

Physical Characterization and Mass Modeling of Sleman Single Origin Robusta Green Beans

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ABSTRACT

Robusta coffee (*Coffea canephora*) is a strategic commodity in Indonesia, and efficient postharvest handling requires reliable information on the physical properties of green beans. This study characterized the physical properties of Sleman Single Origin Robusta green beans and evaluated their relationships with individual bean mass. A total of 299 beans were analyzed for dimensions, sphericity, volume, surface area, and projected area. Mean length, width, thickness, geometric mean diameter, and mass were 10.05 ± 0.77 mm, 7.76 ± 0.51 mm, 5.09 ± 0.53 mm, 7.33 ± 0.43 mm, and 0.26 ± 0.04 g, respectively. Mean sphericity was 0.73 ± 0.07 . Ellipsoid volume, prolate spheroid volume, and surface area averaged 207.82 ± 35.57 mm³, 414.95 ± 80.80 mm³, and 169.53 ± 19.73 mm², respectively. Linear, quadratic, power, and S-curve models were evaluated using the coefficient of determination (R^2) and standard error of estimate (SEE). Quadratic models based on length and ellipsoid volume produced the highest R^2 (0.92), with SEE values of 0.022 and 0.012, respectively. The power model based on geometric mean diameter also performed well ($R^2 = 0.90$; SEE = 0.013), whereas the criteria projected area model showed lower predictive performance ($R^2 = 0.71$; SEE = 0.022). These findings provide physical parameters and predictive models for designing and calibrating grading and sorting systems for Sleman Single Origin Robusta green beans.

Key words: *Coffea canephora*; grading; postharvest technology; sleman robusta.

1 INTRODUCTION

Robusta coffee (*Coffea canephora*), often referred to simply as “Robusta,” is among the most widely cultivated coffee species worldwide. In 2023/2024, Robusta varieties accounted for approximately 40% of global coffee production, with Vietnam and Brazil leading as major contributors (Campuzano-Duque & Blair, 2022). Other notable producers include Indonesia, Uganda, India, and Malaysia (International Coffee Organization - ICO, 2025). Within Southeast Asia, Indonesia holds a prominent position as the second-largest coffee-producing country, supported by favorable growing conditions across its archipelago (Ashardiono & Trihartono, 2024). Historically, Indonesian coffee has held commercial value since the Dutch colonial era, when it was exported to European markets (Pradadimara, 2018). Today, this tradition continues, especially with the growing international recognition of Indonesian-origin coffee. A notable example is Sleman Robusta, cultivated on the southern slopes of Mount Merapi in the Cangkringan District. Grown at elevations exceeding 433 meters above sea level ($7^{\circ}34'51''$ – $7^{\circ}47'30''$ S; $110^{\circ}15'03''$ – $110^{\circ}29'30''$ E), these plantations benefit from fertile volcanic soils and a unique microclimate characterized by temperatures of 17–28°C and high humidity (61%–87%). These specific agro-climatic conditions have earned Sleman Robusta a Geographical Indication (GI) status, legally certifying its

unique quality and origin (Fitri et al., 2024). However, the distinct morphological characteristics resulting from this volcanic terroir necessitate specialized postharvest modeling. Understanding the physical properties and mass-volume relationships of this specific GI variety is critical for designing precision processing equipment that preserves its premium value in both domestic and international markets.

Postharvest handling of coffee cherries in smallholder systems remains largely characterized by labor-intensive, semi-manual operations that lack the standardization necessary for consistent quality. Once the beans have been hulled from the parchment stage, they are subjected to drying, sorting, grading, and packaging processes that directly influence quality and market value (Gallego et al., 2025). Sorting is commonly conducted manually or with basic sieving tools based on visual inspection and bean size (Ansar et al., 2021). Alternatively, mechanical grading systems, incorporate vibration, aerodynamic separation, or multi-stage screening to classify beans based on size and density (Ansar et al., 2021; Ji et al., 2024). However, the efficiency of these systems is often limited by a lack of variety-specific data, particularly the physical characteristics and mass-to-volume correlations required to optimize machine calibration for regional cultivars.

Accurate mass modeling based on geometric dimensions is therefore essential for the design of pneumatic separators and gravity tables used in coffee processing. The aerodynamic

and physical behaviour of beans during processing is dictated by critical attributes such as length, width, thickness, surface area, and projected area affect the performance of downstream equipment and the consistency of end-product quality (Araujo et al., 2021). In the absence of standardized measurement protocols, classification remains imprecise, leading to inefficiencies in processing and inconsistent output (Celhay et al., 2024). In the context of modern postharvest technology, the incorporation of mass-based classification methods, particularly those that integrate physical dimensions with bean weight, can support the development of automated grading and packaging solutions (Barnavo et al., 2025; Sangeetha & Mohan, 2021). These systems enable reduced labor dependency, faster throughput, and improved consistency (Ojo & Baiyegunhi, 2024). Therefore, establishing the relationship between physical characteristics and mass of Robusta green beans is essential for engineering optimized equipment and for supporting innovations in mechanized postharvest technologies within the regional coffee sector.

Extensive research has been conducted on the physical characterization and mass modeling of various agricultural commodities to optimize postharvest handling. Studies have successfully developed predictive models for crops including Kendu (Panda et al., 2020), pepper berries (Azman et al., 2021), strawberry (Birania et al., 2022), jujube (Kumar et al., 2024), wood apple (Grover et al., 2024), and loquat (Gugliuzza et al., 2025). These investigations typically employ geometric, volumetric, and surface parameters as independent variables. For example, Azman et al. (2021) achieved a high determination coefficient ($R^2 = 0.995$) when modeling the mass of pepper berries based on actual volume. Panda et al. (2020) identified strong correlations between mass and geometric dimensions in Kendu fruits. Regarding model selection, power models are frequently recommended for their practical accuracy, though Grover et al. (2024) found that S-curve modeling based on ellipsoid volume provided superior results ($R^2 = 0.955$) for wood apple.

While previous studies provide a robust framework for mass prediction in larger fruits, the unique asymmetrical morphology of Robusta coffee beans characterized by a flat ventral side and an ellipsoidal dorsal side requires specialized modeling to ensure grading precision. Despite this mechanical requirement, a notable research gap remains concerning the individual physical characterization of Robusta green beans (*Coffea canephora*), particularly region-specific cultivars such as Sleman Robusta. Existing literature largely focuses on fresh cherries or bulk-level analyses, offering limited insights into bean-level physical traits necessary for the development of automated sorting, grading, and packaging systems. This lack of data constrains the design of standardized postharvest equipment and hinders the adoption of mass-based classification methods, which are essential for improving efficiency, reducing labor, and enhancing product

uniformity. Therefore, the goal of this study is to investigate the relationship between physical characteristics and individual mass in Sleman Robusta green beans. By modeling parameters such as length, width, thickness, and projected area, this study supports the development of precision postharvest technologies and provides a foundational dataset for future research and innovation within Robusta coffee value chain.

2 MATERIAL AND METHODS

2.1 Materials

The green beans (*Coffea canephora*) used in this study were sourced from smallholder plantations located on the southern slopes of Mount Merapi, Sleman Regency, Yogyakarta, Indonesia. The samples were derived from red ripe cherries, hand-harvested during the peak production period from June to August 2025 to ensure optimal maturity, and dried naturally under sunlight until they reached a moisture content below 12% (wet basis). To maintain high sample purity, defective, cracked, or broken beans were removed manually prior to analysis. From the bulk collection, a representative sample of 299 individual beans were randomly selected to ensure uniformity in sample quality. All samples were stored in airtight polyethylene bags under ambient conditions to prevent moisture fluctuations (Rossetti et al., 2022). All experiments in the laboratory were conducted at room temperature ($25 \pm 2^\circ\text{C}$).

2.2 Research Methods

2.2.1 Measurements of Physical Properties

The green beans mass (M) was measured using a digital analytical balance with a precision of 0.001 g. Three linear dimensions (Figure 1), namely length (L), width (W), and thickness (T), were measured along three mutually perpendicular axes using a digital vernier calliper with an accuracy of 0.01 mm. The equation 1-2 were used to figure out the sphericity (Φ) and geometric mean diameter (D_g) (Tscheuschner, 1987).

$$D_g = (LWT)^{\frac{1}{3}} \quad (1)$$

$$\phi = \frac{(LWT)^{\frac{1}{3}}}{L} \quad (2)$$

To calculate the volume properties, two distinct geometric approximations were employed. Initially, the green bean shape was assumed to be a regular geometric solid, specifically an ellipsoid spheroid (Vellip) and an prolate spheroid (Vpro). The volume was calculated using equations 3-4 (Gugliuzza et al., 2025):

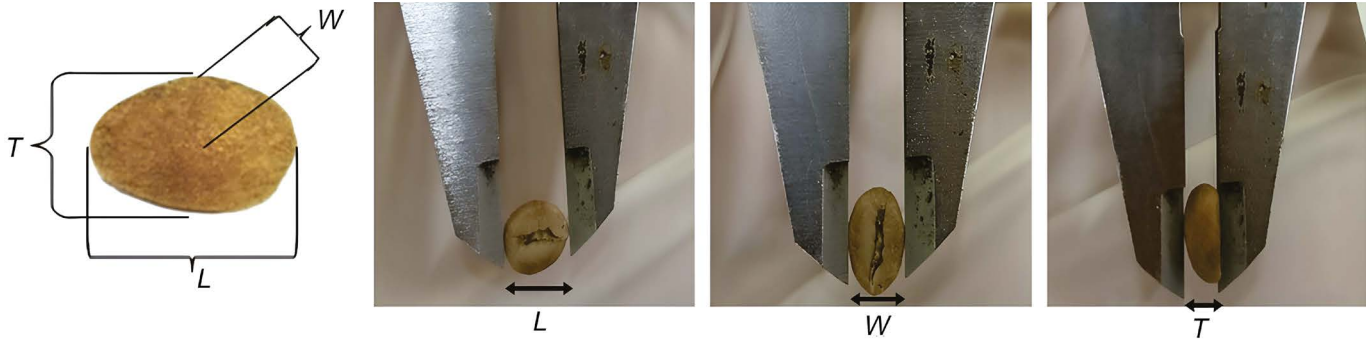


Figure 1: Principal dimensions of the coffee bean.

$$v_{ellip} = \frac{4\pi}{3} \frac{L}{2} \frac{W}{2} \frac{T}{2} \quad (3)$$

$$v_{pro} = \frac{4\pi}{3} \frac{L^2}{2} \frac{W}{2} \quad (4)$$

The surface area of the green bean, which is equal to the total area of all surfaces with three-dimensional shapes, was determined by using the equation 5 (Azman et al., 2021; Grover et al., 2024).

$$SA_{sp} = \pi D_g^2 \quad (5)$$

Using equations 6-8 (Azman et al., 2020), the projected areas perpendicular to thickness (PA_T), length (PA_L), and width (PA_W) were determined. The CPA was then computed using Equation (9). (Azman et al., 2020) proposed the following equations:

$$PA_T = \frac{\pi TW}{4} \quad (6)$$

$$PA_L = \frac{\pi LW}{4} \quad (7)$$

$$PA_W = \frac{\pi WW}{4} \quad (8)$$

$$CPA = \frac{PA_L + PA_T + PA_W}{3} \quad (9)$$

2.2.2 Regression Analysis and Mass Modelling

Four categories of models were used for mass modelling based on physical characteristics, projected area, volume, and

surface area as listed below (Khodabakhshian & Emadi, 2016; Pathak et al., 2019):

(1) Green bean mass is regressed in a single variable as a function of length (L), width (W), thickness (T), and geometric mean diameter (Dg).

(2) Based on projected green bean areas and criteria projected areas (CPA), a single-variable regression of green bean fruit mass was performed.

(3) Volumes of the bean were assumed to be prolate spheroid (Vpro) and ellipsoid shapes (Vellip) in a single-variable regression analysis of green bean mass.

(4) Regression of green bean mass in a single variable based on surface area

To establish the most accurate relationship between physical attributes and bean mass, the experimental data were subjected to regression analysis using four mathematical models: the Linear, Quadratic, Power, and S-curve models. These models were evaluated to determine their predictive performance. The following models are presented in Equations 10-13:

$$\text{Linear: } M = a + bX \quad (10)$$

$$\text{Quadratic: } M = a + bX + cX^2 \quad (11)$$

$$\text{Power: } M = aX^b \quad (12)$$

$$\text{S-curve: } M = a + \frac{b}{X} \quad (13)$$

where M stands for mass (g) as the dependent variable, X for independent variable (dimensions, volume, projected area, or surface area), and a, b, and c for curve fitting parameters based on various equations.

2.2.3 Statistical analysis

Statistical analysis and mass prediction modeling were performed using SigmaPlot (Version 12.0) with a significance level of 1%. The coefficient of determination (R^2) and the standard error of estimate (SEE) were utilized as primary performance indicators to determine the predictive accuracy

and robustness of each model. The best model was selected based on the criteria of maximizing R^2 value and minimizing SEE value (Sujinda et al., 2021).

3 RESULTS

Table 1 summarizes the mean and standard deviation of key physical properties of Sleman Robusta green beans, measured using standard methods. The average length (L), width (W), and thickness (T) were 10.05 ± 0.77 mm, 7.76 ± 0.51 mm, and 5.09 ± 0.53 mm, respectively. Among these dimensions, length exhibited the highest mean value, confirms the characteristic prolate ellipsoidal shape typical of the Robusta variety. The geometric mean diameter (Dg) was 7.33 ± 0.43 mm, with an average individual bean mass of 0.26 ± 0.04 g. The average sphericity (Φ) was 0.73 ± 0.07 , suggesting a near-spherical form in many samples. These values serve as critical baseline data for the calibration of screen-based separators and pneumatic grading systems.

Table 2 presents regression models that predict bean mass using various physical properties. Model performance was evaluated based on coefficient of determination (R^2) and SEE. Models with higher R^2 and lower SEE were considered better fits.

4 DISCUSSION

4.1 Physical Properties of Sleman Robusta Bean

Regarding volumetric characteristics, the ellipsoid volume (V_{ellip}) was 207.82 ± 35.57 mm³, and the prolate spheroid volume (V_{pro}) was 414.95 ± 80.80 mm³. The surface

area of prolate spheroid (SA_{sp}) averaged 169.53 ± 19.73 mm². These volumetric and surface attributes are essential for modeling heat and mass transfer during the drying and roasting stages. For projected areas, which influence the aerodynamic behavior of the beans in pneumatic separators, were measured as: $PA_L = 61.47 \pm 7.62$ mm², $PA_W = 47.21 \pm 7.41$ mm², and $PA_T = 31.04 \pm 4.32$ mm². The criteria projected area (CPA), representing the average orientation of the bean during freefall, calculated as the mean of PA_L , PA_W , and PA_T , was 46.56 ± 5.38 mm². These physical characteristics are critical for optimizing postharvest grading, sorting, and machine design (Mahawar et al., 2019).

Compared to Robusta beans from Lampung and Temanggung, which had larger dimensions (e.g., length = 11.78 mm and 11.04 mm) and higher masses (0.31 g and 0.29 g), the Sleman beans in this study were slightly smaller (Table 2). Interestingly, the sphericity observed in this study (0.73 ± 0.07) suggests a more compact morphology than the 0.67–0.70 range reported for other Indonesian regions (Kurniasari et al., 2023). These variations are likely attributable to the unique agroclimatic conditions of the Merapi slopes and regional variations in cultivar and sun-drying practices. More compact beans tend to fall through holes faster if the hole diameter is based on the width (W) or geometric mean diameter (Dg). The ellipsoid volume (207.82 ± 35.57 mm³) was slightly lower than those reported by Kurniasari et al. (2023), who estimated bean volumes at approximately 250–260 mm³. The surface area (169.53 ± 19.73 mm²) was broadly consistent with their reported values of 189–195 mm², highlighting the distinct physical profile of Sleman Single Origin coffee.

Table 1: Physical properties of Sleman Robusta green bean.

Parameter	Mean	Maximum	Minimum
L (cm)	10.05 ± 0.77	12.25	7.9
W (cm)	7.76 ± 0.51	8.8	6.4
T (cm)	5.09 ± 0.53	7.1	3.9
Mass (kg)	0.26 ± 0.04	0.35	0.15
Geometric Mean Diameter (Dg) (cm)	7.33 ± 0.43	8.49	5.92
Sphericity (Φ)	0.73 ± 0.07	0.97	0.59
V_{ellip} (cm ³)	207.82 ± 35.57	321.06	108.42
V_{pro} (cm ³)	414.95 ± 80.8	644.94	218.83
Sasp (cm ²)	169.53 ± 19.73	228.05	109.94
PA_L (cm ²)	61.47 ± 7.62	84.49	41.55
PA_T (cm ²)	31.04 ± 4.32	63.30	18.91
PA_W (cm ²)	47.67 ± 10.46	81.03	29.21
CPA (cm ²)	46.56 ± 5.38	65.3	32.55

Table 2: The most accurate and precise models for predicting the mass of Sleman Robusta based on a set of independent variables.

Dependent Parameter	Independent Parameter	Model Equation	Regression			Statistical Parameters	
			a	b	c	R ²	SSE
M (g)	L (mm)	Quadratic	0.012	0.001	0.002	92%	0.022
M (g)	T (mm)	Quadratic	-0.613	0.286	-0.022	53%	0.027
M (g)	W (mm)	Quadratic	-0.613	0.286	-0.022	53%	0.027
M (g)	Geometric Mean Diameter (Dg)	Power	0.152	-0.065	0.011	90%	0.013
M (g)	V _{ellip} (mm ³)	Quadratic	0.011	1.29E-03	-4.23E-07	92%	0.012
M (g)	V _{pro} (mm ³)	Quadratic	0.080	4.29E-04	-1.04E-07	74%	0.021
M (g)	Sasp	Quadratic	-0.073	1.97E-03		87%	0.015
M (g)	PAL (mm ²)	Quadratic	0.125	-2.80E-04	3.92E-05	73%	0.021
M (g)	PAT (mm ²)	Quadratic	-0.225	2.24E-02	-2.15E-04	73%	0.022
M (g)	PAW (mm ²)	Quadratic	0.293	-1.56E+00		2%	0.041
M (g)	CPA (mm ²)	Power	-0.040	0.006	-7.6421E-07	71%	0.022

4.2 Modelling based on dimensional dimensions

Among the dimensional parameters, bean length (L) was the most reliable predictor of mass. The quadratic model utilizing length demonstrated superior predictive performance, yielding a high coefficient of determination ($R^2 = 0.92$) and a low SEE = 0.022, indicating a strong and consistent relationship where the mass of the Sleman Robusta bean increases predictably with its longitudinal axis. From an engineering perspective, the high accuracy of this length-based model is highly significant; it suggests that precision grading can be achieved by monitoring a single physical parameter, simplifying the design of high-speed optical or mechanical sorting systems compared to models requiring multi-dimensional or volumetric inputs. The fitted equation 14 is:

$$M = 0.012 + 0.001X + 0.002X^2 \quad (14)$$

In contrast, models based on thickness (T) and width (W) as independent variables showed considerably lower predictive accuracy, with both producing $R^2 = 0.53$ and SEE = 0.027, highlighting the limited strength of these dimensions in estimating bean mass. This disparity underscores the limited reliability of lateral dimensions for mass estimation in Sleman Robusta. The poor performance of these models suggests that while bean mass is strongly correlated with longitudinal growth (L), the lateral development of the bean likely constrained by the internal space of the coffee cherry does not follow a similarly predictable linear or quadratic progression.

The geometric mean diameter (D_g) also demonstrated robust predictive performance when fitted with a quadratic model, achieving $R^2 = 0.90$ and SEE = 0.013. The corresponding equation 15 is:

$$M = 0.152 - 0.065X + 0.011X^2 \quad (15)$$

These results are consistent with previous studies by Panda et al. (2020) for Kendu fruit and Pathak et al. (2019) for *Terminalia chebula*, further supporting the geometric mean diameter as a robust predictor for modeling fruit or seed mass. However, it is noteworthy that for Sleman Robusta, the single dimension of length (L) provided a slightly higher accuracy ($R^2 = 0.92$) than the composite D_g . This suggests that while D_g remains a scientifically sound predictor, the longitudinal axis is the primary driver of mass variation in this specific variety.

4.3 Modelling based on volume

Volume-based models provided reliable predictions of bean mass. The quadratic model using ellipsoid volume (V_{ellip}) showed the highest predictive accuracy, with an R^2 of 0.92 and a SEE of 0.012. In comparison, the model based on prolate spheroid volume (V_{pro}) produced lower accuracy, with $R^2 = 0.74$ and SEE = 0.021. These results suggest that the tri-axial ellipsoid model provides a superior approximation of the actual shape and mass distribution of Robusta green beans compared to the prolate spheroid model. Similar findings have been reported in mass modeling studies of *Terminalia chebula* (Pathak et al., 2019), and pepper berries (Azman et al., 2021), where volume-based quadratic equations demonstrated strong predictive power for agricultural commodities with non-spherical geometries. The best-fitting relationship derived from V_{ellip} is described by the following equation 16:

$$M = 0.011 - 0.0013X - 0.0000004X^2 \quad (16)$$

4.4 Modelling based on bean project areas

The power model based on longitudinal projected area (PA_L) yielded an R^2 73% and a SEE 0.021, indicating only a moderate correlation between PA_L and bean mass. This result shows that while PAL captures the largest cross-sectional profile of the bean, its predictive ability is inferior to models based on length ($R^2 = 0.92$), ellipsoid volume ($R^2 = 0.92$), and geometric mean diameter ($R^2 = 0.90$). The higher error associated with projected area models may be attributed to the natural variation in bean thickness and the irregular flat-side morphology of the Robusta bean, which PA_L being a 2D measurement cannot fully account for. Consequently, while projected area remains essential for calculating aerodynamic drag in pneumatic separators, it is a less reliable proxy for mass estimation than linear or volumetric parameters.

5 CONCLUSION

This study characterized Sleman Robusta green beans and developed models for predicting bean mass. The ellipsoid-volume quadratic model provided the highest precision ($R^2 = 0.92$; SEE = 0.012), while the length-based quadratic model achieved comparable predictive performance ($R^2 = 0.92$; SEE = 0.022) using a simpler measurement. These findings support the use of ellipsoid volume and length for calibrating automated grading systems and provide baseline physical parameters for future modeling of mass and dimensional changes during roasting.

6 AUTHOR CONTRIBUTIONS

Conceptual idea: Anoraga, S.B.; Sari, A.R.; Nabila, P.R.; Methodology design: Anoraga, S.B.; Sari, A.R.; Data collection: Cahyani, Z.Z.; Riscahyani, A.; Data analysis and interpretation: Anoraga, S.B.; Sari, A.R.; and Writing and editing: Anoraga, S.B.; Sari, A.R.; Nabila, P.R.; Bachtiar, W. B.; Hardiyanti, R.

7 DATA AVAILABILITY STATEMENT

Data available upon request to authors.

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