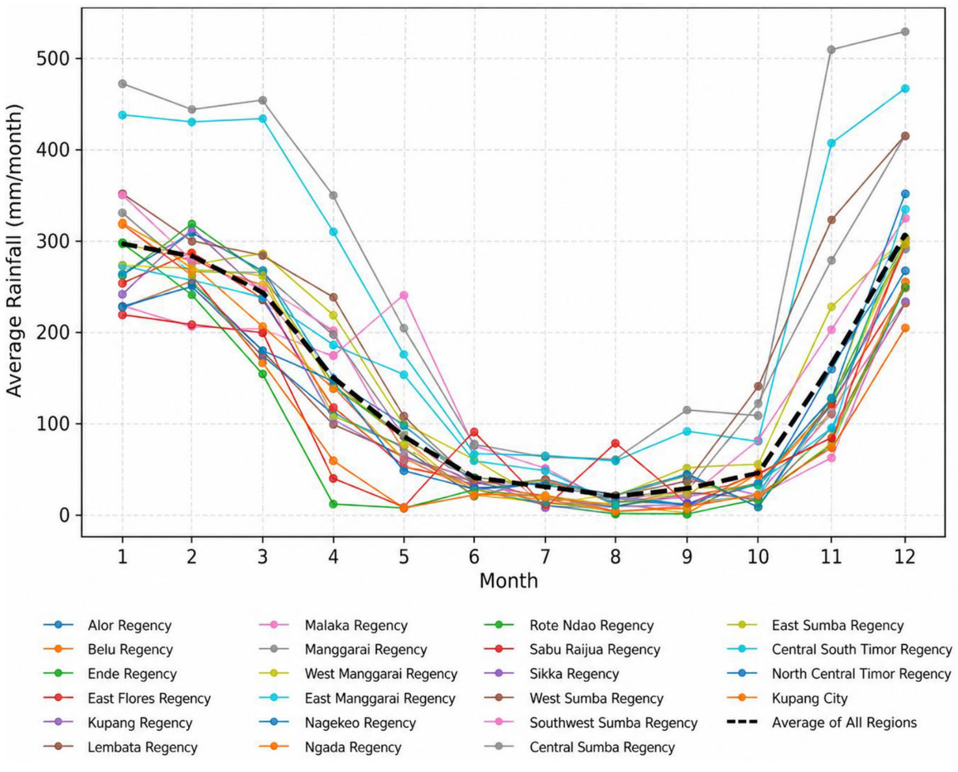


Figure 2. Monthly rainfall climatology (1991–2020)

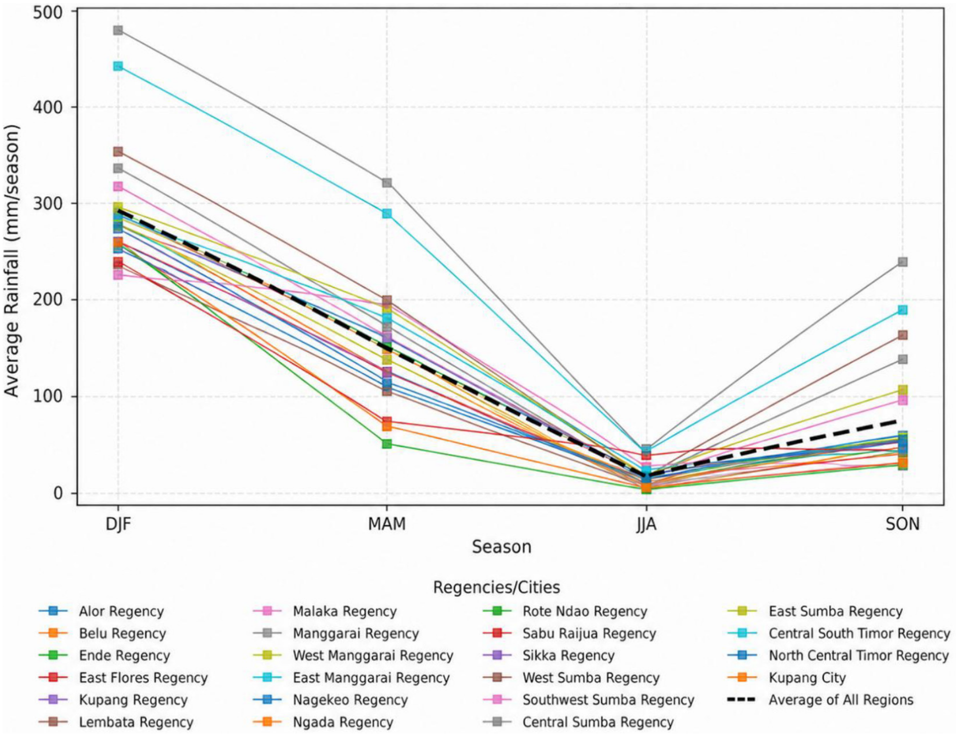


Figure 3. Spatial distribution of seasonal rainfall (DJF, MAM, JJA, SON)

agricultural systems in the region, particularly in rainfed environments where water availability is strongly dependent on seasonal rainfall patterns.

At the monthly scale, rice production shows a clear seasonal pattern that aligns with the regional cropping calendar (Figure 4). Production typically begins to rise in March and April, peaks around May, and then declines sharply after June, reaching its lowest levels during the peak dry season from August to September. This pattern reflects the timing of planting and harvesting, with rice cultivation generally coinciding with the onset of the rainy season and harvesting occurring shortly after peak rainfall (Laborte et al., 2017).

Monthly production dynamics are closely tied to rainfall availability, with higher outputs during periods of sufficient precipitation and a decline as the dry season intensifies. In addition, climate variability plays an important role in shaping this seasonal pattern. Large-scale climate phenomena, such as the El Niño–Southern Oscillation, can alter rainfall distribution and subsequently affect rice production levels. Historical evidence also shows that fluctuations in rainfall have long influenced rice yields, emphasizing the sensitivity of production systems to climatic variability (Shrestha et al., 2022).

The observed seasonal cycle highlights the strong dependence of rice cultivation on rainfall availability. The synchronization between rainfall onset and planting activities is crucial for achieving relatively uniform harvest periods across districts, while deviations in rainfall timing and intensity can disrupt this alignment, leading to shifts in production timing and variability in yields. Rice cultivation systems that are closely aligned with favorable rainfall conditions have been shown to achieve improved yields, emphasizing the importance of optimizing planting schedules under variable climate conditions (Liu et al., 2023).

Rice production varies significantly across districts (Figure 5). Higher production levels are consistently observed in regions such as western Flores and parts of central Timor, which likely benefit from higher, more reliable rainfall and better water availability.

In contrast, districts in drier areas, including Sumba and smaller southern islands, tend to show lower and more variable production levels, reflecting constraints related to limited water resources and higher rainfall variability. These spatial differences may also be influenced by land–atmosphere interactions, which can further amplify variability in crop yields across regions (Liu et al., 2023).

These spatial disparities underscore the important role of environmental and climatic

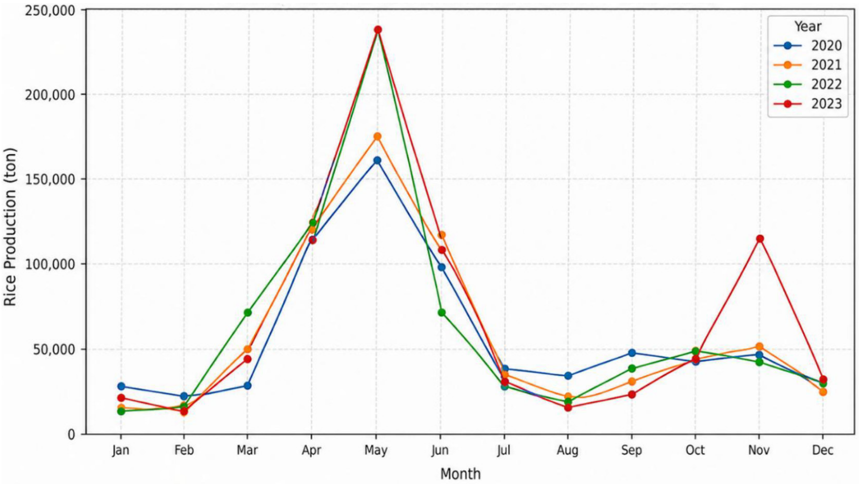
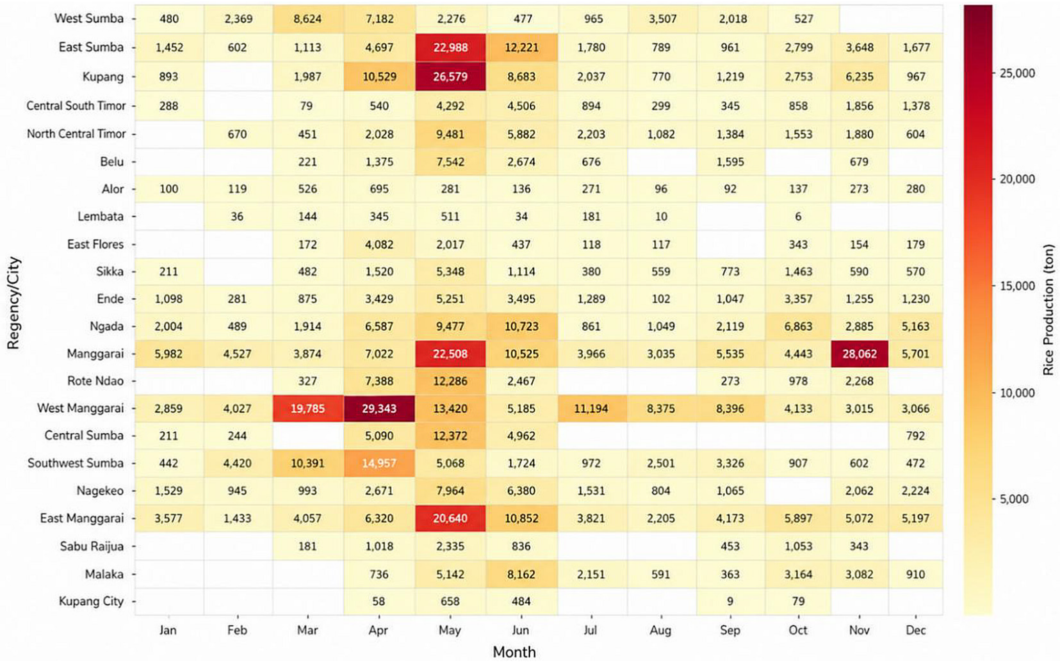


Figure 4. Annual rice production in East Nusa Tenggara (2020–2023)

constraints in shaping agricultural productivity (Figure 6). Regions with more favorable, reliable rainfall regimes tend to support higher, more stable rice production, whereas areas with limited, highly variable rainfall face greater challenges in maintaining consistent yields. This finding aligns with previous studies showing that climate variability contributes substantially to crop yield variability at both regional and global scales. In particular, precipitation has been identified as a key determinant of rice yield variability in monsoonal regions, where rainfall indices can effectively capture production fluctuations (Kattelus et al., 2016).

These patterns are further substantiated by the quantitative district-level data. Among the 22 districts analysed, districts in western Flores – particularly West Manggarai and Manggarai – consistently recorded the highest mean annual rice production over the 2020–2023 period, while districts in eastern Timor, Sumba, and the smaller southern islands (such as Rote Ndao and Sabu Raijua) reported the lowest production levels. This west-to-east gradient in production closely mirrors the spatial pattern of mean annual rainfall derived from CHIRPS data, in which western and central districts receive substantially higher precipitation than eastern and island districts. The



Regency/City	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
West Sumba	480	2,369	8,624	7,182	2,276	477	965	3,507	2,018	527		
East Sumba	1,452	602	1,113	4,697	22,988	12,221	1,780	789	961	2,799	3,648	1,677
Kupang	893		1,987	10,529	26,579	8,683	2,037	770	1,219	2,753	6,235	967
Central South Timor	288		79	540	4,292	4,506	894	299	345	858	1,856	1,378
North Central Timor		670	451	2,028	9,481	5,882	2,203	1,082	1,384	1,553	1,880	604
Belu			221	1,375	7,542	2,674	676		1,595		679	
Alor	100	119	526	695	281	136	271	96	92	137	273	280
Lembata		36	144	345	511	34	181	10		6		
East Flores			172	4,082	2,017	437	118	117		343	154	179
Sikka	211		482	1,520	5,348	1,114	380	559	773	1,463	590	570
Ende	1,098	281	875	3,429	5,251	3,495	1,289	102	1,047	3,357	1,255	1,230
Ngada	2,004	489	1,914	6,587	9,477	10,723	861	1,049	2,119	6,863	2,885	5,163
Manggarai	5,982	4,527	3,874	7,022	22,508	10,525	3,966	3,035	5,535	4,443	28,062	5,701
Rote Ndao			327	7,388	12,286	2,467			273	978	2,268	
West Manggarai	2,859	4,027	19,785	29,343	13,420	5,185	11,194	8,375	8,396	4,133	3,015	3,066
Central Sumba	211	244		5,090	12,372	4,962						792
Southwest Sumba	442	4,420	10,391	14,957	5,068	1,724	972	2,501	3,326	907	602	472
Nagekeo	1,529	945	993	2,671	7,964	6,380	1,531	804	1,065		2,062	2,224
East Manggarai	3,577	1,433	4,057	6,320	20,640	10,852	3,821	2,205	4,173	5,897	5,072	5,197
Sabu Raijua			181	1,018	2,335	836			453	1,053	343	
Malaka				736	5,142	8,162	2,151	591	363	3,164	3,082	910
Kupang City				58	658	484			9	79		

Figure 5. Monthly rice production patterns (2020–2023)

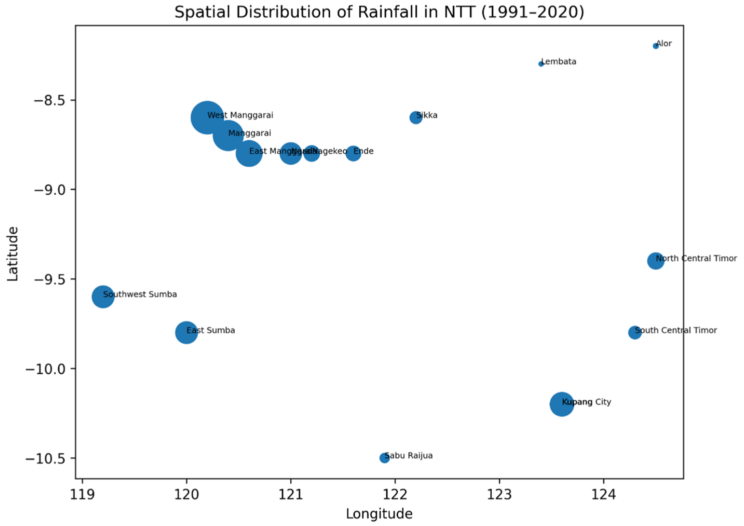


Figure 6. Spatial distribution of average rice production across districts

quantitative alignment between rainfall distribution and production levels across districts thus provides direct empirical support for the spatial hypotheses of this study.

Overall, rice production dynamics in East Nusa Tenggara reflect a climate-constrained agricultural system, in which both temporal and spatial variability in rainfall play a central role in determining production performance. Climate variability, including extreme events, can disrupt cropping patterns and lead to non-synchronized changes in production, further increasing uncertainty in agricultural systems. These findings highlight the strong dependence of rainfed agriculture on rainfall conditions and reinforce the importance of incorporating climatic factors into agricultural analysis and planning (Demir and Mahmud, 2002).

Rainfall–rice production relationship and lag effect

The contemporaneous relationship between rainfall and rice production was first examined at zero lag. At zero lag (k = 0), the correlation between rainfall and rice production is weak and not statistically significant ($r = -0.26$, $p = 0.074$; Figure 6). This indicates that rainfall in the same month does not directly correspond to production levels. The negative slope observed in the regression further reflects the temporal mismatch between peak rainfall and peak harvest periods, where rice is typically harvested after the rainy season has declined. This pattern is consistent with the regional cropping calendar, in which planting occurs during the wet season and harvesting follows several months later.

The negative correlation at zero lag suggests that higher rainfall in a given month does not necessarily translate into increased rice production within the same period (Figure 7). This reflects the complex relationship between rainfall and crop growth, in which rice development depends more on cumulative water availability over the growing cycle than on instantaneous rainfall. Previous studies have shown that rainfall variability, both monthly and seasonal, can significantly influence rice yields, particularly when excessive rainfall occurs during critical growth stages. In some cases, excessive precipitation may lead to adverse conditions such as waterlogging, reduced solar radiation, and increased pest and disease incidence, ultimately reducing crop performance (Maiti et al., 2024).

To further examine this delayed response, a lag-correlation analysis was conducted. The results indicate that the relationship between rainfall and rice production varies across lags, confirming that rainfall influences production with a temporal delay. This finding is consistent with studies showing that crop responses to rainfall are not immediate and may exhibit lagged effects due to cumulative moisture conditions and non-linear responses to precipitation. Moreover, rainfall does not uniformly affect production. Moderate, well-distributed rainfall can enhance yields, whereas excessive or poorly timed rainfall may have negative impacts, highlighting the importance of both timing and distribution in determining production outcomes.

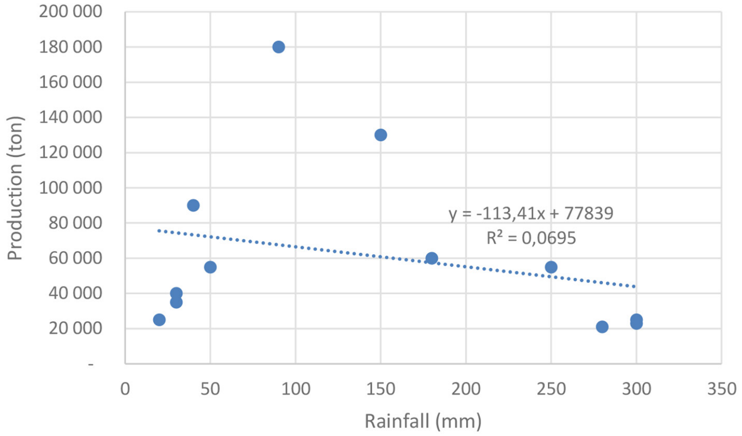


Figure 7. Scatter plot of rainfall vs rice production (r = −0.26)

The lag correlation analysis (Figure 8) shows a clear increase in the strength of the rainfall–production relationship with increasing lag. At lag 0, the correlation is weak and non-significant (r = −0.26, p = 0.074), while it becomes positive but still non-significant at lag 1 (r = 0.17, p = 0.248). The relationship strengthens substantially at lag 2 (r = 0.68, p < 0.001) and reaches its maximum at lag 3 (r = 0.81, p < 0.001).

This pattern suggests that rainfall occurring approximately 2–3 months prior to the production reference period is strongly associated with rice output. This temporal window is consistent with the biological growth cycle of rainfed rice, during which water availability during vegetative and reproductive stages plays a critical role in determining final yields (Laborte et al., 2017).

However, given the strong seasonal structure of both rainfall and production data, part of the observed correlation may reflect shared seasonal patterns rather than a purely causal relationship. Therefore, the identified lag should be interpreted as a dominant temporal association rather than a definitive causal effect. Both rainfall and rice production in East Nusa Tenggara exhibit pronounced intra-annual cycles driven by the Asian–Australian monsoon: rainfall peaks in January–February and production peaks around May, with both variables declining sharply during the dry season. Because no seasonal detrending or differencing was applied prior to analysis, the correlation coefficients reported here − including the peak value of r = 0.81 at lag 3 − may be partially inflated by these shared seasonal cycles. This does not invalidate the lag finding; indeed, the consistent peak at lag 3 aligns with the known biological growth cycle of rainfed rice and is ecologically interpretable. Nevertheless, future analyses should apply seasonal decomposition or first-differencing to isolate the inter-annual component of the rainfall–production relationship and provide a more conservative estimate of the association strength.

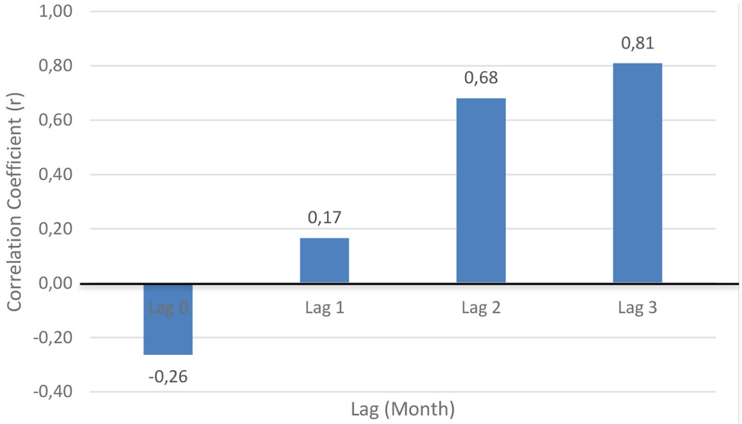


Figure 8. Lag correlation between rainfall and rice production

These findings underscore the importance of incorporating temporal dynamics into climate–agriculture analyses. Relying solely on contemporaneous correlations may underestimate the true influence of rainfall on crop production, particularly in systems with pronounced seasonal cropping patterns. The observed lag effect aligns with previous studies showing that crop responses depend not only on total precipitation but also on its timing and distribution throughout the growing season. However, while early rainfall is generally beneficial, excessive or poorly timed precipitation can create unfavorable conditions, such as increased disease incidence or nutrient loss, thereby offsetting potential gains in productivity.

Furthermore, the relatively weak overall correlation suggests that rainfall is not the sole determinant of rice production in the region. Other factors, including planting schedules, soil conditions, irrigation practices, and local management strategies, may also play important roles in shaping production outcomes. This indicates that agricultural systems in East Nusa Tenggara are somewhat adapted to rainfall variability.

Overall, the rainfall–production relationship in East Nusa Tenggara is marked by a delayed, nonlinear response, in which the timing of rainfall is more critical than its instantaneous magnitude. These results underscore the importance of time-sensitive agricultural planning, particularly in monsoonal dryland environments with high rainfall variability.

Several methodological limitations should be considered when interpreting the correlation results. First, the standard assumptions of Pearson's correlation − linearity, normality, and temporal independence of observations − were not formally tested prior to analysis. The monthly time series used here ($n = 48$) is likely to contain autocorrelation, meaning consecutive observations are not fully independent. This can reduce the effective sample size and cause p-values to appear more significant than warranted; therefore, the significance levels reported (notably $p < 0.001$ at lag 3) should be treated as indicative rather than definitive. Second, rice production data were originally available only at annual resolution and were converted to monthly estimates using a cropping calendar-based disaggregation approach. This procedure introduces artificial structure into the monthly production series, as the observed seasonal peaks partly reflect the allocation weights used in disaggregation rather than independently measured monthly outputs. Consequently, the lag-correlation results − including the peak at lag 3 − may be partially shaped by the assumptions embedded in the disaggregation model. These limitations do not negate the overall finding, as the 3-month lag is consistent with the known biology of rainfed rice and is corroborated by the regional cropping calendar. However, they underscore the importance of collecting actual sub-annual production data in future studies to provide more robust estimates of the rainfall–production relationship.

CONCLUSIONS

This study demonstrates that rainfall variability plays a significant role in shaping rice production patterns in East Nusa Tenggara, both spatially and temporally. The spatial analysis reveals clear disparities in production across districts, with higher outputs concentrated in western regions and lower production in eastern and smaller island areas, reflecting differences in rainfall distribution.

Correlation and lag analysis reveal a clear lag-dependent relationship between rainfall and rice production. The contemporaneous correlation is weak and non-significant ($r = -0.26$, $p = 0.074$), whereas correlations become strongly significant at lag 2 ($r = 0.68$, $p < 0.001$) and peak at lag 3 ($r = 0.81$, $p < 0.001$). These results indicate that accumulated rainfall during the crop growth cycle − particularly 2–3 months before harvest − is more strongly associated with rice production than rainfall at the time of harvest.

Overall, these findings highlight the importance of incorporating temporal lag dynamics into climate–agriculture analyses in monsoonal dryland systems. The identification of a 3-month dominant lag provides a quantitative basis for improving planting schedule recommendations, early warning systems, and adaptive agricultural strategies in East Nusa Tenggara and comparable rainfed environments.

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