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Remote Sensing–Based Automated Machine Learning for Arabica Coffee Yield Prediction in Bandung Regency, Indonesia

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Abstract

Monitoring coffee productivity is crucial for maximizing export potential, yet conventional field-based methods remain inefficient for large-scale applications. Remote sensing offers spectral and environmental insights linked to crop physiology, enabling spatially and temporally explicit yield prediction. This study aimed to develop an efficient and accurate yield-prediction model by integrating AutoML with remote-sensing–derived predictors, including vegetation indices, soil temperature, climate, and topographic variables. The study was conducted in 2023 in Bandung

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Regency, West Java, Indonesia, using yield observations from 73 field plots. Decision tree (DT), random forest (RF), extremely randomized trees (ExtraTrees), extreme gradient boosting (XGBoost), and light gradient boosting machine (LightGBM) as individual models and ensemble structure were implemented using the AutoML tool in ArcGIS Pro. Among them, the ensemble structure achieved the highest predictive performance (R^2 = 0.85; RMSE = 960.17 kg ha^{-1}), outperforming all individual models. Model interpretation indicated that Land Surface Temperature (LST) and precipitation (CHIRPS) were the most influential predictors governing yield variability across smallholder coffee plots. These findings demonstrate the potential of integrating AutoML and remote-sensing–derived variables as an efficient, scalable approach for yield prediction in heterogeneous smallholder coffee systems.

Keywords: Coffee productivity; precision agriculture; machine learning; remote sensing.

1. Introduction

Coffee is a key agricultural commodity contributing to Indonesia's foreign exchange, with the main varieties cultivated being robusta and arabica. Although robusta still dominates production, its plantation area has declined by 1.42% over the past two decades, while arabica has increased by 10.07% due to its superior taste and higher market value (Kementerian Pertanian, 2022; Mishra & Slater, 2012; Sepúlveda et al., 2016). Bandung Regency, a major arabica-producing region in West Java with 14,001.51 ha of plantations, is home to Java Preanger, one of Indonesia's 17 specialty coffees (Dinas Pertanian Kabupaten Bandung, 2018; Rokhmah et al., 2023). Despite its high export potential, Arabica coffee production, which smallholder farms predominantly manage, faces constraints related to limited resources and poor management (Byrareddy et al., 2019; Sundana & Raharja, 2022). To maximize its export potential, effective and efficient productivity monitoring is essential to ensure sustainable Arabica coffee production.

The success of production monitoring relies on the accuracy of predictive models and their input variables. Field-based predictors often yield high accuracy but are inefficient for large areas, whereas remote sensing offers a practical alternative. Bolaños et al. (2023), highlighted that remote sensing enables early yield prediction, supports nutrient management decisions, and allows temporal monitoring with minimal resources. This capability stems from satellite-derived spectral variations that reflect soil and crop characteristics, facilitating the identification of agricultural patterns (Damian et al., 2020; Kayad et al., 2019; Santana et al., 2021).

To predict Arabica coffee productivity, several influencing factors must be considered, including climate, topography, soil quality, and crop characteristics, as the soil–crop–environment dynamics directly affect yield (Bolaños et al., 2023; Giraldo-Sanclemente et al., 2025; Núñez et al., 2024). These factors can be effectively represented using remote sensing–derived variables and ancillary geospatial data. Climatic variability can be captured through rainfall data from CHIRPS and land surface temperature (LST) derived from Landsat thermal bands, which reflect water availability and thermal stress affecting coffee growth (Funk et al., 2015; Qin et al., 2001). Topographic factors such as elevation and slope shape local microclimate, soil moisture, and nutrient dynamics, thereby influencing productivity (Sarmiento-Soler et al., 2020). Spectral indices such as Normalized Difference Vegetation Index (NDVI), Modified Chlorophyll Absorption in Reflectance Index 1 (MCARI1), Inverted Red-Edge Chlorophyll Index (IRECI), and Green Chlorophyll Index (CIGreen) utilize reflectance in the red, green, red-edge, and near-infrared (NIR) regions, which are closely linked to chlorophyll concentration, nitrogen status, and leaf area—key indicators of crop vigor and productivity (Chemura et al., 2018; Frampton et al., 2013; Gitelson et al., 2005; Haboudane et al., 2004; Tucker, 1979). Additionally, the Normalized Difference Water Index (NDWI) and the Normalized Difference Drought Index (NDDI) exploit shortwave infrared (SWIR) and NIR wavelengths to assess canopy and soil moisture status, thereby capturing the effects of climatic and surface cover variations on crop performance(Gao, 1996; Gu et al., 2007).

The advancement of machine learning has substantially improved the accuracy of predictive models compared with traditional statistical approaches (Alves et al., 2022). To improve usability, Automated Machine Learning (AutoML) was created to automate the process of model selection, training, and hyperparameter tuning, helping to find the best algorithm for a specific dataset. Thereby improving predictive performance while reducing computational time and complexity, making advanced machine learning techniques more accessible to researchers and practitioners (He et al., 2021; Zöller & Huber, 2021). Previous studies have demonstrated the potential of AutoML in various agricultural applications, such as soil organic carbon (SOC) mapping and processing tomato yield prediction (Darra et al., 2023; Tran et al., 2023). However, its integration with multi-source remote sensing data for perennial crops, particularly Arabica coffee, remains limited. Therefore, this study aims to develop an efficient and accurate yield-prediction framework by integrating remote-sensing–derived variables with AutoML techniques.

2. Materials and Methods

2.1 Study Area

This research was carried out in 2023 in Bandung Regency, West Java, Indonesia, located between 6°41'–7°19' S and 107°22'–108°50' E, covering 176,240 ha. A total of 73 observation points were used. The area consists mainly of Andisols and Inceptisols (USDA Keys to Soil Taxonomy). Coffee plots were situated on slopes of 0–70% and elevations of 900–2000 m a.s.l. During the 2022/2023 production cycle, rainfall peaked in October 2022 (361.81 mm) and reached its minimum in August 2023 (7.06 mm).

2.2 Data Collection

2.2.1 Coffee Productivity and Management

Coffee productivity was measured as harvested coffee cherry weight (kg ha^{-1}) during the main harvest season. Data were obtained through farmer questionnaires across major arabica-producing areas in Bandung Regency after the 2023 main harvest (August), minimizing recall bias. Sampling sites were selected purposively to represent the main Arabica coffee–growing areas in Bandung Regency, considering variations in topographic conditions, soil type, and management practices. Elevation ranged from around 900 to 2,000 m a.s.l., with slopes varying from 0% to over 70%, covering a gentle and steep volcanic terrains landscape. Soil types were predominantly Andisols and Inceptisols, which are typical of highland coffee-growing zones. Sampling locations were georeferenced using Avenza Maps, with photographs taken for field validation. Additional management data, such as fertilization, pruning, shading, and land conditions, were recorded. Most sampled farms were low-input smallholder systems. Only coffee plants aged 5–20 years (optimal productive stage) were included to ensure yield consistency.

2.2.2 Coffee Productivity Predictor

Predictor variables included vegetation indices, CHIRPS rainfall, land surface temperature (LST) from Landsat 8, and topographic variables (slope, elevation) from the Indonesian DEMNAS dataset (Table 1). Vegetation indices were extracted from Sentinel-2A imagery (July 2022–January 2023) using Google Earth Engine (GEE). Images were preprocessed through geometric/radiometric corrections and cloud masking. CHIRPS precipitation and LST data were also obtained from GEE for the same temporal window, enabling pre-harvest yield prediction (Luong & Bui, 2025). DEMNAS (0.27 arc-second resolution) was procured from the Indonesian Geospatial Information Agency and processed in ArcGIS Pro 3.1 to derive topographic attributes.

2.3 Automated Machine Learning (AutoML)

An Automated Machine Learning (AutoML) framework implemented in ArcGIS Pro 3.1 was used to develop predictive models of Arabica coffee productivity. Traditional machine learning workflows in agriculture generally require substantial expert involvement for algorithm selection, feature engineering, and hyperparameter tuning. AutoML streamlines these processes by automating key components of the modeling pipeline, reducing computational burden, and minimizing reliance on specialized technical expertise (Darra et al., 2023; Zöller & Huber, 2021).

In this study, the *Train Using AutoML* tool (Basic Mode) was applied to build the models. Preprocessing steps included data cleaning, variable stacking, descriptive statistical assessment, normality checks, and manual feature selection based on Spearman's correlation and iterative model testing to determine the predictive relevance of each variable (Barbosa et al., 2021). The AutoML workflow subsequently performed automated data partitioning, algorithm comparison, internal hyperparameter optimization, and selection of the best-performing model while minimizing overfitting (ESRI, 2022).

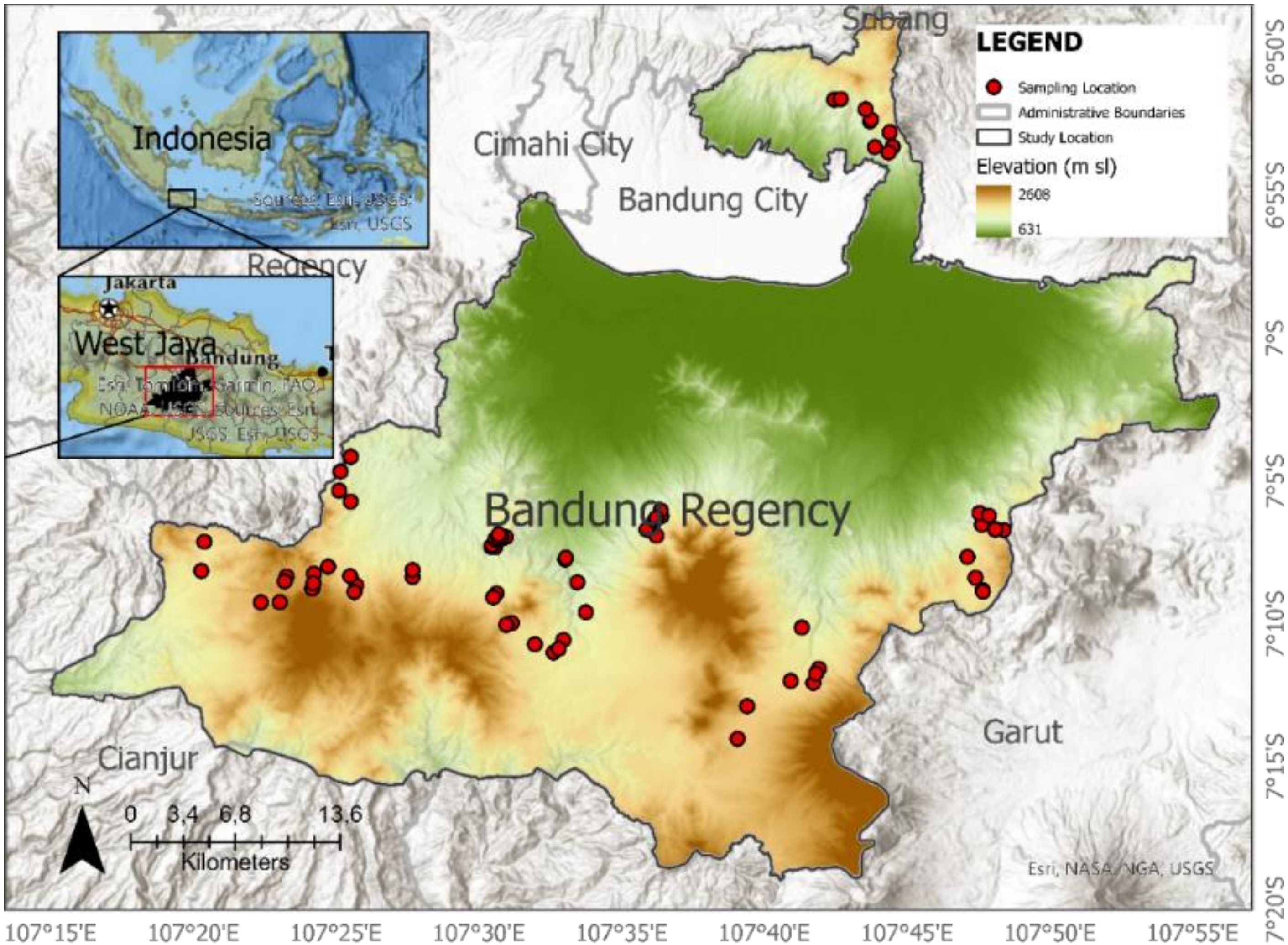

Fig. 1. Study Location in Bandung Regency

Table 1. List and description of candidate predictor variables for modeling

No.	Candidate of predictor variables	Description/Formula	Source/Reference
1.	Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - RED}{NIR + RED}$	(Tucker, 1979)
2.	Normalized Difference Water Index (NDWI)	$\frac{NIR - SWIR1}{NIR + SWIR1}$	(Gao, 1996)
3.	Normalized Difference Drought Index (NDDI)	$\frac{NDVI - NDWI}{NDVI + NDWI}$	(Gu et al., 2007)
4.	Green Chlorophyll Index (CIgreen)	$\frac{NIR}{GREEN} - 1$	(Gitelson et al., 2005)
5.	Modified Chlorophyll Absorption in Reflectance Index 1 (MCARI1)	$1{,}2[2{,}5(NIR - RED) - 1{,}3(NIR - GREEN)]$	(Haboudane et al., 2004)
6.	Inverted Red-Edge Chlorophyll Index (IRECI)	$\frac{NIR - RED}{RE2/RE1}$	(Frampton et al., 2013)
7.	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)	-	https://www.chc.ucsb.edu/ data/chirps
8.	Land Surface Temperature (LST)	Calculated from Landsat 8 TIRS using Mono-Widow Algorithm	(Qin et al., 2001)
9.	Elevation	Calculated from the Digital Elevation Model (DEM)	https://tanahair.indonesia. go.id/portal-web/
10.	Slope		

The AutoML system evaluated several supervised learning algorithms, including Decision Tree (DT), Random Forest (RF), Extremely Randomized Trees (ExtraTrees), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM). DT is a nonparametric supervised algorithm for classification and regression, structured hierarchically from a root node to terminal leaves (Chowdhury et al., 2022).

While interpretable and accurate, DT often suffers from overfitting. RF extends DT by aggregating multiple trees trained on bootstrapped samples and random feature subsets, reducing correlation and improving generalization (Breiman, 2001). ExtraTrees further enhances diversity by randomizing split thresholds, often achieving greater accuracy and computational efficiency (Geurts et al., 2006). Boosting-based methods sequentially build trees to minimize residual errors. XGBoost applies gradient boosting with scalability through parallel computing and sparsity-aware learning (Chen & Guestrin, 2016). LightGBM improves efficiency using Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB), making it suitable for large, high-dimensional datasets (Ke et al., 2017). Ensemble structures integrate multiple learners through bagging, boosting, or stacking, with the AutoML framework in ArcGIS Pro applying forward stepwise selection to maximize predictive performance via weighted averaging or voting (Caruana et al., 2004; ESRI, 2022).

Model performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE), which were used as the primary criteria to determine predictive strength and error magnitude, respectively. These metrics are widely adopted in agricultural yield prediction studies and provide a reliable basis for comparing model performance (Nogueira et al., 2018; Rashid et al., 2021; Shahhosseini et al., 2020). Model interpretability was further enhanced using SHAP (Shapley Additive Explanations) values to quantify the relative contribution of each predictor, enabling transparent identification of key environmental and spectral factors influencing Arabica coffee productivity. These evaluation and interpretability tools are also fully integrated within the AutoML framework in ArcGIS Pro 3.1, allowing standardized performance assessment and efficient model interpretation within a single workflow.

3. Results and Discussion

3.1 Results

3.1.1 Selected Predictor Variable

Feature selection was conducted using a hybrid approach that combined filter and wrapper methods. In the filter stage, Spearman's rank

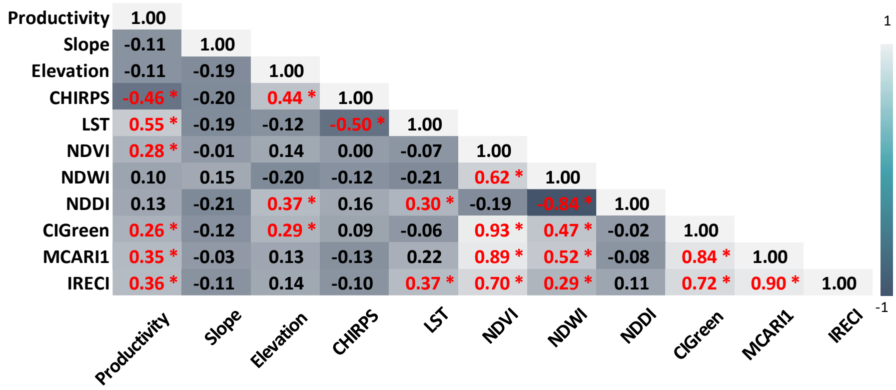

Fig. 2. Correlation Matrix of candidate predictor variables. Asterisk (*) indicates significance at the 0.05 level

correlation was calculated to assess the relationship between each predictor and coffee productivity, as well as to identify pairs of highly correlated variables (Fig. 2). This step provided an initial guideline for feature reduction; however, multicollinearity was not entirely removed, as the prediction models employed (tree-based and non-parametric algorithms) are generally robust to collinear predictors (Chowdhury et al., 2022). The retained predictors were subsequently evaluated through an iterative model-based procedure, in which different feature subsets were trained and compared across multiple algorithms. This wrapper stage followed a principle similar to recursive feature elimination (RFE), where features were incrementally added or removed, and the resulting model accuracy was used as the selection criterion (Venkatesh & Anuradha, 2019). The final subset of predictors was determined from the feature combination that achieved the highest predictive performance. The predictor variables selected in this study were LST, CHIRPS, IRECI, MCARI1, CIGreen, slope, and elevation.

3.1.2 Model Performance for Arabica Coffee Productivity

The predictive performance of five tree-based machine learning algorithms for coffee yield estimation revealed notable variability (Table 2). The DT model achieved the best performance among the single models, with an R^2 of 0.68 and an RMSE of 1,389.44 kg ha^{-1}. In contrast, RF, ExtraTrees, and LightGBM yielded substantially lower R^2 values (0.14–0.24) and higher RMSE (2,145–2,280 kg ha^{-1}). XGBoost performed slightly better than other ensemble learners, attaining an R^2 of 0.33 with an RMSE of 2,010.09 kg ha^{-1}. However, when several models were integrated into an ensemble structure, prediction accuracy increased markedly, achieving the highest coefficient of determination (R^2=0.85) and the lowest error (RMSE=960.17 kg ha^{-1}).

3.1.3 Feature Importance Analysis Based on SHAP Values

To better understand the contribution of each predictor to coffee productivity estimation, a model interpretation was conducted using values derived from the AutoML framework in ArcGIS Pro. SHAP provides a unified measure of feature influence by quantifying the marginal contribution of each variable to model predictions, allowing transparent interpretation across multiple machine learning algorithms (Lundberg & Lee, 2017). Table 3 summarizes the SHAP-based feature importance rankings for all predictor variables across the five machine learning models. The ranking reflects the relative contribution of each feature to yield prediction, with the most influential feature indicated by rank 1. A higher number indicates a decrease in the level of influence, while a dash (–) indicates a variable with a very small or insignificant contribution to the model.

Feature ranking across models revealed that LST consistently emerged as the most influential predictor, ranking within the top two in all algorithms. Precipitation (CHIRPS) was also highly ranked, particularly in DT, RF, and XGBoost, underscoring the climatic sensitivity of Arabica coffee. Vegetation indices such as MCARI1 and CIgreen showed moderate importance, though their rankings varied across models, reflecting differences in how algorithms

Table 2. Model performance

Model	Model Parameter	R^2	RMSE (kg ha⁻¹)
DT	n_jobs: 1; criterion: mse; max_depth: 3 explain_level: 2; validation_type: split; train_ratio: 0.75; shuffle: True	0.68	1,389.44
RF	n_jobs: 1; criterion: mse; max_features: 0.9; min_samples_split: 30; max_depth: 4; explain_level: 2; validation_type: split; train_ratio: 0.75; shuffle: True	0.24	2,148.63
ExtraTrees	n_jobs: 1; criterion: mse; max_features: 0.9; min_samples_split: 30; max_depth: 4; eval_metric_name: rmse; explain_level: 2; validation_type: split; train_ratio: 0.75; shuffle: True	0.14	2,279.74
LightGBM	n_jobs: 1; objective: regression; num_leaves: 63; learning_rate: 0.05; feature_fraction: 0.9; bagging_fraction: 0.9; min_data_in_leaf: 10; metric: rmse; custom_eval_metric_name: None; explain_level: 2; validation_type: split; train_ratio: 0.75; shuffle: True	0.24	2,145.2
XGBoost	n_jobs: 1; objective: reg:squarederror; eta: 0.075; max_depth: 6; min_child_weight: 1; subsample: 1.0; colsample_bytree: 1.0; eval_metric: rmse; explain_level: 2; validation_type: split; train_ratio: 0.75; shuffle: True	0.33	2,010.09
Ensemble Structure	Decision Tree (weight = 4) and Random Forest (weight = 2)	0.85	960.168

Table 3. SHAP feature importance ranks

Model Feature	DT	RF	ExtraTrees	XGBoost	LightGBM
LST	2	1	2	2	1
CHIRPS	1	3	5	3	6
IRECI	-	-	4	7	7
MCARI1	-	4	1	4	4
CIGreen	3	-	6	1	2
Slope	-	2	3	6	5
Elevation	-	-	7	5	3

capture canopy-related variability. Topographic predictors (elevation and slope) were regularly placed in the mid-ranking positions rather than among the primary predictors. Overall, the consistency of LST and CHIRPS highlights their robustness as core predictors of coffee productivity, while the variable rankings of spectral indices and topographic factors indicate algorithm-specific sensitivities.

3.2 Discussion

3.2.1 Correlation between Predictor Variables and Productivity

Vegetation remote sensing utilizes the reflectance of electromagnetic radiation recorded by passive sensors, where spectral responses vary according to plant biochemical, structural, and physiological conditions (Babar et al., 2006; Liu et al., 2016; Xue & Su, 2017). Consequently, vegetation indices derived from satellite imagery are widely used to predict Arabica coffee productivity due to their strong relationships with plant biophysical and biochemical parameters (Chemura et al., 2017). In this study, the IRECI exhibited the strongest correlation with coffee productivity (r = 0.37), indicating its higher sensitivity to yield-related parameters such as chlorophyll content and leaf area index (LAI), which is consistent with previous findings highlighting the superior performance of red-edge-based indices in capturing canopy density and biomass dynamics (Frampton et al., 2013; Gitelson et al., 2005; Xie et al., 2018). MCARI1 and NDVI also showed significant but weaker positive correlations with productivity (r = 0.35 and r = 0.28, respectively), reflecting their ability to represent photosynthetic activity and canopy vigor, while CIgreen exhibited the lowest correlation (r = 0.26), likely due to the limited penetration of the green band in dense coffee canopies; nevertheless, CIgreen remains useful for capturing spatial variability in canopy vigor where red-edge information is unavailable (Bolaños et al., 2023; Haboudane et al., 2004; Merzlyak & Gitelson, 1995; Nguy-Robertson et al., 2014).

In addition to vegetation indices, environmental variables such as LST, precipitation CHIRPS, slope, and elevation were also considered, as these factors influence canopy vigor and ultimately determine coffee yield across different landscapes. LST exhibited a moderate and statistically significant positive correlation with coffee productivity (r = 0.55), indicating that productivity tends to increase with rising surface temperature. This relationship suggests that warmer surface conditions may enhance nutrient mineralization and availability in the soil, thereby supporting plant growth (Vogel et al., 2008). Similarly, Silva et al. (2004), reported that low temperatures can directly constrain both growth and photosynthetic activity in coffee plants, reinforcing the sensitivity of coffee productivity to thermal variations within its optimal temperature range. CHIRPS showed a significant negative correlation (r = −0.46) with productivity. This indicates that higher rainfall amounts were associated with lower yields, likely due to the disruptive effects of excessive moisture during key phenological stages. Rainfall variability influences all growth phases of coffee, particularly flowering, fruiting, and ripening, where prolonged wet conditions can hinder pollination, fruit set, and cherry development (Soares et al., 2021). Consistent with this finding, studies conducted in the eastern and northwestern regions of Uganda also reported that excessive precipitation significantly reduced coffee yield (Wang et al., 2015).

3.2.2 Model Performance for Arabica Coffee Productivity

Based on the results in model performance (Table 2), these findings highlight that model complexity does not necessarily guarantee higher predictive accuracy. The relatively simple DT produced robust predictions (R^2 = 0.68), effectively capturing nonlinear patterns in the data. This outcome aligns with Hastie et al. (2009), who emphasized the effectiveness of DT for datasets with clear structural relationships. In contrast, RF and ET failed to achieve comparable performance, both exhibiting low explanatory power ($R^2 \leq 0.24$). This is contrary to the statement that random forests are generally superior to decision trees (Chowdhury et al., 2022; Kayad et al., 2019). This may be attributed to the limited sample size and potential data noise, which reduced the advantages of bootstrap aggregation and random feature selection. Tang et al. (2018), highlighted that RF models can exhibit poor performance when trained on small or overly simple datasets, as these conditions heighten the tendency toward overfitting. In addition, low accuracy can also be caused by inadequate parameter optimization and strong correlations between predictors. As Breiman (2001), emphasized, high inter-feature correlation constrains the algorithm's capacity to select informative variables during node partitioning, which ultimately weakens model performance. Boosting-based models, LightGBM and XGBoost, which are generally recognized for superior performance on large and complex datasets (Chen & Guestrin, 2016; Ke et al., 2017), did not perform optimally in this study. With R^2 values of 0.24 and 0.33, respectively, their predictive ability remained limited, likely due to non-optimized hyperparameters and the modest dataset size.

The Ensemble Structure Model substantially outperformed all individual models (R^2 = 0.85). This result underscores the power of ensemble learning, which leverages the strengths of multiple models while mitigating their weaknesses. In this research, the ensemble model was constructed from a weighted combination of a DT (weight = 4) and an RF (weight = 2). By prioritizing the contribution of the DT, which already exhibited the strongest predictive ability among the base learners, the ensemble achieved the highest accuracy (R^2 = 0.85) and the lowest prediction error (RMSE = 960.17 kg ha^{-1}). According to Dietterich (2000), ensembles improve predictive accuracy by reducing both bias and variance, thereby enhancing generalization. The ensemble effectively compensated for these variations by leveraging the complementary predictive strengths of its base models, resulting in a more generalized and reliable prediction framework.

3.2.3 Model Interpretation and Ecophysiological Implications of SHAP-Derived Feature Importance

The SHAP-based feature importance analysis revealed variation in the relative influence of predictors across algorithms, reflecting the distinct learning mechanisms of each ensemble model (Table 3). LST consistently emerged as one of the most influential variables across all models, ranking first in Random Forest and LightGBM, and second in DT, ExtraTrees, and XGBoost. This pattern suggests that thermal conditions play a dominant and stable role in determining Arabica coffee productivity, aligning with prior studies reporting strong temperature sensitivity in coffee yield and bean quality (Bunn et al., 2015; Craparo et al., 2015). In contrast, CHIRPS showed moderate importance ranking high in DT and RF but lower in LightGBM, indicating that rainfall variability contributes meaningfully to productivity but interacts with other climatic or terrain factors rather than acting as a primary driver.

Vegetation indices such as MCARI1, CIgreen, and IRECI exhibited model-dependent behavior. MCARI1 was most influential in ExtraTrees and moderately important in boosting models, whereas CIgreen was highly ranked in XGBoost and LightGBM. Slope and elevation ranked lower overall, though they remained moderately important in LightGBM and ExtraTrees, indicating a more localized effect rather than a global control. These findings align with the SHAP framework, where importance reflects each feature's marginal contribution to the model's output (Adler & Painsky, 2022; Lundberg & Lee, 2017). Differences in feature ranking across algorithms, therefore, represent complementary model behaviors. Bagging methods (e.g., Random Forest, ExtraTrees) tend to privilege stable, globally consistent predictors because they aggregate multiple randomized trees using impurity-based splits across full datasets. In contrast, boosting methods (e.g., XGBoost, LightGBM) focus sequentially on modeling residual errors, enabling them to emphasize predictors associated with conditional or localized variation—not just overall trends (Adler & Painsky, 2022; Das et al., 2022). Overall, the consistency of LST as a top-ranked predictor underscores its critical role as a key environmental determinant of Arabica coffee productivity, while variation among other features highlights the complementary strengths of models in representing complex ecophysiological processes.

4. Conclusion

This study demonstrates the potential of integrating AutoML with remote sensing data to model Arabica coffee productivity in Bandung Regency, Indonesia. The ensemble model achieved the highest predictive performance (R^2 = 0.85), indicating that AutoML is effective in capturing yield variability under heterogeneous smallholder farming conditions. These findings highlight the value of remote sensing and AutoML as a reliable and efficient approach for agricultural yield prediction, especially for coffee crops in tropical regions with limited field data.

Despite the promising results, the limited temporal coverage of the dataset and the high variability in coffee yield may restrict model generalizability. Future studies should incorporate multi-year datasets, additional agro-climatic and soil variables, and broader spatial coverage to improve model robustness and transferability. Such improvements will further enhance the application of AutoML-based models as decision-support tools for precision agriculture and sustainable coffee production.

Disclaimer (Artificial Intelligence)

The author(s) hereby declare that generative AI technologies were used in a limited manner during the editing of the manuscript. ChatGPT (OpenAI, GPT-4) was used to assist with language refinement and to improve the clarity and readability of text drafted by the authors. Grammarly was used for grammar checking, spelling correction, and language clarity. All scientific content, data analysis, interpretation of results, and conclusions were developed by the authors, who reviewed and edited the text and assume full responsibility for the final manuscript.

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Competing Interests

Authors have declared that they have no known competing financial interests, non-financial interests, or personal relationships that could have appeared to influence the work reported in this paper.

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