



Quantifying Food Deficit Risk under Seasonal Climate Variability Using a Compound Periodic Poisson Process

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Abstrak

Variabilitas iklim meningkatkan frekuensi kejadian cuaca ekstrem, sehingga memperbesar ketidakpastian produksi pertanian dan risiko defisit pangan. Studi terdahulu umumnya menggunakan pendekatan deterministik atau ekonometrik yang mengestimasi perubahan produksi rata-rata tanpa secara eksplisit mengkuantifikasi risiko produksi stokastik. Penelitian ini mengusulkan kerangka compound periodic Poisson process untuk mengkuantifikasi risiko produksi pangan akibat iklim dengan memodelkan kejadian periodik curah hujan ekstrem menggunakan data curah hujan harian selama sebelas tahun (2015–2025) di Provinsi Sulawesi Selatan. Intensitas kejadian curah hujan ekstrem, yang didefinisikan sebagai curah hujan harian melebihi persentil empiris ke-90 atau 31,4 mm/hari, menunjukkan siklus musiman yang jelas, dari kurang dari 1 kejadian per bulan pada musim kemarau (Juni–September) hingga sekitar 7–8 kejadian per bulan pada puncak musim hujan (Desember–Februari). Deret Fourier orde kedua yang disesuaikan dengan intensitas bulanan menjelaskan 98,2% variasi musiman yang diamati, sedangkan estimasi maximum likelihood terhadap waktu kejadian harian menghasilkan pola musiman yang sama. Karena data produksi pertanian hanya tersedia dalam resolusi tahunan, yaitu delapan tahun untuk padi dan lima tahun untuk jagung, komponen tingkat keparahan dan kerugian produksi agregat belum dapat diestimasi dengan ketelitian statistik yang dipersyaratkan model compound Poisson. Oleh karena itu, kedua komponen tersebut dilaporkan secara deskriptif dan menjadi keterbatasan penelitian yang perlu ditangani melalui data produksi per musim tanam. Hasil penelitian menunjukkan bahwa komponen Poisson periodik memberikan dukungan empiris untuk mendeskripsikan kejadian curah hujan ekstrem, sedangkan komponen risiko defisit pangan masih bersifat awal dan memerlukan data produksi yang lebih rinci agar hubungan antara kejadian iklim ekstrem dan kerugian produksi dapat diestimasi secara andal pada penelitian selanjutnya.

Kata kunci: compound periodic Poisson process; risiko pertanian; defisit produksi pangan; variabilitas iklim; teori risiko kolektif

Abstract

Climate variability has increased the frequency of extreme weather events, leading to greater uncertainty in agricultural production and a higher risk of food production deficits. Existing studies predominantly employ deterministic or econometric approaches that estimate average production changes without explicitly quantifying stochastic production risk. This study proposes a compound periodic Poisson process framework to quantify climate induced food production risk

by modelling the periodic occurrence of extreme rainfall events using eleven years (2015-2025) of daily rainfall observations for South Sulawesi Province. The estimated occurrence intensity of extreme rainfall events (daily rainfall exceeding the empirical 90th percentile, 31,4 mm/day) exhibits a pronounced seasonal cycle, ranging from below 1 event per month during the dry season (June-September) to approximately 7-8 events per month during the peak rainy season (December-February). A second order Fourier series fitted to the monthly intensity explains 98,2% of the observed seasonal variation, and maximum likelihood fit to the daily event times reproduces the same seasonal shape. Because the available agricultural production records for the study area are reported only at an annual resolution (eight years for rice and five years for maize), the severity and aggregate production loss components of the model could not be estimated with the statistical rigor that a compound Poisson severity model requires; these components are therefore reported descriptively and identified as a limitation to be addressed with sub round level (per planting season) production data in future work. These results suggest that the periodic Poisson component of the proposed framework provides empirical support for describing extreme rainfall occurrence, while the food deficit risk component remains preliminary pending finer grained production data.

Keywords: compound periodic Poisson process; agricultural risk; food production deficit; climate variability; collective risk theory

1. INTRODUCTION

Climate change has intensified the frequency and severity of extreme weather events, including droughts, floods, and anomalous rainfall, which have directly affected agricultural production, particularly rice as Indonesia's primary strategic food commodity (Surmaini & Agus, 2020). Seasonal and periodic climate variability introduces substantial uncertainty into agricultural production. This uncertainty can, in turn, destabilize food supplies, trigger price fluctuations, and elevate the risk of regional food deficits (Prihady & Djinar, 2022). South Sulawesi Province is one of Indonesia's major agricultural regions, with approximately 0,95 million hectares of harvested rice area. However, this cultivated area has declined compared with previous years due to increasing climate variability and the occurrence of extreme weather events (BPS-Statistics Indonesia Sulawesi Selatan, n.d.). According to the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG), extreme rainfall in this region frequently reaches high to very high intensity levels, particularly during the peak rainy season. This trigger widespread flooding and significant damage to agricultural land (BMKG - *Badan Meteorologi, Klimatologi, Dan Geofisika*, n.d.).

Assessing the risk of food production deficits resulting from climate variability has become increasingly important in the context of growing uncertainty within global food systems (Jägermeyr et al., 2021; Ortiz-Bobea et al., 2021). Climate change not only reduces average agricultural productivity but also increases production volatility and the probability of crop failure (Kluge et al., 2021; Sulistyowati et al., 2023). Weather index-based approaches have gained considerable attention because of their administrative simplicity and operational efficiency, as they eliminate the need for direct field verification of crop damage (Riaman et al., 2021). Stochastic process modelling provides a more appropriate mathematical framework than these deterministic approaches for

representing the uncertainty associated with climate-induced agricultural production losses (Hoffmann et al., 2021; Lathika & Sheeba, 2023; Su & Bai, 2020).

Despite this body of work, three gaps remain unaddressed in the literature on climate-induced food production risk. First, studies on food security in Indonesia have predominantly relied on descriptive analyses or deterministic econometric approaches that estimate changes in average production, rather than explicitly modelling the stochastic occurrence of the underlying climatic disturbances. Second, few existing frameworks separate the frequency of disruptive climate events from the severity of the production losses they cause, even though these two sources of risk are conceptually distinct and follow the collective risk modelling paradigm already well established in actuarial science (Albrecher et al., 2022; Furusawa et al., 2023; Komisarenko et al., 2022). Third, none of the reviewed studies exploit the seasonal periodicity of tropical rainfall directly within the stochastic process itself; extreme events are typically treated as arriving at a constant average rate, which does not reflect the pronounced wet-dry seasonal cycle characteristic of regions such as South Sulawesi. The compound periodic Poisson process addresses precisely this gap: by allowing the event-arrival intensity to vary periodically over the year, it provides a mathematically rigorous way to represent seasonally clustered climate disruptions and to separate their frequency from the severity of the production losses they cause (Cifuentes-Amado & Cepeda-Cuervo, 2015; Fatah, 2024; Goyal et al., 2022). This paper's contribution is to adapt this framework to food-production risk and to evaluate, using real observational data, which of its components can currently be estimated with statistical rigor.

The objective of this study is to develop a stochastic model that quantitatively measures the risk of food production deficits caused by climate variability through a mathematically rigorous yet practically applicable framework. Specifically, this study addresses the following research questions. First, how can a stochastic model based on a compound periodic Poisson process be constructed to represent the risk of climate induced disruptions in food production? Second, given currently available data, to what extent can the probability of food production deficits exceeding a predetermined critical threshold be estimated within the proposed stochastic framework, and what data are required to estimate it with full statistical rigor?

The proposed study offers a conceptually and methodologically more advanced approach than both the authors' previous work and existing studies on climate induced agricultural production risk. Most recent research investigating the impacts of climate change on food production has primarily relied on panel econometric models, spatial regression techniques, or climate scenario-based simulations, with emphasis placed on estimating changes in average agricultural production and price volatility (Hultgren et al., 2025;

Ortiz-Bobea et al., 2021). While these approaches provide valuable insights into the statistical characteristics of extreme events, they generally do not explicitly model the stochastic occurrence of discrete and periodically recurring climatic disturbances that are inherently associated with agricultural planting cycles (Fu et al., 2023; Zampieri et al., 2020).

The principal novelty of the proposed study lies in the adoption of the compound periodic Poisson process as a unified mathematical framework for representing agricultural production losses as the aggregate consequence of random, discrete, and seasonally recurring extreme climate events (Adriani et al., 2025). In contrast to conventional deterministic models and time-series regression approaches, the proposed framework explicitly separates two fundamental sources of production risk: the frequency of climate induced disruption events and the severity of production losses associated with each event. This paper reports full empirical results for the frequency (occurrence intensity) component and presents the severity/aggregate-loss component as a preliminary illustration pending production data of adequate granularity.

2. RESEARCH METHODS

2.1 Data Sources

The proposed stochastic model was evaluated using historical climate and agricultural production data collected from secondary sources. Daily rainfall observations (2015-01-01 to 2026-06-30; 11 complete years, 2015-2025, used for the intensity analysis) were obtained from secondary meteorological records for South Sulawesi Agency for Meteorology, Climatology, and Geophysics (BMKG). Agricultural production statistics were obtained from the Central Bureau of Statistics (BPS) of South Sulawesi Province, comprising annual harvested area, productivity, and total production for rice (2018-2025, $n = 8$ years) and maize (2021-2025, $n = 5$ years).

The rainfall dataset provides daily precipitation measurements (mm/day) with 4.181 of 4.199 calendar days recorded (99,5% completeness). The remaining 0.5% of missing days were filled using linear interpolation between the nearest available observations. Linear interpolation was chosen, rather than a more elaborate imputation method, because the missing days are isolated single-day gaps rather than extended sequences; under these conditions linear interpolation introduces negligible bias into daily-scale rainfall series, and the resulting values affect neither the classification of a day as extreme (Section 2.3) nor the monthly event counts in any of the eleven years analyzed. The 5% threshold adopted here as the upper limit for acceptable interpolation follows common practice in climatological data quality control, where missing-data proportions below this level are generally considered unlikely to materially bias derived statistics. The agricultural production data available for this study are reported at an annual resolution rather than per planting season (sub round). This is an important departure from the original study

design, in which production loss was intended to be quantified per extreme rainfall event within each planting season. Because only annual totals were available, the severity component of the model (Section 3.3) is estimated at the annual level as a provisional approximation, and the corresponding results should be interpreted with the sample-size limitations of $n = 8$ (rice) and $n = 5$ (maize) explicitly in mind. Table 1 summarizes the variables considered in this study.

Table 1. Variables Used in the Proposed Stochastic Model

Variable	Symbol	Unit	Description
Daily rainfall	R_t	mm/day	Daily precipitation
Extreme rainfall event	I_t	binary	Indicator of rainfall exceeding threshold
Harvested area	A_t	ha	Harvested rice area
Paddy production	Y_t	ton	Total rice production
Production loss	X_t	ton	Difference between expected and observed production
Aggregate production loss	S_t	ton	Sum of production losses within one planting season

2.2 Estimation Framework

Within the proposed compound periodic Poisson process framework, the occurrence of climatic disturbances is represented by a counting process whose intensity varies periodically over time. Consequently, unlike the classical homogeneous Poisson process, the arrival rate is assumed to depend explicitly on the planting season. Let $N(t), t \geq 0$, denote the cumulative number of extreme rainfall events observed up to time t . The counting process is assumed to satisfy $N(t) \sim CPPP(\lambda(t+T))$, where $\lambda(t) > 0$. Is a continuous periodic intensity function satisfying $\lambda(t) = \lambda(t+T)$, with T representing one complete seasonal cycle.

The periodicity assumptions reflect the climatological characteristics of tropical agricultural regions, where rainfall exhibits regular annual fluctuations associated with monsoonal circulation. This component of the model is estimated directly from the daily rainfall observations described in Section 2.1 and is the part of the framework for which the available data are fully adequate.

2.3 Definition of Extreme Climate Events

Prior to estimating the intensity function, extreme rainfall events must first be identified from the historical observations. Let R_t denotes the observed daily rainfall. An indicator variable is defined as $I_t = \begin{cases} 1, R_t > u, \\ 0, R_t \leq u, \end{cases}$ where u is the climatological threshold representing extreme rainfall.

In this study, the threshold was selected using the empirical 90th percentile of the full 2015-2026 daily rainfall series, yielding $u = 31,4$ mm/day. The 90th percentile was chosen, rather than a fixed physical rainfall amount, because it adapts to the local rainfall distribution of the study area and is a threshold criterion widely used in climate extremes research (e.g., the percentile-based indices recommended by the World Meteorological Organization's Expert Team on Climate Change Detection and Indices); this makes the resulting threshold comparable across locations with different baseline rainfall climatologies, at the cost of not directly reflecting an agronomic damage threshold specific to rice or maize.

Using this criterion, the daily rainfall series was transformed into a binary event sequence suitable for stochastic counting-process analysis. Across the eleven complete years 2015-2025, 397 extreme events were identified, an average of 36,1 events per year.

3. RESULTS AND DISCUSSION

3.1 Exploratory Analysis

3.1.1 Descriptive Statistics

Before constructing the stochastic model, descriptive statistics were computed to characterize rainfall variability and agricultural production. Table 2 presents the descriptive statistics of the principal variables, computed directly from the datasets described in Section 2.1.

Table 2. Descriptive Statistics of the Observed Variables

Variable	Mean	SD	Minimum	Maximum
Rainfall (mm/day)	9,401	21,273	0	263
Rice production, South Sulawesi (2018-2025, n = 8 years)				
Harvested area (ha)	1.019.497	78.148	951.309	1.185.484
Production (ton)	5.165.933	393.229	4.708.465	5.952.616
Maize production, South Sulawesi (2021-2025, n = 5 years)				
Harvested area (ha)	192.096	8.958	181.801	205.723
Production (ton)	1.127.614	100.723	1.025.516	1.295.646

The rainfall observations exhibited substantial variability throughout the observation period, with a standard deviation more than double the mean. This indicates considerable dispersion. Such dispersion is consistent with a stochastic, rather than deterministic, representation of rainfall occurrence. Rice and maize production likewise varied from year to year, although as discussed in Section 3.3, the number of annual observations available ($n = 8$ and $n = 5$, respectively) is too small to characterize the distributional shape of production losses with statistical confidence, only broad descriptive tendencies are reported here.

3.1.2 Seasonal Behavior of Rainfall

One of the fundamental assumptions underlying the proposed compound periodic Poisson process is the existence of seasonal variation in the occurrence intensity of extreme climate events. Figure 1 illustrate the monthly average rainfall observed during the study period.

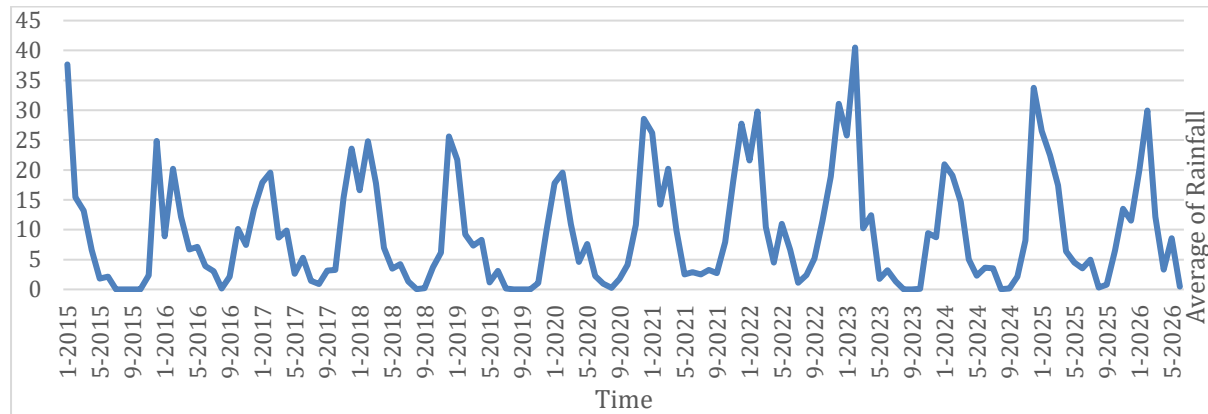


Figure 1. Monthly Average Rainfall Distribution

The rainfall pattern clearly demonstrates a recurring seasonal cycle. Higher precipitation levels consistency occurred between November and March, while significantly lower rainfall observed during the dry season from June to September. This cyclic behavior suggests that the event arrival intensity is not constant over time. Consequently, the assumption of a homogeneous Poisson process becomes inappropriate because the arrival rate varies according to seasonal climatic conditions. Instead, the observed periodic behavior supports the adoption of a periodic intensity function $\lambda(t) = \lambda(t + T)$, where T denotes one complete planting cycle. The seasonal intensity observed in Figure 1 provides preliminary empirical evidence supporting the proposed stochastic framework.

3.1.3 Identification of Extreme Climate Events

The occurrence of extreme rainfall events represents the triggering mechanism in the proposed stochastic process. An extreme event was defined whenever daily rainfall exceeded a predetermined threshold, $R_t > u$, where u denotes the climatological threshold corresponding to the upper percentile of historical rainfall observations. Figure 2 illustrates the temporal occurrence of extreme rainfall events.

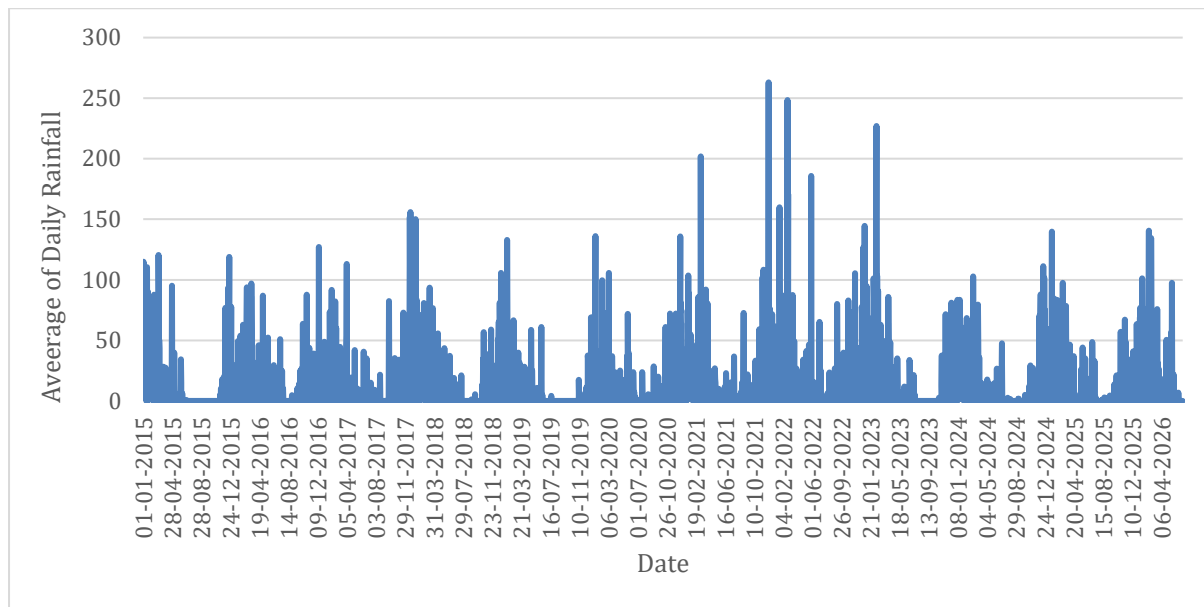


Figure 2. Occurrence of Extreme Rainfall Events

Several characteristics can be observed. First, extreme events are irregular, indicating that their occurrence cannot be predicted deterministically. Second, the events tend to cluster during the rainy season. Third, multiple events may occur within a single planting season. These observations strongly suggest that the event process follows a counting process rather than a deterministic sequence. Consequently, modeling the event occurrence using a periodic Poisson process becomes theoretically justified.

3.1.4 Exploratory Analysis of Production Loss

Because production data are available only at an annual resolution, production loss in this study is defined, as a provisional annual level proxy, as $X_t = \max(0, Y_t^* - Y_t)$, where Y_t^* denotes the production level predicted by a linear trend fitted to the observed annual series and Y_t denotes the observed production in year t . For rice, the linear trend explains only a small share of year to year variation ($R^2 = 0.073$), and 5 of the 8 observed years show a positive loss under this definition (mean loss among loss years $\approx 261,000$ tons; range $\approx 98,000$ -525,000 tons). For maize, the trend explains a larger share of variation ($R^2 = 0.528$), with 2 of 5 years showing a positive loss ($\approx 46,500$ and 102,100 tons).

These sample sizes (2 to 5 nonzero loss observations per commodity) are far too small to reliably characterize a severity distribution. Consequently, unlike the event level severity variable originally envisaged in the model (Section 2.1), we do not fit a parametric severity distribution to these annual values; instead, they are reported descriptively as an indicative signal that production shortfalls do occur in years with more intense extreme-rainfall exposure, pending confirmation with sub round level data.

3.2 Seasonal Intensity

3.2.1 Exploratory Estimation of Seasonal Intensity

The empirical arrival intensity was initially estimated by calculating the average number of extreme rainfall events occurring within each month over the observation period. Let n_j denote the total number of extreme events observed during month j , and let m represent the total number of observation years. The empirical monthly intensity was estimated as

$$\hat{\lambda}_j = \frac{n_j}{m} \quad (1)$$

Table 3 presents the simulated monthly estimates of the periodic intensity using Equation (1), computed directly from 397 identified extreme events.

Table 3. Estimated Monthly Occurrence Intensity of Extreme Rainfall Events

Month	n_j	Estimated Intensity ($\hat{\lambda}_j$)
January	87	7.909
February	77	7.000
March	46	4.182
April	22	2.000
May	15	1.364
June	10	0.909
July	6	0.545
August	1	0.091
September	3	0.273
October	14	1.273
November	33	3.000
December	83	7.545

The estimated intensity demonstrates a pronounced seasonal pattern. The highest event frequencies occur during December till January, corresponding to the peak rainy season. Conversely July till September exhibit substantially lower event intensities, reflecting the dry season. These findings provide empirical support for modelling the arrival process using a periodic rather than homogeneous intensity function.

3.2.2 Fourier Representation of the Periodic Intensity

To obtain a smooth representation of the seasonal behavior, the empirical intensity estimates in Table 3 were approximated using a truncated Fourier series. The periodic intensity function is expressed as

$$\lambda(t) = a_0 + \sum_{k=1}^K \left[a_k \cos\left(\frac{2k\pi t}{T}\right) + b_k \sin\left(\frac{2k\pi t}{T}\right) \right]. \quad (2)$$

A second-order Fourier series ($K = 2$) was fitted to the twelve monthly intensity estimates by ordinary least squares, yielding

$$\lambda(t) = 3.008 + 2.920 \cos\left(\frac{2\pi t}{12}\right) + 2.231 \sin\left(\frac{2\pi t}{12}\right) + 0.871 \cos\left(\frac{4\pi t}{12}\right) + 1.142 \sin\left(\frac{4\pi t}{12}\right) \quad (3)$$

The fitted periodic function explains approximately 98,2% of the variation in the empirical monthly occurrence intensities ($R^2 = 0.982$), with an RMSE of 0.378 and an MAE of 0.274. These results indicate that the second order Fourier approximation successfully captures the dominant annual oscillation while providing a smooth and continuous representation of the seasonal rainfall occurrence intensity.

3.2.3 Maximum Likelihood Estimation

As a refinement of the ordinary-least-squares fit above, parameters of an exponentiated Fourier intensity, $\lambda(t) = \exp\left(a_0 + \sum_{k=1}^K \left[a_k \cos\left(\frac{2k\pi t}{T}\right) + b_k \sin\left(\frac{2k\pi t}{T}\right)\right]\right)$ which guarantees $\lambda(t) > 0$ for all t , unlike the additive form in Equation (2), were estimated directly from the 397 daily event times (rather than the twelve monthly aggregates) using Maximum Likelihood Estimation

$$L(\theta) = \prod_{i=1}^n \lambda(t_i; \theta) \exp\left(-\int_0^T \lambda(u; \theta) du\right), \quad (4)$$

where $\theta = (a_0, a_1, b_1, \dots, a_K, b_K)$ is the vector of unknown Fourier coefficients. The corresponding log likelihood becomes

$$\ell(\theta) = \sum_{i=1}^n \log \lambda(t_i; \theta) - \int_0^T \lambda(u; \theta) du. \quad (5)$$

maximized numerically. The optimizer converged successfully; the fitted model implies an expected 36,1 extreme events per year, matching the observed average exactly.

Table 4. Comparison of Observed, OLS Fourier Fitted, and MLE Fitted Monthly Intensity

Month	Observed ($\hat{\lambda}_j$)	OLS Fourier Fit (Eq.3)	MLE Fit (Eq.4)
January	7.909	8.076	8.947
February	7.000	6.953	6.285
March	4.182	4.367	4.221
April	2.000	2.055	2.313
May	1.364	1.041	1.384
June	0.909	0.959	0.700
July	0.545	0.787	0.401
August	0.091	0.168	0.301
September	0.273	-0.095	0.404
October	1.273	1.111	1.049
November	3.000	3.868	3.044
December	7.545	6.799	7.076
RMSE	-	0.378	0.417
MAE	-	0.274	0.296

Table 4 allows both fitted curves to be judged directly against the observed monthly counts rather than through summary statistics alone. Both approximations reproduce the overall seasonal shape, a peak around December-January and a trough around July-September, and their RMSE and MAE values are of comparable magnitude, with the OLS fit showing

marginally closer agreement to the empirical monthly averages. The two approaches nonetheless serve different purposes: the OLS fit in Equation (3) is estimated directly from the twelve monthly averages and is simple to interpret, but it can produce a negative fitted intensity, as seen for September (-0.095), which is not meaningful for a Poisson rate. The MLE fit in Equation (4) is estimated from all 397 individual event times rather than twelve aggregated points, and its exponential parameterization guarantees a strictly positive intensity for every day of the year. The two fits therefore agree closely on the dominant seasonal pattern while offering a trade-off between simplicity (OLS) and distributional validity (MLE).

3.3 Exploratory Assessment Aggregate Production Loss

3.3.1 Severity of Production Loss

Given the sample size constraints described in Section 3.1.4, this study does not fit and compare parametric severity distributions to the annual loss proxy, since two to five observations per commodity cannot support such comparisons with any statistical reliability. Instead, Table 4 reports the descriptive characteristics of the annual loss proxy for each commodity.

Table 4. Descriptive Summary of the Annual Production Loss Proxy

Commodity	n (years)	Years with loss > 0	Mean loss among loss years (ton)	Range (ton)
Rice	8	5	$\approx 261,000$	98,000 – 525,000
Maize	5	2	$\approx 74,300$	46,500 – 102,100

3.3.2 Expected Aggregate Production Loss

For illustrative purposes only, and strictly conditional on the annual level approximation described above, a rough order of magnitude expected aggregate loss can be computed as the product of the observed annual loss frequency and the mean loss conditional on a loss occurring. Under the compound process formulation,

$$E[S(t)] = E[N(t)]E[X]. \quad (6)$$

where $\mu_X = E[X]$.

Applying this to the rice series (5 of 8 years, i.e. an annual loss “occurrence rate” of 0,625, with mean conditional loss ≈ 261.000 tons) gives an indicative expected annual loss of the order of 163.000 tons. Given the extremely small sample underlying this calculation, this figure should be treated as illustrative only and not as a validated risk estimate. We do not report a corresponding variance, confidence interval, or Central Limit Theorem based deficit probability, because the asymptotic justification for such an approximation requires a substantially larger number of loss observations than is currently available.

3.4 Towards a Food Deficit Probability Assessment

The framework's intended final quantity of interest is the probability $P(S > d)$ that seasonal (or, at present, annual) aggregate production loss $S(t)$ exceeds a critical threshold d , where d may be determined from regional food demand, historical production records, or governmental food security standards. This remains the target quantity for the proposed framework.

With only 8 (rice) and 5 (maize) annual observations, a Central Limit Theorem based normal approximation to $S(t)$ is not statistically defensible: asymptotic normality requires a substantially larger number of underlying loss events than is available here. Rather than report a numerically precise but statistically unsupported probability and return period, we report only the descriptive frequency established in Section 3.3.1 (5 of 8 years for rice, 2 of 5 years for maize showed a production shortfall relative to trend) as a preliminary indication that food production shortfalls associated with climate variability are a recurring, non negligible phenomenon in the study area, without assigning it a specific probability or return period until sub round level production data become available.

3.4 Comparison with Prior Studies

The seasonal pattern identified in this study, extreme rainfall intensity peaking in December-February and reaching a minimum in July-September, is consistent with the general monsoonal rainfall regime reported for Indonesian agricultural regions, including South Sulawesi (Surmaini & Agus, 2020), and supports the characterization of Indonesian extreme rainfall risk as strongly seasonal rather than uniformly distributed across the year. Methodologically, the use of a Fourier based periodic intensity function fitted by maximum likelihood follows an approach similar in spirit to nonhomogeneous Poisson process applications in other natural hazard settings, such as modelling of earthquake occurrence in Iraq and Cifuentes-Amado and Cepeda-Cuervo's (2015) application to seasonal health events (Fatah, 2024); in both cases, as in the present study, a periodic intensity function was found to represent the seasonal clustering of discrete events more adequately than a homogeneous-rate assumption. Compared with stochastic rainfall prediction approaches such as the hybrid Bayesian model which present framework does not attempt to forecast future rainfall values; instead, it characterizes the long run seasonal *risk profile* of extreme event occurrence (Lathika & Sheeba, 2023), which is the quantity required as an input to the compound loss framework in Sections 3.3-3.4. This distinction clarifies the framework's scope relative to rainfall-forecasting studies: the periodic Poisson component developed here is a risk-characterization tool, not a short-term prediction tool, and its value lies in feeding a statistically grounded frequency estimate into the wider food-deficit-risk assessment once production data of adequate granularity become available.

4. CONCLUSION

This study makes three main contributions. First, it shows that the occurrence of extreme rainfall events in South Sulawesi follows a well-defined seasonal pattern that a compound periodic Poisson process can represent with empirical support: a second order Fourier series explains 98.2% of the seasonal variation in monthly intensity, and an independent maximum-likelihood fit to the daily event times reproduces the same seasonal shape (Section 3.2, Table 3a). Second, it demonstrates that the severity and aggregate loss components of the same framework cannot currently be validated with the same rigor, because the available production records are annual rather than per planting season, leaving only 8 (rice) and 5 (maize) usable observations; under these constraints, this study reports descriptive evidence of production shortfalls rather than a formally fitted severity distribution or food deficit probability. Third, realizing the framework's full potential, including a statistically defensible estimate of the probability that aggregate production loss exceeds a critical threshold, will require production data disaggregated to the planting season (subround) level, which is identified here as the priority for future work.

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6. LIMITATIONS AND RECOMMENDATIONS

This study has two main limitations that should guide its interpretation and future extensions. First, the current model assumes independence between event occurrence and production loss severity and considers rainfall as the primary climatic factor affecting agricultural production. Future research should extend the proposed framework by incorporating additional climatic variables, such as temperature, humidity, soil moisture, and wind speed, as well as testing this independence assumption directly. Second, and more materially for the present results, the agricultural production data available for this study were reported only at an annual resolution, whereas the compound Poisson severity framework is designed to operate at the level of individual extreme rainfall events within a planting season. As a direct consequence, the severity and food deficit probability results in Sections 3.3-3.4 are descriptive and indicative rather than statistically validated. Future work should prioritize obtaining BPS sub round level (per planting season) production data for South Sulawesi, which would allow the full compound periodic Poisson severity model, including formal severity distribution fitting, expected aggregate loss with variance, and a Central Limit Theorem based food deficit probability and return period,

to be estimated with statistical rigor. Beyond this, developing nonstationary or multivariate stochastic processes and integrating the model with real time climate forecasting and weather index agricultural insurance systems would further enhance its practical applicability for food security assessment and climate risk management.

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