



Relationship model of land biophysical properties and their influence on Arabica coffee production in Bandung Regency, Indonesia by using the PCR method

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ABSTRACT

Coffee is an essential agricultural commodity that significantly contributes to Indonesia's foreign exchange revenue. Arabica coffee (*Coffea arabica* L.), generally grown in highland areas at elevations between 1,000 to 2,000 m above sea level, exhibits persistently low productivity within the country. A primary factor influencing this low yield is the biophysical condition of the land. This study aims to examine the impact of land biophysical characteristics on Arabica coffee productivity and to investigate the interrelationships among those biophysical factors. This study was conducted in Bandung Regency, West Java Province, Indonesia. This study utilized 60 data sets encompassing 22 land biophysical parameters and one plant parameter, specifically coffee productivity. The data collection utilized a survey approach. Land biophysical data were collected through field observations and laboratory analyses, whereas coffee productivity data were obtained through farmer interviews. The principal component regression (PCR) method, incorporating principal component analysis (PCA) and multiple regression, was employed for statistical analysis. The findings indicated 7 principal components (PC) with a data representation level of 75.8%. PC1 comprises primary components consisting of sand content, clay content, exchangeable Mg, Ca, and Na, with a representation level of 18.6%. PC2 consists of exchangeable K and potential K₂O, while PC3 consists of total N, organic C, altitude, and slope. These components are the most significant factors influencing Arabica coffee production. The application of K and N fertilizers along with organic materials is expected to increase Arabica coffee production.

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1. INTRODUCTION

Coffee represents a promising agricultural commodity for Indonesia. Despite constituting a modest share of total plantation commodity exports at 2.91%, coffee exports have experienced significant annual growth (Pusdatin, 2023). Export values have increased from US\$ 99,836 in 1975 to US\$ 1,148,383 in 2022 (Ditjenbun, 2023). The value of coffee exports during the period of 2015-2022 exhibited fluctuations. In 2017, the coffee export value reached its peak at US\$1,186,866, accompanied by an export volume of 467,796 tons. Indonesia's coffee exports predominantly

consist of coffee beans, accounting for 97.35%, dominated by Arabica and Robusta varieties. The remaining exports are in the form of crushed coffee and coffee powder (Ditjenbun, 2023).

Arabica coffee (*Coffea arabica* L.) ranks as the second most prevalent coffee variety cultivated in Indonesia, following Robusta coffee. Arabica coffee thrives in mineral-rich soil, particularly at altitudes exceeding 1000 m above sea level. In contrast, Robusta coffee is optimally cultivated at altitudes ranging from 300 to 900 m above sea level. Elevated

altitudes influence the quality of Arabica coffee. [Worku et al. \(2018\)](#) reported that the content of caffeine and chlorogenic acid in wet-processed coffee beans diminished with rising altitude, whereas sucrose content increased with altitude. It was reported that acidity increased with altitude for coffee grown under shade; however, altitude had no significant effect on coffee grown without shade. Coffee cultivated in non-shade conditions typically exhibits superior physical quality in dry beans relative to wet-processed beans ([Worku et al., 2022](#)). The phenomenon results from the intricate interplay of altitude, shading conditions, and post-harvest processing, which together influence the biochemical composition and overall quality of Arabica coffee beans.

Bandung Regency ranks among the largest producers of Arabica coffee in West Java, encompassing a cultivation area of 14,374 hectares and yielding an annual production of 8,183 tons. This figure represents 56.31% of the total Arabica coffee production in West Java Province ([Ditjenbun, 2023](#)). The low level of productivity represents a significant challenge in coffee development in Indonesia, particularly in West Java. In 2022, Indonesia's coffee production totalled 794.8 thousand tonnes, cultivated over a harvest area of 1,285.8 thousand ha. Indonesia's coffee productivity in 2022 was 0.62 tonnes ha⁻¹, markedly lower than that of Brazil and Vietnam, the leading coffee-producing nations, with recorded productivity levels of 1.69 and 2.94 tonnes ha⁻¹, respectively ([FAO, 2024](#)).

The productivity of a commodity is influenced by multiple factors, including biophysical land characteristics and the cultivation techniques employed. Land biophysical factors, including soil properties, topography, and climate, significantly affect plant growth and coffee productivity, alongside geographical location and socioeconomic factors ([Yadessa et al., 2020](#)). The complex interaction of these characteristics results in diverse coffee production systems; each managed with varying intensities. Various soil properties, such as low soil physicochemical characteristics, may lead to reduced Arabica coffee production ([Benevenuto et al., 2025](#); [Siahaan et al., 2022](#)). Improving Arabica coffee productivity requires a thorough understanding of the limiting factors affecting production and the biophysical characteristics of the land essential for optimal growth and yield. Moreover, the impact of these interrelated factors on crop performance is recognized to differ across geographic regions.

Principal component analysis (PCA) serves as a systematic and objective method for determining the weights of multiple factors ([Sappe et al., 2022](#)). This method has been used to evaluate the variability of properties in the upper layer of Cambisols taxa and their correlation with altitude and forest ecosystems in the Western Carpathians ([Pivková et al., 2024](#)). This method was used to identify soil quality indicators for the assessment and evaluation of the soil quality index (SQI) within the agroforestry system in the Upper Citarum Watershed, Indonesia ([Mulyono et al., 2019](#)). PCA has been extensively utilized to identify biophysical factors affecting Arabica coffee productivity and quality across diverse global contexts, including the integration of elevation and agroforestry in Ethiopia ([Getachew et al., 2023](#)) and climate-

vegetation models in Vietnam ([Thao et al., 2022](#)). This study introduces a novel application of PCA that specifically examines soil biophysical properties in relation to Arabica coffee productivity in the Indonesian highlands. This study differentiates itself from prior research by focusing on soil physicochemical components and topographic indicators, thereby establishing their statistical relationship with yield. This approach offers site-specific insights for evaluating land suitability and managing nutrients in Arabica coffee systems.

The effective development of a commodity, encompassing both quality and production, is significantly influenced by land suitability, defined as the extent to which a specific area of land is suitable for designated use. Suitability is assessed based on various land qualities, specifically complex attributes that affect the potential for sustainable cultivation. Land suitability, shaped by the interplay of diverse biophysical properties and cultivation practices, is crucial for attaining sustainable production. Land suitability for coffee production is determined by the interplay of biophysical properties, including soil characteristics, elevation, and climate, alongside cultivation practices.

This research aims to determine the model that elucidates the relationship between the biophysical properties of land and their impacts on coffee productivity in Indonesia, employing the principal component analysis (PCA) method. The PCA method is a technique for dimensionality reduction in datasets, enhancing interpretability and minimizing information loss. This is achieved by generating new uncorrelated variables, referred to as principal components, that sequentially maximize the variance in the data ([Jolliffe & Cadima, 2016](#)). The advantage in this case is that the influential variables are not treated as a singular factor; rather, the primary components comprise interrelated factors. Furthermore, multiple regression analysis is employed to determine the impact of these primary components on Arabica coffee productivity.

2. MATERIALS AND METHODS

2.1. Description of the study area

The research was conducted in Bandung Regency, West Java Province, Indonesia ([Fig. 1](#)) in 2023. The Bandung Regency area is situated between 107°27' to 107°49' East Longitude and 7°16' to 6°48' South Latitude. Arabica coffee plantations in this region are located in forested areas and on agricultural land, typically at elevations >1000 meters above sea level. Coffee plantations are typically overseen by small-scale farmers who utilize low levels of technological input, characterized by limited management practices and minimal or absent fertilization. The terrain is predominantly hilly to mountainous, characterized by slopes >15%. However, certain areas exhibit flat to rolling land with slopes <15%. The average annual rainfall varies between 1,500–3,000 mm year⁻¹. The geological conditions of the research area consist of volcanic rocks, sedimentary rocks, and intrusive rocks ([Alzwar et al., 1992](#); [Silitonga, 1973](#)). The primary soil units consist predominantly of Inceptisols and Andisols ([BBSDLP, 2016](#)).

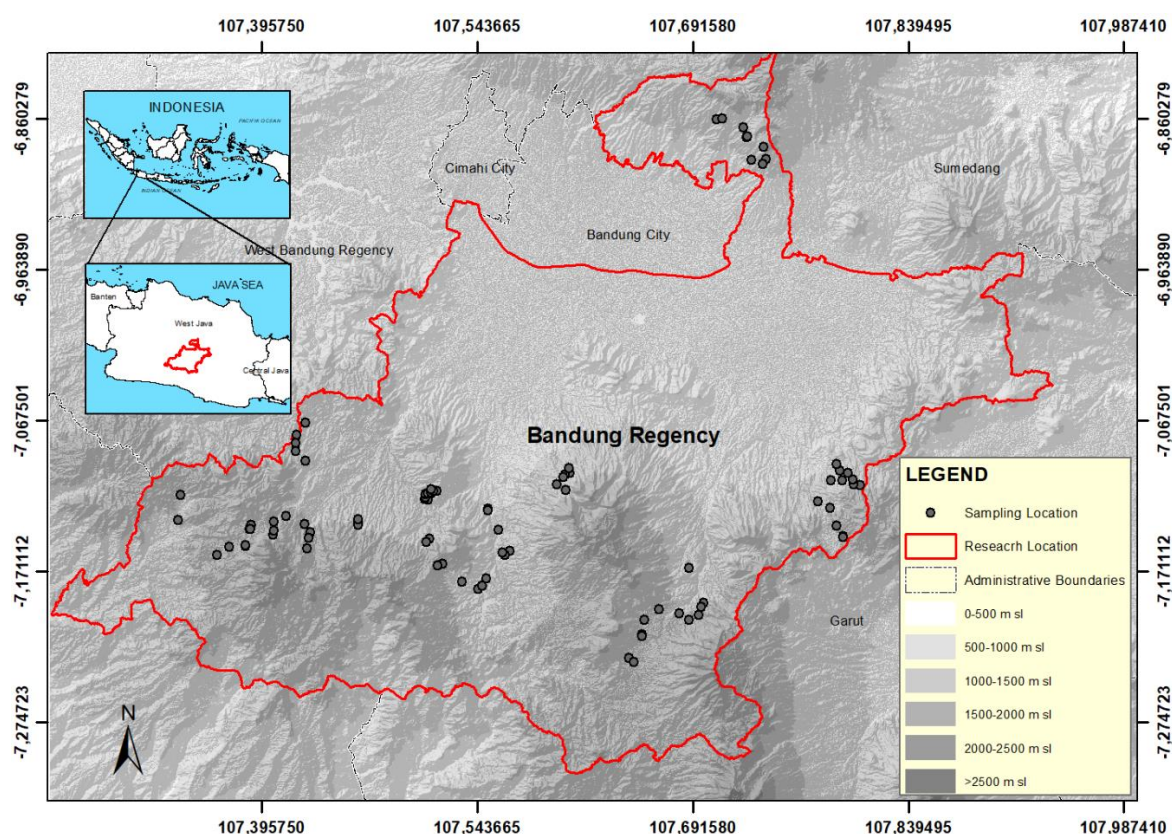


Figure 1. Research location in Bandung Regency

2.2. Data collections

The field data collection was carried out using a survey approach, involving land identification and characterization at 60 observation points within the Arabica coffee plantation area (Fig. 1). The selection of observation locations and the collection of soil and plant samples were conducted purposively, taking into account the diversity of soil parent materials, topography, elevation, soil type, land management practices, the distribution of Arabica coffee plantations and land use types associated with Arabica coffee cultivation. Diversity significantly influences land characteristics and biophysical conditions, which in turn affect Arabica coffee productivity.

Identification and characterization of land in the field aim to obtain data on biophysical conditions of the land, such as altitude, slope, rock outcrop (ROC), soil drainage, and soil solum depth. Furthermore, 1 kg of composite soil samples was collected from a depth of 0-30 cm at each observation point to analyze the physicochemical properties of the soil in the laboratory. Composite soil samples collected from the field were air-dried for 1-3 days, subsequently ground, and sieved to achieve a particle size of less than 2 mm, which is required for laboratory soil analysis.

The content of the clay and sand fraction is determined through soil particle size analysis. The sand fraction was isolated through wet sieving with a 50 mm sieve. The pipette method was employed to determine silt and clay contents. Soil pH was determined utilizing a glass electrode in a mixture of water and 1M KCl at a soil: solution ratio of 1:5. Organic carbon was determined through the wet combustion method (Walkley and Black method), and total N was determined

using distillation (Kjeldahl method). Exchangeable cations (Ca, Mg, K, Na) were extracted using 1M NH_4OAc pH 7.0 and analyzed using an atomic absorption spectrometer (AAS). Cation exchange capacity was determined through saturation with 1M NH_4OAc pH 7.0, followed by direct distillation measurement. Base saturation is defined by CEC, which encompasses all exchangeable alkaline cations present in the soil. Exchangeable acidity (Al^{3+} and H^+) was extracted using 1M KCl and quantified using titration. The measurement of potential P_2O_5 and K_2O was conducted using the 25% HCl extraction method, whereas available P_2O_5 was determined using the Bray 1 extraction method. The extract is subsequently diluted, and the nutrients are quantified using AAS. The chemical measurement methods employed in this study are detailed in the Soil Survey Laboratory Methods Manual (Soil Survey Staff, 2014), and the evaluation of soil properties adhered to the Technical Guidelines for Soil, Plant, Water, and Fertilizer Chemical Analysis (Eviati et al., 2023). The methods, instruments, and manufacturers used for the analysis of biophysical parameters are presented in Table 1.

The data for annual rainfall is derived from Climate Data (2024). This model generates data on rainfall for each village area. This data serves as rainfall information for the soil and plant sampling locations. In this study, Arabica coffee productivity serves as the independent variable. Data were collected through interviews with farmers to ascertain the average production of Arabica coffee per hectare per year at each observation site. Nearly all collected data is numerical, with the exception of soil drainage conditions. Soil drainage is categorized into 7 classes: very poor drainage, poor drainage, rather poor drainage, fairly good drainage, good drainage, rather excessive drainage, and excessive drainage.

Table 1. Biophysical parameters, analytical methods, instruments, and manufacturers

Category	Parameters	Method of Data Acquisition	Instruments and Manufacturer
Climate	Annual rainfall	Secondary data from regional climatological sources	-
Terrain	Elevation, slope, solum depth, drainage, rock outcrops (ROC)	Field observation (GPS, clinometer, soil auger, visual assessment)	- Elevation was recorded using a Garmin eTrex 32x GPS (Garmin Ltd., Olathe, KS, USA). - Slope (%) was measured using a Suunto PM-5/360 PC clinometer (Suunto, Vantaa, Finland). - Soil depth, rock outcrops, and drainage were assessed visually and classified using FAO Land Evaluation Guidelines (FAO, 2007).
Soil Texture	Sand and clay content	Particle size analysis via pipette method	Glassware + precision balance (AND GF-3000, A&D Co. Ltd., Tokyo, Japan)
Soil Chemical Properties	Organic C	Walkley and Black wet oxidation method	Spectrophotometer (Shimadzu UV-1800, Kyoto, Japan)
	Total N	Kjeldahl digestion method	Digestion and distillation unit (Gerhardt Kjeldatherm, Königswinter, Germany)
	Soil pH	Measured in a 1:5 soil-to-water suspension	pH meter (Hanna Instruments HI2211, Woonsocket, RI, USA)
	Exchangeable bases (K^+ , Ca^{2+} , Mg^{2+} , Na^+)	Extracted with 1 M NH_4OAc ; analyzed with AAS	AAS (PerkinElmer AAnalyst 400, USA)
	Exchangeable acidity (Al^{3+} , H^+)	Extracted with 1 M KCl	Titration method
	Cation Exchange Capacity (CEC)	Determined using 1 M NH_4OAc at pH 7, followed by NaCl displacement	AAS after displacement by NaCl
	Base Saturation (%)	Calculated as: $(\sum \text{exchangeable base cations} / \text{CEC}) \times 100$	-
	Al saturation (%)	Calculated as: $(\text{exchangeable Al} / \text{CEC}) \times 100$	-
	Available phosphorus (P)	Bray I extraction method	Spectrophotometer (Shimadzu UV-1800, Japan)
	Potential P_2O_5 and K_2O	Extracted with 25% HCl, then diluted and analyzed via AAS	Atomic Absorption Spectrophotometer (AAS) (PerkinElmer AAnalyst 400, Waltham, MA, USA)

Soil drainage is categorized as follows: very poor and poor drainage receive a score of 1, fairly poor drainage is assigned a score of 2, fairly good drainage is rated 3, good drainage is given a score of 4, and excessive drainage is scored 5.

This research utilizes 60 data sets comprising 22 land biophysical parameters as independent variables and Arabica coffee productivity as the dependent variable. The data analysis employs the principal component regression (PCR) method, which integrates principal component analysis (PCA) with multiple regression methods. PCR is a method designed to address issues of multicollinearity (Supriyadi, 2017). Data standardization is essential prior to PCA analysis due to PCA's sensitivity to variable scales. The PCA reduces variables to a limited number of substitute variables, referred to as principal components (PC). Each principal component represents a linear combination of the original variables, with

weights established by the eigenvectors. The eigenvalues indicate the variance of a PC, reflecting the proportion of the total variable accounted for by that component. The PCA method necessitates additional analysis to elucidate the relationship between the independent substitute variables (Principal components) and coffee productivity as the dependent variable. The relationship was established through multiple regression analysis. This research employs Minitab 14 for data analysis.

3. RESULTS

3.1. Description of biophysical land properties data

The soil texture at the research site ranges from sand to clay, exhibiting a sand fraction content of 3 to 93% and a clay fraction content of 1 to 58%.

Table 2. Description of dependent and independent variable data

Variables	Mean	CV	Min	Median	Max	Range
Coffee Productivity (kg ha ⁻¹ year ⁻¹)	2,662	91.56	90	1,639	8,889	8,779
Sand fraction (%)	28	88	3	21	92	89
Clay fraction (%)	25	62	1	26	58	57
Soil pH	5.63	8.38	4.60	5.60	7.29	2.69
Organic C (%)	5.12	29.41	2.30	4.97	8.91	6.61
Potential P ₂ O ₅ (mg 100 g ⁻¹)	123.20	89.48	31.20	80.40	460.00	428.80
Potential K ₂ O (mg 100 g ⁻¹)	19.87	90.42	3.24	13.35	87.46	84.22
CEC (cmol _c kg ⁻¹)	19.11	36.56	3.00	19.08	34.67	31.67
Exchangeable Ca (cmol _c kg ⁻¹)	5.97	55.80	1.19	5.51	21.11	19.92
Exchangeable Mg (cmol _c kg ⁻¹)	1.49	58.18	0.18	1.65	4.36	4.18
Exchangeable K (cmol _c kg ⁻¹)	0.36	101.88	0.03	0.24	1.79	1.76
Exchangeable Na (cmol _c kg ⁻¹)	0.23	36.19	0.06	0.22	0.52	0.46
Base saturation (%)	44.22	39.03	9.00	46.50	100.00	91.00
Available P (mg kg ⁻¹)	32.30	106.99	0.85	20.00	143.44	142.59
Total N (%)	0.52	53.02	0.13	0.43	1.32	1.19
Exchangeable Al (cmol _c kg ⁻¹)	0.23	199.20	0.00	0.00	2.19	2.19
Exchangeable H (cmol _c kg ⁻¹)	0.47	118.03	0.00	0.28	3.17	3.17
Slope (%)	31	52	1	30	78	77
Soil drainage	4.0	15.0	3	4	5	2
ROC (%)	1.0	533.04	0	0	40	40
Solum depth (cm)	103	24.21	38	120	134	96
Elevation (m asl)	1,373	13.01	970	1,335	1,850	880
Annual rainfall (mm year ⁻¹)	3,440	12.06	1,839	3,277	4,156	2,317

Notes: CV = coefficient of variation, CEC = cation exchange capacity, ROC = rock out of crop

The soil chemical analysis indicated a pH value range of 4.6 (acidic) to 7.2 (neutral). Organic C levels ranged from 2.3% (moderate) to 8.9% (very high), while total N varied from 0.13% (low) to 1.32% (very high). The potential P₂O₅ content ranges from moderate to very high, with values between 31.2 and 460.0 mg 100 g⁻¹. The levels of potential K₂O and available P₂O₅ range from low to very high, with measurements of 3.24–87.46 mg 100 g⁻¹ and 0.85–143.44 mg 100 g⁻¹, respectively. CEC values are classified from low to high, spanning a range of 3.0–34.67 cmol_c kg⁻¹, while base saturation varies from very low to very high, with a range of 9.0–100%. Exchangeable bases, comprising Ca, Mg, K, and Na, exhibit values from 0 to 21.11 cmol_c kg⁻¹, indicating a low to high classification. In contrast, exchangeable Al is categorized as low to medium, with values ranging from 0 to 2.19 cmol_c kg⁻¹. The soil physical analysis revealed that slope level ranges from 1 to 78%, drainage conditions are moderate to very fast, rock cover on the surface ranges from 0 to 40%, elevation from 970 to 1,850 m above sea level, and annual rainfall fluctuates from 1,839 to 4,156 mm.

The mean coffee productivity at the research site is 2,662 kg ha⁻¹ year⁻¹, with a range from 90 to 8,889 kg ha⁻¹. Table 2 presents the biophysical land properties and productivity data categorized as dependent and independent variables is presented in.

3.2. The results of Pearson correlation analysis

A Pearson correlation analysis of soil biophysical properties data was carried out to determine the relationship between variables. These results showed that several variables have strong positive correlations with other variables. On the other hand, several variables have a strong

negative correlation, indicating that these indicators show a mutually weakening relationship. In Table 3, the correlations between pairs of variables that are strong and positive ($R > 0.6$) at a significance level of <0.01 including potential K₂O and exchangeable K (0.99), potential P₂O₅ and available P (0.79), total N and organic C (0.76), exchangeable Mg and exchangeable Ca (0.73), exchangeable Mg and clay fraction (0.67), base saturation and exchangeable Ca (0.65), and base saturation and exchangeable Mg (0.61). Additionally, several relationships between pairs of variables that have a high negative correlation ($R < -0.6$) at a significance level of <0.01 , including clay and sand fraction content (-0.66), exchangeable Mg and sand fraction content (-0.62), and soil pH and exchangeable Al (-0.62).

The analysis of land biophysical properties using the PCA method resulted in seven new independent principal components (PC). The constituent variables within each PC are closely interrelated, both positively and negatively. PCs were selected based on an eigenvalue greater than 1 (Table 4). The total variance value of the seven PCs is 0.758. This shows that the seven main components can explain around 75.8% of all independent variable data analyzed.

Data processing of land biophysical properties using factor analysis from the PCA method produces factor loading values for the 22 variables. The factor loading values that have been rotated and sorted for each of these variables for each main component factor are presented in Table 5. These factors' loading values determine the biophysical parameters of the land that have a major influence on the main components. The greater the loading factor of a parameter, the greater its role in a principal component (factor index).

Table 3. Correlation matrix between independent variables

Parameters	Sand	Clay	pH	C-org	P-pot	K-pot	CEC	Ca-exc	Mg-exc	K-exc	Na-exc	BS	P_avl	N_tot	Al-exc	H-exc	slope	drainage	ROC	Solum	Elv
Clay	-0.66**	1																			
pH	0,034	-0,076	1																		
C-org	-0,131	0,075	-0.255*	1																	
P-pot	0,156	-0,019	-0.39**	0,222	1																
K-pot	-0,174	0,012	0,134	0,147	0,026	1															
CEC	-0.583**	0,054	0,038	0.286*	-0,09	0,18	1														
Ca-exc	-0.451**	0.346**	0,041	0,157	0,131	0.426**	0.414**	1													
Mg-exc	-0.622**	0.669**	-0,011	0,105	-0,04	0.329*	0.269*	0.73**	1												
K-exc	-0,183	0,031	0,146	0,136	-0,006	0.995**	0,173	0.437**	0.354**	1											
Na-exc	-0.441**	0.439**	-0,097	0,099	0,095	-0,1	0,179	0,283	0,19	-0,086	1										
BS	-0,025	0.373**	0,079	-0,116	0,046	0,334	-0.37**	0.647**	0.612**	0.359**	0,128	1									
P_avl	0.329*	-0,216	-0,044	-0,017	0.786**	0,04	-0,053	0,099	-0,161	0,014	-0,174	-0,01	1								
N_tot	-0,049	-0,122	-0,251	0.761**	0.417**	0,047	0.306*	0,159	-0,066	0,027	0,204	-0,197	0,139	1							
Al-exc	-0,02	0,009	-0.615**	0,211	0.381**	0,188	-0,027	0,132	0,05	0,178	-0,063	0,063	0.271*	0,084	1						
H-exc	-0,134	0,118	-0.325*	-0,231	0,195	-0,052	-0,106	-0,149	-0,033	-0,057	-0,046	-0,098	0,162	-0,251	0.432**	1					
slope	-0,167	0,029	0,137	0,213	-0,085	0,125	0,253	0,153	0,151	0,093	0,068	0,012	-0,201	0.365**	-0,196	-0.267*	1				
Drainage	0,206	-0,209	-0,017	0,257	-0,07	0,154	0,092	-0,089	-0,162	0,148	-0,19	-0,125	0,006	0,193	-0,039	-0.277*	0,028	1			
ROC	0,096	-0,136	0.426**	0,059	-0,01	0.284**	0,107	-0,048	-0,085	0.28**	-0,085	-0,126	0,188	0,003	0,009	-0,065	0,065	0,217	1		
Solum	-0,1	0,062	-0,047	0,215	0,051	0,139	0,2	0,11	0,08	0,123	0,135	-0,061	0,11	0,226	-0,013	-0,315	0,24	0,254	0,054	1	
Elv	0.321*	-0.378**	-0,254	0.32**	0,386	-0,067	-0,065	-0,1	-0.286**	-0,103	-0,113	-0,126	0.278*	0.573**	0,202	-0,094	0,25	0,122	-0,055	-0,022	1
Rainfall	0,216	-0,154	0,07	-0,178	0,062	-0,141	-0,101	-0,096	-0.262*	-0,159	0,084	-0,077	0,136	0,08	-0.263*	-0.305*	0,126	0,145	0,014	0.256*	0,158

Notes: C-org = organic Carbon, P-avl = available Phosphorus, P-pot = Potential Phosphorus, K-pot = Potential Potassium, K-avl = available Potassium, Ca-exc = exchangeable Calcium, Mg = exchangeable Magnesium, K-exc = exchangeable Potassium, Na-exc = exchangeable Natrium, N-tot = total Nitrogen, Al-exc = exchangeable Aluminium, H-exc = exchangeable Hydrogen, CEC = cation exchange capacity, BS = base saturation, , ROC = rock out of the crop, , Elv = elevation, **correlation is significant at the 0.01 level (2-tailed), * correlation is significant at the 0.05 level

Table 4. The results of eigen analysis

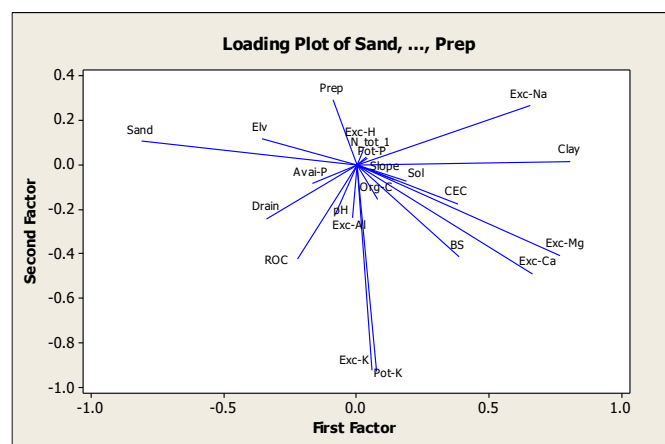
Indicator	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC7
Eigenvalue	4.09	3.22	2.72	2,39	1.72	1.36	1.16
Proportion	0.186	0.146	0.124	0.109	0.078	0.062	0.053
Cumulative	0.186	0.332	0.456	0.565	0.643	0.705	0.758

Note: PC = Principal component

Table 5. The loading factor values are rotated based on the results of factor analysis of land biophysical parameters

Land Biophysical Properties	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
Sand fraction	<u>-0.811</u>	0.105	0.027	-0.07	0.228	-0.378	-0.097
Clay fraction	<u>0.808</u>	0.014	0.159	0.117	-0.121	-0.098	0.013
Exchangeable Mg	<u>0.768</u>	-0.408	-0.016	0.015	-0.113	-0.200	0.099
Exchangeable Ca	<u>0.665</u>	-0.489	-0.192	-0.086	0.178	-0.191	0.022
Exchangeable Na	<u>0.654</u>	0.263	-0.095	-0.040	0.081	0.061	-0.132
Exchangeable K	0.077	<u>-0.929</u>	-0.024	0.014	-0.009	-0.006	-0.062
Potential K ₂ O	0.059	<u>-0.924</u>	-0.050	0.016	0.017	0.008	-0.069
Total N	0.038	0.032	<u>-0.880</u>	0.094	0.199	0.158	-0.166
Organic C	0.081	-0.155	<u>-0.735</u>	0.283	-0.060	0.177	-0.167
Elevation	-0.359	0.114	<u>-0.698</u>	0.095	0.298	-0.151	0.061
Slope	0.144	-0.071	<u>-0.581</u>	-0.379	-0.145	0.037	-0.026
Soil pH	-0.080	-0.223	0.210	<u>-0.852</u>	-0.061	0.121	0.084
Exchangeable Al	-0.016	-0.236	-0.043	<u>0.781</u>	0.265	0.009	0.111
Exchangeable H	0.023	0.061	0.359	<u>0.520</u>	0.191	0.193	0.484
Available P ₂ O ₅	-0.167	-0.084	0.031	0.071	<u>0.920</u>	0.030	-0.047
Potential P ₂ O ₅	0.040	0.030	-0.245	0.311	<u>0.847</u>	-0.079	0.005
Base saturation	0.386	-0.413	0.092	-0.079	0.061	<u>-0.775</u>	0.074
CEC	0.382	-0.175	-0.296	-0.079	-0.065	<u>0.704</u>	-0.055
Rock out of crop	-0.222	-0.422	0.108	-0.317	0.229	<u>0.437</u>	-0.065
Solum depth	0.189	-0.075	-0.100	0.005	0.080	0.129	<u>-0.774</u>
Soil drainage	-0.339	-0.242	-0.136	0.102	-0.177	0.097	<u>-0.620</u>
Annual rainfall	-0.087	0.289	0.007	-0.351	0.259	-0.152	<u>-0.560</u>

Note: The underlined numbers indicate the most influential variables in the same factor



Notes: Sand = Sand fraction, Clay = Clay fraction, pH = Soil pH, Org-C = Organic C, Pot-P = Potential P₂O₅, Pot-K = Potential K₂O, CEC= Cation Exchange Capacity, Exc-Ca = Exchangeable Ca, Exc-Mg = Exchangeable Mg, Exc-K = Exchangeable K, Exc-Na = Exchangeable Na, BS = Base saturation, Avai-P = Available P, Tot-N = Total N, Exc-Al = Exchangeable Al, Exc-H = Exchangeable H, ROC = Rock out of Crop, and Prep = Annual rainfall

Figure 2. Plot Loading

The results of Pearson correlation analysis showed that several variables have a strong positive correlation with other

variables or are mutually reinforcing, and conversely, several variables have a strong negative correlation with others or are mutually weakening. Table 2 shows the correlation between various land biophysical parameters used in this study. Several land biophysical properties were correlated positively (mutually reinforcing) and negatively (mutually weakening). Land biophysical properties that were closely and positively correlated ($R > 0.6$) were between available K and potential K₂O, available P and potential P₂O₅, organic C and total N, exchangeable Ca and exchangeable Mg, clay content and exchangeable Mg-dd, clay fraction content and exchangeable Ca, and base saturation and exchangeable Ca. Meanwhile, several biophysical properties of land that are closely and negatively correlated ($R < -0.6$) are the relationship between sand fraction and clay fraction content, sand fraction content with exchangeable Mg, and exchangeable Al with soil pH.

3.3. The results of principal component regression analysis

The application of the PCA method in analyzing land biophysical properties resulted in the generation of seven independent principal components (PC). The constituent variables in each PC exhibit close relationships, both positive and negative. Factor analysis utilizing the PCA method on land biophysical properties data yields factor loading values for 22

Regression Analysis: Prod versus PC1, PC2, ...					
Predictor	Coef	SE Coef	T	P	VIF
Constant	2661.9	318.3	8.36	0.000	
PC1	-138.9	321.0	-0.43	0.667	1.0
PC2	467.6	321.0	1.46	0.151	1.0
PC3	359.7	321.0	1.12	0.268	1.0
PC4	-270.4	321.0	-0.84	0.404	1.0
PC5	-112.9	321.0	-0.35	0.727	1.0
PC6	134.4	321.0	0.42	0.677	1.0
PC7	-330.9	321.0	-1.03	0.307	1.0
S = 2465.80 R-Sq = 9.8% R-Sq(adj) = 0.0%					
PRESS = 420459190 R-Sq(pred) = 0.00%					
Analysis of Variance					
Source	DF	SS	MS	F	P
Regression	7	34263588	4894798	0.81	0.587
Residual Error	52	316167910	6080152		
Total	59	350431498			

Figure 3. Regression analysis

land related to biophysical properties. The factor loading values significantly influence the principal components related to land biophysical parameters. A higher loading factor of a parameter indicates a more significant role in the PC. Figure 2 illustrates a loading plot that depicts the relationship between factor 1 and factor 2. A positive value indicates a positive correlation between factor 1 and factor 2. A negative value signifies an inverse relationship between the two factors.

The biophysical parameters of land significantly influencing each PC are outlined as follows: *PC1* comprises the sand fraction, clay fraction, and the levels of exchangeable magnesium (Mg), calcium (Ca), and sodium (Na). The influence of land characteristic variables on this factor is determined to be 18.6%; *PC2* consists of available K and potential K₂O. The influence of these two characteristic variables is approximately equivalent, and they mutually reinforce each other. The certainty level of these two variables in the factor index is 14.6%; *PC3* comprises total nitrogen (N), organic carbon (C), elevation, and slope. The influence of these land characteristic variables on this factor index is determined to be 12.4%; *PC4* consists of soil pH, aluminum (Al), and hydrogen (H). The influence of these land characteristic variables on this factor index is quantified at a certainty level of 10.9%; *PC5* includes both available P and potential P₂O₅. The influence of these two land characteristic variables on this factor index is quantified at a certainty level of 7.8%; *PC 6* comprises base saturation, CEC (cation exchange capacity), and rocks out of the crop. The influence of these land characteristic variables on this factor index is quantified at a certainty level of 6.2%; *PC7* consists of solum depth, drainage conditions, and rainfall. The influence of these land characteristic variables on this factor index is quantified at a certainty level of 5.3%.

3.4. Multiple regression analysis

The multiple regression analysis results indicate a relationship between productivity, the dependent variable,

and biophysical index factors (PC), the independent variables, with a coefficient of determination (R^2) of 9.8%. This value indicates that the model accounts for only a minor portion of the factors influencing Arabica coffee productivity, with other variables excluded from this study. PCA-based regression approaches in agricultural studies often exhibit limitations, as PCA reduces data dimensionality while potentially obscuring the influence of individual variables on complex outcomes such as crop productivity (Jolliffe & Cadima, 2016). PCA continues to be an effective method for uncovering underlying structures and patterns in multivariate datasets, particularly within biophysical and ecological research (Abdi & Williams, 2010). Figure 3 presents the regression analysis conducted between productivity and principal components. The equation delineating the relationship between Arabica coffee productivity and biophysical indices is expressed using Equation 1.

$$Y_{\text{prod}} = 2662 - 139PC1 + 468PC2 + 360PC3 - 270PC4 - 113PC5 + 134PC6 + 331PC7 \dots\dots\dots [1]$$

where: Y_{prod} : Arabica coffee productivity ($\text{kg ha}^{-1} \text{ year}^{-1}$); PC1: Sand content (%), clay content (%), exchangeable Mg, Ca, and Na ($\text{cmol}_c \text{ kg}^{-1}$); PC2: exchangeable K ($\text{cmol}_c \text{ kg}^{-1}$) and potential K₂O ($\text{mg } 100 \text{ g}^{-1}$); PC3: Total N (%), organic C (%), elevation (m asl), and slope (%); PC4: Soil pH, exchangeable Al and H ($\text{cmol}_c \text{ kg}^{-1}$); PC5: available P (mg kg^{-1}) and potential P₂O₅ ($\text{mg } 100 \text{ g}^{-1}$); PC6: Rock out of crop (%), solum depth (cm), and soil drainage; PC7: annual rainfall (mm year^{-1})

A very low R^2 value indicates the presence of unexplained components within the multiple regression model, which is deemed unacceptable. Pest and disease occurrences, agricultural management practices, and genetic variation may affect productivity (Liliane & Charles, 2020).

4. DISCUSSION

The study's primary finding reveals that the biophysical characteristics of land have a significant effect on Arabica coffee productivity in Bandung Regency. Principal component

regression (PCR) analysis showed that PC1 explained the greatest variance (18.6%), incorporating variables such as sand and clay fractions, along with exchangeable Mg, Ca, and Na. The variables reflect soil texture and base saturation status, which influence water retention capacity, cation exchange dynamics, and root development, all essential for plant growth.

PC2 comprises exchangeable K and potential K_2O , which are essential for carbohydrate metabolism, fruit development, and stress resistance in coffee plants. An adequate supply of potassium is recognized to enhance bean size and uniformity, consequently improving yield. PC3 encompasses total N, organic C, elevation, and slope, reflecting soil fertility and topographic influences. Increased organic matter and nitrogen levels enhance microbial activity and nutrient availability, whereas elevation and slope affect microclimatic factors, including temperature and drainage, essential for Arabica coffee growth. The principal components collectively account for the spatial variability of coffee productivity identified in the study area.

The relationship among the variables in this group indicates that increased clay content facilitates greater exchange complexes in the soil, thereby enhancing the levels of exchangeable bases present in the soil. The value of CEC is influenced by the quantity and type of colloids present in the soil (Tan, 2010). These relationships indicate that soil properties are interdependent. Sandy soils, characterized by larger particle sizes, exhibit a low specific surface area, leading to reduced CEC values for Mg, Ca, and Na. The limited capacity to retain these cations results in a diminished level of interchangeable bases. In contrast, clay soils possess a high specific surface area, resulting in elevated CEC and an increased ability to retain exchangeable bases. The strong correlation among land biophysical properties is also observed in other PCs. The correlation coefficient between available K and potential K_2O in PC2 is 0.99, indicating a strong relationship. The correlation coefficients observed are significant: 0.76 between total N and organic C in PC3, -0.62 between pH and exchangeable Al in PC4, and 0.79 between potential P and available P in PC5.

The relationship between exchangeable K and potential K_2O is robust and mutually reinforcing, as potential K_2O serves as the primary source of exchangeable K. The release of potassium elements from potential K_2O in the primary mineral adsorption complex in soil, due to the weathering or alteration of primary minerals such as feldspar, leads to an increase in the content of exchangeable K in the soil solution. Soil potassium exists in four forms: (1) K within the primary mineral crystal structure (unavailable), (2) K in non-exchangeable positions within secondary minerals (slowly available), (3) K in an exchangeable form on soil colloid surfaces (readily available), and (4) potassium ions that are soluble in water (readily available). Potassium does not play as directly influential on environmental quality as phosphorus; however, insufficient levels of this element frequently restrict crop growth and reduce crop quality (Brady & Weil, 2000).

The relationship between soil pH and exchangeable Al is significant and mutually reinforcing, consistent with the

findings of Gillespie et al. (2021). An increase in soil pH, such as liming, results in a decrease in the level of exchangeable Al. Dolomitic lime supplies Ca and Mg, enhancing the microbial activity in acidic soils, improving the availability of nutrients such as N and P in acidic soils, and ultimately increasing yield. The addition of Ca cations to the soil raises soil pH; concurrently, it displaces Al from the soil's adsorption complex, resulting in a reduction of exchangeable Al (Shaaban et al., 2024).

The relationship between organic C content and total N is significant, as a substantial portion of organic-N originates from the decomposition of organic matter. In China's slope cropland, a significant positive correlation exists between the C/N ratio and SOC (He et al., 2025). N mineralization exhibited a correlation with C mineralization, while the decomposition of soil organic matter (SOM) quantifies the relative proportions of biologically available carbon (C) and nitrogen (N) for decomposition.

The relationship between available P and potential P_2O_5 is significant and mutually reinforcing. The availability of P nutrients is influenced by the potential P_2O_5 content and P fixation within the soil solution. The P_2O_5 present in the primary mineral adsorption complex serves as a source of P nutrients in soil solution, facilitated by the gradual release of P through the weathering or alteration of these minerals. Soils formed from volcanic ash or tuff, characterized by high levels of amorphous or allophane minerals, typically exhibit low P nutrient availability due to P fixation by these minerals. The application of P fertilizer to these soils is essential for enhancing land productivity and crop yield. Phosphorus is an essential element in both natural and agricultural ecosystems globally. It ranks second to nitrogen in significance in producing healthy plants and the attainment of profitable yields. The quantity of phosphorus in native soils is limited, with a significant portion being unavailable to plants (Brady & Weil, 2000). Phosphorus is a crucial macronutrient for coffee plantations, as it serves as an energy source for the growth of new branches for future harvests, supports the growth of the vegetative and reproductive branches, and provides essential nutrients (Dias et al., 2015). This study also revealed that coffee plantations exhibit positive responses to the application of P fertilizer.

The multiple regression equation has identified the key components influencing land productivity for Arabica coffee; however, it exhibits a very low R^2 value. A low R^2 value signifies the limitations of the multiple regression equation model that incorporates numerous variables. The low R^2 value may result from additional factors influencing Arabica coffee productivity that are not accounted for as dependent variables, such as cultivation management, climate, and socio-economic factors. Rubinfeld (2011) suggests that a low R^2 may signify the existence of unmeasured or excluded variables that significantly affect the dependent variable.

The regression analysis results indicated that all the PCs utilized as independent variables in this model were statistically significant at <0.05 (Fig. 3). This indicates that these PCs do not significantly affect the productivity of Arabica coffee. PC2 exhibits the smallest p-value among the PCs, indicating a more specific influence relative to others.

PC2 represents the factor index exhibiting the highest absolute coefficient value. This consists of exchangeable potassium K and potential K₂O. PC3 follows this PC and includes total N, organic C, elevation, and slope, indicating that the contribution of the factor value is the highest. This suggests that these two PCs are the primary contributors to the increase in Arabica coffee production within the research area.

The role of potassium in coffee production is linked to its involvement in enzyme activation for various metabolic processes in the plant, such as photosynthesis, synthesis of proteins and carbohydrates, and the maintenance of cell turgidity (Dias et al., 2018). Nitrogen (N) fertilization is essential for achieving high coffee yields, as N is the primary nutrient necessary for vegetative growth and the second most exported to the beans. The potassium (K) requirement is often regarded as equivalent to the N requirement; however, in contrast to N, K is predominantly located in the pulp of coffee beans (Clemente et al., 2015). Organic carbon significantly contributes to the stability of soil aggregates. Budiastuti et al. (2020) indicated that agroforestry-based land management systems represent the most effective approach for reducing soil erosion rates.

Livestock manure serves as an important source of fertilizer. Manure application is often more beneficial than chemical fertilizers for enhancing soil fertility, owing to its high organic matter content and extensive array of mineral elements for plant growth. Numerous studies indicate that the application of livestock manure increases the concentrations of organic carbon, nitrogen, phosphorus, potassium, and various other nutrients in the soil (Adekiya et al., 2020; HuaGang et al., 2023; Yao et al., 2020). Manure and compost have garnered significant attention due to their beneficial effects on soil structure, stability, nitrogen levels, and carbon content. The biological components of soil contribute to the formation of soil humus, nutrient cycling, soil structure development, and various other functions (Esmailzadeh & Ahangar, 2014). Applications of organic matter, including compost and manure, enhance organic C and K levels in soil, improve CEC, and diminish disease incidence in coffee plantations (Resende et al., 2022). The amendment improved total soil organic matter and soil pH, while reducing exchangeable aluminum (Muktamar et al., 2020). Liming and compost application enhanced soil N availability, and the activities of enzymes related to C and N cycling (Resende et al., 2022).

The relationship model established between the biophysical properties of the land and the influence of Arabica coffee production is not comprehensive for the entire Arabica coffee growing region, remaining confined to the research area in Bandung Regency. Utilizing extensive and varied datasets across broader regions enables the resultant model to effectively represent a larger coffee-growing area. The R² value of 9.8% in the multiple regression analysis suggests the presence of additional unmeasured factors, such as pest and disease occurrence, agricultural management practices, and genetic variation, that may influence productivity. Future research incorporating a larger dataset from various locations

and including additional agronomic variables may enhance the robustness of the predictive model.

5. CONCLUSION

The principal component analysis (PCA) results demonstrate that the various land characteristics evaluated can be succinctly condensed into seven principal component indices, which collectively explain 75.8% of the total variance in the data. The first principal component (PC1) encompasses variables such as sand and clay content, along with exchangeable magnesium (Mg), calcium (Ca), and sodium (Na), accounting for the largest proportion of variance at 18.6%. The multiple regression analysis reveals that the principal components utilized as independent variables do not have a statistically significant effect on Arabica coffee productivity. However, PC2 is identified as the most influential among them, followed by PC3. PC3 includes total nitrogen (N), organic carbon (C), altitude, and slope factors, which are identified as the primary contributors to variations in Arabica coffee yield.

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Declaration of Competing Interest

The authors declare that no competing financial or personal interests may appear to influence the work reported in this paper.

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