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ENHANCING COFFEE PRODUCTION FACTOR ASSESSMENT USING LINEAR REGRESSION AND AHP FOR RELIABLE WEIGHT CONSISTENCY

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***Abstract**— The agricultural sector, particularly coffee production, plays a crucial role in Indonesia's economy as both a domestic commodity and an export product. However, efforts to optimize coffee production are often constrained by traditional Multi-Criteria Decision-Making (MCDM) methods that rely heavily on subjective judgments, leading to potential inconsistencies—especially in the presence of multicollinearity among variables. This study addresses that challenge by proposing a data-driven and consistent weighting method that integrates Multiple Linear Regression (MLR) with the Analytic Hierarchy Process (AHP). Regression coefficients derived from MLR—based on variables such as the area of immature (-0.2419), mature (0.8357), and damaged (0.5119) coffee plantations—are normalized and incorporated into the AHP pairwise comparison matrix. The resulting Consistency Ratio (CR) values are all below 0.1, indicating high internal consistency and statistical reliability of the derived weights. This integrated approach offers an objective and systematic foundation for MCDM in coffee production analysis, enhances the accuracy of agricultural planning, and supports evidence-based policymaking, while also providing a replicable model for addressing similar challenges in other sectors.*

***Keywords**: AHP, coffee production, consistency ratio, MCDM, multiple linear regression.*

Intisari—*Sektor pertanian, khususnya produksi kopi, memainkan peran krusial dalam perekonomian Indonesia, baik sebagai komoditas domestik maupun produk ekspor. Namun, upaya optimalisasi produksi kopi seringkali terhambat oleh metode pengambilan keputusan multikriteria (MCDM) tradisional yang sangat bergantung pada penilaian subjektif, sehingga berisiko menimbulkan inkonsistensi—terutama ketika terdapat multikolinearitas antar variabel. Penelitian ini mengatasi tantangan tersebut dengan mengusulkan metode pembobotan yang konsisten dan berbasis data melalui integrasi Multiple Linear Regression (MLR) dengan Analytic Hierarchy Process (AHP). Koefisien regresi yang diperoleh dari MLR—berdasarkan variabel seperti luas lahan kopi belum menghasilkan (-0.2419), menghasilkan (0.8357), dan tidak menghasilkan (0.5119)—dinormalisasi dan dimasukkan ke dalam matriks perbandingan berpasangan AHP. Nilai Consistency Ratio (CR) yang dihasilkan seluruhnya berada di bawah ambang batas 0.1, menunjukkan konsistensi internal yang tinggi dan keandalan statistik dari bobot yang dihasilkan. Pendekatan terintegrasi ini menawarkan landasan yang objektif dan sistematis untuk analisis MCDM dalam produksi kopi,*

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meningkatkan akurasi perencanaan pertanian, dan mendukung pengambilan kebijakan berbasis data, serta menyediakan model yang dapat direplikasi untuk menghadapi tantangan serupa di sektor lainnya.

Kata Kunci: *AHP, produksi kopi, rasio konsistensi, MCDM, regresi linear berganda.*

INTRODUCTION

Coffee is one of Indonesia's strategic agricultural commodities, contributing significantly to the national economy through rural income generation and export performance. In the 2024/2025 marketing year, Indonesia ranked fourth among the world's largest coffee producers, accounting for about 6% of global output after Brazil, Vietnam, and Colombia [1]. Optimizing national coffee production remains challenging due to the complex interrelationships among cultivation stages—immature, mature, and damaged plantation areas—requiring a data-driven approach capable of objectively quantifying their contributions within a Multi-Criteria Decision-Making (MCDM) framework.

Multiple Linear Regression (MLR) is a well-established statistical method for analyzing relationships between dependent and multiple independent variables [2]–[10]. Beyond prediction, MLR effectively quantifies variable influence and has been applied across diverse domains, including energy forecasting [5], [8], [11], industrial performance [9], [11], material property evaluation [12], and agricultural yield prediction [4], [6]. Its ability to provide objective quantitative insights makes MLR suitable for identifying key factors influencing coffee production.

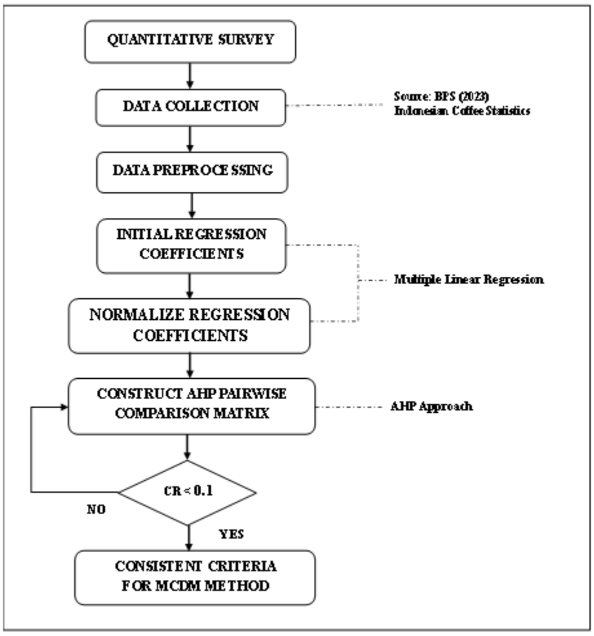
In Decision Support Systems (DSS), MLR has also proven valuable in integrating predictive modeling with decision optimization—such as in fuel consumption estimation for shipping and performance evaluation in material science [11], [12]. Moreover, MLR-derived coefficients can serve as objective weights within MCDM techniques like the Analytic Hierarchy Process (AHP), reducing reliance on subjective expert judgment [11], [21]. Ensuring the logical consistency of these weights through a Consistency Ratio (CR) test is essential for reliable decision-making [16]–[20].

Therefore, this study proposes an integration of MLR and AHP within the MCDM framework to develop an objective and consistent criteria-weighting method for analyzing Indonesia's coffee production factors—Immature Coffee Plantation (ICP), Mature Coffee Plantation (MCP), and Damaged Coffee Plantation (DCP). The resulting model aims to support data-driven strategic decisions and enhance national coffee productivity through efficient and measurable resource allocation.

MATERIALS AND METHODS

This study adopts a quantitative approach to develop an objective criteria weighting method by integrating Multiple Linear Regression (MLR) into a Multi-Criteria Decision Making (MCDM) framework. The research methodology, as illustrated in Figure 1, consists of several key stages.

The stages in Figure 1 begin with data collection through a quantitative survey, using secondary data sourced from Indonesian Coffee Statistics (BPS, 2023) [22]. The next stage involves data preprocessing, including normalization, handling missing values, and standardizing the format and units of data. Subsequently, the determination of criteria weights is carried out using MLR, and the results are integrated into the Analytic Hierarchy Process (AHP) framework. A consistency check is performed by calculating the Consistency Ratio (CR); if the CR value is less than 0.1, the process continues to the final stage—decision-making using the MCDM method. If not, the weighting process is revised to improve consistency.



Source: (Research Results, 2025)
Figure 1. Research Methodology

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A. Data Collection and Preprocessing

The data used in this study were obtained from Statistics Indonesia (Badan Pusat Statistik – BPS, 2023), which serves as the official national statistical agency responsible for collecting, processing, and publishing Indonesia's socio-economic and agricultural data. BPS applies standardized data collection methods, periodic field surveys, and rigorous validation procedures that adhere to national and international statistical standards. These include cross-verification with regional agricultural offices and consistency checks across time series data to ensure data accuracy and reliability.

The dataset utilized in this study includes comprehensive information on coffee plantation areas categorized as immature, mature, and damaged across all major coffee-producing provinces in Indonesia. As such, the dataset is considered both representative and reliable for analyzing patterns and determinants of coffee production at the national level. By relying on BPS as the primary data source, this study ensures the integrity of the empirical analysis and minimizes measurement or sampling bias.

High-quality data is essential for ensuring the validity and robustness of research findings. The accuracy and consistency of the dataset directly influence the reliability of the statistical and modeling results, as any measurement errors or inconsistencies could lead to biased estimates or misleading interpretations. By using verified and standardized data from Statistics Indonesia (BPS), this study minimizes the risk of data-related bias and enhances the credibility of the empirical outcomes. Consequently, the validity of the conclusions drawn from this analysis is strongly supported by the integrity of the data foundation.

Table 1. Area of Coffee by Condition of Crops, Coffee Production, and Productivity of Indonesian Coffee Plantation by Province, 2023

No.	Province	*Area (Ha)*				Production (ton)	Yield (Kg/Ha)
		Immature	*Mature*	*Damaged*	*Total*		
1	Aceh	12.226	86.327	15.416	113.968	71.084	823
2	Sumatera Utara	19.252	68.604	10.736	98.592	89.610	1.306
3	Sumatera Barat	6.605	16.218	945	23.768	13.623	840
4	Riau	1.795	1.808	726	4.328	1.795	993
5	Jambi	7.532	20.931	2.833	31.296	19.434	928
6	Sumatera Selatan	16.502	230.862	20.019	267.383	207.320	898
7	Bengkulu	14.959	73.296	2.635	90.891	50.745	692
8	Lampung	7.873	137.760	6.980	152.614	105.807	768
9	Bangka Belitung	236	105	8	349	86	820
10	Kepulauan Riau	10	3	5	18	0	131
11	DKI Jakarta	0	0	0	0	0	0
12	Jawa Barat	17.520	32.857	3.866	54.243	22.628	689
13	Jawa Tengah	9.966	38.599	1.587	50.153	27.227	705
14	D.I. Yogyakarta	176	1.591	68	1.836	1.872	1.177
15	Jawa Timur	12.238	69.934	9.136	91.309	47.577	680
16	Banten	337	4.780	1.129	6.246	1.994	417
17	Bali	3.582	27.879	2.317	33.778	13.005	466
18	Nusa Tenggara Barat	3.932	9.507	599	14.039	6.429	676
19	Nusa Tenggara Timur	18.036	48.077	9.442	75.555	25.737	535
20	Kalimantan Barat	985	3.805	2.662	7.453	2.969	780
21	Kalimantan Tengah	977	439	649	2.066	194	441
22	Kalimantan Selatan	526	1.395	310	2.231	884	634
23	Kalimantan Timur	196	467	667	1.330	125	267
24	Kalimantan Utara	292	301	330	923	112	372
25	Sulawesi Utara	1.428	5.498	865	7.791	3.728	678
26	Sulawesi Tengah	4.387	5.119	1.761	11.267	2.744	536
27	Sulawesi Selatan	13.005	55.643	10.478	79.126	30.727	552
28	Sulawesi Tenggara	2.215	5.934	1.410	9.559	2.799	472
29	Gorontalo	140	591	574	1.305	125	212
30	Sulawesi Barat	3.103	6.873	6.689	16.664	4.720	687
31	Maluku	312	757	239	1.308	444	586
32	Maluku Utara	94	56	241	392	15	262
33	Papua Barat	91	77	89	257	10	130
34	Papua	5.349	6.119	3.343	14.811	3.156	516
	INDONESIA	185.878	962.213	118.757	1.266.848	758.725	789

Source: (BPS, 2023)

Table 1 presents the dataset, which includes **ICP**, **MCP**, and **DCP**—representing the areas of

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immature, mature, and damaged coffee plantations, respectively, measured in hectares—and **TCP** (Total Coffee Production), measured in tons.

Data were obtained from publicly available agricultural statistics over a defined period and cleaned to remove inconsistencies or missing values. Each independent variable (**ICP, MCP, DCP**) was normalized to standardize the scale before regression modeling.

B. Multiple Linear Regression (MLR) Modeling

The primary analysis involved constructing an MLR model to estimate the relationship between coffee production factors (independent variables) and total coffee production (dependent variable). The general form of the MLR model is expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \quad (1)$$

Where Y represents the dependent variable (**TCP**), and X_1, X_2, X_3 are the independent variables (**ICP, MCP, DCP**). Parameter β_0 is the intercept term. Parameters $\beta_1, \beta_2, \beta_3$ denote the regression coefficients were interpreted as the relative contribution of each factor to the total production., and ε represents the error term.

If the data are expressed in matrix form, then **Y** is a 34×1 vector of the dependent variable. **X** is a 34×4 matrix, where the first column consists of ones to account for the intercept, and the subsequent columns represent the independent variables X_1, X_2, X_3. And $\boldsymbol{\beta}$ is a 4×1 vector of regression coefficients (including intercept), and ε is the vector of errors (residuals).

The regression coefficients ($\widehat{\boldsymbol{\beta}}$) are estimated using the Ordinary Least Squares (OLS) method with the following formula:

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y} \quad (2)$$

C. Determination of Criteria Weighted from Regression Coefficients

For the purpose of MCDM weighting, the absolute value of each independent variable's regression coefficient is taken:

$$w_i = \left|\hat{\beta}_i\right| \quad (3)$$

Normalization is then performed to ensure that the total weight equals 1:

$$w_i^* = \frac{w_i}{\sum_{j=1}^{n} w_j} = \frac{|\widehat{\beta}_i|}{\sum_{j=1}^{n}|\widehat{\beta}_j|} \quad (4)$$

Where w_i^* is a normalized weight for criteria i and the values of $\hat{\beta}_i$ are standardized regression coefficients with n criteria (n = 3). These weights reflect the objective importance of each criterion (**ICP, MCP, DCP**) based on their statistical influence on **TCP**.

D. Integration into the AHP Matrix and Consistency Testing

The normalized weights were inserted into the AHP pairwise comparison matrix $\boldsymbol{A} = [a_{ij}]$, is an nxn square matrix used to compare n criteria in pairs using the AHP scale (1-9). Each element a_{ij} represents the relative importance of criteria i compared to criteria j

$$a_{ij} = \frac{w_i^*}{w_j^*} \quad (5)$$

The element a_{ij} satisfies the following properties:

1. Reciprocal property: $a_{ji} = \frac{1}{a_{ij}}$, for all $i \neq j$
2. Identify property: $a_{ii} = 1$, for all i
3. Positive values: $a_{ij} > 0$, for all i, j

These properties ensure logical consistency within the matrix, which is essential for deriving valid and interpretable priority weights.

Once the pairwise comparison matrix $\boldsymbol{A}$ has been constructed based on expert judgments using the AHP scale, the next step is to derive the priority vector (eigenvector) and assess the consistency of the matrix. These steps ensure the reliability of the resulting weights.

Step 1: Calculating the Priority Vector (Eigenvector)

To obtain the weight of each criterion, the normalized principal eigenvector is calculated. This vector represents the relative weights of the criteria.

Procedure: Given the pairwise matrix $\boldsymbol{A} = [a_{ij}]$, perform the following:

1. **Sum each column of the matrix:**

$$\boldsymbol{s_j = \sum_{i=1}^{n} a_{ij}} \quad (6)$$

2. **Normalize the matrix** by dividing each element by its column total:

$$\hat{a}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} \boldsymbol{a_{ij}}} = \frac{a_{ij}}{\boldsymbol{s_j}} \quad (7)$$

3. **Calculate the average of each row** of the normalized matrix to obtain the priority vector.

$$w_i = \frac{1}{n} \sum_{j=1}^{n} \hat{a}_{ij} \tag{8}$$

Step 2: Calculating the Principal Eigenvalue (λ_{max})

To measure consistency, the maximum eigenvalue λ_{max} Of matrix $\boldsymbol{A}$ is estimated as follows:

$$\lambda_{max} = \frac{\sum_{i=1}^{n}(\frac{(A.w)_i}{w_i})}{n} \tag{9}$$

Where $A.w$ is the matrix-vector multiplication, and w is the priority vector obtained from step 1

Step 3: Calculating Consistency Index (CI)

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{10}$$

Step 4: Calculating Consistency Ratio (CR)

The Consistency Ratio compares the CI with a Random Index (RI), which is the average CI of a randomly generated matrix of size n

$$CR = \frac{CI}{RI} \tag{11}$$

Where RI values for typical matrix sizes are:

Table 2. Random Index with 5 Criteria

n	1	2	3	4	5
RI	0.0	0.0	0.58	0.9	1.12

Source: (Research Results, 2025)

Consistency Decision Rule:

If $CR < 0.1$ indicate acceptable consistency, while values approaching this threshold may reflect minor subjective inconsistencies that could affect ranking stability.

If $CR \geq 0.1$: The judgments are too inconsistent and should be revised.

RESULTS AND DISCUSSION

This study aims to determine the most influential criteria in national coffee production using a quantitative modeling approach. A Multiple Linear Regression (MLR) model was employed to analyze the impact of three plantation variables: Immature Coffee Plantation (**ICP**), Mature Coffee Plantation (**MCP**), and Damaged Coffee Plantation (**DCP**). The regression output, as presented in Figure 2, showed that the model is statistically significant with an R-squared of 0.965 and an adjusted R-squared of 0.962, indicating excellent explanatory power.

Figure 2 below shows that among the three predictors or independent variables, **MCP** exhibited the strongest and most statistically significant influence on coffee production, with a coefficient of 0.8357 (p < 0.001). This result is expected, as mature plantations directly contribute to harvestable yield. The **DCP** variable also had a positive coefficient (0.5119), though it was not statistically significant (p = 0.418), suggesting some contribution to production, possibly from partially productive damaged plants. Conversely, the **ICP** variable had a negative coefficient (-0.2419) and was not statistically significant (p = 0.500), indicating that immature plantations currently do not contribute positively to production.

```
Summary of Regression Results:
                            OLS Regression Results
==============================================================================
Dep. Variable:             Production   R-squared:                       0.965
Model:                            OLS   Adj. R-squared:                  0.962
Method:                 Least Squares   F-statistic:                     277.4
Date:                Sun, 01 Jun 2025   Prob (F-statistic):           5.84e-22
Time:                        14:15:41   Log-Likelihood:                -352.79
No. Observations:                  34   AIC:                             713.6
Df Residuals:                      30   BIC:                             719.7
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -1799.7816   1901.617     -0.946      0.351   -5683.402    2083.839
ICP           -0.2419      0.354     -0.683      0.500      -0.965       0.481
MCP            0.8357      0.057     14.640      0.000       0.719       0.952
DCP            0.5119      0.623      0.822      0.418      -0.760       1.784
==============================================================================
Omnibus:                       30.745   Durbin-Watson:                   2.023
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              108.627
Skew:                           1.780   Prob(JB):                     2.58e-24
Kurtosis:                      11.000   Cond. No.                     7.52e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.52e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Source: (Research Results, 2025)

Figure 2. The Summary of The OLS Regression

The regression analysis strongly indicates that the maturity level of coffee plantations is the most critical determinant of production outcomes. The dominance of MCP in the model underscores the importance of maintaining and expanding mature coffee areas as a direct strategy to enhance productivity. This finding aligns with agronomic theories emphasizing that yield performance reaches its optimal level during the mature phase, where plants are in their highest productive cycle. Furthermore, the insignificant impact of ICP highlights that replanting and regeneration programs require a longer maturation period before contributing to output. This study provides a quantitative confirmation that maturity structure plays a more decisive role than damage control or replanting speed. However, the moderate positive coefficient of DCP found in this study introduces an interesting dimension — suggesting that some damaged plantations may still have partial productivity, possibly due to incomplete crop loss or mixed-age structures within the same plantation

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block. This nuance contributes to the growing body of knowledge emphasizing the need for a more granular classification of plantation condition beyond the binary healthy–damaged distinction, which could enhance data accuracy in agricultural modeling.

The results have important implications for agricultural policy and coffee production management. The high weight assigned to MCP suggests that government or cooperative programs should prioritize maintenance, rejuvenation, and protection of mature coffee areas. Investments in pest control, pruning, and fertilization during the mature phase can yield immediate productivity gains. Meanwhile, resources allocated to ICP should focus on long-term sustainability rather than short-term yield increase. In practice, regional agricultural offices could use the derived MCDM-AHP weights as a decision-support tool to allocate budgets and technical assistance proportionally across plantation categories. For example, areas with a declining MCP-to-ICP ratio may require policy interventions to prevent future production deficits.

Integrating MLR-derived coefficients into an AHP framework bridges statistical and decision-making methodologies, ensuring that the weighting system is both data-driven and logically consistent. This hybrid approach enhances the reliability of multi-criteria evaluation in agricultural contexts, where subjective expert judgments often dominate. The use of normalized regression coefficients as AHP inputs minimizes bias and provides a quantitative foundation for subsequent pairwise comparisons. This method addresses a common challenge in MCDM studies, where criteria weights are often based solely on expert perception without empirical backing. By grounding the AHP matrix in regression results, the study introduces a replicable model that can be applied to other crops or agricultural policy assessments.

To incorporate these findings into a Multi-Criteria Decision Making (MCDM) framework, the regression coefficients were first converted into positive values and then normalized to form preliminary weights in Table 3:

Table 3. Normalized Weights of Coffee Production Criteria Based on MLR Positive Coefficients

Criteria	Positive Coefficient	Normalized Weight
ICP	0.2419	0.1522
MCP	0.8357	0.5258
DCP	0.5119	0.3221

Source: (Research Results, 2025)

Table 3 presents the transformation of regression coefficients derived from the Multiple Linear Regression (MLR) model into criteria weights applicable in a Multi-Criteria Decision Making (MCDM) framework. The "Positive Coefficient" column displays the absolute values of the regression coefficients for the three input variables, i.e. **ICP**, **MCP**, and **DCP**.

These values were then normalized to produce the "Normalized Weight", representing the relative importance of each criterion in contributing to the national total coffee production. The weights sum to 1, making them suitable for further MCDM analysis such as integration with the Analytic Hierarchy Process (AHP). The normalized weights indicate that **MCP** has the highest influence on total coffee production (0.5258), suggesting that **MCP** should be prioritized in strategic resource allocation, followed by **DCP** (0.3221) and **ICP** (0.1522), which have a relatively lower immediate impact on output. To ensure logical consistency of the derived weights, the normalized coefficients were used to construct a pairwise comparison matrix for AHP processing (matrix $\boldsymbol{A}$):

Table 4. Pairwise Comparison Matrix for AHP

	ICP	MCP	DCP
ICP	1.000	0.289	0.473
MCP	3.455	1.000	1.630
DCP	2.116	0.613	1.000

Source: (Research Results, 2025)

Matrix $\boldsymbol{A}$ in Table 4 represents the relative importance of one criterion compared to another. Values > 1 indicate the row criteria are more important than the column criteria. Values < 1 indicate the row criteria are less important than the column criteria. Example: **MCP** vs **ICP** = 3.455 means **MCP** is about 3.455 times more important than **ICP**. From this matrix, the priority vector (AHP weights) was calculated as follows:

Table 5. Calculate Priority Vector

	ICP	MCP	DCP	w_i	$A.w$	$\boldsymbol{\lambda}$
ICP	1.000	0.289	0.473	1.000	0.457	3.000
MCP	3.455	1.000	1.630	3.455	1.578	3.000
DCP	2.116	0.613	1.000	2.116	0.966	3.000

Source: (Research Results, 2025)

Table 5 presents a detailed calculation process from the Analytic Hierarchy Process (AHP) methodology to derive the priority vector (weights) and assess the consistency of the pairwise comparison matrix. To validate the logical coherence of the pairwise comparisons, the AHP consistency ratio (CR) was computed. With a maximum eigenvalue $(\boldsymbol{\lambda_{max}})$ of 3.000, a consistency index (CI) can be calculated:

$$CI = \frac{\lambda_{max} - n}{n - 1} = \frac{3 - 3}{3 - 1} = \frac{0}{2} = 0$$

and a random index (RI) of 0.58, the resulting CR is:

$$CR = \frac{CI}{RI} = \frac{0.0}{0.58} = \mathbf{0.0 < 0.1}$$

The calculated CR value of 0.0 confirms that the decision matrix is perfectly consistent. Such a result indicates strong coherence between empirical findings (from MLR) and expert reasoning embedded in AHP comparisons. In decision analysis, maintaining a CR below 0.1 is essential to avoid distortions in ranking outcomes. This study not only meets but surpasses that threshold, implying a high degree of methodological reliability.

Nonetheless, it is crucial to recognize that perfect consistency is rare in practice. Future research could test the robustness of this matrix through sensitivity analysis, perturbing input judgments slightly to observe the stability of ranking results. Such analysis would ensure that the final weights remain valid even under varying decision contexts or stakeholder preferences.

This indicates that the pairwise comparison matrix is **consistent** and the weights can be reliably used in subsequent MCDM stages and the judgments provided by decision makers were logically consistent and the derived weights are reliable. However, when a CR value approaches the threshold, it may signal minor inconsistencies arising from subjective perception differences among respondents. Such inconsistencies can potentially affect the stability of ranking results. Therefore, it is important to interpret CR values not only as numerical indicators of consistency but also as reflections of decision reliability. In practice, when CR values are close to 0.1, performing a sensitivity analysis is recommended to test whether small perturbations in judgments could alter the final priority rankings.

Beyond methodological validation, the study provides an applied framework for integrating quantitative modeling into agricultural planning. The combined use of MLR and AHP offers policymakers a structured, transparent mechanism to prioritize interventions. Future research could extend this model by including socio-economic or climatic variables, such as rainfall, altitude, or labor productivity, to further enrich the decision-making process. Additionally, incorporating dynamic or time-series regression could capture evolving relationships between plantation characteristics and yield over multiple harvest periods, offering a more adaptive decision support system for sustainable coffee production.

Overall, the findings demonstrate that a data-driven MCDM approach enhances both the analytical depth and the decision quality in agricultural productivity studies. By integrating MLR and AHP, the study achieves a balance between statistical rigor and practical decision relevance. The developed framework not only validates the relative importance of plantation variables but also offers a reproducible pathway for policymakers to design targeted, evidence-based strategies to improve national coffee production efficiency.

CONCLUSION

This study effectively integrates Multiple Linear Regression (MLR) and the Analytic Hierarchy Process (AHP) to evaluate critical factors influencing coffee production. By utilizing MLR-derived coefficients as initial weights and validating them through AHP pairwise comparisons, the model achieves both statistical objectivity and logical consistency. The findings highlight the area of Mature Coffee Production (**MCP**) as the most significant factor (0.8357), followed by the area of Damage Coffee Production (**DCP**, 0.5119) and the area of Immature Coffee Production (**ICP**, 0.2419). This study also demonstrates that integrating Multiple Linear Regression (MLR) with the Analytic Hierarchy Process (AHP) provides a robust, objective, and consistent approach for determining criteria weights in Multi-Criteria Decision-Making (MCDM), particularly in the context of coffee production in Indonesia. By using regression coefficients as data-driven inputs for the AHP matrix, the model effectively addresses subjectivity and multicollinearity issues inherent in traditional weighting methods. A consistency ratio (CR) of 0 confirms the reliability of judgments, establishing the hybrid MLR-AHP model as a robust framework for prioritizing production determinants.

Future research can extend this framework by incorporating additional criteria—such as environmental conditions, technological adoption, or policy support—within a multi-level AHP structure. Integration with other MCDM techniques like TOPSIS or VIKOR may enhance analytical robustness and facilitate comparative evaluations. Applying the model across diverse regional contexts and incorporating time-series analysis could capture evolving factor dynamics. Moreover, the development of a decision support system grounded in this hybrid model would offer valuable insights for practitioners and policymakers, with stakeholder engagement improving the model's relevance and applicability.

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