

Multi-Objective Chili Pepper Production Optimization Using HSA Under Price and Rainfall Variability

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Abstract: Chili pepper production faces uncertainty associated with price dynamics and agroclimatic conditions, particularly rainfall variability. This study develops a multi-objective optimization model based on the Harmony Search Algorithm (HSA) to determine chili pepper production levels while considering gross revenue, exposure to rainfall deviations, and total production. The analysis uses 36 monthly periods from January 2022 to December 2024. Three objective functions are formulated: maximizing gross revenue, minimizing exposure to rainfall deviations, and maximizing total production. The reported HSA run, using 1,000 iterations, produced a fitness value of 0.6537, with gross revenue of Rp462.463.225.492.496,44, rainfall-deviation exposure of 804.788.341,60, and total production of 9.158.801,66 tons. The corresponding normalized objective values were 0.8165, 0.3476, and 0.7969. A post-hoc sensitivity analysis of the objective weights shows that the aggregated fitness changes when greater emphasis is placed on revenue, rainfall exposure, or production, indicating that the equal-weight solution should be interpreted as one compromise specification rather than a unique optimum. Because annual FAOSTAT production was evenly disaggregated into monthly baseline values, the production series has limited temporal variation (CV 0.56%); consequently, correlation and regression results should be interpreted as exploratory rather than as evidence of actual monthly causal relationships. The HSA was executed once in the original analysis; therefore, no statistical claim of algorithmic superiority or solution stability is made. The proposed model provides a framework for integrating economic and agroclimatic considerations into chili production planning, subject to these data and computational limitations.

Keywords: Chili Pepper; Harmony Search Algorithm; Mathematical Model; Multi-Objective Optimization; Rainfall

INTRODUCTION

Chili peppers (*Capsicum annuum* L.) are one of Indonesia's strategic horticultural commodities, making a significant contribution to food security, farmers' incomes, and the stability of national food inflation. Unlike most other food commodities, chili peppers are perishable, have a relatively short harvest season, and are highly sensitive to changes in environmental conditions, leading to high production and price fluctuations. These conditions make chili peppers one of the main contributors to food inflation in Indonesia, as even relatively small changes in production can trigger significant price spikes. (Susanawati, 2021) (Jamhari, Nasir, Nugroho, Ismiasih, & Yonekura, 2022) (Indriyana, Taridala, & Yusria, 2025).

Chili pepper production is influenced by the interaction of various agroclimatic and economic factors. Among these agroclimatic factors, rainfall is one of the most critical variables because it affects vegetative growth, flowering, fruit set, and the intensity of pest and disease outbreaks. Rainfall exceeding optimal conditions increases environmental humidity, leading to flower drop, increased fungal infections, and reduced crop productivity. On the other hand, the decline in production resulting from these climatic conditions directly affects the balance between supply and demand, thereby triggering a rise in chili prices. Various studies indicate that rainfall and price are the two dominant factors influencing the dynamics of chili production in Indonesia. (Nugroho, Ardhitama,

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Sartohadi, Qadafi, Siswoko, & Al Adilah, 2025) (Indriyana, Taridala, & Yusria, 2025) (Widowati, Dhamira, Anggrasari, & Seleky, 2023) (Wasita, Hidayat, & Suprehatin, 2025).

On the other hand, research on chili pepper production during the 2019 – 2025 period has focused primarily on analyzing the relationship between climatic factors particularly rainfall and crop productivity, as well as the relationship between production and prices, using statistical and econometric approaches and forecasting methods. (Nugroho, Ardhitama, Sartohadi, Qadafi, Siswoko, & Al Adilah, 2025) shows that rainfall is one of the main factors affecting chili pepper productivity, whereas (Prihandi, Wijono, Sembiring, & Maria, 2025) reported that changes in production due to weather conditions directly affect fluctuations in chili prices. Other studies have also shown that chili is a horticultural commodity with a high level of price volatility due to changes in supply and climatic conditions (Macias-Bobadilla, Vargas-Hernandez, Guevara-Gonzalez, Rico-Garcia, Ocampo-Velazquez, & Torres-Pacheco, 2020) (Adekaldy, Amponsah, Tuffour, Adu, & Agyare, 2021); (Lestari, Prajanti, Wibawanto, & Adzim, 2022) (Jamhari, Nasir, Nugroho, Ismiasih, & Yonekura, 2022) (Wasita, Hidayat, & Suprehatin, 2025). However, these studies generally only describe the relationships between variables without producing an optimization model capable of providing recommendations for optimal production decisions. Furthermore, rainfall as an agroclimatic factor and chili prices as an economic factor are still analyzed separately, even though these two variables interact with one another in determining the productivity, profitability, and risks of chili farming.

The complexity of the relationship between production, price, and rainfall means that chili pepper production planning can involve several objectives, such as increasing production value, maintaining production levels, and minimizing exposure to adverse rainfall conditions. Therefore, a multi-objective optimization approach is relevant because it can represent these objectives simultaneously. (Begam, Jain, Arora, & Marwaha, 2023) (Li, Zhang, & Huo, 2023) (Moges, Lema, & Berhanu, 2026).

Research on multi-objective optimization in the agricultural sector has advanced rapidly through the application of various metaheuristic algorithms and uncertainty-based optimization approaches. Research conducted by (Ullah & Nehring, 2021) utilized the Non-dominated Sorting Genetic Algorithm II (NSGA-II) mathematical model for irrigation water allocation optimization, as well as various fuzzy optimization approaches, such as Fuzzy Credibility-Based Multi-Objective Optimization (Li, Zhang, & Huo, 2023), Type-2 Fuzzy Chance-Constrained Programming (T2FCCP) (Zhang & Yang, 2022), and the Intuitionistic Fuzzy Multi-Objective Cropland Allocation Problem (MOCLAP) (Moges, Lema, & Berhanu, 2026). According to (Randall, Schiller, Lewis, Montgomery, & Alam, 2024), a systematic review of crop planning optimization indicates that agricultural optimization objectives are most commonly related to maximizing revenue and yield and minimizing water use, while some studies are beginning to integrate environmental factors and climate change. These findings suggest that a multiobjective optimization approach is appropriate for representing the trade-offs between economic interests, productivity, and environmental risks. Although these studies have successfully improved the efficiency of water use, land allocation, and economic returns, they generally remain focused on agricultural resource management and have not specifically accommodated the characteristics of horticultural commodities such as chili peppers which exhibit high volatility in both production and price. To solve the formulated multi-objective optimization problem, a metaheuristic algorithm is needed that can explore the solution space flexibly without relying on a highly specific form of the objective function. The Harmony Search Algorithm (HSA) is a metaheuristic algorithm that operates through a mechanism inspired by musical harmony and utilizes Harmony Memory, Harmony Memory Considering Rate (HMCR), Pitch Adjusting Rate (PAR), and Bandwidth (BW) in the process of generating new solutions. according to (Gregorio, Mateos, Hernández, & Zavaleta, 2021) A systematic review has shown that HSA has a relatively simple structure, is easy to implement, and is capable of maintaining a balance between exploration and exploitation during the search for solutions. According to (Li, Zhang, & Huo, 2023), HSA and its various variants have been applied to a wide range of real-world optimization problems, although the basic algorithm still faces potential premature convergence and accuracy limitations in complex problems. HSA has also been applied to agricultural problems, specifically for harvest scheduling, where the algorithm is capable of determining decision-making solutions by considering various production constraints and achieving performance comparable to GAMS-based solutions (Nensi, Pangesti, Syukri, Maida, & Notodiputro, 2025). Further developments in HSA have shown that adaptively adjusting HMCR and PAR can improve the exploration–exploitation balance and enhance convergence speed as well as the solution’s resistance to local optimal (Zhang & Yang, 2022). Based on these characteristics, the HSA was selected in this study as the solution search engine to obtain a compromise solution for chili pepper production that simultaneously considers economic benefits, production levels, and risks associated with rainfall variability.

Although research on chili price volatility, the impact of agroclimatic conditions on production, multi-objective agricultural optimization, and the application of Harmony Search has advanced, these four aspects are still largely studied in isolation. Research on agricultural optimization has shown that a multi-objective approach can address conflicts between economic objectives, resource use, and environmental risks, while Harmony Search-based research demonstrates its ability to find solutions to complex optimization problems. However, based on the literature review conducted, there is still limited research that simultaneously treats chili pepper production as a

decision variable by integrating chili pepper prices as an economic factor and rainfall as an agroclimatic factor into a single multiobjective optimization mathematical model. These limitations highlight the need to develop an approach that not only explains the relationship between price, climate, and production but is also capable of generating production decisions that adapt to changing market and environmental conditions. Therefore, this study develops a multi-objective optimization mathematical model based on the Harmony Search Algorithm (HSA), with chili pepper production as the decision variable and three main objectives: maximizing production value or gross revenue, maximizing production, and minimizing exposure to rainfall deviations. These three objectives are combined through a weighted fitness function and solved using HSA to obtain a compromise solution for chili production levels in each observation period. With this approach, this study not only analyzes the relationships between price, rainfall, and production but also translates them into quantitative decisions regarding production levels that can be adjusted to changes in economic and agroclimatic conditions. This approach is expected to provide a data-driven decision-making framework for chili production planning and to support increased productivity and resilience of the chili production system in Indonesia.

LITERATURE REVIEW

Multi-objective optimization is increasingly used in agricultural planning because production decisions typically involve several conflicting objectives, such as profit, productivity, resource efficiency, and environmental impact. Previous studies have applied approaches such as NSGA-II, MOPSO, and fuzzy multi-objective optimization to obtain compromise solutions in agricultural resource management (Ullah & Nehring, 2021) (Zhang & Yang, 2022) (Begam, Jain, Arora, & Marwaha, 2023) (Li, Zhang, & Huo, 2023). However, most of these studies have focused on water, irrigation, and resource efficiency, and have not specifically addressed optimizing chili pepper production levels by simultaneously considering economic and agroclimatic factors.

Table 1. Comparison of Previous Studies

Study	Method	Focus	Research Gap
(Ullah & Nehring, 2021)	NSGA-II	Water and environmental efficiency	Does not focus on chili pepper production
(Zhang & Yang, 2022)	T2FCCP	Profit and risk	Does not simultaneously integrate price and rainfall
(Begam, Jain, Arora, & Marwaha, 2023)	MOPSO	Profit and water requirements	Does not focus on chili pepper production
(Li, Zhang, & Huo, 2023)	Fuzzy Multiobjective	Profit, water, and emissions	Does not focus on chili pepper production
(Nugroho, Ardhitama, Sartohadi, Qadafi, Siswoko, & Al Adilah, 2025)	Regression	Rainfall and chili pepper production	Focuses on relationship analysis rather than optimization-based decision-making
(Prihandi, Wijono, Sembiring, & Maria, 2025)	ARIMA	Price and production	Predictive in nature
(Li, Zhang, & Huo, 2023)	Hybrid HSA	Irrigation networks	Focuses on irrigation systems

For chili peppers, price and rainfall are factors that influence production trends. According to (Nugroho, Ardhitama, Sartohadi, Qadafi, Siswoko, & Al Adilah, 2025). There is a correlation between rainfall and chili pepper production, while (Prihandi, Wijono, Sembiring, & Maria, 2025) used a forecasting approach to analyze price and production dynamics. Although these approaches provide information on the relationships and patterns of change among variables, they have not yet yielded optimal production levels for each period. Thus, there remains a need to transform this economic and agroclimatic information into production decisions through an optimization approach. The Harmony Search Algorithm (HSA) has been used to solve various agricultural optimization problems, particularly in irrigation management and resource allocation (Fadare, Agele, & Ajayi, 2025) (Li, Zhang, & Huo, 2023). The HSA's ability to search for solutions in complex decision spaces makes it relevant to agricultural production problems. However, the application of the HAS which integrates revenue, total production, and rainfall variability as optimization objectives in chili pepper production remains limited.

Based on previous research, the research gap in this study lies in the lack of integration of economic, productivity, and agroclimatic aspects into a single chili pepper production optimization model. Previous studies have tended to analyze or predict the relationship between price, rainfall, and production, while optimization studies have focused more on water, irrigation, and resource allocation. This study addresses this gap by using production as the decision variable and integrating price, rainfall, and production into a multiobjective optimization model.

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The main contribution of this study is the development of a multiobjective Harmony Search model that simultaneously maximizes production/revenue, maximizes total production, and minimizes exposure to rainfall variability. This approach yields production levels that can adaptively vary across periods, thereby not only focusing on maximum production but also taking economic and agroclimatic conditions into account. Thus, this study offers a more integrated and adaptive decision-making framework for chili pepper production.

METHOD

Data and Data Sources

This study uses secondary data from 2022–2024 covering chili prices, rainfall, and chili production. Chili price data were collected as monthly averages at the farmer level (Rp/kg), while rainfall data were collected as monthly accumulations (mm/kg). National chili pepper production data (tons) were obtained in the form of annual data for the 2022–2024 period. Differences in the temporal frequency among variables were a key consideration during the data preparation stage to ensure that all variables had the same temporal resolution before being used in the analysis and optimization. The data were obtained by integrating three official data sources, namely chili pepper prices from Bank Indonesia's National PIHPS <https://www.bi.go.id/hargapangan/TabelHarga/PasarTradisionalKomoditas>, Rainfall data from NASA POWER <https://power.larc.nasa.gov/data-access-viewer/>, and chili pepper production from FAOSTAT <https://www.fao.org/faostat/en/#data/QCL>.

Since FAOSTAT production data are available on an annual basis, data cleaning and temporal adjustments were performed to align the production time resolution with the monthly price and rainfall data. The data cleaning process included checking data formats, adjusting observation periods, ensuring unit consistency, handling missing values, and removing duplicate data. Furthermore, since FAOSTAT production data is available on an annual basis, temporal disaggregation was performed by dividing the total annual production evenly across the 12 months of the same year. Mathematically, the monthly baseline production is calculated as:

$$Y_{y,m} = \frac{Y_y}{12} \quad (1)$$

Notes:

Y_y = Total national chili pepper production in year y according to FAOSTAT (tons);

$Y_{y,m}$ = Baseline production for month m in year y (tons), where $m = 1, \dots, 12$

With this approach, the baseline production for the twelve months of the same year has the same value, while month-to-month variations are represented through changes in monthly prices and rainfall. This baseline production is used as a historical reference value, not as an observation of actual monthly production. The results of this stage produce an integrated dataset comprising 36 monthly periods from January 2022 to December 2024, which is subsequently used for exploratory analysis, analysis of relationships between variables, and the formulation of optimization models.

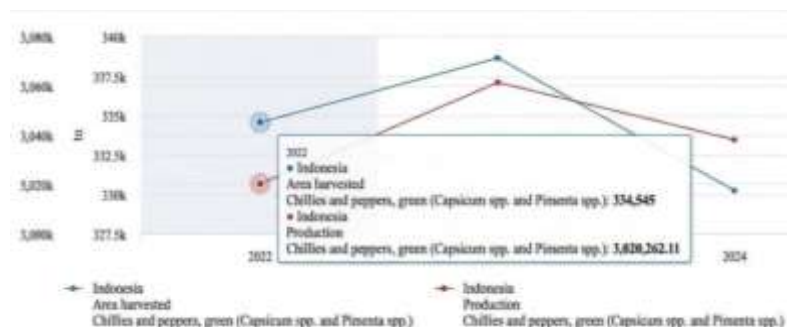


Figure 1. Production conditions and harvested area of green chili peppers in Indonesia in 2022

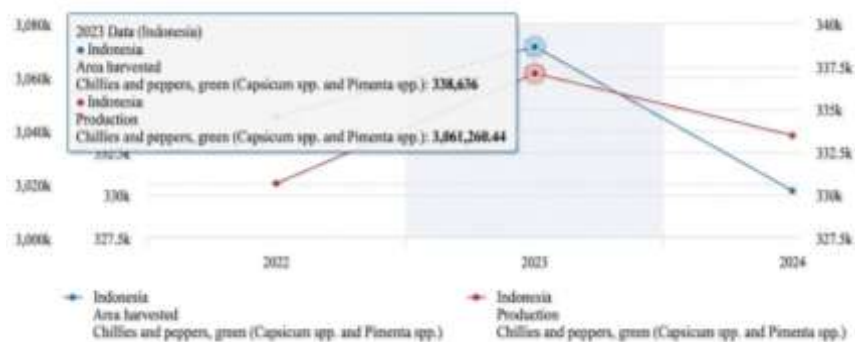


Figure 2. Production conditions and harvested area of green chili peppers in Indonesia in 2023

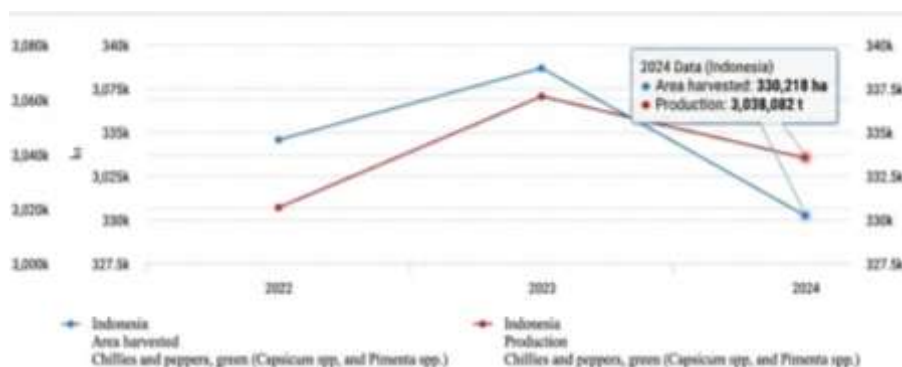


Figure 3. Production conditions and harvested area of green chili peppers in Indonesia in 2024

Based on the graphs showing green chili production and harvested area in Indonesia for the 2022–2024 period (Figures 1, 2, and 3), it can be seen that chili production increased from 2022 to 2023, then declined again in 2024. The highest production occurred in 2023 with a total of approximately 3,061,260 tons, while the lowest production occurred in 2022 at approximately 3,020,262 tons. A similar pattern is also evident in the harvested area, which increased in 2023 to approximately 338,636 hectares and then declined again in 2024.

Research Phases

The operational design of this study was structured through nine systematic and interconnected stages. The process begins with data collection from official sources, followed by data cleaning and identification of missing values or outliers. The third stage applies linear interpolation where required, followed by Exploratory Data Analysis (EDA). Pearson correlation analysis is then conducted, with two-sided p-values reported, followed by multiple linear regression as an exploratory analysis. Regression diagnostics include the coefficient of determination, joint significance, residual normality indicators, and the Durbin-Watson statistic to assess serial dependence. The empirical analysis is used only as supporting evidence for the model formulation, not as a causal or predictive production model. The multi-objective mathematical model is then formulated and solved using HSA in Google Colab. Because the original computational experiment used a single HSA run, the study does not make a statistical claim of algorithmic superiority or solution stability. A post-hoc sensitivity analysis of the objective weights is added to assess how the aggregation value changes under alternative weighting specifications.

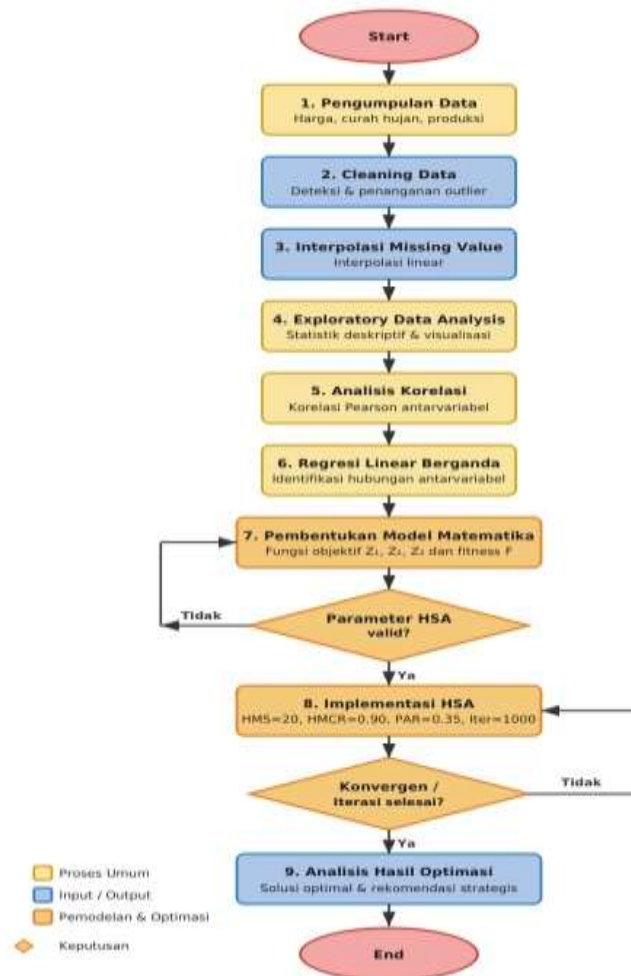


Figure 4. Flowchart of the research and HSA implementation stages for chili pepper production optimization
Multiple Linear Regression Model

The multiple linear regression model used in this study was employed to determine the relationship between chili prices and rainfall on chili production. The regression model uses chili price and rainfall (R_t) as variables that consistently influence productivity at harvest. In general, the multiple linear regression model is formulated as follows:

$$Y_t = \beta_0 + \beta_1 H_t + \beta_2 R_t + \varepsilon_t$$

Note:

Y_t = Chili production in period $-t$

β_0 = Regression constant

β_1 = Chili price coefficient

β_2 = Rainfall coefficient

H_t = Chili price in period $-t$

R_t = Rainfall in period $-t$

ε_t = Model error or disturbance term in period $-t$

This regression model is used as a first step to measure the sensitivity of production to macroeconomic variables, which then serve as input parameters in the HAS fitness function.

Multi-Objective Optimization Mathematical Model

In the model formulation, historical parameters and decision variables are explicitly distinguished. The chili price P_t and rainfall R_t are used as monthly parameters representing economic and agroclimatic conditions in period t . Production $Y_{y,m}$ is the baseline production obtained from annual FAOSTAT data through a process of temporal disaggregation, while x_t is the decision variable that determines the level of chili production recommended by the optimization model. Model parameters are values obtained from historical data or determined

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based on system characteristics and kept constant throughout the optimization process, whereas x_t is the value being sought and adjusted by the Harmony Search Algorithm to obtain the optimal production recommendation. This distinction is necessary to ensure that historical baseline production is not equated with the optimal production level generated by the model.

Model Parameters:

$$P_t, R_t, Y_{y,m}, \bar{R}$$

Note:

P_t = Chili price in period $-t$ (Rp/kg);

R_t = Rainfall in period $-t$ (mm/month);

$Y_{y,m}$ = Baseline period in month m of year y (tons);

$\bar{R}$ = Historical average rainfall over the past 36 months (mm/month);

Decision Variables:

x_t = optimal chili pepper production at period t (tons)

Dengan,

$t = 1, 2, \dots, 36$

Where t denotes the month of observation from January 2022 to December 2024

Objective Function:

1. Objective Function for Maximize production value or gross revenue

$$\max Z_1 = \sum_{t=1}^T 1000P_t x_t \quad (2)$$

2. Objective Function for Minimizing Production Exposure to Rainfall Deviations

$$\bar{R} = \frac{1}{36} \sum_{t=1}^T R_t \quad (3)$$

$$\min Z_2 = \sum_{t=1}^T x_t \cdot |R_t - \bar{R}| \quad (4)$$

3. Recommended Objective Function for Maximizing Total Chili Pepper Production

$$\max Z_3 = \sum_{t=1}^T x_t \quad (5)$$

Constraint Functions:

4. Non-Negative Production Constraints

$$x_t \geq 0 \quad (6)$$

5. Production Capacity Constraints Based on Historical Data

$$Y_{min} \leq x_t \leq Y_{max} \quad (7)$$

Where:

$$Y_{min} = \min(Y_{y,m}) \quad (8)$$

$$Y_{max} = \max(Y_{y,m}) \quad (9)$$

With:

Z_1 = Total production value during the observation period (Rp);

Z_2 = Total production exposure to rainfall deviation (metric tons/month);

Z_3 = Recommended total chili pepper production (ton);

T = The observation period was 36 months;

1000 = Conversion factor from metric tons to kilograms;

R_{max} = The maximum amount of rainfall that chili plants can tolerate

Y_{min} = Minimum chili pepper production limits based on historical data

Y_{max} = Maximum chili pepper production limits based on historical data

Objective function Z_1 aims to maximize production value or gross revenue based on recommended prices and production levels, without taking production costs into account. Objective function Z_2 aims to minimize production exposure to rainfall variability based on the absolute deviation from the historical average, such that larger deviations in rainfall result in higher agroclimatic exposure. The objective function Z_3 aims to maximize the recommended total production, while keeping x_t within the model's constraints and taking into account production values and rainfall deviation exposure. Constraint (6) ensures that the recommended production is not negative, while constraint (7) limits the optimal production level to remain within the range of historical baseline production. Thus, the HSA does not produce solutions that fall outside the observed production characteristics during the study period.



Normalization of Objective Functions

The three objective functions have different objectives and units. Z_1 and Z_3 are maximization functions, while Z_2 is a minimization function. Furthermore, Z_1 is expressed in Rupiah, while Z_2 and Z_3 have different units. Therefore, normalization to the range $[0,1]$ is required to convert the values of each objective function to the same scale before aggregation is performed using the weighted sum method.

6. Production value

$$N_1 = \frac{Z_1 - Z_1^{\min}}{Z_1^{\max} - Z_1^{\min}} \quad (10)$$

7. Overview of Rainfall Deviations

$$N_2 = \frac{Z_2^{\max} - Z_2}{Z_2^{\max} - Z_2^{\min}} \quad (11)$$

8. Total Production

$$N_3 = \frac{Z_3 - Z_3^{\min}}{Z_3^{\max} - Z_3^{\min}} \quad (12)$$

With:

$$0 \leq N_1, N_2, N_3 \leq 1$$

A value of $N = 1$ indicates that the solution achieves the optimal value for the objective function, while $N = 0$ indicates the lowest value within the range of solutions used for comparison.

Multi-Objective Aggregation Function

The three normalized objective functions are then combined using the weighted sum method to form the fitness function:

$$F(x) = w_1 N_1 + w_2 N_2 + w_3 N_3 \quad (13)$$

$$w_1 + w_2 + w_3 = 1, w_i \geq 0 \quad (14)$$

Dengan:

F = Optimization Aggregation Value

w_1, w_2, w_3 = the weight of each objective function

In this study, the three objective functions are assigned equal weights, namely:

$$w_1 = w_2 = w_3 = \frac{1}{3} \quad (15)$$

The fitness function $F(x)$ represents the overall performance of a production solution based on three normalized objectives. A higher value of $F(x)$ indicates a better solution in terms of achieving a balance between production value, low exposure to rainfall deviations, and production rate. This aggregation function is then used as the fitness function in the search process using the harmony search algorithm.

Implementation of the Harmony Search Algorithm

The Harmony Search Algorithm (HSA) is used as a search method to obtain a compromise solution that maximizes the aggregation function $F(x)$. The Harmony Memory is formed using feasible solutions within the specified production constraints; then, new harmonies are generated based on HMCR and PAR, evaluated using the fitness function, and used to replace the worst solution if they yield a higher fitness value. The HSA parameters are set as follows: HMS = 20, HMCR = 0,90, PAR = 0,35, and a maximum of 1.000 iterations. The solution with the highest fitness at the end of the process is designated as the optimal production level x^* .

$$x^* = \arg \max_{x \in \Omega} F(x) \quad (16)$$

Where Ω is the set of solutions that satisfy all the model's constraints.

RESULT**Exploratory Data Analysis (EDA)**

EDA was conducted to understand the characteristics of the data using descriptive statistics, time-series graphs, scatter plots, and correlation heatmaps. The results of the descriptive statistical analysis of the three research variables are presented in Table 3 below.

The EDA results show that chili prices averaged Rp50.480,56/kg with a CV of 21,77%, while rainfall averaged 200,02 mm/month with a CV of 53,01%. This indicates that rainfall exhibits higher variability than prices. Baseline production averaged 253,322.35 tons per month with a CV of 0,56%. The low variation in production is a consequence of disaggregating annual FAOSTAT production data into 12 months and using it as a baseline in the optimization process. The variability of prices and rainfall subsequently serves as the basis for integrating economic and agroclimatic aspects into the multi-objective optimization model. Thus, temporal

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variation in the dataset is primarily represented by changes in prices and rainfall, while baseline production serves as a historical reference in the optimization process

Table 2. Descriptive Statistics for the Research Variables

Variabel	N	Mean	Std. Deviasi	Minimum	Median	Maximum	CV (%)
Price (IDR/kg)	36	50480.56	10990.94	33150.00	49675.00	77300.00	21.77
Rainfall (mm/month)	36	200.02	106.04	4.72	196.79	403.48	53.01
Baseline Production (tons)	36	253322.35	1418.60	251688.50	253173.50	253173.50	0.56

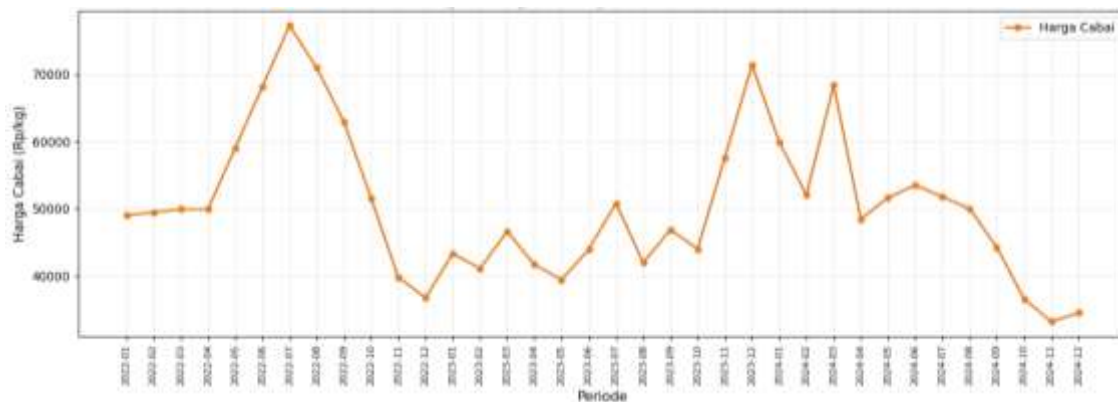


Figure 5. Graph of chili pepper price trends for the 2022–2024 period

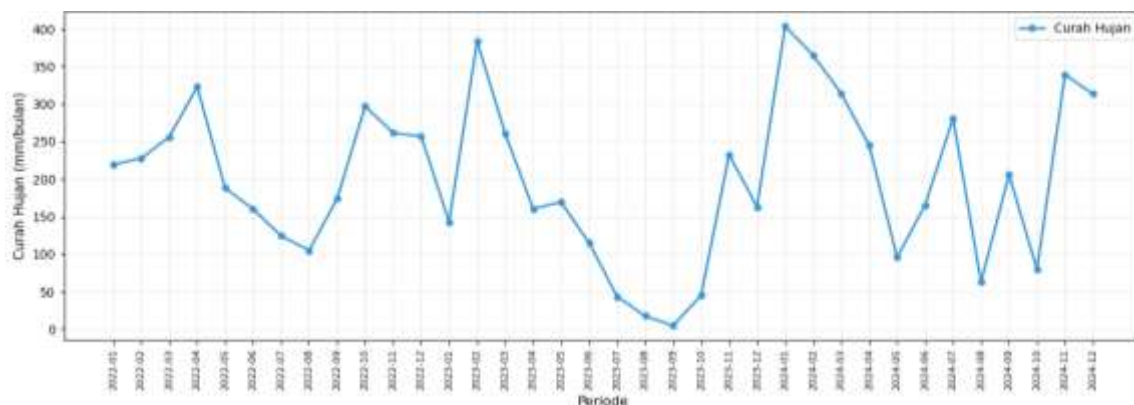


Figure 6. Rainfall trend graph for the 2022–2024 period

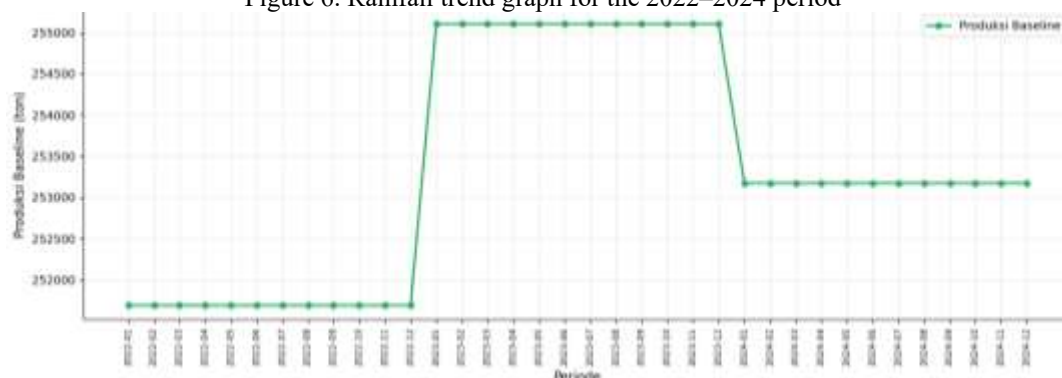


Figure 7. Baseline chili pepper production trend graph for the 2022–2024 period

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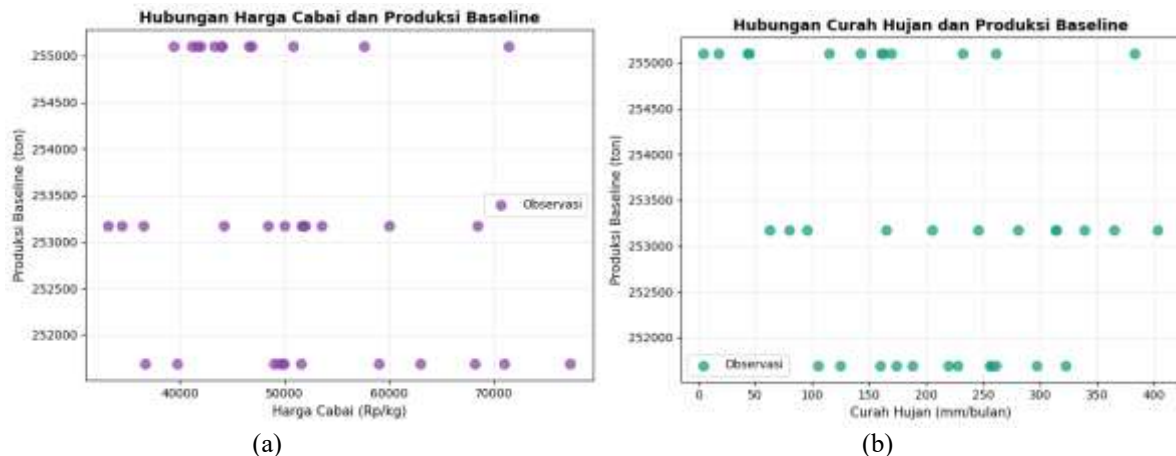


Figure 8. Scatter Plot of Chili Prices versus Baseline Chili Production (a) Figure 9. Scatter Plot of Rainfall versus Baseline Chili Production (b)

Based on Figures 5, 6, and 7, the scatter plot shows three baseline production groups representing annual production levels, while prices vary across periods. No strong linear pattern is evident between prices and baseline production. This is because the baseline production figures were derived from the disaggregation of annual FAOSTAT data; therefore, the graphs are used for exploratory purposes rather than as evidence of a causal relationship. Based on the scatter plots (Figures 8 and 9), the distribution of observations shows considerable variation in prices and rainfall, while baseline production forms three clusters corresponding to annual production levels. No clear linear pattern is observed between either prices or rainfall and baseline production. These results are used for exploratory analysis, while prices and rainfall deviations are subsequently integrated into the objective functions Z_1 and Z_2 .

Correlation Analysis

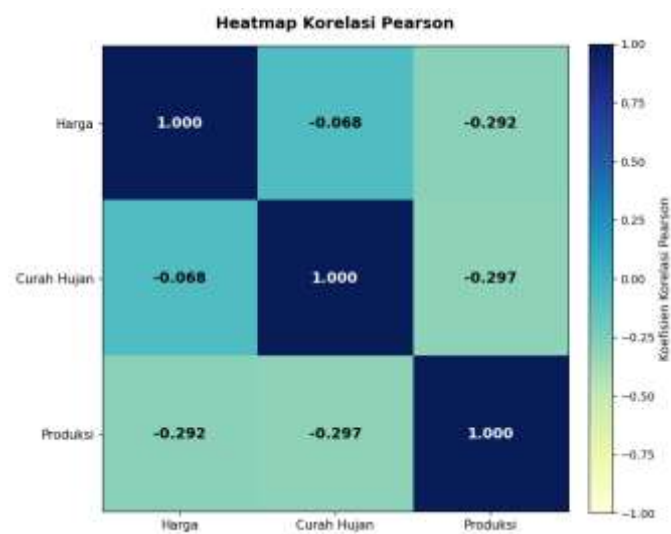


Figure 10. Heat Map of Variable Correlations

Pearson's correlation analysis (Figure 10) shows a weak negative relationship between chili prices and baseline production ($r = -0.292$, two-sided $p = 0.084$) and between rainfall and baseline production ($r = -0.297$, two-sided $p = 0.079$). The correlation between price and rainfall is very weak ($r = -0.068$, $p = 0.694$). Thus, none of the pairwise Pearson correlations is statistically significant at the 5% level for $n = 36$. These results should be interpreted cautiously because the production series was constructed by evenly disaggregating annual FAOSTAT totals into monthly baseline values. Consequently, the correlations primarily describe the association between price/rainfall and an artificial monthly baseline rather than actual observed monthly production. In the optimization model, price is used in the production-value objective, whereas agroclimatic conditions are represented by the deviation of rainfall from the historical average in function Z_2 . These findings are supported by (Prihandi, Wijono, Sembiring, & Maria, 2025), (Lestari, Prajanti, Wibawanto, & Adzim, 2022), and (Wasita, Hidayat, & Suprehatin, 2025). Meanwhile, the negative relationship between rainfall and production indicates that high rainfall

can reduce chili productivity due to increased humidity, which triggers diseases and disrupts plant growth, as shown in studies by (Nugroho, Ardhitama, Sartohadi, Qadafi, Siswoko, & Al Adilah, 2025), (Widowati, Dhamira, Anggrasari, & Selek, 2023) and (Abdila, Nugroho, & Setyawan, 2022).

Results of Multiple Linear Regression

The multiple linear regression model developed using chili pepper production as the dependent variable and chili pepper price and rainfall as independent variables yields the following equation:

$$Y_t = 256105,95 - 0,0405H_t - 4,2591R_t$$

The multiple linear regression model was used as an exploratory analysis rather than as a predictive or causal model. Figure 11 reports $R^2 = 0.186$ and an overall F-test p-value of 0.0334. The price coefficient is negative ($\beta = -0.0405, p = 0.055$), while the rainfall coefficient is negative ($\beta = -4.2591, p = 0.051$). Thus, although the overall model is statistically significant at the 5% level, the individual coefficients are close to but above the 5% threshold. Importantly, the Durbin-Watson statistic is 0.373, indicating substantial positive serial dependence in the residuals, while the Omnibus test gives $p = 0.048$. These diagnostics indicate that the classical OLS assumptions are not fully satisfied for the 36-month series. Accordingly, the regression results are not used to claim causal effects or to provide monthly production forecasts; they are retained only as exploratory evidence supporting the inclusion of price and rainfall as dimensions in the optimization model. These results are consistent with those of (Widowati, Dhamira, Anggrasari, & Selek, 2023), who also demonstrated a significant influence of climatic factors on production. The coefficient of determination ($R^2 = 0.186$) indicates that price and rainfall together explain 18,6% of the variation in production, while the remainder is influenced by other factors such as soil conditions, variety, cultivation techniques, pest and disease infestations, and socioeconomic factors.

The regression coefficients are therefore interpreted only as exploratory associations. The price and rainfall variables are incorporated into the optimization model through the gross-revenue and rainfall-deviation objectives, respectively. Given the low variation of the baseline production series and the detected serial dependence, the regression should not be interpreted as evidence that observed monthly production responds directly to price or rainfall. This qualification has been added to the limitations and discussion sections. This relationship is consistent with the findings of (Nugroho, Ardhitama, Sartohadi, Qadafi, Siswoko, & Al Adilah, 2025) (Widowati, Dhamira, Anggrasari, & Selek, 2023) (Abdila, Nugroho, & Setyawan, 2022) and (Indriyana, Taridala, & Yusria, 2025) (Wasita, Hidayat, & Suprehatin, 2025). Subsequently, the three objective functions production value, rainfall deviation exposure, and total production are aggregated and optimized using the Harmony Search Algorithm.

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OLS Regression Results						
Dep. Variable:	Produksi	R-squared:	0.186			
Model:	OLS	Adj. R-squared:	0.137			
Method:	Least Squares	F-statistic:	3.773			
Date:	Wed, 26 Aug 2026	Prob (F-statistic):	0.0334			
Time:	14:39:34	Log-Likelihood:	-388.14			
No. Observations:	36	AIC:	622.3			
Df Residuals:	33	BIC:	627.0			
Df Model:	2					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	2.562e+05	1155.882	221.664	0.000	2.54e+05	2.59e+05
Harga	-0.0405	0.020	-1.992	0.055	-0.082	0.001
Curah_Hujan_mm	-4.2591	2.106	-2.023	0.051	-8.543	0.025
Omnibus:	6.414		Durbin-Watson:		0.373	
Prob(Omnibus):	0.040		Jarque-Bera (JB):		2.366	
Skew:	0.250		Prob(JB):		0.306	
Kurtosis:	1.848		Cond. No.		2.72e+05	

Figure 11. Results of Multiple Linear Regression

Results of Multi-Objective Optimization

Based on the established multi-objective formulation, the optimization process was conducted to determine the chili production level that provides a compromise between production value, exposure to rainfall variability, and total production. The three objective functions were first normalized to the range [0,1], then combined using a weighted sum with equal weights ($w_1 = w_2 = w_3 = 1/3$). Next, the Harmony Search

*name of corresponding author



Algorithm was used to find the production combination x_t that maximizes the fitness value while still meeting the specified production limits.

Table 3. Multi-Objective Optimization Results

Objective	Optimal Value	Normalized Value	Direction
Z_1 Gross production value	Rp462.463.225.492.496,44	0,8165	Maximize
Z_2 Rainfall-deviation exposure	804.788.341,60	0,3476	Minimize
Z_3 Total production	9.158.801,66 ton	0,7969	Maximize
Overall fitness	0.6537	—	Maximize

The reported HSA run produced a fitness score of 0.6537 with equal weights across the three objective functions. The solution yielded gross revenue of Rp462.463.225.492.496,44 with a normalized value of 0.8165, total production of 9.158.801,66 tons with a normalized value of 0.7969, and rainfall-deviation exposure of 804.788.341,60 with a normalized value of 0.3476. These results represent one compromise solution under the equal-weight specification. They should not be interpreted as evidence that HSA is superior to other algorithms, because the original study used one HSA run and did not include a comparative benchmark.

Sensitivity Analysis of Objective Weights

To examine the effect of the weighting specification, a post-hoc sensitivity analysis was calculated from the normalized objective values of the reported solution ($Z_1 = 0.8165$, $Z_2 = 0.3476$, $Z_3 = 0.7969$). The alternative weight vectors preserve the same solution and therefore measure the change in the aggregation value only; they do not constitute independent HSA re-optimizations.

Table 4. Post-hoc sensitivity of the weighted aggregation value at the reported HSA solution

Scenario	w_1 Revenue	w_2 Rainfall	w_3 Production	Aggregated fitness
Equal weights	1/3	1/3	1/3	0.6537
Revenue emphasis	0.50	0.25	0.25	0.6944
Rainfall emphasis	0.25	0.50	0.25	0.5772
Production emphasis	0.25	0.25	0.50	0.6895
Moderate revenue emphasis	0.40	0.30	0.30	0.6700

The equal-weight specification gives the reported fitness of approximately 0.6537. Increasing the revenue or production weight raises the aggregation value for the same reported HSA solution, whereas increasing the rainfall-risk weight lowers it because the rainfall objective has the lowest normalized value. This post-hoc analysis shows that the choice of objective weights affects the aggregate fitness and should be treated as a modelling preference. However, because the alternative weights were evaluated using the same reported HSA solution, they do not represent independently optimized solutions. A full sensitivity analysis of the optimal production allocation would require rerunning HSA under each weight vector.

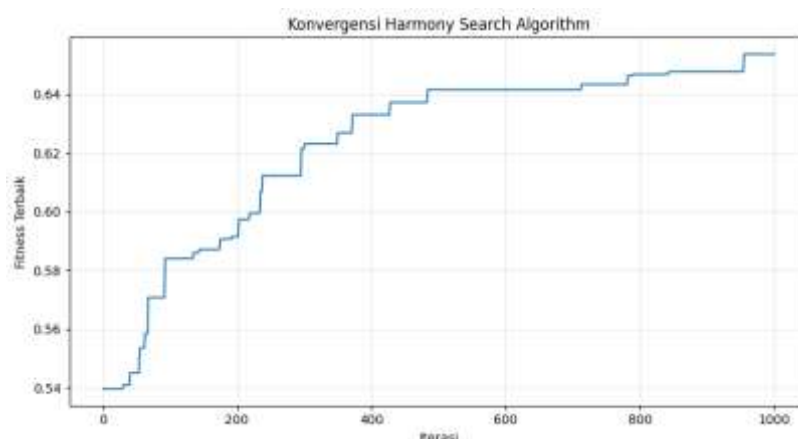


Figure 12. Convergence Plot for Harmony Search Optimization

The Harmony Search convergence graph (Figure 12) illustrates the improvement of the best fitness value over 1,000 iterations in the reported run. The curve rises rapidly during the early iterations and then shows smaller improvements toward the end of the run. This pattern indicates convergence within that particular run, but it does

*name of corresponding author



not establish statistical solution stability across independent runs. Because no repeated runs were recorded in the original computational experiment, the figure is interpreted only as a within-run convergence diagnostic.

Figure 13 shows a comparison of baseline production and HSA-optimized results for the period from January 2022 to December 2024. The results indicate that the optimal production allocation is dynamic and varies from period to period. In 2022, optimal production was consistently higher than the baseline, with the largest increase reaching 1,36% in June and November. In contrast, in 2023, when the baseline was at the maximum production limit of 255.105,04 tons, HSA chose to reduce production during most of the period, with the largest decrease of 1,30% occurring in August 2023. In 2024, optimal production was again higher than the baseline during most periods, although there were some periods with a decline in production. The optimization results show that the HSA adaptively allocates production levels in each period to achieve a compromise between economic revenue, total production, and exposure to rainfall deviations. This is evidenced by variations in optimal production levels across periods, with some periods approaching the maximum production limit, while others fall below baseline production when price and rainfall conditions result in a less favorable trade-off. This pattern indicates that production decisions are not solely focused on achieving maximum output but also take rainfall conditions into account, resulting in a more balanced allocation pattern that supports sustainable production planning. Thus, changes in the optimal production level across periods are not driven solely by the goal of achieving maximum output but reflect trade-offs between objectives as defined by the fitness function.

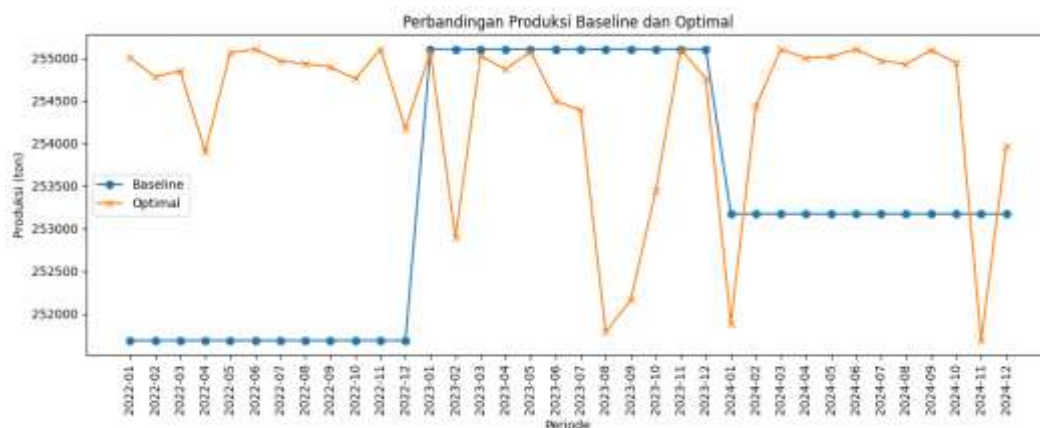


Figure 13. Graph Comparing Baseline and Optimal Production

DISCUSSIONS

The results indicate that the model integrates economic and agroclimatic dimensions, but the statistical analysis requires careful qualification. Pearson correlations are weak and not statistically significant at the 5% level (price-production: $r = -0.292, p = 0.084$; rainfall-production: $r = -0.297, p = 0.079$; price-rainfall: $r = -0.068, p = 0.694$). The regression gives $R^2 = 0.186$ and an overall F-test $p = 0.0334$, while the individual price and rainfall coefficients have p-values of 0.055 and 0.051, respectively. The Durbin-Watson statistic of 0.373 indicates strong positive serial dependence, so the regression results should not be interpreted as satisfying standard independent-error assumptions. These diagnostics are consistent with the decision to use regression only as exploratory support for model construction. (Prihandi, Wijono, Sembiring, & Maria, 2025) (Nugroho, Ardhitama, Sartohadi, Qadafi, Siswoko, & Al Adilah, 2025) (Wasita, Hidayat, & Suprehatin, 2025).

Based on these characteristics, this study does not use regression as a model for predicting production, but rather as an empirical basis for constructing a multi-objective optimization model. The three objectives used maximizing gross production/revenue, minimizing exposure to rainfall deviations, and maximizing total production enable the model to simultaneously consider economic aspects, agroclimatic risks, and productivity. This approach differs from studies that merely analyze the relationship between rainfall and production or forecast prices and production. The multi-objective approach is also in line with developments in agricultural optimization research, which has begun to integrate economic objectives, resource use, and environmental aspects simultaneously. (Ullah & Nehring, 2021) (Begam, Jain, Arora, & Marwaha, 2023) (Li, Zhang, & Huo, 2023).

The reported Harmony Search run yielded a best fitness value of 0.6537 after 1,000 iterations. The solution yielded gross revenue of Rp462.463.225.492.496,44, rainfall-deviation exposure of 804.788.341,60, and total production of 9.158.801,66 tons. The normalized objective values were 0.8165, 0.3476, and 0.7969, respectively. Because the three objectives were assigned equal weights, the result is best interpreted as a compromise solution under that weighting specification rather than as a universally optimal or economically superior solution.

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The convergence pattern shows improvement in the best fitness value within the single reported HSA run, followed by smaller gains near the final iterations. This indicates within-run convergence, but repeated independent runs would be required to quantify stochastic stability using measures such as mean fitness, standard deviation, and confidence intervals. Such repeated-run statistics were not available from the original computational experiment and are therefore not fabricated in this revision. (Nensi, Pangesti, Syukri, Maida, & Notodiputro, 2025) (Li, Zhang, & Huo, 2023) (Arta, Chozin, & Ritonga, 2024) (Dai, et al., 2023).

A comparison of baseline and optimal production shows that the HSA solution is adaptive across periods. For most of 2022, optimal production was above the baseline, with a maximum increase of approximately 1,36% in June and November. Conversely, for most of 2023, optimal production was slightly below the baseline, with the largest decrease of approximately 1,30% in August. In 2024, the model again produced increases in production during some periods and decreases during others. This pattern indicates that the HSA does not always drive production toward its maximum limit but adjusts production levels based on a trade-off between revenue, total production, and exposure to rainfall deviations. Thus, a solution that is lower than the baseline in a given period does not automatically indicate poorer performance but may reflect the outcome of a trade-off among objectives.

Several limitations affect the interpretation of the findings. First, annual FAOSTAT production data were evenly disaggregated into monthly baseline values, resulting in a very low production CV (0.56%). Therefore, the monthly production series does not represent actual observed monthly production, and the correlation and regression results should be regarded as exploratory associations rather than evidence of actual monthly relationships or causality. Second, the observation period contains only 36 months. Third, the main optimization run uses equal objective weights, while the added sensitivity analysis is a post-hoc assessment of the reported solution rather than a full re-optimization under alternative weights. Fourth, HSA was executed once in the original analysis; consequently, solution stability across random seeds and comparative performance against other algorithms cannot be statistically established. Fifth, computation time was not recorded in the original run and is therefore reported as a limitation rather than estimated retrospectively. Future research should use actual monthly production data, extend the observation period, repeat HSA with multiple independent seeds, report computation time, compare alternative algorithms, and perform full weight-sensitive re-optimization.

CONCLUSION

This study developed a multi-objective optimization model based on the Harmony Search Algorithm (HSA) to determine chili pepper production levels while considering three objectives: maximizing gross revenue, minimizing exposure to rainfall deviations, and maximizing total production. The exploratory statistical analysis indicates weak and non-significant pairwise correlations between price, rainfall, and the constructed monthly baseline production series. Because the production baseline is derived from annual data disaggregation, these statistical results are interpreted cautiously.

The reported HSA run produced a best fitness value of 0.6537, with gross revenue of Rp462.463.225.492.496,44, rainfall-deviation exposure of 804.788.341,60, and total production of 9.158.801,66 tons. The normalized objective values were 0.8165, 0.3476, and 0.7969, respectively. These values describe the compromise obtained under equal objective weights and should not be interpreted as proof of algorithmic superiority or farmer profit because the economic objective is gross revenue and does not subtract production costs.

The HSA allocation exhibits an adaptive pattern across periods, with increases and decreases relative to the baseline. The largest increase is approximately 1.36%, while some periods show decreases. These changes reflect the trade-offs encoded in the weighted objective function. The post-hoc weight sensitivity analysis further shows that the aggregate fitness value changes when greater emphasis is assigned to revenue, rainfall exposure, or production, indicating that objective weighting is an important modelling choice.

Overall, the study provides a mathematical framework for integrating price, production baseline, and rainfall variability into chili production planning. The findings should be interpreted within the limitations of the data construction and single-run computational experiment. Future research should use actual monthly production observations, conduct full sensitivity re-optimization, perform multiple independent HSA runs, report computation time, and compare HSA with alternative optimization algorithms.

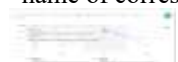
REFERENCES

- Abdila, W., Nugroho, B., & Setyawan, C. (2022). Effect of Extreme Rainfall Pattern on The Growth and Yield of Chili Peppers. *Jurnal Teknik Pertanian Lampung*, 117-129.
- Adekald, E., Amponsah, W., Tuffour, H. O., Adu, M. O., & Agyare, W. A. (2021). Response of chilli pepper to different irrigation schedules and mulching technologies in semi-arid environments. *Journal of Agriculture and Food Research*, 1-10.



- Arta, I. M., Chozin, M. A., & Ritonga, A. W. (2024). Evaluation of growth and yield potential of three varieties of chili pepper (*Capsicum frutescens*) intercropped with maize (*Zea mays*) at different planting times. *Biodiversitas*, 3985–3994.
- Begam, S., Jain, R., Arora, A., & Marwaha, S. (2023). Multi-objective particle swarm optimization for regional crop planning. *Indian Journal of Agricultural Sciences*, 237–240.
- Dai, Z., Zhao, X., Yan, H., Qin, L., Niu, X., Zhao, L., et al. (2023). Optimizing water and nitrogen management for green pepper (*Capsicum annuum* L.) under drip irrigation in sub-tropical monsoon climate regions. *Agronomy*, 1-14.
- Fadare, O., Agele, S., & Ajayi, G. (2025). Integrating soil, plant and microclimate variables for optimizing resource use and yield of greenhouse grown pepper in a rainforest environment. *Journal of Scientific Agriculture*, 88-100.
- Gregorio, G. T., Mateos, G. R., Hernández, P. J., & Zavaleta, G. S. (2021). Yield and economic analysis of three chili hybrids (*Capsicum annuum* L.) in Cuatro Caminos, San Gabriel, Jalisco, Mexico. *Horticulture International Journal*, 10-12.
- Indriyana, Taridala, S. A., & Yusria, W. O. (2025). Time Series Trend Analysis of the Effect of Rainfall on the Productivity of Cayenne Pepper (*Capsicum frutescens* L.) in Southeast Sulawesi Province. *International Journal of Technology and Education Research*, 21-33.
- Jamhari, J., Nasir, M. A., Nugroho, A. D., Ismiasih, I., & Yonekura, H. (2022). Does the Sleman chili auction market affect the local, regional and national market prices in Indonesia? *AGRARIS: Journal of Agribusiness and Rural Development Research*, 231–247.
- Lestari, E., Prajanti, S., Wibawanto, E., & Adzim, F. (2022). ARCH-GARCH Analysis: An Approach to Determine The Price Volatility of Red Chili. *AGRARIS: Journal of Agribusiness and Rural Development Research*, 90-105.
- Li, G., Zhang, C., & Huo, Z. (2023). Reconciling crop production and ecological conservation under uncertainty: A fuzzy credibility-based multi-objective simulation-optimization model. *Science of the Total Environment*, 1-43.
- Macias-Bobadilla, I., Vargas-Hernandez, M., Guevara-Gonzalez, R. G., Rico-Garcia, E., Ocampo-Velazquez, R. V., & Torres-Pacheco, I. (2020). Differential response to water deficit in chili pepper (*Capsicum annuum* L.) growing in two types of soil under different irrigation regimes. *Agriculture*, 1-15.
- Moges, D. M., Lema, A. A., & Berhanu, Z. K. (2026). Intuitionistic fuzzy mathematical model for optimization of multi-objective cropland allocation problem in small scale irrigation system: A case-study in Sidama region, Ethiopia. *Scientific African*, 1-14.
- Nensi, A. I., Pangesti, W., Syukri, N., Maida, M. A., & Notodiputro, K. A. (2025). Implementing LSTM-based deep learning for forecasting food commodity prices with high volatility: A case study in East Java Province. *Proceedings of the International Conference on Data Science and Official Statistics*, 1032–1041.
- Nugroho, B. D., Ardhitama, A., Sartohadi, J., Qadafi, M., Siswoko, B. D., & Al Adilah, A. H. (2025). Effect of climate variability on chili pepper (*Capsicum frutescens* L.) cultivation in Indonesia. *Environment and Natural Resources Journal*, 459–468.
- Prihandi, I., Wijono, S., Sembiring, I., & Maria, E. (2025). Implementation of ARIMA with Min-Max normalization for predicting the price and production quantity of red chili peppers in North Sumatra Province considering rainfall and sunlight duration factors. *Engineering, Technology & Applied Science Research*, 21876–21887.
- Randall, M., Schiller, K., Lewis, A., Montgomery, J., & Alam, M. S. (2024). A systematic review of crop planning optimisation under climate change. *Water Resources Management*, 1867–1881.
- Susanawati*, H. A. (2021). Supply chain efficiency of red chili based on the performance measurement system in Yogyakarta, Indonesia. *Open Agriculture*, 202-211.
- Susanawati, S. A. (2021). Supply chain efficiency of red chili based on the performance measurement system in Yogyakarta, Indonesia. *Open Agriculture*, 202-211.
- Ullah, G. M., & Nehring, M. (2021). A multi-objective mathematical model of a water management problem with environmental impacts: An application in an irrigation project. *PLOS ONE*, 1-16.
- Widowati, Dhamira, A., Anggrasari, H., & Seleky, R. N. (2023). Climatic factors and its effect on chili production: One step forward combating climate change. *BIO Web of Conferences*, 1-7.
- Wasita, R., Hidayat, N. K., & Suprehatin. (2025). Effects of Supply and Commodity Substitution on Chili Price Volatility at Kramat Jati Wholesale Market, Jakarta, Indonesia. *Agro Bali : Agricultural Journal*, 781-795.
- Zhang, Y., & Yang, P. (2022). Agricultural productive carrying capacity improve and water optimal allocation under uncertainty based on remote sensing data in Lancang County, Southwest China. *Water*, 1-23.

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