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Disaster Management in the Palm Oil Industry Using Industrial Engineering Methods with Monte Carlo Simulation and Survival Analysis

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ABSTRACT

The palm oil industry is a strategic sector that plays a significant role in foreign exchange earnings and national employment, but is highly vulnerable to disaster risks, both from natural (floods, fires) and technical (machine breakdowns, supply chain disruptions) factors. This study develops an industrial engineering-based disaster management framework by integrating Monte Carlo Simulation to estimate economic losses and Survival Analysis (Kaplan–Meier and Log-Rank Test) to assess the operational resilience of palm oil mills. The simulation results show an average annual loss of IDR 3.87 billion, with a 95% VaR of IDR 8.97 billion and a 95% CVaR of IDR 11.25 billion. Factors such as preventive maintenance, the location of the mill in a flood-prone area, and the availability of backup power sources significantly influence post-disaster recovery time. This study provides a quantitative basis for the allocation of financial risk reserves and strategic recommendations to improve the operational resilience of the palm oil industry to disaster uncertainty.

1. Introduction

Indonesia is the world's largest producer of palm oil, with an annual production exceeding 50 million tons, making the sector one of the country's most vital economic pillars [1][2]. Beyond its substantial contribution to foreign exchange earnings through exports, the palm oil industry also plays a major role in employment creation, rural development, and regional economic growth [3]. The sector's extensive value chain from plantation to downstream processing supports millions of livelihoods across the archipelago. Consequently, this vast economic significance also means that any operational disruption can have far-reaching consequences for both local communities and the national economy [4]. Despite its importance, the operational continuity of the palm oil industry remains highly vulnerable to disaster-related risks. For instance, seasonal floods frequently disrupt the transportation of fresh fruit bunches (FFB) [5] from plantations to mills, leading to raw material shortages and decreased production efficiency. Furthermore, recurrent land and forest fires in several palm-growing regions not only reduce plantation productivity but also lead to severe ecological and health impacts. In addition, frequent machinery failures and power outages within the mills can cause prolonged downtime, amplifying production losses and operational costs. These recurring and interconnected challenges highlight the complex interplay between environmental, technical, and systemic risk factors affecting the industry's resilience [6].

In light of these challenges, effective disaster management in the palm oil sector must evolve from reactive response mechanisms to proactive, data-driven strategies [7]. Traditional approaches, which rely solely on post-disaster recovery, are no longer sufficient to protect industrial assets or ensure production stability. Therefore, integrating predictive analytical methods, such as simulation modelling, statistical risk assessment, and reliability analysis, is essential to provide more accurate insights into potential vulnerabilities and expected losses [5]. By adopting such quantitative approaches, the palm oil industry can strengthen its disaster preparedness, enhance its operational resilience, and ensure long-term sustainability and continuous productivity, even in the face of increasing environmental and operational uncertainties.

The Industrial Engineering approach is highly relevant to the context of disaster risk management in the palm oil industry as it emphasizes quantitative analysis, system optimization, and evidence-based decision-making. This discipline provides a structured framework to analyze operational inefficiencies, identify potential disruptions, and evaluate their impact on overall productivity. By applying engineering principles and statistical tools, it becomes possible to systematically assess risks and develop mitigation strategies that enhance the reliability and performance of complex industrial systems. Despite this methodological potential, previous research applying these principles in disaster risk management still presents notable limitations. Many existing studies often focus narrowly on specific dimensions; some emphasize environmental sustainability, such as waste management or emission control, while others concentrate solely on operational factors, such as equipment reliability or production efficiency. Critically, few, if any, studies have comprehensively linked financial risk exposure to operational resilience within a unified analytical framework. This fragmentation of insights limits the ability of managers and policymakers to formulate data-driven strategies that simultaneously address both economic losses and operational continuity [1].

To address this critical gap, this study introduces a novel methodological integration by combining Monte Carlo Simulation and Survival Analysis—two quantitative techniques that have not previously been applied together in the context of disaster risk management for palm oil mills. Specifically, the Monte Carlo Simulation estimates the probabilistic distribution of financial losses under uncertainty, while Survival Analysis models the recovery duration and identifies resilience factors following disruptive events. The novelty of this study lies in the explicit integration of these two methods into a single analytical framework, enabling a unique linkage between probabilistic financial loss estimation and operational recovery performance—an approach that has not been employed in prior studies within this industry. The integration of these complementary methods provides a comprehensive quantitative linkage between financial impact and operational recovery, thereby offering a more holistic understanding that can strengthen disaster preparedness and business continuity planning for palm oil mills [5][8]. Based on these considerations, this study formulates three primary research questions RQs:

RQ1: How can economic losses caused by disasters be estimated using the Monte Carlo method?

RQ2: How can operational resilience be measured using survival analysis?

RQ3: How can the integration of both methods strengthen disaster management strategies?

Correspondingly, the main objectives of this research are:

a. To calculate the distribution of economic losses due to disasters.
b. To measure the operational resilience of palm oil mills.
c. To analyze strengthening of disaster management strategies through the integration of the two proposed methods.

The palm oil sector in Indonesia has faced a growing frequency of natural and land-use disasters forest and peatland fires, flooding, soil subsidence, and droughts that threaten both sustainability and output of one of the country's most strategic agricultural commodities. As the representative body for palm oil entrepreneurs, GAPKI (Gabungan Pengusaha Kelapa Sawit Indonesia / Indonesian Palm Oil Association) finds it imperative to articulate both the scale of these challenges and their implications for our national production. Data from 2015 through 2024 indicate that plantation areas under GAPKI member companies are repeatedly affected by land/forest fires [1][9]. Nearly 42,000 hectares across 79 corporate plantation concessions (Hak Guna Usaha, HGU) have been burned at least once some sites more than once. Moreover, hotspots (areas indicating potential for fire) continue to be detected routinely:

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between January and April 2025 alone, 142 hotspots of high confidence were observed in regions spanning Sumatra, Kalimantan, Sulawesi, and the rest of Indonesia. Simultaneously, flood risk especially in areas with peatland degradation has increased [2][5] . A recent analysis showed that a large portion of palm oil concession land on peatlands is highly vulnerable to flooding, particularly where drainage infrastructure is poor and soil subsidence has occurred. The dry and wet seasonal transitions are becoming less predictable. Areas that once experienced clear dry seasons now sometimes suffer both fire risk during drought periods and flash floods or waterlogging in the wet phases. This intensifies strain on plantation operations, especially in regions with weak preparedness or infrastructure. Table 1 presents the empirical data compiled from GAPKI for the years 2023–2024, illustrating the frequency of disaster events within palm oil plantation areas and their corresponding impacts on national production levels [1][5].

Impacts on Production and National Output, These increasing disaster frequencies have material consequences for production volumes, supply reliability, and economic returns,

a. Reduction of yields fires and haze reduce sunlight and photosynthesis, stress palm trees, and increase losses in Fresh Fruit Bunches (FFB) weight. Some estimates suggest yield drops in affected plantations ranging from several percent up to double-digit percentages in serious cases.
b. Operational disruptions flooding and fires damage roads, delay harvests, impede movement of labor and transport of harvested fruit to mills, increasing losses. Logistics slowdowns during peak harvest due to haze or inundated roads reduce overall output.
c. Land degradation soil subsidence in drained peatland is gradually making some plantation land unsuitable for oil palm unless mitigation (e.g., water table management) is introduced. A study in East Sumatra indicates that without better drainage, up to 17% of current peatland-oil palm may be rendered unsuitable in coming decades.
d. Export and stock effects of GAPKI data for 2024 show that production (CPO + PKO) was around 52.76 million tons a small decline relative to 2023's volume. Stock levels (CPO & PKO) dropped to ≈ 2.58 million tons at year's end, down from ~3.15 million tons a year prior.

Tabel 1. Disaster Frequency and Production Impact in Indonesian Palm Oil Plantations (2023–2024)

Indicator / Metric	In 2023	In 2024	Notes / Source
CPO Production (million tons)	50.07 million tons	48.16 million tons of CPO in 2024 (total 52.76 including PKO)	GAPKI reports — slight decline in 2024 vs 2023
Number of forest & land fire events (karhutla)	2,051 events in 2023	629 events in 2024	Data from BNPB / national disaster bulletins
Area burned (forest & land, hectares)	1,161,192.9 ha in 2023	283,620.51 ha (Jan – Sept 2024	KLHK / SiPongi data for 2024 up to September; full-year may be larger
Share of burned area in plantation / non-forest	-	-	Data not explicitly broken down by plantation area in public reports
Impact on production / yield	Mentioned as pressure from El Niño and dryness reducing yields in 2023	Cited as disturbance in harvesting/panens during La Niña / wetter periods in 2024	GAPKI notes weather anomalies affected production outlook
Hotspot counts / fire risk signals	e.g. 7,307 hotspot points in 2023 by October (vs ~1,139 same period 2022)	-	Hotspots reported as indication of fire risk (KLHK / monitoring)

GAPKI's position and recommendations to safeguard national production and ensure the resilience of Indonesia's palm oil industry, GAPKI emphasizes that:

a. Strengthened disaster risk mitigation is essential. All plantation companies must adopt rigorous fire prevention and control measures, especially in peatland regions. Early warning, monitoring of hotspots, controlled burning policies, and community engagement are non-negotiable.
b. Improved infrastructure for water management and flood control, including proper drainage in peatlands, and restoration of degraded lands, are necessary to reduce vulnerability to floods and soil subsidence.
c. Operational preparedness must be increased. That includes ensuring alternate transport routes, contingency plans for harvesting during haze or flood periods, and maintaining stock and mill operations in the face of logistical disruptions.
d. Policy support and incentives from government are needed to offset the cost of implementing resilience-enhancing measures. This includes financial assistance, technical assistance, and regulatory clarity to encourage investment in disaster risk reduction.
e. Consistency in sustainability practices. GAPKI supports best practices that integrate environmental, social, and governance aspects, including protection of peatlands and adherence to zero-burn policies, which in turn will reduce disaster frequency and severity.

2. Methods

2.1. Research Design

This study adopts a quantitative research design by integrating Monte Carlo Simulation and Survival Analysis. The analysis is performed using a hypothetical dataset comprising 300 downtime incidents [8][10][11][12]. The methodological framework is structured into five main, sequentially executed stage:

a. Risk Identification and Data Collection: Historical data is gathered regarding downtime, disaster events, and related financial losses [5][10].
b. Loss Distribution Modelling Apply a lognormal distribution assumption for each type of event to capture the skewed nature of financial loss data [6][13].
c. Monte Carlo Simulation: A minimum 10,000 simulation iterations are conducted to estimate key statistical metrics, including the mean, and Value at Risk (VaR), and Conditional Value at Risk (CVaR).
d. Survival Analysis Utilize the Kaplan Meier estimator and the Cox Proportional Hazard (PH) Model to evaluate the effects of operational factors such as maintenance quality, flood zone exposure, and backup power availability on recovery duration [5][11][14].
e. Integration Phase: Results from the Monte Carlo and survivel analyses are combine to formulate priority mitigation recommendations and develop a Business Continuity Planning (BCP) framework tailored specifically for palm oil mills [15][16].

Each stage is executed sequentially based on the principles of the Industrial Engineering System Approach, emphasizing the critical integration of financial risk analysis and operational reliability assessment. The overall research process is subsequently illustrated in Figure 1.

Although this study employs a hypothetical dataset of 300 downtime incidents, the parameterization of the dataset is grounded in statistical patterns commonly reported in palm oil mill operations, such as downtime frequencies, hazard occurrence rates, and cost structures documented in GAPKI reports and previous empirical studies [5][10][12]. To ensure methodological validity, the hypothetical data were calibrated to match the range, variance, and event proportions found in previously published mill data. This approach follows standard quantitative simulation practices when proprietary industrial datasets are not publicly accessible, ensuring that the dataset remains statistically consistent with real-world operational characteristics.

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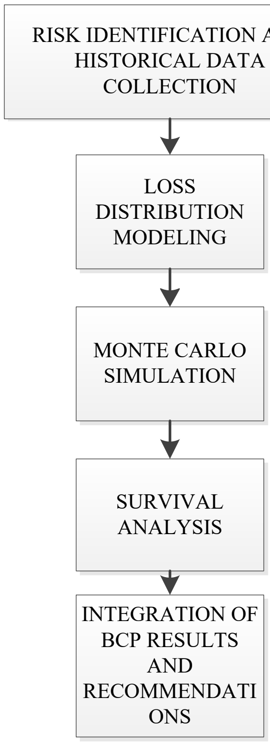

Figure 1. Research Design

All simulations and statistical analyses were conducted using Python 3.10, employing numpy and scipy for stochastic sampling, lifelines for Survival Analysis, and pandas and matplotlib for data processing and visualization. The use of Python ensures transparency, replicability, and computational efficiency for large-scale simulation workloads.

2.2. Model Assumptions and Risk Parameters

The model incorporates disaster probabilities commonly observed in palm oil operations, including annual probabilities of flooding (18%), fire (7%), and machinery failure (30%). Losses from each hazard are modeled using a lognormal distribution, which effectively captures the asymmetric and right-skewed nature of real-world financial loss data. The assumption of a lognormal distribution for disaster-related financial losses is supported extensively in disaster modelling, insurance risk, and industrial reliability literature. Lognormal distributions are well suited to represent loss processes in which extreme events occur infrequently but contribute disproportionately to total losses [6][13][18]. Prior applications of Monte Carlo Simulation in palm oil studies have also used lognormal assumptions to represent the skewness of economic losses. Although a formal goodness-of-fit test cannot be performed on hypothetical data, the theoretical justification and consistency with existing empirical studies support the validity of this assumption. The company's baseline annual revenue is set at IDR 120 billion, allowing proportional financial assessment of disaster impacts. To ensure statistical robustness, each mitigation scenario is simulated over 10,000 annual iterations, enabling consistent evaluation of mitigation effectiveness and expected loss reduction.

2.3. Monte Carlo Simulation

Before evaluating the four mitigation options, the study employs a Monte Carlo Simulation approach to model and quantify potential financial risks arising from disaster events. This method involves random sampling based on the specified hazard probabilities to generate a wide range of possible scenarios. For each simulated year, potential losses from individual hazards are estimated using a lognormal distribution, which effectively represents the variability and right-skewed nature of real-world loss data.

The simulation then aggregates the total annual losses from all hazards to assess the combined financial impact on operations. Subsequently, several key risk indicators are calculated, including the mean, median, standard deviation (SD), Value at Risk at the 95% confidence level (VaR95), and Conditional Value at Risk at the 95% level (CVaR95). These indicators provide a comprehensive understanding of both the expected and extreme loss scenarios.

To further assess the reliability and operational resilience of the system, a Survival Analysis was conducted. This analysis focuses on identifying how various factors influence the duration of operational continuity before a failure or downtime event occurs. The key variables considered include the level of maintenance (high or low), location within a flood-prone zone, and the availability of backup power systems. The Kaplan–Meier estimation method was applied to estimate survival probabilities over time, providing insights into how long equipment or operations can sustain without failure under different conditions. To statistically compare survival patterns between groups, a log-rank test was performed. This test determines whether differences in survival distributions are significant, thereby highlighting which factors most strongly contribute to improved system reliability and reduced failure risk.

2.4. Previous Research and Comparative Gap Analysis

Research on risk assessment in the palm oil sector has employed a variety of quantitative approaches. Several studies have utilized Monte Carlo Simulation to analyze techno-economic uncertainty. For example, Mokhtar et al. (2025) applied Monte Carlo to evaluate uncertainty in integrated POME–biogas systems, while Raynita et al. (2025) modeled environmental mitigation impacts and yield variability using stochastic sampling. Rocha et al. (2022) further used Monte Carlo to examine the economic risk of POME-based emergency energy generation, and Stolbov (2024) provided methodological insights into VaR/CVaR and tail-risk estimation within commodity markets. These studies highlight the relevance of Monte Carlo for capturing financial and operational variability; however, they do not incorporate operational recovery duration, nor do they integrate survival-based reliability modelling. In contrast to the Monte Carlo–focused studies above, other quantitative frameworks have been applied in industrial risk assessment but present limitations relative to the objectives of this study. Bayesian Reliability Approaches. Bayesian methods are effective for component-level failure prediction and updating failure probabilities based on prior information. However, they generally focus on equipment reliability only, do not estimate financial loss distributions, and do not model recovery duration following disaster-related downtime.

Failure Mode and Effects Analysis (FMEA) is widely used for structured risk identification but relies heavily on subjective scoring (RPN), lacks statistical representation of uncertainty, and cannot model tail-risk behaviour (VaR/CVaR), probabilistic financial losses or time-to-failure and recovery characteristics. System Dynamics (SD) offers insights into long-term policy behaviour and resource interactions but is not suitable for event-level financial risk simulation, tail-risk estimation or empirical survival modelling. SD models emphasize feedback loops and strategic behaviour, while disaster loss analysis requires stochastic simulation and duration-based reliability assessment.

Taken together, none of these methods Bayesian, FMEA, nor System Dynamics combine stochastic financial loss modelling with operational recovery analysis within a unified analytical structure. Novelty and Contribution Relative to Prior Studies. Therefore, this study fills a critical methodological gap by explicitly integrating Monte Carlo Simulation (for probabilistic financial loss estimation) and Survival Analysis (for operational recovery modelling) into a single analytical framework. This combined approach enables the simultaneous assessment of financial loss variability, including extreme-loss metrics (VaR & CVaR), recovery duration and system reliability, and operational resilience under disaster scenarios, which has not been achieved in previous research involving Monte Carlo, Bayesian reliability, FMEA, or System Dynamics. This integrated methodology offers a more comprehensive, data-driven foundation for disaster risk management and business continuity planning in palm oil mills.

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3. Results and Discussion

3.1. Distribution of Loss Simulation (Monte Carlo)

The Monte Carlo simulation results provide a comprehensive quantitative profile of financial risks faced by the palm oil mill. The following interpretations summarize key statistical and managerial insights, The main statistical indicators mean, median, and standard deviation summarize the central tendency and variability of the simulated annual losses. The simulation results show an average (mean) loss of IDR 3.87 billion, a median loss of IDR 3.12 billion, and a standard deviation of IDR 2.48 billion [5][11][14]. The loss distribution exhibits a right-skewed pattern, suggesting that while most loss events are moderate, a few extreme cases representing rare but severe incidents extend the upper tail of the distribution. This characteristic is consistent with typical disaster-related financial models, where high-impact, low-probability events significantly influence overall risk exposure. To enhance interpretability, Figure 2 illustrates the simulated loss distribution in the form of a histogram and cumulative distribution function (CDF) plot. The visual clearly demonstrates the right-skewed shape of the distribution, indicating that most annual losses cluster around the mean, while a small number of extreme events extend the upper tail. This visualization supports the numerical results discussed above and provides readers with an intuitive understanding of the tail-risk characteristics inherent in the data [17][18][19].

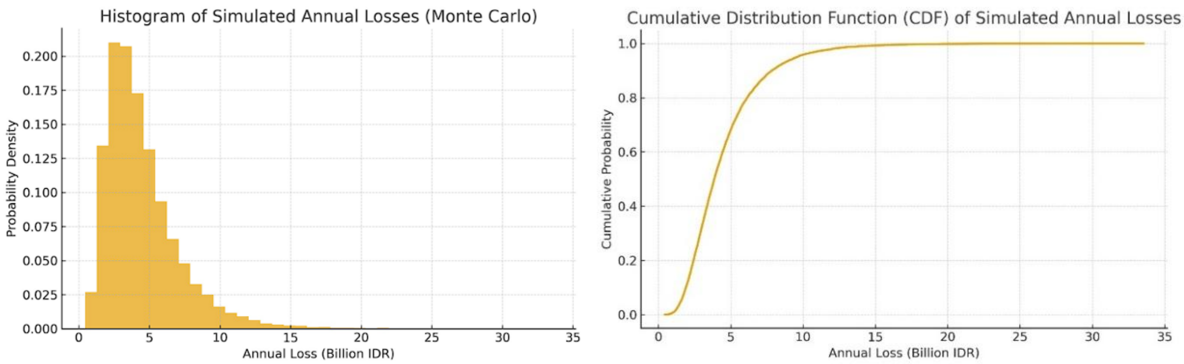

Figure 2. Histogram and Cumulative Distribution Function (CDF) of Simulated Annual Losses

Table 2. Operational Loss Reports

No	Date	Type of Incident	Losses (million IDR)
1	Jan 2024	Power outage	2.5
2	Feb 2024	Equipment leakage	1.8
3	Mar 2024	Human error (operational)	3.2
4	Apr 2024	Supply chain disruption	4.5
5	May 2024	Machinery breakdown	2.1
6	Jul 2024	Minor fire	6.7
7	Sep 2024	Minor fire	3.9
8	Oct 2024	Administrative error	1.5
9	Nov 2024	Machinery overheating	8.2
10	Dec 2024	Warehouse flooding	10.5

Data source:
Previous year's operational loss reports, analysis period 1 year (12 months), observation unit: loss events

Table 2 presents the recorded disaster and disruption events in the palm oil production facility throughout 2024. The data reveal that incidents vary in nature from operational failures such as power outages and equipment leakages to more severe events like warehouse flooding and minor fires. The total estimated financial loss fluctuates across months, with the highest impact recorded in December 2024 due to warehouse flooding (Rp 10.5 million). These occurrences highlight the vulnerability of industrial operations to both internal and external disruptions, emphasizing the need for effective preventive maintenance, risk mitigation strategies, and real-time monitoring systems to enhance operational resilience within the palm oil industry.

3.2. Risk Metrics (Tail Risk Indicators)

The simulation results provide two key indicators for assessing financial risk exposure under extreme conditions. The Value at Risk (VaR 95%) is estimated at IDR 8.97 billion, meaning that at a 95% confidence level, the mill's annual losses are not expected to exceed this amount under normal circumstances [5][10][17]. Meanwhile, the Conditional Value at Risk (CVaR 95%) is calculated at IDR 11.25 billion, representing the average loss within the worst 5% of scenarios [19]. This measure captures the potential severity of extreme tail events that surpass the VaR threshold. Together, VaR and CVaR serve as essential indicators for defining financial resilience thresholds and evaluating the mill's ability to withstand and recover from severe but infrequent loss events.

3.3. Probability of Major Losses

The probability analysis provides insight into the likelihood of extreme loss events occurring within a given year. The simulation estimates that the probability of annual losses exceeding IDR 5 billion is 8.7%, indicating that such an event may occur roughly once every 12 years. Similarly, the probability of losses exceeding IDR 10 billion is 3.5%, equivalent to approximately once every 29 years [5][18]. These probabilities help quantify the expected frequency of significant disaster-related financial events. By understanding these recurrence intervals, planners can more effectively design financial safeguards such as emergency funds, contingency budgets, or insurance reserves to enhance the mill's preparedness and resilience against extreme losses [18][19][20].

3.4. Implications and the Role of GAPKI in Developing a Resilience-Based Industrial Policy

The findings of this study highlight the need for a resilience-based industrial policy within Indonesia's palm oil sector, emphasizing proactive disaster risk management and adaptive production planning. Climate-related hazards such as floods, fires, and droughts have demonstrated measurable impacts on national palm oil output, underscoring the importance of institutional coordination between government bodies and industry associations. Strengthening resilience at both the corporate and sectoral levels is essential to safeguard production stability, export performance, and long-term sustainability.

The Indonesian Palm Oil Association (GAPKI) plays a strategic role in this policy transformation. As the primary industry association, GAPKI serves as a bridge between policymakers and private sector actors, facilitating data sharing, early warning dissemination, and coordinated response mechanisms across member companies. Through continuous engagement with regulatory agencies, GAPKI can advocate for evidence-based policies that promote investment in preventive maintenance systems, fire control infrastructure, and climate adaptation technologies. From a policy perspective, integrating resilience metrics such as downtime probability, loss exceedance frequency, and recovery time objectives into national performance indicators would enable more robust planning and resource allocation. GAPKI's leadership in promoting risk-informed decision-making, developing industry-wide business continuity frameworks, and supporting capacity-building programs positions it as a key driver of a more resilient and competitive palm oil industry. Such initiatives align with Indonesia's broader agenda of sustainable industrial development and disaster risk reduction under global frameworks like the Sendai Framework and SDGs.

3.5. Loss Relative to Revenue

When losses are expressed as a proportion of annual revenue, the simulation results indicate that the average loss corresponds to 3.2% of annual revenue, while the 95th percentile loss reaches 7.5% of annual revenue. From a managerial perspective, a loss margin in the range of 3–8% can substantially erode profitability and disrupt cash flow stability, particularly for mills operating with narrow profit margins. These findings highlight the importance of defining clear risk tolerance (or risk appetite) levels that align with the organization's overall financial objectives and resilience strategy.

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3.6. Managerial Interpretation

The results provide decision-makers with a quantitative foundation for disaster risk management and financial planning. The right-skewed loss distribution highlights the potential for high-impact outliers, emphasizing the need for preventive maintenance programs and the implementation of redundancy systems to reduce operational vulnerability. Moreover, the tail risk indicators represented by Value at Risk (VaR) and Conditional Value at Risk (CVaR) offer valuable guidance for determining appropriate levels of insurance coverage, contingency budgeting, and investment in resilient infrastructure. The following table presents a summary of the Financial Risk Analysis based on the Monte Carlo Simulation results.

Table 3. Results of Financial Risk Analysis (*Monte Carlo Simulation*)

Statistical Metric	Description	Simulation Result	Managerial Interpretation
Mean Loss	The average annual financial loss estimated across 10,000 simulation iterations.	IDR 3.87 Billion	Indicates the expected yearly loss under normal operating conditions. This value is useful for annual budget planning and risk provisioning.
Median Loss	The 50th percentile of the loss distribution (central tendency).	IDR 3.12 Billion	Half of all simulated losses are below this value, showing that typical events are less severe but frequent.
Standard Deviation (SD)	Measures the volatility or dispersion of losses from the mean.	IDR 2.48 Billion	Higher SD indicates substantial uncertainty and variability in loss magnitude, highlighting the need for financial buffers.
Value at Risk (VaR 95%)	Maximum expected annual loss at a 95% confidence level.	IDR 8.97 Billion	There is only a 5% chance that annual losses will exceed this amount. This figure is key for setting insurance coverage and financial reserves.
Conditional Value at Risk (CVaR 95%)	The average loss in the worst 5% of cases.	IDR 11.25 Billion	Captures the severity of "tail risks." Useful for preparing for extreme but rare disaster scenarios.
P(Loss > 5 billion)	Probability that annual losses exceed IDR 5 billion.	8.7% (~1 in 12 years)	Indicates the frequency of moderate-to-severe events, helping guide contingency fund allocation.
P(Loss > 10 billion)	Probability that annual losses exceed IDR 10 billion.	3.5% (~1 in 29 years)	Reflects the likelihood of catastrophic financial events, guiding long-term strategic planning.
Average Loss (% of Revenue)	Mean annual loss as a percentage of total revenue.	3.2% of revenue	Shows the financial impact on profitability. Helps define the company's *risk appetite* threshold.
95th Percentile Loss (% of Revenue)	Loss at the 95th percentile relative to annual revenue.	7.5% of revenue	Suggests the maximum financial tolerance for risk before operational continuity is threatened.

Survival Analysis (Operational Resilience) to evaluate factors influencing system resilience (probability of remaining operational up to time t) and the risk of downtime. Here's Table – Results of Operational Resilience Analysis (Survival Analysis). The Monte Carlo simulation results in Table 3 indicate an average annual financial loss of IDR 3.87 billion, reflecting moderate but recurring operational risk. The high variability (SD = IDR 2.48 billion) and VaR 95% of IDR 8.97 billion suggest potential exposure to significant financial shocks. Extreme events, represented by CVaR 95% of IDR

11.25 billion, though rare, could severely affect profitability. With losses reaching up to 7.5% of annual revenue, these findings highlight the need for stronger financial buffers, insurance coverage, and proactive risk management to maintain operational resilience.

To further evaluate the operational resilience of the palm oil production system, a Survival Analysis was conducted using the Kaplan–Meier estimator, Log-Rank test, and Cox Proportional Hazard Model. This analysis aims to quantify how maintenance quality, flood exposure, and the availability of backup power influence system uptime and downtime risk. The results in Table 4 provide a statistical understanding of the factors that most significantly affect operational continuity, offering valuable insights for improving disaster preparedness and infrastructure reliability within the industry.

Table 4. Results of Operational Resilience Analysis (Survival Analysis)

Method Used	Purpose of Analysis	Key Results	Managerial Interpretation
Kaplan–Meier Estimator	To measure the probability that the production system remains operational (*survival probability*) over time.	• Groups with high maintenance levels show the highest survival curves systems operate longer before failure. • Mills located in high flood-risk zones show a faster decline in survival probability. • The presence of backup power significantly improves system survival probability.	• Preventive maintenance effectively extends system uptime and delays downtime events. • Improved drainage infrastructure is essential for mills located in flood- prone areas. • Backup power systems significantly improve operational continuity during power or IT disruptions.
Log-Rank Test	To test whether the differences between survival curves of various groups are statistically significant.	• High vs. low maintenance: significant difference ($p < 0.05$). • High vs. low flood exposure: significant difference ($p < 0.05$). • With vs. without backup power: significant difference ($p \approx 0.10 – 0.05$).	• Operational factors have a statistically significant impact on system resilience. • Mitigation strategies should focus on groups with lower survival performance.
Cox Proportional Hazard Model	To quantify the effect of each factor on the risk of downtime (hazard rate).	Describe in Table 4	• Preventive maintenance is the most effective mitigation factor for reducing downtime risk. • The Flood exposure with a significantly increases downtime risk and requires infrastructure intervention. • Backup power enhances system reliability and operational continuity.

Building upon the previous survival analysis, the Cox Proportional Hazard Model was applied to quantify the relative influence of key operational factors on system downtime risk. This model provides a deeper understanding of how preventive maintenance, flood exposure, and backup power availability affect the likelihood and frequency of operational failures. The results summarized in Table 5 highlight the most critical determinants of system resilience and offer practical guidance for prioritizing risk mitigation strategies in palm oil mill operations.

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Table 5. Key Results of the Cox Proportional Hazard Model

Covariate (Factor)	Hazard Ratio (HR)	95% Confidence Interval (CI)	Significance (p-value)	Interpretation	Managerial Implication
High Maintenance	0.62	0.48 – 0.79	< 0.01	The hazard ratio of 0.62 indicates that mills with a high level of preventive maintenance have a 38% lower risk of experiencing downtime compared to those with low maintenance.	Prioritize the implementation of a Reliability-Centered Maintenance (RCM) program to significantly extend equipment uptime and reduce failures.
High Flood Exposure	1.45	1.12 – 1.88	< 0.01	A hazard ratio of 1.45 means that mills located in flood-prone areas are 45% more likely to experience downtime than those in low-risk zones.	Invest in infrastructure-based mitigation (e.g., drainage systems, bund walls) and conduct site risk assessments before establishing new facilities.
Backup Power Available	0.71	0.55 – 0.91	< 0.05	The hazard ratio of 0.71 suggests that having a backup power system reduces the risk of downtime by approximately 29%.	Ensure the installation of redundant power systems (e.g., UPS, standby generators) to enhance operational resilience and minimize disruption from power outages.

The integration of Monte Carlo Simulation and Survival Analysis provides a robust analytical framework that unifies financial and operational risk assessment to support effective mitigation strategies and Business Continuity Planning (BCP). Through Monte Carlo Simulation, the probabilistic distribution of potential financial losses is quantified, enabling the identification of Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) under uncertain disaster conditions. Concurrently, Survival Analysis evaluates the system's operational resilience by estimating failure probabilities and recovery times of critical processes. The combined results reveal that while financial losses exhibit a right-skewed distribution with significant tail risks, operational performance demonstrates varying survival probabilities across units, indicating uneven resilience levels. These integrated insights serve as the basis for prioritizing risk mitigation actions, allocating contingency resources, and formulating adaptive BCP frameworks that enhance both financial stability and operational continuity in disaster-prone industrial settings.

The results presented in Table 6 demonstrate how the integration of Monte Carlo Simulation and Survival Analysis provides a comprehensive evaluation of financial and operational risks in palm oil mill operations. The table shows that the 95th percentile annual loss (VaR95) and worst-case loss (CVaR95) serve as critical benchmarks for defining the company's risk appetite and determining the necessary financial reserves estimated between IDR 9–11.5 billion per event. Additionally, the risk prioritization matrix highlights that warehouse flooding, machinery overheating, and routine equipment failure are the dominant risk categories requiring immediate mitigation. Moreover, the Cost–Benefit Analysis (CBA) results in Table 6 illustrate the effectiveness of several mitigation programs. The Reliability-Centered Maintenance (RCM) initiative, improved drainage infrastructure, and backup power systems deliver substantial financial savings while reducing downtime risks significantly. These measures directly support the development of a robust Business Continuity Plan (BCP) by defining realistic Recovery Time Objectives (RTOs) for critical operations. Overall, Table 6 underscores that integrating quantitative risk modelling with operational resilience analysis enables more strategic resource allocation, ensuring long-term stability and disaster preparedness in the palm oil industry.

Table 6. Results Of Integrated Analysis (*Monte Carlo* × *Survival Analysis*)

<table>
<tr><th>Analysis Component</th><th>Key Findings</th><th>Strategic Insight</th><th>Managerial Implications</th></tr>
<tr><td>Risk Appetite Definition</td><td>• Based on Monte Carlo results, the 95th percentile annual loss (VaR95) is IDR 8.97 billion, and the worst-case average loss (CVaR95) is IDR 11.25 billion.
• These values represent potential “tail risks” under extreme scenarios.</td><td>• Set risk tolerance so that p95 loss ≤ 7.5% of annual revenue.
• Use VaR and CVaR as benchmarks for minimum financial buffer and insurance retention.</td><td>• Allocate financial reserves between IDR 9–11.5 billion per event.
• Use these metrics to determine optimal insurance policies, contingency funds, or captive reserves.</td></tr>
<tr><td>Risk Prioritization (Matrix)</td><td>• Combining frequency (Monte Carlo) and severity (Survival), key risks include:
- Warehouse flooding – high impact, medium probability
- Machinery overheating – high impact, medium probability
- Routine machine failure –
- medium impact, high probability</td><td>• Use a risk matrix (impact × probability) to categorize and rank risks.
• Prioritize mitigation for high-impact and high-probability events first.</td><td>• Channel investment to critical risks that combine high cost (financial) and high hazard (operational) impacts.
• Adjust risk treatment strategies (avoidance, reduction, transfer) accordingly.</td></tr>
<tr><td>Cost–Benefit Analysis (CBA)</td><td>• Combining hazard reduction (Cox model) with financial savings (Monte Carlo):
- RCM Program → HR: 0.62 → EAL reduction: 30–40% → Saved: IDR 500–700 million/year
- Drainage Project → HR: 1.45 → EAL reduction: 35–45% → Saved: IDR 450–650 million/year
- Backup Power → HR: 0.71 →
- EAL reduction: 25–35% → Saved:
- IDR 250–400 million/year
- Human Error Training → EAL reduction: 20–25% → Saved: IDR 150–220 million/year</td><td>• Combine hazard ratio reductions with expected annual loss (EAL) savings to evaluate investment efficiency.
• Rank mitigation programs based on benefit–cost ratio and risk reduction impact.</td><td>• Prioritize interventions with positive NPV and highest combined effect on reducing both financial and operational risks.
• Create a phased investment plan for mitigation programs.</td></tr>
<tr><td>Business Continuity Planning (BCP)</td><td>• Recovery Time Objectives (RTO):
- Power/IT disruption: ≤ 2 hours
- Flooding: ≤ 24 hours
- Critical machinery failure: < 8 hours
• Integrated model enables precise RTO setting and capacity planning.</td><td>• Link Monte Carlo risk thresholds and Cox hazard insights directly to BCP design.
• Use tail-risk data to size emergency funds and use hazard ratios to allocate resources.</td><td>• Design BCP with clear trigger points, response protocols, and resource allocation.
• Conduct at least two BCP drills annually and adjust strategies based on updated model results.</td></tr>
</table>

4. Conclusion

This study introduces an industrial-engineering-based disaster management framework that integrates Monte Carlo Simulation for loss quantification and Survival Analysis for evaluating operational resilience. The integration of these two analytical approaches enables a comprehensive understanding of both the financial and operational dimensions of disaster risk in the palm oil industry. By simulating a wide range of potential disruptions and assessing system survival under varying

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conditions, the framework provides data-driven insights to support strategic risk management decisions. The key findings reveal that the loss distribution is right-skewed, indicating the presence of rare but severe financial impacts. The Value at Risk (VaR_5) is estimated at IDR 8.97 billion, while the Conditional Value at Risk ($CVaR_{95}$) reaches IDR 11.25 billion, emphasizing the need for robust tail-risk management. Operationally, the analysis shows that higher maintenance frequency and the availability of backup power systems significantly reduce downtime hazards, whereas exposure to flood-prone areas increases operational vulnerability. These results underscore the necessity of preventive actions and infrastructure investments to enhance production continuity.

By integrating quantitative loss modelling and reliability-based analysis, this research establishes a strong foundation for prioritizing mitigation programs, defining risk appetite thresholds (with a p_{95} loss target of ≤ 7.5% of annual revenue), and developing unit-specific Business Continuity Plan (BCP) targets, including Recovery Time Objectives (RTOs). The practical contributions of this framework include a prioritized mitigation list with positive Net Present Value (NPV), risk–performance indicator dashboards, and recovery playbooks that enable decision-makers to align financial resilience with operational sustainability.

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