Eksakta : Berkala Ilmiah Bidang MIPA
VOLUME 27 NO 06 2026, pp 1111-1129
ISSN : Print 1411-3724 — Online 2549-7464
DOI : https://doi.org/10.24036/eksakta/vol27-iss06/779

Eksakta
Berkala Ilmiah Bidang MIPA
http://www.eksakta.ppj.unp.ac.id/index.php/eksakta

Article

An Operational Risk Model for Coffee Drying Processes to Support Production Decision-Making

Article Info

Article history :
Received October 14, 2026
Revised November 10, 2026
Accepted November 16, 2026
Published December 30, 2026
In Press

Keywords :
Coffee drying,
operational risk,
soft systems methodology,
multiple linear regression,
monte carlo simulation

Demi Ramadian[1*], Adlina Safitri Helmi[1], Indah Kurnia Ramadhani[2], Rizaldi Sardani[2]

[1]Program Study of Agro Industrial Engineering, Politeknik ATI Padang, Padang, Indonesia
[2]Program Study of Agro Industrial Logistic Management, Politeknik ATI Padang, Padang, Indonesia

Abstract. Coffee is one of Indonesia's leading commodities. The drying stage is a critical process because it affects the moisture content and quality of coffee beans. At the Solok Sirukam Sepakat Producer Cooperative, sun-drying remains the drying method. Although cost-effective, this method is dependent on environmental conditions. This study aimed to characterize operational risks in coffee drying using an integrated approach combining Soft Systems Methodology (SSM), multiple linear regression, and Monte Carlo simulation. Operational risks were identified through stakeholder interviews and analyzed using rich pictures, CATWOE, and root definitions. Quantitative analysis was conducted using data from 88 coffee-drying batches collected between January and August 2026. Five variables were examined: temperature, drying duration, coffee volume, sunshine duration, and humidity.The results showed that coffee cherry accumulation due to limited processing capacity was the most frequent risk event, occurring in 38.6% of observations. Multiple linear regression indicated no statistically significant relationships, with R^2 values of 10.9% for moisture content and 4.7% for operational risk scores. Monte Carlo simulation (10,000 iterations) produced an average risk score of 21.241, matching the historical average of 21.136. These findings characterize historical operational risk patterns and provide a basis for risk evaluation in cooperative-based coffee drying systems.

This is an open acces article under the CC-BY license.

This is an open access article distributed under the Creative Commons 4.0 Attribution License. which permits unrestricted use. distribution. and reproduction in any medium. provided the original work is properly cited. ©2026 by author.

Corresponding Author :
Demi Ramadian
Program Study of Agro Industrial Engineering, Politeknik ATI Padang, Padang, Indonesia
Email : demiramadian@poltekatipdg.ac.id

1. Introduction

Coffee is one of Indonesia's leading agricultural commodities, characterized by relatively stable market prices and playing a significant role in national income generation and rural economic development. The continuous increase in coffee production has positioned Indonesia as one of the largest coffee-producing countries in the world. Currently. Indonesia ranks as the fourth-largest coffee producer and exporter globally, following Brazil, Vietnam, and Colombia. The most widely cultivated coffee varieties in Indonesia are Robusta and Arabica, as they are recognized for their distinctive and high-quality flavor profiles [1]. According to data from the Foreign Agricultural Service of the United States Department of Agriculture (USDA) [2], Indonesia's coffee production reached 11 million bags in 2024, with major export destinations including Europe, the United States, and Egypt.

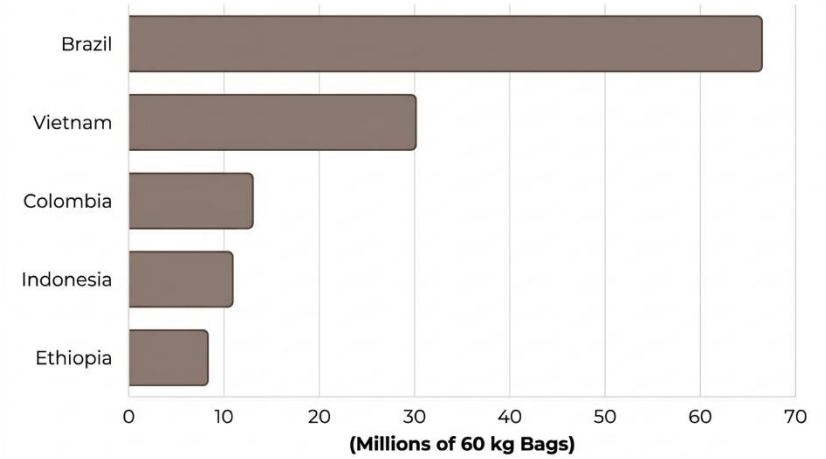


Figure 1. Global Coffee Production by Leading Producing Countries in 2024

In general, the coffee production process in Indonesia consists of several stages. The first stage involves coffee bean harvesting, followed by coffee fruit sorting. The subsequent stage includes the removal of the outer skin of ripe coffee cherries. followed by fermentation and washing processes. The next stage is the drying process. after which the dried coffee beans undergo hulling to remove the parchment and silver skins. The process continues with coffee bean sorting and the final stages involve packaging and storage.

Within the coffee production process, drying is considered a critical postharvest stage that significantly influences the final quality of coffee beans, while also enhancing their flavor and aroma characteristics [3]. The primary objective of the drying process is to reduce the moisture content of coffee beans to achieve the required quality standards. According to the Indonesian National Standard [4], the recommended moisture content for coffee beans ranges from 12% to 14%. The optimal characteristics obtained after the drying process determine the overall quality and market acceptance of coffee products. However, coffee drying is frequently conducted using manual or semi-mechanical methods, which are often constrained by limited resources technological capabilities, and quality control systems.

Based on preliminary observations, coffee beans are dried using sun-drying methods in open areas or designated drying facilities. This method offers advantages in terms of cost efficiency; however. it is highly affected by environmental variability, including rainfall, humidity, and solar radiation duration. The drying process is associated with various operational risks, such as weather uncertainty affecting natural drying performance and fluctuations in temperature and humidity that may lead to defects in coffee beans. These conditions result in unpredictable drying durations, inconsistent coffee bean quality, increased risks of production delays, and fungal growth on coffee beans.

Coffee drying processes at the small and medium-sized enterprise (SME) level involve multiple actors, resources, and operational decisions, thereby forming a complex production system. The uncertainty within the drying process becomes more significant due to limitations in process control technologies and the limited adoption of data-driven decision support systems. Consequently, production decisions are often based on operator experience or intuition, which may increase quality variability and the risk of production delays. These conditions indicate that coffee drying processes cannot be fully analyzed using a deterministic approach. Literature on production systems and digital agriculture highlights that simulation approaches, such as Monte Carlo simulation, enable the evaluation of various operational scenarios and the estimation of failure probabilities under highly variable conditions.

Research on coffee drying processes has predominantly focused on technical approaches and laboratory-based experiments, while the development of probabilistic operational risk models for coffee drying systems affected by weather uncertainty remains limited. Coffee drying methods have been shown to influence the physical and sensory quality characteristics of coffee, including final moisture content and storage stability, thereby improving overall product quality [5]. The drying method also significantly affects the physical and organoleptic attributes of coffee beans. such as final moisture content, color, and flavor profile [3]. Furthermore, the development of solar hybrid coffee dryers has been reported to improve energy efficiency and reduce drying time compared with conventional sun-drying methods [6]. Meanwhile, several studies have focused on decision support systems for agro-industrial applications in general; however, their implementation has not specifically addressed coffee drying processes and associated operational risks [7-10]. Although previous studies have contributed significantly to understanding coffee drying technologies, product quality, and agricultural decision-support systems, they have largely focused on technical performance and have not explicitly integrated operational system analysis, risk assessment, and quantitative risk simulation within cooperative-based coffee drying operations. Consequently, operational risks arising from the interactions among processing capacity, production activities, environmental conditions, and stakeholder decision-making remain insufficiently understood.

To address this gap, this study proposes an integrated operational risk modeling framework for coffee drying processes at the Producer Cooperative Solok Sirukam Sepakat, Indonesia. The framework combines Soft Systems Methodology (SSM), multiple linear regression, and Monte Carlo simulation to capture both the socio-organizational complexity of the operational system and the quantitative characteristics of operational risks. SSM is employed to explore system complexity, stakeholder interactions, and operational risk sources through rich picture analysis, CATWOE, and root definition, leading to the identification of relevant risk events. These risk events are subsequently transformed into measurable indicators and aggregated into a weighted operational risk score. Multiple linear regression is applied to examine the relationships between operational and environmental variables, namely drying temperature, drying duration, coffee volume, sunshine duration, and air humidity, and two response variables: final coffee moisture content and the operational risk score. To evaluate risk uncertainty, Monte Carlo simulation is conducted through random resampling of 88 historical observations over 10,000 iterations, preserving the observed combinations of risk events and generating a probability distribution of operational risk scores based on historical patterns.

The integration of these methods is complementary rather than sequential: SSM provides contextual understanding and risk identification, regression analysis examines relationships between operational conditions and observed outcomes, and Monte Carlo simulation characterizes risk variability and uncertainty. By combining these analytical perspectives, the proposed framework extends previous research beyond purely technical assessments and provides a risk-based decision-support tool for prioritizing operational risks and improving drying process control, coffee quality, and production efficiency in cooperative-based coffee production systems.

2. Experimental Section

2.1. Soft System Methodology

Soft Systems Methodology (SSM) is an approach that applies an investigative perspective rather than serving as a conventional problem-solving methodology. SSM is designed to facilitate learning and reflection within complex human activity systems, with the ultimate objective of identifying potential actions for improvement rather than seeking definitive solutions. SSM is not intended to solve problems in the traditional cognitive problem-solving sense; instead, it aims to establish a process of inquiry, group discussion, and systematic investigation that leads to solutions considered both systemically desirable and culturally feasible [11-12].

The SSM methodology provides additional insights for understanding complex organizational problems. SSM assists teams in defining ambiguous system requirements and aligning them with organizational objectives. The SSM approach facilitates structured problem analysis in environments where multiple stakeholders possess different perspectives regarding the system [13-14]. The SSM methodology consists of seven stages [15-17], as illustrated in Figure 2. The stages are as follows:

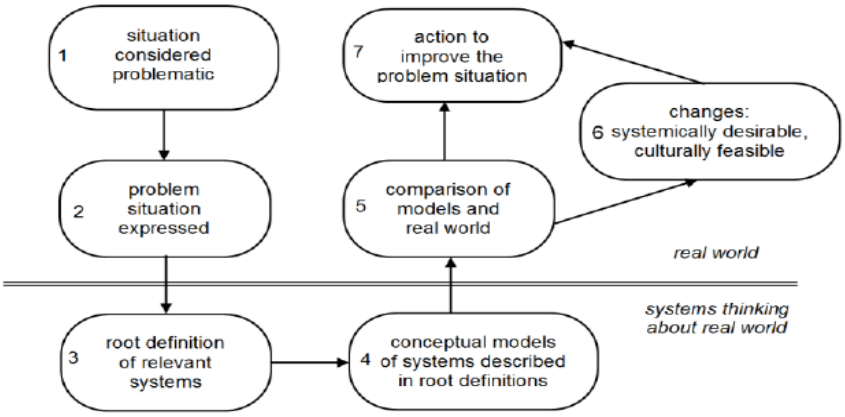


Figure 2. The Seven Stages of Soft Systems Methodology (SSM)

CATWOE serves as an analytical instrument within the Soft Systems Methodology (SSM) framework to examine complex and multidimensional problems in social and organizational environments. This perspective positions a system as both a technical and socio-organizational construct, enabling CATWOE to reveal diverse stakeholder perspectives and generate holistic solutions that are contextually relevant [18-19].

2.2. Linear Regression

Multiple linear regression is a regression analysis technique used to explain the relationship between a response variable (dependent variable) and multiple influencing factors (independent variables). When the output or class variable is numerical and all attributes are also numerical, linear regression is an appropriate technique for solving prediction problems [20-21]. Multiple linear regression is used to express the response variable as a linear combination of attributes with predetermined coefficients or weights. The general equation of multiple linear regression can be expressed as follows [22-23] :

$$y = a + b1x1 + b2x2 + \cdots + bnxn \quad (1)$$

Where **y** represents the response variable (class), $x1.2.\ldots.xn$ represents the attributes (independent variables) and $a,b1\ldots..bn$ represent the regression coefficients (weights). The coefficients are estimated based on sample data. The definitions of the variables are as follows [24-26] :

y = Dependent variable (predicted value)
x = Independent variable
a = Constant (the value of y when $x1,2\ldots..xn=0$) 10
b = Regression coefficient (the value representing an increase or decrease in the response variable)
The values of $a,1\ldots..bn$ can be calculated using the normal equation method as follows:

$$\Sigma Y=an+b1\Sigma X1+b2\Sigma X2 \quad (2)$$
$$\Sigma X1Y=a\Sigma X1+b1\Sigma X1X2+b2\Sigma X1X2 \quad (3)$$
$$\Sigma X2Y=a\Sigma X2+b1\Sigma X1X2+b2\Sigma X1X2 \quad (4)$$

2.3 Monte Carlo Simulation

Monte Carlo simulation is a widely applied and practical approach for solving problems involving uncertainty [27]. This method is based on the use of random numbers and probability distributions to simulate systems and understand their behavior under uncertain conditions [28-30]. The Monte Carlo simulation technique consists of several stages, as follows [31-32] :

2.3.1 Determining the Probability Distribution

The probability distribution is determined by dividing the frequency of each observed value by the total frequency. The probability distribution can be established using the following formula:

$$DP = \frac{Fi}{TF} \quad (5)$$

where DP represents the probability distribution, Fi represents the frequency and TF represents the total frequency.

2.3.2 Determining the Cumulative Distribution

The cumulative distribution is determined by adding the probability value of the i-th observation to the sum of the previous probability values. The cumulative distribution can be calculated using the following formula:

$$DPK = Ki + Pi \quad (6)$$

where DPK represents the cumulative probability distribution. Ki represents the i-th probability value and Pi represents the cumulative sum of the previous probability values.

2.3.3 Determining Random Number Intervals

In the Monte Carlo simulation process, the determination of random number intervals plays a crucial role in defining the boundaries between different variables. The random number intervals consist of lower and upper limits, which serve as references for assigning the corresponding values of Zi. The determination of random number intervals is presented as follows:

a. The first lower limit is set to 0.
b. The upper limit is obtained by multiplying the cumulative probability distribution value of each period by10,000.
c. The lower limit of the subsequent period is obtained by adding 1 to the upper limit of the previous period.

2.3.4 Generating Random Numbers

Risk simulation in this study was performed using a historical resampling (risk bootstrapping) approach, which utilizes actual historical observations as the source for generating risk scenarios.

Unlike parametric Monte Carlo simulation, which requires assumptions regarding theoretical probability distributions such as normal or lognormal distributions. this approach directly employs the available operational data. Consequently, the empirical characteristics of the observed risk events are preserved. enabling the simulation results to better represent the actual operating conditions of the coffee drying process [33].

In this study, the simulation was based on 88 historical observations collected during the data collection period. For each simulation iteration, one risk-score observation was randomly selected from the historical dataset using a sampling-with-replacement mechanism, allowing each observation to be selected multiple times across iterations. The process was repeated 10,000 times to generate the probability distribution of risk scores. The simulation outputs were subsequently used to estimate the average risk level risk variability, event probabilities and support decision-making related to risk mitigation priorities in coffee drying operations.

2.3.5 Simulating the Experimental Process

At this stage, the generated random numbers are matched with the random number intervals obtained in the previous stage. The corresponding values determined from these intervals are then used as the predicted values.

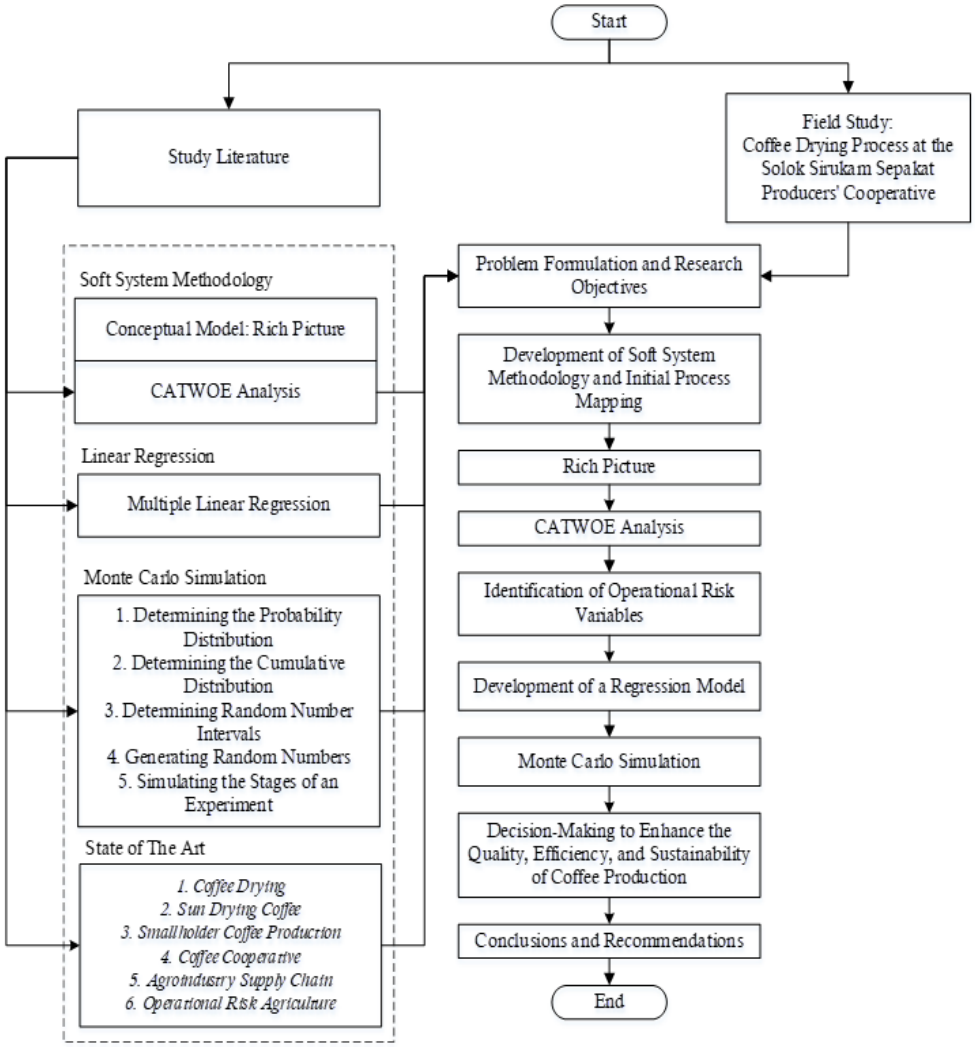


Figure 3. Research Flowchart

3. Results and Discussion

3.1 Formulation of Soft Systems Methodology (SSM) and Preliminary Process Mapping

After the initial identification stage, the SSM framework was developed to achieve a holistic understanding of the system. This stage began with initial process mapping, which aimed to describe the sequence of operational activities, material flows, and stakeholder involvement throughout each process stage. The process mapping served as the foundation for developing a rich picture that illustrates the relationships among actors. coffee material flows, operational information flows, and external/environmental factors affecting the system, such as weather conditions and air humidity. The rich picture developed at this stage represents an initial representation of the system based on preliminary observations and literature studies, which will subsequently be validated through field data collection [12],[17]. The rich picture is presented in Figure 4.



Figure 4. Rich Picture

3.2 CATWOE Analysis

Based on the rich picture, a CATWOE analysis was conducted to conceptually define the system and determine its boundaries [34]. The CATWOE analysis was performed to identify the actors involved in the coffee drying process, the transformation occurring within the system, the overall system perspective, the parties responsible for decision-making. and the environmental constraints influencing the coffee drying process [19].

The primary transformation within the system is the conversion of wet coffee into dried coffee beans with moisture content that complies with coffee quality standards. The CATWOE analysis helps clarify the role of the cooperative as the main processing actor and provides a foundation for determining operational risk variables. The analysis positions consumers as the recipients of the system outcomes; farmers, cooperatives, and distribution parties as the actors involved; the transformation of wet coffee into dried coffee beans with the targeted moisture content as the core transformation; and the perspective that well-managed drying processes are required to maintain quality and reduce risks as the system worldview.

The cooperative is considered the primary entity capable of controlling the system, while temperature, drying duration, coffee volume, sunshine duration, and humidity are identified as process and environmental factors that require consideration. From an SSM perspective, the coffee

drying problem is not merely related to achieving the target moisture content; it also involves the system's capability to manage material flows and respond to operational disturbances. The formulated system definition directs activities toward understanding the process, identifying risks, evaluating process and environmental factors, and utilizing the evaluation results as a basis for decision-making considerations. The outcomes of this mapping process serve as the foundation for determining quantitative variables and interpreting statistical results. Therefore, SSM functions as a framework for defining the problem boundaries and connecting numerical findings with the operational context of the cooperative, rather than serving as a method that independently establishes causal relationships.

3.3 Identification of Operational Risk Variables

The next stage involves identifying the research variables derived from the system analysis conducted through the rich picture and CATWOE analysis. The variables were selected based on factors that directly influence the success of the coffee drying process and can be quantitatively measured in the field [23-26]. The independent variables consist of drying temperature, drying duration, coffee drying volume, sunshine duration, and air humidity. Meanwhile, the dependent variables include the final moisture content and the operational risk level of the drying process. The identification of these variables serves as the foundation for developing the regression model.

Table 1. The operational risk factors associated with coffee drying

Code	Risk Factor	Occurrence Criteria (0/1)	Weight
R1	Coffee cherries accumulation during the harvesting season due to insufficient processing capacity	1 = occured; 0 = did not occur	20
R2	Coffee beans with moisture content below 9% (over-dried condition) become more susceptible to breakage during the hulling process. resulting in reduced production output due to defective products	1 = occured; 0 = did not occur	20
R3	Excessive exposure to direct sunlight during prolonged open-air drying may reduce coffee quality	1 = occured; 0 = did not occur	15
R4	High rainfall intensity causes the drying process to exceed the targeted drying duration	1 = occured; 0 = did not occur	15
R5	Coffee requires repeated drying because the moisture content has not reached the target level (not following the drying SOP). resulting in fungal growth and product defects	1 = occured; 0 = did not occur	15
R6	Drying equipment (drying rack) failure or damage due to excessive loading beyond capacity limits	1 = occured; 0 = did not occur	15

The risk weights presented in Table 1 were determined through stakeholder-based expert judgment involving individuals directly engaged in coffee drying operations at the Solok Sirukam Sepakat Producer Cooperative, including cooperative managers, processing unit supervisors, and representatives of farmer groups. The weighting process was conducted through structured discussions to assess the relative importance of each risk factor in terms of its impact on coffee quality, production continuity, and operational losses. Based on this assessment, coffee cherry accumulation caused by limited processing capacity (R1) and coffee bean defects (R2) were assigned the highest weights of 20% due to their perceived significant influence on product quality and production performance. The remaining risks (R3-R6) were each assigned a weight of 15%, reflecting stakeholder consensus that their impacts were relatively similar. The total weight was normalized to 100% for the calculation of operational risk scores.

3.4 Research Hypothesis

A research hypothesis represents a preliminary assumption regarding the relationship or influence between independent variables and dependent variables, which is subsequently tested empirically based on research data. In this study, the hypotheses are formulated to examine the effects of drying temperature, drying duration, coffee drying volume, sunshine duration, and air humidity on the final moisture content and total risk score in the coffee drying process.

The independent variables used in this study consist of Drying Temperature (X1), Drying Duration (X2), Coffee Drying Volume (X3), Sunshine Duration (X4), and Air Humidity (X5). The dependent variables consist of Final Moisture Content (Y1) and Total Risk Score (Y2). The research hypotheses are formulated into two regression models, namely the Final Moisture Content model and the Total Risk Score model.

Hypotheses for the Final Moisture Content Model (Y1)
Partial Hypotheses:

H01: Drying temperature (X1) has no significant effect on the final moisture content (Y1).
H11: Drying temperature (X1) has a significant effect on the final moisture content (Y1).
H02: Drying duration (X2) has no significant effect on the final moisture content (Y1).
H12: Drying duration (X2) has a significant effect on the final moisture content (Y1).
H03: Coffee drying volume (X3) has no significant effect on the final moisture content (Y1).
H13: Coffee drying volume (X3) has a significant effect on the final moisture content (Y1).
H04: Sunshine duration (X4) has no significant effect on the final moisture content (Y1).
H14: Sunshine duration (X4) has a significant effect on the final moisture content (Y1).
H05: Air humidity (X5) has no significant effect on the final moisture content (Y1).
H15: Air humidity (X5) has a significant effect on the final moisture content (Y1).

Simultaneous Hypotheses:

H06: Drying temperature (X1). drying duration (X2). coffee drying volume (X3). sunshine duration (X4). and air humidity (X5) simultaneously have no significant effect on the final moisture content (Y1).
H16: Drying temperature (X1). drying duration (X2). coffee drying volume (X3). sunshine duration (X4). and air humidity (X5) simultaneously have a significant effect on the final moisture content (Y1).

Hypotheses for the Total Risk Score Model (Y2)
Partial Hypotheses:

H07: Drying temperature (X1) has no significant effect on the total risk score (Y2).
H17: Drying temperature (X1) has a significant effect on the total risk score (Y2).
H08: Drying duration (X2) has no significant effect on the total risk score (Y2).
H18: Drying duration (X2) has a significant effect on the total risk score (Y2).
H09: Coffee drying volume (X3) has no significant effect on the total risk score (Y2).
H19: Coffee drying volume (X3) has a significant effect on the total risk score (Y2).
H010: Sunshine duration (X4) has no significant effect on the total risk score (Y2).
H110: Sunshine duration (X4) has a significant effect on the total risk score (Y2).
H011: Air humidity (X5) has no significant effect on the total risk score (Y2).
H111: Air humidity (X5) has a significant effect on the total risk score (Y2).

Simultaneous Hypotheses:

H012: Drying temperature (X1). drying duration (X2). coffee drying volume (X3). sunshine duration (X4). and air humidity (X5) simultaneously have no significant effect on the total risk score (Y2).

H112: Drying temperature (X1). drying duration (X2). coffee drying volume (X3). sunshine duration (X4). and air humidity (X5) simultaneously have a significant effect on the total risk score (Y2).

Basis for Hypothesis Testing

Hypothesis testing was conducted using multiple linear regression analysis at a significance level of 5% ($\alpha = 0.05$).

a. t-Test (Partial Test). The t-test was used to determine whether each independent variable partially had a significant effect on the dependent variable. If the Sig. value < 0.05, then H0 is rejected and the alternative hypothesis is supported. If the Sig. value ≥ 0.05, then H0 is not rejected and the alternative hypothesis is not supported.
b. F-Test (Simultaneous Test). The F-test was used to determine whether variables X1–X5 simultaneously had a significant effect on the dependent variable. If the Sig.F value < 0.05, then H0 is rejected and the alternative hypothesis is supported, f the Sig. F value ≥ 0.05, then H0 is not rejected and the alternative hypothesis is not supported.

3.5 Regression Model Development

The regression model was developed to analyze the relationships among variables involved in the coffee drying process and their effects on the final drying outcomes. The model aims to identify the variables that have dominant influences on moisture content and operational risk, thereby establishing quantitative cause-and-effect relationships among variables. The results of this analysis provide inputs for the uncertainty analysis stage, which is further processed using Monte Carlo simulation. In general, the regression model used in this study can be expressed as follows [21].

$$y= a+b1x1+b2x2+\ldots+bnxn$$

y1= final moisture content
y2= operational risk level of the coffee drying process
x1= drying temperature
x2= drying duration
x3= coffee drying volume
x4= sunshine duration
x5= air humidity

3.6 Frequency and Combination of Risk Events

Based on 88 observations, the risk of coffee cherry accumulation due to insufficient processing capacity (R1) was the most frequently recorded event, occurring in 34 observations or 38.6% of the total observations. The predominance of coffee cherry accumulation indicates that processing capacity remains a critical operational issue within the cooperative. Similar challenges have been reported in coffee agroindustrial systems where production fluctuations, capacity limitations, and coordination among stakeholders influence operational performance and supply chain efficiency [12],[15-17].

The risk of coffee bean damage during the hulling process (R2) and drying facility damage due to excessive capacity (R6) were each recorded 20 times or 22.7%. Delayed drying caused by high rainfall intensity (R4) occurred in 19 observations or 21.6%, while repeated drying due to moisture content not reaching the target level (R5) was recorded in 13 observations or 14.8%. The risk of quality degradation caused by excessive sun-drying duration (R3) was not observed during the study period.

Table 2. Risk Occurrence Frequency

Code	Risk	Occurrence	Frequency (%)
R1	Coffee cherry accumulation due to insufficient processing capacity	34	38.6
R2	Coffee bean damage during the hulling process	20	22.7
R3	Quality degradation due to excessive drying duration	0	0.0
R4	Delay caused by high rainfall intensity	19	21.6
R5	Repeated drying due to moisture content not meeting the target level	13	14.8
R6	Facility damage due to excessive capacity load	20	22.7

The high frequency of R1 indicates that capacity management should become one of the main focuses of operational evaluation. This finding is further supported by the occurrence of R6, which is also associated with excessive facility capacity. The combination of R1 and R6 was recorded simultaneously in eight observations (9.1% of all observations). This combination indicates historical situations in which material capacity constraints and facility capacity issues occurred within the same observation period. However, these observational data are insufficient to conclude that R1 directly causes R6.

The examination of risk combinations shows that multiple risks may occur simultaneously. A total of 30 observations recorded two or more risks, 40 observations recorded a single risk event, and 18 observations did not record any risk based on the applied indicators. The occurrence of simultaneous risks is important because operational decisions may need to consider multiple disturbances at the same time, for example, when high material volume coincides with unfavorable weather conditions. Therefore, risk evaluation based solely on the frequency of individual risks should be complemented by an assessment of risk combination patterns.

The absence of R3 occurrences during the observation period should be interpreted as an unobserved event within the dataset, rather than as a risk that is impossible to occur. When historical data are used as the basis for probabilistic analysis, the absence of an event in the sample may result in the risk not appearing in the simulation outcomes. Longer observation periods and consistent operational definitions of risk indicators are required to distinguish genuinely rare events from events that have not yet been recorded.

3.7 Descriptive Statistics of the Drying Process

Descriptive analysis of 88 observations showed that the drying temperature ranged from 28.50–32.50 °C. with an average temperature of 30.53 °C. The drying duration ranged from 168–240 hours. with an average duration of 205.64 hours or approximately 8.57 days. The volume of dried coffee varied between 1.80 and 525.40 kg. with an average of 137.64 kg and a standard deviation of 134.73 kg. The average sunshine duration was recorded at 8.47 hours per day, while the average air humidity was 78.70%.

The final moisture content ranged from 12–14% [4], with an average of 12.96% and a standard deviation of 0.58%. This range is within the target moisture content specified in the study. Although the final moisture content results were concentrated within a relatively narrow range, the total risk score still varied from 0 to 65. This difference indicates that achieving the desired moisture content and the occurrence of operational risks represent two distinct evaluation dimensions. Moisture content describes the final product performance, whereas the risk score summarizes operational events based on the predefined indicators and weighting criteria. Previous studies have also reported that drying

conditions significantly affect coffee moisture reduction, storage stability, and overall product quality [3],[5].

Table 3. Descriptive Statistics Results

Variable	Minimum	Maximum	Mean	Standard Deviation
Drying temperature (°C)	28.50	32.50	30.53	0.94
Drying duration (jam)	168	240	205.64	26.44
Coffee volume (kg)	1.80	525.40	137.64	134.73
Sunshine duration (hours/day)	7.54	9.46	8.47	0.48
Air humidity (%)	71.20	85.80	78.70	3.37
Final moisture content (%)	12.00	14.00	12.96	0.58
Total risk score	0	65	21.136	14.93

The large variation in coffee volume compared with other variables indicates that the amount of material handled was not uniform across observations. This condition is important in system interpretation because space requirements and facility capacity needs may change depending on the incoming volume. However, the high variation in volume does not necessarily prove that volume is the primary determinant of moisture content or risk score, this relationship needs to be further evaluated through correlation and regression analysis.

3.8 Results of Correlation Analysis Among Variables

Pearson correlation analysis showed a weak positive and significant relationship between drying temperature and final moisture content ($r = 0.272$; $p = 0.010$). Drying duration exhibited a weak negative and significant relationship with final moisture content ($r = -0.218$; $p = 0.041$). In the observed data, higher drying temperatures tended to be associated with higher final moisture content, whereas longer drying durations tended to be associated with lower final moisture content. Since the strength of these relationships was weak and the analysis was based on observational data, the direction of the relationships cannot be interpreted as evidence of causal effects.

Coffee volume, sunshine duration, and air humidity did not show significant correlations with the final moisture content at the 5% significance level. Similarly, no significant linear relationships were identified between the five independent variables and the total risk score based on the reported correlation analysis. These findings should be interpreted within the context of data variability, measurement approaches, and the characteristics of the risk score, which was constructed from a combination of weighted binary indicators.

The correlation analysis among independent variables revealed relatively strong relationships among several variable pairs, including drying duration and air humidity ($r = 0.835$). drying duration and sunshine duration ($r = -0.808$), sunshine duration and air humidity ($r = -0.783$), and drying temperature and drying duration ($r = -0.760$). These patterns indicate that process and environmental conditions in the dataset are not entirely independent. The interdependence among variables may affect the interpretation of regression coefficients because each coefficient represents the relationship between a predictor and the dependent variable while statistically controlling for the effects of other predictors.

The weak relationships identified in this study suggest that coffee drying outcomes may be influenced by additional factors not included in the current model. Similar observations have been reported in coffee production studies where environmental conditions, cultivation practices, and operational management jointly affect coffee quality and productivity [23-25].

3.9 Regression Model Assumption Testing

The regression assumption testing conducted in this study showed that the residuals of the final moisture content model had a Shapiro–Wilk significance value of 0.062, while the residuals of the total risk score model had a value of 0.061. Both values were above 0.05 indicating that there was insufficient evidence to reject the residual normality assumption based on the applied test. These results do not prove that the residuals are completely normally distributed; rather, they indicate that no significant deviation from normality was detected in the conducted assessment [20-22].

The multicollinearity assessment showed that the Tolerance values were above 0.10 and the Variance Inflation Factor (VIF) values were below 10 for the independent variables in both models. However. the VIF value for drying duration was reported as 6.379, indicating that a relatively strong relationship with other predictors should still be considered. The Glejser test showed no significant indication of heteroscedasticity. while the Durbin–Watson values were 1.998 for the Y1 model and 2.065 for the Y2 model. Overall. the assumption testing did not identify violations of the main regression assumptions based on the criteria applied in this study. Nevertheless. these findings do not change the fact that the explanatory capability of both models remains relatively low.

3.10 Multiple Linear Regression Results

Multiple linear regression analysis was used to evaluate whether drying temperature. drying duration, coffee volume, sunshine duration, and air humidity collectively explain the variation in final moisture content and total risk score. A summary of the model testing results is presented in Table 4.

Table 4. Summary of Multiple Linear Regression Results

Model Indicator	Final Moisture Content (Y1)	Total Risk Score (Y2)
R	0.330	0.217
R^2	0.109	0.047
Adjusted R^2	0.055	−0.011
F	2.007	0.809
F-test Significance	0.086	0.547
Conclusion at $\alpha = 0.05$	Not significant	Not significant

In the final moisture content model, the F-value was 2.007 with a significance value of 0.086. Since $p > 0.05$, the five independent variables simultaneously did not show a statistically significant relationship with the final moisture content. The R^2 value of 0.109 indicates that the model explained 10.9% of the variation in final moisture content within the sample, while the adjusted R^2 value of 0.055 represents the explanatory capability of the model after considering the number of predictors and sample size.

In the total risk score model, the F-value was 0.809 with a significance value of 0.547. This model was also not statistically significant at the 5% significance level. The R^2 value of 0.047 indicates that the five independent variables explained 4.7% of the variation in the risk score, while the adjusted R^2 value of −0.011 suggests that the inclusion of these predictors did not provide sufficient improvement in explanatory capability compared with a simpler model based on the adjusted measurement.

The partial hypothesis testing results showed that none of the independent variables had statistically significant coefficients at the 5% significance level for either Y1 or Y2 in the regression models. For Y1, the coefficient of drying temperature was 0.173 ($p = 0.085$), drying duration was −0.002 ($p = 0.691$), coffee volume was 0.001 ($p = 0.235$), sunshine duration was 0.115 ($p = 0.630$), and air humidity was 0.036 ($p = 0.304$). The temperature coefficient was close to the significance

threshold; however, it still did not meet the criterion of $p < 0.05$. Therefore, this variable cannot be stated to have a significant effect based on the applied model.

For Y2, the coefficient of drying temperature was −1.578 ($p = 0.555$), drying duration was −0.215 ($p = 0.165$), coffee volume was −0.021 ($p = 0.131$), sunshine duration was −3.010 ($p = 0.639$), and air humidity was 0.538 ($p = 0.567$). All significance values were above 0.05. The direction of the coefficients only indicates statistical tendencies within the sample after controlling for other predictors; without sufficient statistical significance. these directions cannot be used as a basis for claiming variable effects.

The low R^2 values in both models indicate that the analyzed variables were not sufficient to explain the variation in drying outcomes and risk scores. Other factors not included in the models may contribute to the observed variations. such as initial material characteristics, fruit maturity conditions, drying layer thickness, material turning practices, facility conditions, recording standards, or corrective actions. These factors represent potential areas for further investigation rather than variables that have been proven to explain the outcomes in this study. Although the regression models were not statistically significant, similar studies have demonstrated that environmental and operational variables may influence coffee production and processing outcomes under different production contexts [23],[25-26]. The relatively low explanatory power observed in this study may indicate the presence of additional operational factors that were not captured in the model, such as raw material characteristics, handling practices, facility conditions, and managerial responses during drying operations.

The results of correlation and regression analyses should also be interpreted differently. The bivariate correlations between temperature and drying duration with final moisture content were significant. However, the simultaneous regression model was not statistically significant. This situation may occur when correlations among predictors are relatively strong, causing overlapping information among independent variables. Therefore, the findings should be interpreted as insufficient evidence to support the applied multivariate explanatory model, rather than evidence that process and environmental conditions are unimportant in coffee drying.

3.11 Monte Carlo Simulation Results

The Monte Carlo simulation was conducted by randomly selecting one of the 88 historical records in each iteration, preserving the complete R1–R6 risk occurrence patterns, and recalculating the total risk score based on the indicator weights. This procedure maintains the risk combinations that have previously occurred, allowing the simulated output distribution to represent a resampling process of historical risk patterns. A summary of the results from 10,000 iterations is presented in Table 5.

Table 5. Monte Carlo Simulation Results

Measure	Simulation Result	Interpretation
Number of iterations	10,000	Number of generated scores
Mean of Y2	21.241	Close to the historical mean value of 21.136
Median of Y2	20	Middle value of the simulated distribution
Standard deviation	14.956	Dispersion of risk scores around the mean
Minimum–maximum	0–65	Range of simulated risk scores
P(Y2 = 0)	20.43%	Proportion of iterations with zero risk score
P(Y2 = 20)	27.97%	Most frequently occurring risk score
P(Y2 ≥ 50)	5.92%	Proportion of iterations with risk scores equal to or greater than 50

A risk score of 20 was the most frequently occurring value. appearing in 2,797 out of 10,000 iterations (27.97%). This was followed by a score of 0. which occurred in 2,043 iterations (20.43%), a

score of 15 occurring in 1,722 iterations (17.22%), and a score of 35 occurring in 1,490 iterations (14.90%). A total of 592 iterations (5.92%) generated risk scores of at least 50. This value represents the proportion of historical pattern resampling that produced scores equal to or exceeding the threshold of 50; however, this threshold does not automatically indicate a high-risk category, as risk classification requires an independently established basis.

The mean simulated risk score of 21,241 was close to the historical mean value of 21,136. Both the simulated and historical data had the same median value of 20, and the minimum–maximum score range was also identical (0–65). This consistency is in accordance with the simulation approach, which resamples historical patterns; therefore, it does not represent an independent validation of future predictive capability. The simulation demonstrates how the historical risk score distribution can be represented through repeated random sampling.

The assessment of the number of iterations showed that the mean risk score was 21,605 at 1,000 iterations. 21,168 at 5,000 iterations. and 21,241 at 10,000 iterations. The proportions of zero-risk scores were 21.70%, 20.52%, and 20.43%. respectively, while the proportion of scores equal to or greater than 50 decreased from 7.50% to 5.92% at 5,000 iterations and remained at 5.92% at 10,000 iterations. These results indicate that the compared summary statistics were relatively stable between 5,000 and 10,000 iterations. although random variation may produce slightly different results when the simulation is rerun. Since R3 was not recorded in the 88 observations, this indicator remained zero throughout all simulation iterations. This condition represents an inherent limitation of historical data resampling. To estimate unobserved risks, additional approaches are required, such as collecting longer observation periods or developing scenarios that explicitly incorporate expert judgment and probability assumptions. The inclusion of such scenarios should be distinguished from the historical data-based simulation results reported in this study. The consistency between the simulated and historical distributions confirms that historical resampling adequately represents the observed risk patterns. Similar applications of Monte Carlo simulation have been used to evaluate uncertainty and risk variability in agricultural production and food-processing systems under uncertain operating conditions [28],[30-32].

3.12 Implications for Operational Decision-Making

The integration of SSM findings, risk frequency analysis, regression analysis, and simulation results provides several complementary types of information. SSM supports the identification of actors, system boundaries, and operational issues; risk frequency analysis highlights the most frequently recorded events; regression analysis evaluates the capability of process and environmental variables to explain the outcomes; while simulation illustrates the distribution of risk scores obtained through historical pattern resampling. Each method serves a different analytical purpose, and the results should be interpreted collectively without assuming that one method replaces the others [7-10],[19].

Based on the risk frequency analysis, the initial evaluation can be directed toward R1, namely coffee cherry accumulation due to limited capacity, R6 should also be further examined because it is related to facility conditions and has previously occurred simultaneously with R1. Several actions that can be considered by management as evaluation agendas include reviewing the alignment between incoming coffee volume and drying space capacity, improving the recording of material queues, conducting periodic facility inspections, and documenting actions taken when capacity constraints occur. These actions represent managerial implications that require further verification with the operators and management, rather than interventions whose effectiveness has been empirically validated in this study.

The risks of delays due to rainfall and repeated drying processes also indicate the need for process documentation that links environmental conditions, drying duration, moisture content measurement results, and operator responses. Consistent records can improve data quality for future analyses and enable evaluation of whether risk patterns change across seasons or different material volumes. The

simulation results can assist in reviewing historical patterns associated with higher risk scores; however, they do not provide specific predictions regarding when such events will occur.

The regression models cannot yet be used as a basis for determining the optimal drying temperature or drying duration because both models were not statistically significant simultaneously and had limited explanatory power. Likewise, the simulation approach applied in this study does not compare alternative technical interventions. To develop a more operational decision support system, future research may evaluate scenarios involving incoming volume control, capacity expansion, rainfall protection measures, or alternative drying methods using appropriate datasets. The effectiveness of each alternative should be empirically tested and should not be inferred solely from historical risk score distributions.

3.13 Research Limitations

This study has several limitations. First, the dataset consisted of 88 observations collected from a single cooperative during one observation period. Therefore, the findings may not fully represent the conditions of other coffee cooperatives. Future research should include more cooperatives and longer observation periods to obtain broader data.

Second, the regression models included only five independent variables and produced relatively low R^2 values, indicating that other factors may contribute to the variation in drying outcomes and operational risk scores. High correlations were also found among several independent variables, although the VIF values were below 10. In addition, the operational risk score (Y2) was constructed from six weighted binary indicators. resulting in a discrete and bounded value ranging from 0 to 65. The use of OLS regression may not fully capture these characteristics. Future studies should consider additional variables, alternative regression methods. and approaches such as principal component analysis (PCA) to improve model performance.

Third, the risk score depends on the definitions of risk indicators and their assigned weights. Therefore, it should not be interpreted as a direct probability of risk occurrence or financial loss. Further studies are needed to validate the indicators and weighting scheme.

Fourth, the Monte Carlo simulation used historical resampling from 88 observations. Although it describes the distribution of risk scores based on historical patterns, it cannot generate new scenarios or directly evaluate operational changes. such as increasing drying capacity or prolonged rainfall. Risk R3, which was not observed during the study period, was also not represented in the simulation. Future research should develop scenario-based simulations to evaluate alternative production conditions and mitigation strategies.

Finally, this study did not evaluate the effectiveness of mitigation actions or include human and organizational factors, such as operator experience, drying practices, and corrective actions in response to weather changes. These factors may help explain the weak linear relationships between operational variables and observed risk scores. Future research should incorporate these factors and evaluate mitigation measures through field studies or simulations. Such improvements are expected to provide a more comprehensive basis for operational risk management in coffee drying processes.

4. Conclusion

This study mapped the coffee drying system at the Solok Sirukam Sepakat Producer Cooperative using the Soft Systems Methodology (SSM) approach. The development of the rich picture, CATWOE analysis, root definition, and conceptual model demonstrated that coffee drying represents a system involving multiple actors, facility capacity, material flow, and environmental constraints. This framework was used to connect the problem situation with quantitative analysis. Based on 88 observations, coffee cherry accumulation due to insufficient capacity was identified as the most frequently recorded risk event, accounting for 38.6% of observations. The risks of coffee bean damage during hulling and facility damage due to excessive capacity were each recorded at 22.7%, while delays caused by rainfall occurred in 21.6% of observations. Several risks occurred simultaneously, indicating

that operational evaluation should consider risk combinations in addition to the frequency of individual indicators.

Correlation analysis showed a weak positive relationship between drying temperature and final moisture content, as well as a weak negative relationship between drying duration and final moisture content. However, multiple linear regression analysis indicated that the five independent variables did not have a statistically significant simultaneous effect on either final moisture content or total risk score at the 5% significance level. The R^2 values of the respective models were 0.109 and 0.047, indicating that the explanatory capability of the models remained limited.

The Monte Carlo simulation with 10,000 iterations generated an average risk score of 21.241. a median value of 20. and the most frequently occurring score of 20 with a proportion of 27.97%. These results represent the distribution of risk scores obtained through historical risk pattern resampling rather than causal prediction or the development of new technical scenarios. Overall, the integration of SSM, statistical analysis, and simulation provides a framework for supporting the understanding and preliminary evaluation of operational risks in coffee drying processes. Further development of predictive models or technical optimization approaches requires additional data collection and explicit testing of alternative control strategies.

References

[1] Anggara, A. (2011). *Kopi Si Hitam Menguntungkan: Budi Daya dan Pemasaran*. Cahaya Atma Pustaka.

[2] Foreign Agricultural Service of the United States Department of Agriculture (USDA). 2024. https://www.fas.usda.gov/report-release-announcement/coffee-world-markets-and-trade-6. Diakses pada 20 Mei 2026.

[3] Shofinita, D., Lestari, D., Aliwarga, L. (2024). Drying Methods of Coffee Extracts and Their Effects on Physicochemical Properties: A Review. *Food Bioprocess Technol,* 17, 47–72.

[4] Badan Standardisasi Nasional (BSN). (2008). SNI 01-2907-2008. Biji kopi.

[5] Abreu, D. J. M., Lorenço, M. S., Machado, G. G. L., Silva, J. M., Azevedo, E. C., Carvalho, E. E. N. (2025). Influence of Drying Methods on the Post-Harvest Quality of Coffee: Effects on Physicochemical. Sensory. and Microbiological Composition. *MDPI Foods, 14*(9), 1463.

[6] Suherman, S., Widuri, H., Patricia, S., Susanto, E. E., Sutrisna, R. J. (2020). Energy Analysis of a Hybrid Solar Dryer for Drying Coffee Beans. *International Journal of Renewable Energy Development*, *9*(1), 131–139.

[7] Klerkx, L., Jakku, E., Labarthe, P. (2019). A Review of Social Science on Digital Agriculture. Smart Farming and Agriculture 4.0: New Contributions and a Future Research Agenda. *In NJAS - Wageningen Journal of Life Sciences*, 90–91, 1-16.

[8] Zhai, Z., Martínez, J. F., Beltran, V., Martínez, N. L. (2020). Decision Support Systems for Agriculture 4.0: Survey and Challenges. *In Computers and Electronics in Agriculture,* 170, 1-16.

[9] Sridevy, S., Devi, M. N., Sankar, M. (2023). Decision support systems in agricultural industry perspective. *International Journal of Statistics and Applied Mathematics*, *8*(2), 29–31.

[10] Sondhiya, R. R., Singh, V. K. (2024). Intelligent Agriculture: Integrating IOT and Machine Learning for Soil Nutrients and Crop Selection. *ShodhKosh: Journal of Visual and Performing Arts*, *5*(6), 702-714.

[11] Wattuhewa, S., Pheerathan, S. (2025). Reflective Applications of Soft Systems Methodology (SSM) Across Contexts. *Systemic Practice and Action Research*, *38*(4), 1-11.

[12] Hadi, A.H., Suprihatin., Sukardi., Pramuhadi, G., Marimin., Susantyo, B., Wahyono, E. (2023). Sustainability Concept Design of Robusta Coffee Agroindustry Kalibaru with Soft System and Decisions Support System Methods. *International Journal of Sustainable Development and Planning,* 18 (5), 1339-1350.

[13] Krisnanik, E., Muliawati, A., Tri Wahyono, B., Rahayu, T. (2025). Evaluating a Regional Yield Potential System using the CATWOE Analysis and UCD Approach. *International Journal of Informatics and Computation (IJICOM), 7*(2), 1-13.
[14] González, L. M. S., Vargas, L. A. O., Ruelas, V. A. M. (2021). Evaluation of the soft systems methodology of the chain productive coffee in Guerrero. *Revista Mexicana Ciencias Agrícolas,* 12 (4), 727-734.
[15] Fadhil, R., Maarif, M. S., Bantacut, T., Hermawan, A. (2018). Situational Analysis and Intervention Strategy for Gayo Coffee Agroindustry Institution in Indonesia. *Journal of Food Agriculture and Environment*, *16*(1).
[16] Fadhil, R., Qanytah, Q., Hastati, D. Y., Maarif, M. S. (2018). Development Strategy for a Quality Management System of Gayo Coffee Agro-industry Using Soft Systems Methodology. *Periodica Polytechnica Social and Management Sciences*, *26*(2), 168–178.
[17] Sundana, S., Raharja, S. (2022). Arabica Coffee Agroindustry Supply Chain Strategy in Bandung Regency. *IOP Conference Series: Earth and Environmental Science*, *1063*(1), 1-9.
[18] Arayawut, S., Tan, C. C. (2019). A Community-Based Case Study Of Sustainability-Missioned Speciaty Coffee Farming Business Practice: A Soft-Systems Methodology (SSM) Guide. *Proceedings of the International Conference on Global Trends in Management Economics. Law & Social Sciences – Thailand 2019.*
[19] Effendi, M., Santoso, I., Astuti, R., Mahmudy, W. F. (2026). Systemic framework for coffee roasting decision support in Malang Regency using soft systems methodology. *Advances in Food Science. Sustainable Agriculture and Agroindustrial Engineering (AFSSAAE) 2026,* 9(2), 168-177.
[20] Triyanto, E., Sismoro, H., Laksito, A. D. (2019). Implementasi Algoritma Regresi Linear Berganda untuk Memprediksi Produksi Padi di Kabupaten Bantul. *RABIT (Jurnal Teknologi dan Sistem Informasi Univrab),* 4(2), 66-75.
[21] Maharadja, A. N., Maulana, I., Dermawan, B. A. (2021). Penerapan Metode Regresi Linear Berganda untuk Prediksi Kerugian Negara Berdasarkan Kasus Tindak Pidana Korupsi. *In Journal of Applied Informatics and Computing (JAIC),* 5(1),95-102.
[22] Arfah, A., Putra, A.H.P.K. (2020). Factors Affecting The Export of Coffee In South Sulawesi Province. *Point of View Research Economic Development,* 1(3), 39-50.
[23] Bekele, A., Guadie, T. (2020). Multiple Linear Regression Analysis on Factors Affecting Coffee Production in Bench-Shako Zone: In Case of Mizan-Aman District. Southwest Ethiopia. *Advances in Bioscience and Bioengineering,* 8(2), 24-30. doi: 10.11648/j.abb.20200802.13
[24] Musa, Y., Iswoyo, H., Sarif, L., Herdjiono, M. V. I. (2019). Analysis on correlation of cultivation practices on production of Arabica coffee. *ICROEST. IOP Conf. Series: Earth and Environmental Science 343* 012027. d
[25] Utomo, B., Soedarto, T., Winarno, S. T., Hendrarini, H. (2025). Predicting the Success of Coffee Farmer Partnerships Using Factor Analysis and Multiple Linear Regression. *Acadlore Publishing Services Limited., Hong Kong*, 11(1), 61-71.
[26] Gunaryati, A., Mantoro, T., Andryana, S., Benrahman., Wahyuddin, M. I. (2025). Enhancing Coffee Production Factor Assessment Using Linear Regression And Ahp For Reliable Weight Consistency. *Jurnal Ilmu Pengetahuan dan Teknologi Komputer (JTIK)*, 11(2), 478-486.
[27] Gulo, D. R. P. (2022). Information System Design in Predicting Production Quantity with the Monte Carlo Method. *Journal of Computer Science and Information Technology*, 8 (1), 17-21.
[28] Ovalle-Rivera, O., Van Oijen, M., Läderach, P. (2020). Assessing the accuracy and robustness of a process-based model for coffee agroforestry systems in Central America. *Agroforest Syst 94,* 2033–2051.
[29] Manik, M. B. B., Nasution, P. K., Suyanto, S., Yanti, M. (2024). Kajian Metode Simulasi Monte Carlo. *Journal of Mathematics Computations and Statistics*, *7*(2), 232–242.

[30] Mahmudiono, T., Yasin, G., Jasim, S. A., Alghazali, T. A. H., Khadim, M. M., Iswanto, A. H., Majeed, M. S., Sharma, S., Al-Mawlawi, Z. S., Panduro-Tenazoa, N. M. (2022). Analyzing Food Production Risk with Monte Carlo Simulation. *Food Science and Technology*, 42, 1-5.
[31] Ferreira, H. A., Liska, G. R., Cirillo, M. A., Borém, F. M., Ribeiro, D. E., Cortez, R. M. (2021). Monte Carlo simulation and importance sampling applied to sensory analysis validation of specialty coffees. *Scientific Article.Rev. Ciênc. Agron,* 52 (2).
[32] Habdillah, H., Na'am, J. (2024). Simulasi Monte Carlo untuk Estimasi Pengadaan ATK (Studi Kasus di Institut Teknologi Padang). *Jurnal Teknoif Teknik Informatika Institut Teknologi Padang*, 12 (1), 56–61.
[33] Chauvet, G. (2025). A Review Of Bootstrap Methods For Survey Sampling. *The Survey Statistician,* 91, 14–25.
[34] Ritonga, U. S. (2023). Analisis Soft System Methodology Pembangunan Agroindustri Pangan Berbasis Pengembangan UMKM di Indonesia. *Jurnal Riset Ilmu Ekonomi*, 2(3), 110–129.