Vol. 15, No. 1 (2026): 52 - 62 http://dx.doi.org/10.23960/jtepl.v15i1.52-62

JURNAL TEKNIK PERTANIAN LAMPUNG

ISSN 2302-559X (print) / 2549-0818 (online)
Journal homepage : https://jurnal.fp.unila.ac.id/index.php/JTP

Estimation Model of Robusta Coffee (*Coffea canephora*) Productivity Based on Soil, Plant, and Remote Sensing Data

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Article History:

Received : 17 June 2025
Revised : 21 July 2025
Accepted : 20 August 2025

Keywords:

Coffee,
Crop,
NDVI,
Production estimation,
Soil.

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ABSTRACT

Coffee is an important global commodity, and understanding the relationships among factors influencing its productivity is essential for improving production efficiency. This study aimed to evaluate the effects of soil, plant, and remote sensing variables on Robusta coffee productivity. The production estimation model included soil variables (potassium, pH, and electrical conductivity), crop variables (plant height, crown diameter, and chlorophyll content), and remote sensing data (NDVI). Data were collected directly from field plots measuring 10 m × 10 m. Multiple linear regression models were developed to improve prediction performance. Model accuracy was evaluated using paired t*-tests, RMSE, and RRMSE. The results showed that the model based on soil and crop data (R^2 = 0.85) performed slightly better than the model based on soil, plant, and NDVI data (R^2 = 0.88). Furthermore, the soil and crop data-based model produced lower error values (RMSE = 2659.44; RRMSE = 11%) than the model incorporating NDVI (RMSE = 2737.10; RRMSE = 12%). These findings indicate that soil and plant variables play a dominant role in predicting coffee productivity, while remote sensing data provide complementary information. This study provides a comprehensive understanding of the integrated influence of soil, plant, and remote sensing variables in estimating and improving Robusta coffee productivity.*

1. INTRODUCTION

Coffee is one of the most widely consumed beverages worldwide, primarily produced from Arabica and Robusta beans. Global coffee consumption exceeds 400 billion cups annually, generating an economic value of approximately USD 100 billion (Hunt *et al*., 2020). This increasing trend is expected to continue in the coming years, driven by continuous innovation in coffee-based beverages, the expansion of online trading platforms, and the growing culture of consuming coffee outside the home (Samoggia & Riedel, 2019). Consequently, rising consumer demand must be supported by proportional increases in coffee production.

Global coffee production reached approximately 168.5 million 60-kg bags in 2021, with Brazil as the leading producer, followed by Vietnam, Colombia, and Indonesia (Freitas *et al*., 2024). In Indonesia, national coffee production exceeded 770,000 tons in 2022, with export volumes reaching 270,000 tons, representing approximately 35% of total production (BPS, 2023). These figures highlight the strategic importance of coffee as a major agricultural commodity and emphasize the need to enhance its production potential.

The implementation of good agricultural practices is essential to achieve optimal coffee productivity. A comprehensive understanding of soil–plant interactions, particularly the role of nutrient elements in plant growth and stress tolerance, is fundamental for sustainable production. Nutrients play a crucial role throughout the plant life cycle, from vegetative growth to harvest, with macronutrients being especially important (Toor *et al*., 2021). Among these, potassium has been identified as a key element influencing coffee plant performance by regulating assimilate transport and water balance (Hifnalisa *et al*., 2024). Moreover, potassium contributes to plant resilience against abiotic stresses such as temperature fluctuations, drought, and salinity (Hasanuzzaman *et al*., 2018; Johnson *et al*., 2022).

Various approaches have been developed to forecast coffee production; however, a comprehensive understanding of the interactions among multiple influencing factors remains limited. Linear regression models have been widely applied in agricultural research to estimate and predict plant-related variables based on interrelated parameters. Previous studies have demonstrated the effectiveness of regression-based models using soil and plant data to estimate leaf area and crop productivity, including in coffee cultivation (Muñoz *et al*., 2015; Sholikah *et al*., 2023). Nevertheless, studies integrating soil, plant, and remote sensing variables simultaneously remain scarce.

Therefore, this study aims to evaluate the combined influence of soil properties, plant characteristics, and remote sensing data on Robusta coffee productivity using multiple linear regression models. The findings are expected to contribute to improving productivity estimation and supporting data-driven management strategies in coffee cultivation.

2. MATERIALS AND METHODS

2.1. Research Location and Time

This research was conducted at the Robusta coffee plantation of PT Perkebunan Nusantara I Regional 5, located in Wonosari Subdistrict, Malang Regency, Indonesia. Geographically, the study site is located between 8°03′30.3″–8°05′22.3″ S latitude and 112°28′34.5″–112°29′17.5″ E longitude. Field data collection was conducted from September to November 2024. The study area is situated on the southern slope of Mount Kawi, within the Mount Kawi–Butak geological formation (Qpkb), characterized by volcanic landforms. The plantation lies at an altitude ranging from approximately 400 to 660 meters above sea level (masl).

The plantation consists of two main divisions, namely Besaran and Kampung Baru, which experience an average annual rainfall of 2,100–2,600 mm and a mean temperature of approximately 25 °C. This study focused on the Besaran Division, covering an area of approximately 354.2 hectares.

2.2. Tools and Materials

2.2.1. Soil Sampling and Analysis

Soil sampling was conducted at 30 observation points distributed across the study area (Fig. 1), with samples collected at two depths: 0–30 cm and 30–60 cm. The distribution of observation points was based on the division of the plantation into 10 blocks within the division. Observation points were determined using stratified random sampling according to plant performance in the field. Crop performance was classified into three categories—good, moderate, and poor—based on preliminary field observations. At each observation point, composite soil samples weighing approximately 500 g were collected from five subsampling locations within a 10 × 10 m plot. The collected samples were analyzed in the laboratory for exchangeable potassium (K_ex) using the 1 N NH_4OAc (pH 7) extraction method. Soil pH and electrical conductivity (EC) were determined using the electrometric method.

2.2.2. Crop Sample Measurement

Crop samples were collected at the same locations and during the same period as soil sampling (Figure 1). At each of the 30 observation points, samples were obtained from nine coffee plants. All crop measurements were conducted within 10 × 10 m plots corresponding to the soil sampling locations.

The measured parameters included plant height, crown diameter, leaf chlorophyll content, and fruit yield per plant. The average height of coffee trees in the study area ranged from 1.5 to 2.5 m, with crown diameters between 1.5 and 3.5 m. Plant height and crown diameter were measured manually using a measuring tape. Leaf chlorophyll content was measured using a SPAD-502 Minolta chlorophyll meter and calibrated using the equation proposed by Netto *et al*. (2005). Fruit yield was estimated by counting the number of berries per plant without measuring individual fruit weight, considering that the fruits were at different ripening stages during sampling.

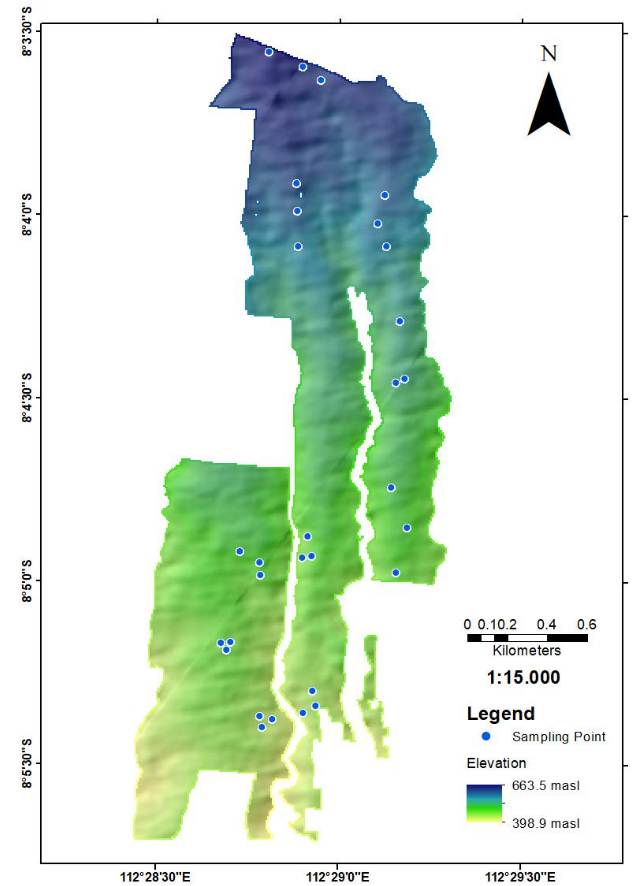

Fig. 1. Research site map

Productivity was determined by counting the average number of berries per cluster, the average number of clusters per productive branch, and the total number of productive branches per tree. Only healthy and fully developed berries were included in the analysis. Coffee productivity was calculated using Equation (1):

$$PA = \bar{B} \times \bar{C} \times PB \tag{1}$$

Notes: PA = Productivity (number of berries), B = average number of berries, C = average number of cluster, PB = number of productive branch.

2.2.3. Remote Sensing Data Collection

This study utilized remote sensing data derived from Sentinel-2 Multispectral Instrument (MSI) imagery that had undergone atmospheric correction and was provided by the European Space Agency through the Copernicus Data Space platform. The Sentinel-2 data were acquired in September 2024 and processed to generate the Normalized Difference Vegetation Index (NDVI).

NDVI is one of the most widely used vegetation indices for assessing vegetation greenness and vigor and has been extensively applied in land and crop analysis (Leroux *et al*., 2016; Ihuoma & Madramootoo, 2017). This index is calculated using reflectance values from the near-infrared (NIR) band (760–900 nm) and the red (R) band (630–690 nm), as originally proposed by Rouse *et al*. (1974), as expressed in Equation (2):

$$NDVI = \frac{NIR - R}{NIR + R} \tag{2}$$

2.3. Development of the Linear Regression Model

The coffee The coffee production estimation model was developed using simple and multiple linear regression approaches. Variable selection was performed using the backward elimination method, in which all candidate independent variables were initially included in the model and subsequently removed if they did not show a statistically significant contribution to the dependent variable (Chowdhury & Turin, 2020).

The significance of each independent variable was evaluated based on its p-value. Variables with p-values lower than the significance level (α = 0.05) were retained in the final model to ensure statistical reliability and predictive accuracy.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \varepsilon \tag{3}$$

2.4. Model Evaluation

The formulated model was evaluated based on its ability to explain variations in the dependent variable using the coefficient of determination (R^2). This parameter is widely used to assess model performance, where an R^2 value close to 1 indicates a strong explanatory power and high predictive efficiency (Despotovic *et al*., 2016).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{4}$$

Model validation continues using a paired t-test to determine whether the results derived from the model can accurately represent field measurement results. If the paired t-test results show that the t-value is smaller than the t-table, the model is considered capable of representing field measurement results (Putra *et al*., 2021).

$$Tp = \frac{\bar{D}}{SD/\sqrt{n}} \tag{5}$$

Model accuracy was evaluated using the Root Mean Square Error (RMSE) and the Relative Root Mean Square Error (RRMSE). RMSE is a widely used indicator for assessing predictive accuracy, where lower RMSE values indicate better model performance (Willmott & Matsuura, 2005; Despotovic *et al*., 2016). RRMSE expresses prediction error as a percentage and reflects the suitability of a model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

$$RRMSE = \frac{RMSE}{y_i} \times 100 \tag{7}$$

Based on Jamieson *et al*. (1991) and Despotovic *et al*. (2016), model performance can be classified as excellent (0–10%), good (10–20%), fair (20–30%), and inadequate (>30%). All statistical analyses and model computations were performed using R software.

3. RESULTS AND DISCUSSION

3.1. Description of Dataset

Soil and crop data used for predicting Robusta coffee production exhibited considerable variability, as indicated by the presence of outliers and relatively high coefficients of variation (CV), including in the production data itself (Figure 2). Electrical conductivity (EC) in the topsoil ranged from 0.04 to 0.14 mS/cm, with an average of 0.08 mS/cm (CV = 29%), while subsoil EC ranged from 0.04 to 0.11 mS/cm, averaging 0.07 mS/cm (CV = 24%). Topsoil pH values varied from 5.88 to 6.41, with a mean of 6.09 (CV = 2%), while subsoil pH ranged from 5.76 to 6.34 (average 6.10, CV = 2%). Exchangeable potassium (K-ex) in the topsoil ranged from 0.05 to 0.32 me/100 g, with a mean of 0.18 me/100 g (CV = 36%), while subsoil K-ex values ranged from 0.05 to 0.32 me/100 g, with an average of 0.19 me/100 g (CV = 42%). Total chlorophyll content varied from 269.65 to 414.04 µmol/m², with a mean of 332.66 µmol/ m², CV = 10%).

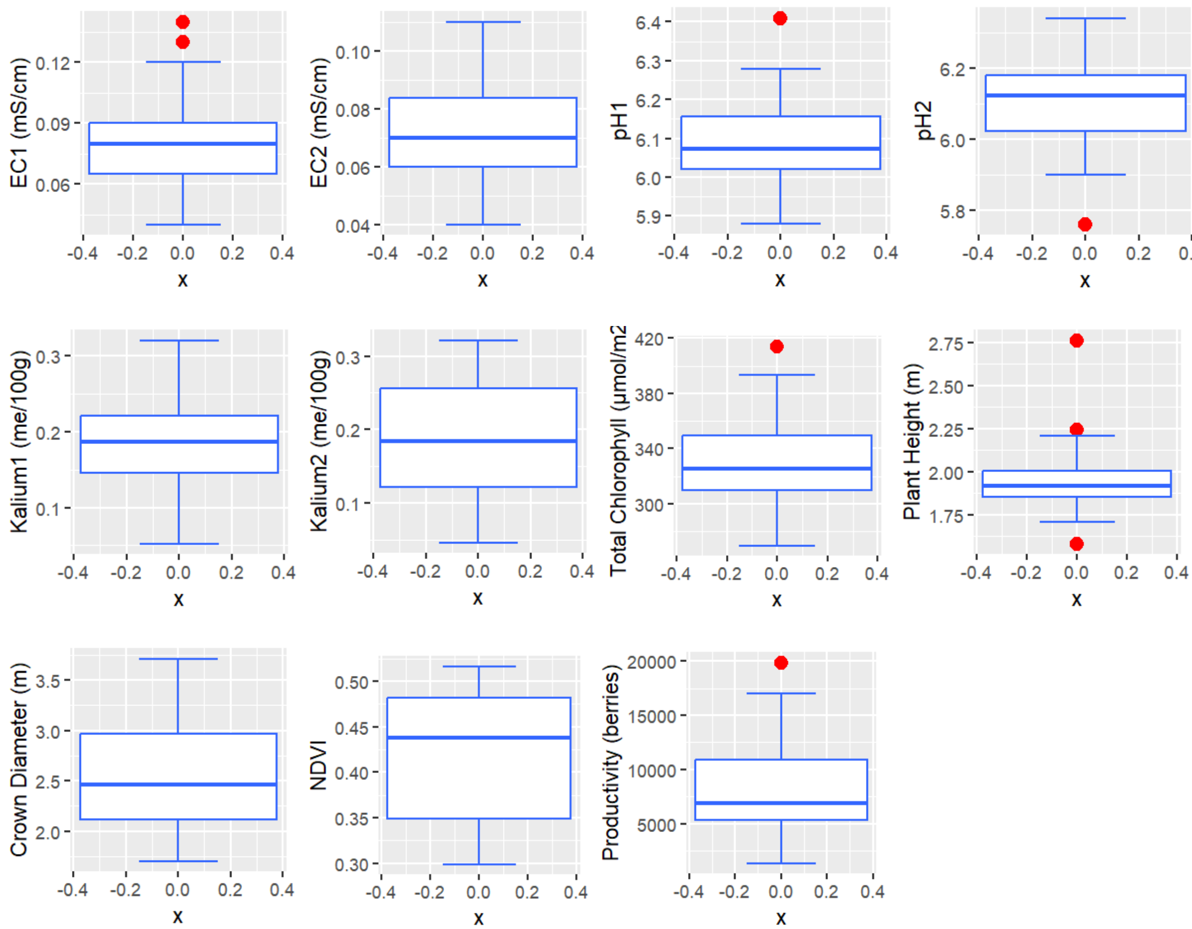

Figure 2. Distribution of measured parameters

Plant height ranged from 1.58 to 2.76 m, averaging 1.95 m (CV = 11%), while crown diameter ranged from 1.70 to 3.71 m, with a mean of 2.59 m (CV = 22%). NDVI values ranged from 0.30 to 0.52, with an average of 0.42 (CV = 17%). Production showed the highest variability, ranging from 1,303.70 to 19,866.00 fruits, with a mean of 8,329.02 fruits (CV = 55%), indicating substantial heterogeneity in yield among sampling sites.

3.2. Model Formulation: Soil Data

The results of the soil data–based coffee production estimation model are presented in Table 1. The analysis showed that several soil variables had a significant effect on coffee production ($p < 0.05$), including potassium1 ($p = 0.009$), pH1 ($p = 0.003$), and potassium2 ($p < 0.001$), while EC1 had a significant effect at the 10% level ($p = 0.08$). These results indicate that soil properties, particularly potassium content, play an important role in determining coffee yield.

Table 1. The results of multiple regression analysis between soil variables on coffee production

Variable	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-180275	53306	-3.382	0.003803
Potassium1 (me/100g)	-64619	21780	-2.967	0.009085
pH1	29198	8463	3.450	0.003294
EC1 (mS/cm)	95885	51346	1.867	0.080273
Potassium2 (me/100g)	78157	16493	4.739	0.000222
pH2	13146	8723	1.507	0.15403
EC2 (mS/cm)	109215	78856	1.385	0.18773

Accordingly, efforts to increase coffee production can be directed toward improving soil potassium availability, especially exchangeable potassium (K-ex), through appropriate fertilization, particularly in soils with low initial K-ex levels (Elephant *et al*., 2023). Furthermore, potassium fertilization has been reported to enhance coffee production by increasing the number of productive branches, clusters per branch, fruits per cluster, and total fruits per plant (Hifnalisa *et al*., 2024). Potassium also plays a fundamental role in supporting plant growth from the vegetative to the generative stage, as its function as an enzyme cofactor is essential for photosynthesis and the translocation of assimilates throughout the plant (Hasanuzzaman *et al*., 2018).

3.3. Model Formulation: Crop Data

The results of the plant data–based coffee production forecasting model are presented in Table 2. The analysis showed that among the evaluated variables, only crown diameter had a significant effect on coffee production ($p = 0.003 < 0.05$), while the other variables were not statistically significant. The influence of crown diameter on production is mainly associated with an increase in the number of branches, which enhances the potential formation of productive branches bearing fruit. In general, higher coffee yield is achieved through an increase in the number of fruits, which is strongly influenced by the number of clusters and productive branches.

Therefore, efforts to improve coffee production can be directed toward increasing crown diameter by promoting the development of productive branches. This can be achieved by ensuring adequate potassium nutrition in plants (Hifnalisa *et al*., 2024). In addition, appropriate pruning practices can be applied to stimulate the formation of new productive branches and improve canopy structure (Karim *et al*., 2021; Permanasari *et al*., 2024).

Table 2. The results of multiple regression analysis between crop variables on coffee production

Variable	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	10576.4	13061.1	0.81	0.42927
Total Chlorophyll (μmol/m^2)	-38.14	37.05	-1.029	0.31776
Plant Height (m)	-3270.92	4652.41	-0.703	0.49154
Crown Diameter (m)	6522.4	1909.03	3.417	0.00329

3.4. Model Formulation: NDVI Data

The results of the crop data–based coffee production forecasting model are presented in Table 3. The analysis indicated that coffee production forecasting using the NDVI index did not have a statistically significant effect on coffee production ($p = 0.527$). Data collection at different times (July) also showed no significant differences, varying only about 10% from the research data (September) (Figure 3). These results contradict those of Aziz & Santosa (2019) and Sholikah *et al*. (2023). Plant production estimation using vegetation indices is one of the most widely used methods at present (Luo *et al*., 2022). The ease of data access and interpretation is the reason for the application of this method in estimating the production of various plants using various approaches. The different results from previous studies may be due to various factors such as chlorophyll content in leaves and leaf area index (LAI). The NDVI formula is formed from the ratio of the red and near-infrared channels, so the absorption and reflection of light waves from the leaves affect the value obtained. Furthermore, AbdelRahman (2023) explains that under optimal conditions, the absorption of the red spectrum is carried out by pigments such as chlorophyll, while the reflection of the near-infrared spectrum is carried out by the leaf tissue. On the other hand, a lower LAI value can affect NDVI due to the plant canopy not being able to fully cover the soil surface, resulting in light spectrum reflection from the soil also being captured in the image. In addition, Nogueira *et al*. (2018) also explain that changes in NDVI values in coffee fields can be caused by differences in LAI at each plant growth stage.

Table 3. The results of simple regression analysis between NDVI variables on coffee production

Variable	Estimate	Std. Error	*t*- value	Pr(>|t|)
Intercept	4154	6885	0.603	0.553
NDVI	10153	15748	0.645	0.527

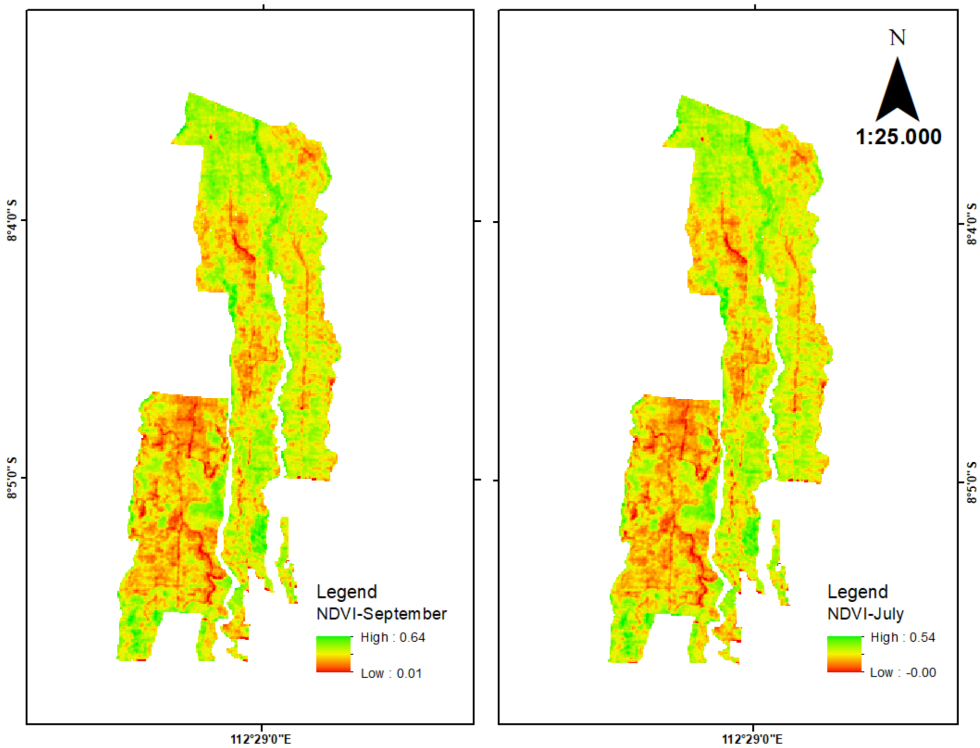

Figure 3. Comparison of NDVI in July and September

3.5. Model Formulation: Soil and Crop Data

The results of the soil and crop data-based coffee production forecasting model are shown in Table 4. The combination of soil and crop data involved several parameters that were selected based on their relevance and potential influence on coffee production. Several soil variables included in this model were potassium1 ($p = 0.001$), pH1 ($p = 0.004$), EC1 ($p = 0.017$), and potassium2 ($p < 0.001$), while the plant variables consisted of plant height ($p = 0.037$) and canopy diameter ($p < 0.001$). The integration of multiple variables into a single model aims to enhance the models performance and accuracy, making it more applicable (Ratner, 2010; Chowdhury & Turin, 2020).

Table 4. The results of multiple regression analysis between soil and crop variables on coffee production

Data	Variabel	Coefficient	Std. Error	*t* value	Pr(>|*t*|)
	Intercept	-130136	39628	-3.284	0.005433
Soil	Potassium1 (me/100g)	-56997	15038	-3.790	0.001989
	pH1	21202	6108	3.471	0.003744
	EC1 (mS/cm)	93777	34790	2.696	0.017409
	Potassium2 (me/100g)	66898	12236	5.468	0.0000829
Crop	Plant Height (m)	-7227	3151	-2.294	0.037805
	Crown Diameter (m)	5401	1182	4.569	0.000438

3.6. Model Formulation: Soil, Crop and NDVI Data

The results of developing a coffee production estimation model based on soil, crop, and NDVI data are shown in Table 5. The addition of NDVI data to the previous model, which had combined soil and crop data, aimed to assess whether there were significant changes in the significance of each variable. The results of the model development indicate that there was no increase in the significance of the influence of each variable from the previous model. This result also proves that the addition of NDVI data to the model does not affect other variables and does not significantly affect coffee production (p = 0.134). The addition of variables to the model in this way is a forward selection approach in variable selection for model formation (Ratner, 2010; Chowdhury & Turin, 2020). However, the result that the addition of NDVI data does not significantly affect coffee production deviates from the principle of parsimony. According to this principle, a simpler model with fewer variables is preferred over a model with complex variables. Additionally, a simpler model is easier to apply and interpret (Steyerberg, 2019).

Table 5. The results of multiple regression analysis between soil, crop and NDVI variables on coffee production

Data	Variabel	Coefficient	Std. Error	t value	Pr(>|t|)
	Intercept	-130338	37602	-3.466	0.00418
Soil	Potassium1 (me/100g)	-55770	14290	-3.903	0.00182
	pH1	20562	5810	3.539	0.00363
	EC1 (mS/cm)	92024	33030	2.786	0.01544
	Potassium (me/100g)	72843	12193	5.974	4.64E-05
Crop	Plant height (m)	-7828	3014	-2.598	0.0221
	Crown diameter (m)	4658	1214	3.836	0.00206
Remote sensing	NDVI	13608	8524	1.597	0.13438

3.7. Model Performance and Validation

Model performance was assessed through analysis of the coefficient of determination (R^2), whereas the higher the coefficient of determination, the greater the ability of a model to describe the variability of field observation results. The highest coefficient of determination among the five models was found in the model based on soil, crop, and NDVI data (R^2 = 0.88), while the lowest coefficient of determination was found in the NDVI-based model (R^2 = 0.02). These results indicate that better performance is found in the model based on soil, plant, and NDVI data with a coefficient of determination value close to 1 (Despotovic *et al*., 2016).

Model accuracy assessment was conducted using several approaches, such as the T-test, RMSE, and RRMSE. Model validation through paired T-tests showed that the T-values of each model were smaller than the two-tailed T-table value (2.31). This indicates that the developed models can produce accurate predictions and are consistent with field measurement results (Prasetya *et al*., 2025; Putra *et al*., 2021).

Accuracy assessments using RMSE and RRMSE were conducted to determine the extent of errors in the models and evaluate their suitability. The soil and crop data-based model yielded the smallest results compared to other models (RMSE = 2,659.44 units, RRMSE = 11%), while the soil data-based model had the largest results (RMSE = 6,079.09 units, RRMSE = 26%). Model evaluation based on RMSE refers to lower values indicating better model accuracy in the field (Jierula *et al*., 2021). Alternatively, model accuracy evaluation using RRMSE refers to the level of suitability, where only the soil-based model has acceptable accuracy (26%), while the other models have good suitability (<20%) (Jamieson *et al*., 1991; Tsele *et al*., 2023).

Table 6. Model Performance and Validation

Data	R^2	T-value	T-Table	RMSE (Berries)	RRMSE (%)
Soil	0.70	0.10	2.31	6079.09	26
Crop	0.50	0.18	2.31	4467.37	19
NDVI	0.02	0.41	2.31	2880.45	12
Soil + Crop	0.85	0.70	2.31	2659.44	11
Soil + Crop+ NDVI	0.88	0.17	2.31	2757.10	12

Based on the results of model accuracy and performance tests, the combination of soil and crop data was found to be capable of representing coffee fruit production. The accuracy test results were better than those of other models, accompanied by a coefficient of determination that was only slightly lower than that of models based on soil, crop, and NDVI data. In line with the principle of parsimony, the fewer variables involved in model development, the more effective the model (Chowdhury & Turin, 2020). The coffee production model based on soil and crop data is presented in Equation (8).

$$Y = -130136 - 56997\,(K1) + 21202\,(pH1) + 93777\,(EC1) + 66898\,(K2) - 7227\,(H) + 5401\,(CD) \qquad (8)$$

with K is Kalium, EC is electrical conductivity, H is plant height, and CD is crown diameter.

4. CONCLUSION

The results of this study indicated that several variables from soil and plant data had a significant influence on coffee production. Therefore, efforts to increase coffee production can be enhanced through the optimization of several related variables, such as the K_{ex} content in the soil and the diameter of the coffee canopy, which have a greater influence than other variables. In efforts to increase coffee production, this model can be widely applied in different locations. However, limitations in certain areas, such as data availability and differences in other factors affecting plant growth, must be considered. Future research is expected to provide more detailed models or methods for predicting the variables that can significantly contribute to coffee production.

AUTHOR CONTRIBUTION STATEMENT

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
MF	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓			
NFI	✓			✓		✓	✓			✓		✓	✓	✓
Soe	✓	✓			✓					✓		✓		
KSW	✓	✓			✓					✓		✓		

C: Conceptualization	Fo: Formal Analysis	O: Writing - Original Draft	Fu: Funding Acquisition
M: Methodology	I: Investigation	E: Writing - Review & Editing	P: Project Administration
So: Software	D: Data Curation	Vi: Visualization	
Va: Validation	R: Resources	Su: Supervision	

ACKNOWLEDGMENT

This research was supported by the Directorate General of Higher Education, Research, and Technology, Ministry of Education, Culture, Research, and Technology under the Masters Education to Doctorate for Excellence Undergraduate with contract number 006/E5/PG.02.00/PLPMDSU/2024. We would also like to thank the field and laboratory assistants for their assistance in sample collection and analysis.

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