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Precision-Driven Classification of Coefficients of Variation in Clonal Eucalyptus Nursery Trials

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Abstract

The coefficient of variation (CV) is widely used to evaluate experimental precision; however, generic classifications may fail to capture the variability in clonal eucalyptus seedlings. This study aimed to propose a reclassification of CV values for morphological traits of *Eucalyptus* sp. seedlings at the dispatch stage, considering different plot sizes (PS). Data from 8200 seedlings were analyzed across six commercial clones and 41 evaluations of 200 seedlings each. Traits evaluated included plant height, stem diameter, shoot, root, and total dry mass, leaf number, leaf area, and slenderness index. Using bootstrap simulation, CV values were estimated for PS ranging from 1 to 100 seedlings. The relationship between CV and PS was fitted using a power model to estimate updated CV values and reclassify them. CV classification limits decreased progressively as plot size increased from 1 to 10 seedlings. Rather than defining a single optimal plot size, the proposed framework provides dynamic, trait-specific CV benchmarks tailored to the chosen PS. The proposed reclassification was more sensitive and appropriate than traditional criteria. In conclusion, adopting trait-specific CV intervals combined with PS provides more consistent evaluations of experimental quality, contributing to technical standardization in forest nurseries and eucalyptus breeding programs.

Keywords: coefficient of variation; bootstrap simulation; *Eucalyptus* sp.; experimental precision; resampling

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1. Introduction

The forest sector has considerable economic importance, particularly eucalyptus plantations established for pulp and paper production, especially in Brazil. Therefore, the production of clonal eucalyptus seedlings plays a strategic role, as the genetic uniformity of clones contributes to greater homogeneity of forest stands and increased predictability of productivity [1,2]. However, even in clonal genotypes, the morphological traits used to assess seedling quality exhibit experimental variability that directly affects the statistical precision of trials and the interpretation of results [3,4].

Experimental precision in seedling studies is frequently assessed using the coefficient of variation (CV), a statistical measure that expresses the magnitude of experimental error relative to the data mean [5]. High CV values indicate a large error mean square and, consequently, increase the minimum significant difference in mean comparison tests, thereby reducing the ability to detect differences among treatments [6]. Despite the widespread use of the classification proposed by Pimentel-Gomes [7], which categorizes CV values as low, medium, high, and very high, several authors have pointed out that this generic approach does not account for factors such as crop species, trait under evaluation, experimental conditions, and data distribution [8,9]. In forest seedlings, particularly eucalyptus, studies have shown that CV values often do not fit within the traditional classification ranges, highlighting the need for context-specific classifications [10,11].

Among the factors that directly influence the CV, experimental plot size (PS) deserves particular attention. Plot sizes smaller than an optimum plot size tend to inflate the coefficient of variation, whereas excessively large plots increase experimental costs without proportional gains in precision [12]. In experiments involving eucalyptus seedlings, considerable variation has been reported in the number of plants per plot, indicating a lack of methodological standardization [13,14]. Furthermore, traditional CV classification methods based on the standard deviation assume data normality, a condition that is often not met in seedling experiments, which has motivated the development of approaches based on the median, pseudo-sigma, and nonparametric methods [15].

Although reclassification schemes for the CV have been proposed for agricultural crops and some morphological traits of eucalyptus seedlings [10], no studies have simultaneously integrated data distribution, the use of clonal materials, and the effect of OPS on CV classification ranges. This gap limits the establishment of more appropriate statistical criteria for forest experiments, compromising both experimental precision and cost optimization. Therefore, this study aimed to evaluate how the coefficient of variation behaves across increasing experimental plot sizes in morphological traits of clonal eucalyptus seedlings under normal and non-normal data distributions. Rather than seeking to define a single optimal plot size, this work demonstrates that CV classification thresholds continuously decrease as PS expands, providing dynamic, trait-specific CV reference ranges tailored to the chosen PS.

2. Materials and Methods

The eucalyptus seedlings were produced through vegetative propagation by the cutting method and obtained from commercial nurseries located in the municipalities of Sooretama, Linhares, and Jaguaré, in northern Espírito Santo State, Brazil. According to the Köppen climate classification, the region has a tropical Aw climate [16] (Figure 1). The evaluated clones were CO 1407, AEC 0144, AEC 0224, and GG 100 (*Eucalyptus urophylla*), as well as BA 7346 and TP 361 (*Eucalyptus urophylla* × *Eucalyptus grandis* hybrids) [17,18].

Morphological analyses were conducted at the Plant Breeding Laboratory of the Centro Universitário Norte do Espírito Santo (CEUNES), Federal University of Espírito Santo (UFES), located in São Mateus, Espírito Santo State, Brazil. The seedlings used in this study (60–120 days old; Table 1), produced in 50 cm^3 polypropylene tubes arranged in 54-cell, were obtained at the dispatch stage, the final phase of production in which seedlings are prepared for field planting [19–21], according to the operational standards adopted by each nursery. The inclusion of evaluations across multiple clones, ages (60–120 days), nursery origins, and seasons was adopted to encompass the broad biological heterogeneity typical of commercial eucalyptus seedling production at the different dispatch stage. For each clone, 200 seedlings were evaluated at each assessment period, totaling 8200 seedlings and 41 assessment periods (Table 2).

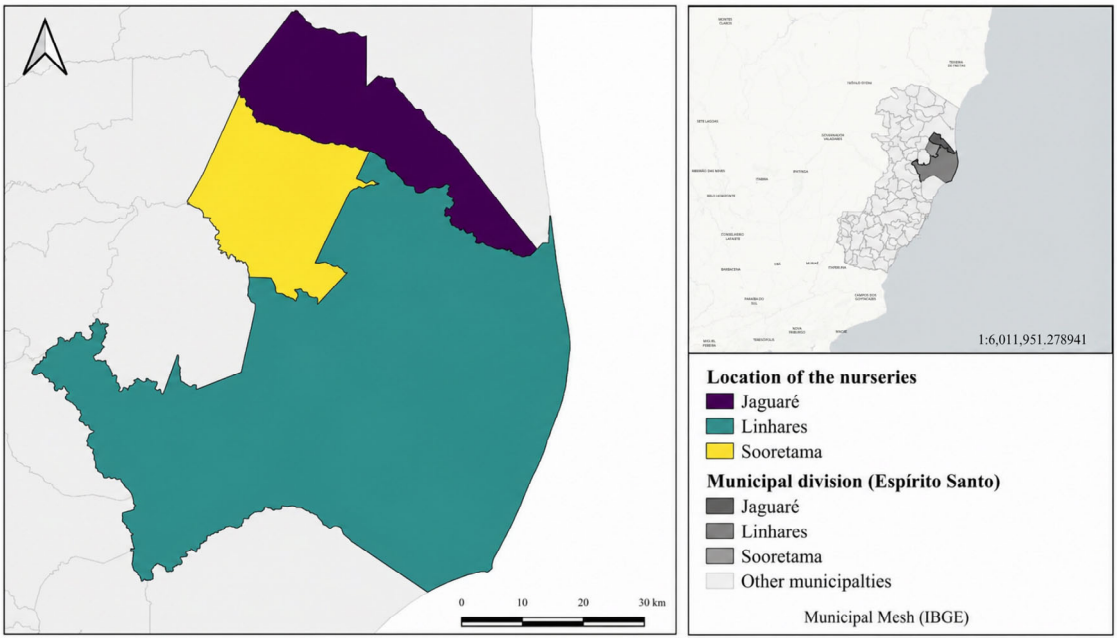


Figure 1. Geographic location of the municipalities where the forest nurseries supplying *Eucalyptus* sp. seedlings are located in Espírito Santo State, Brazil.

Table 1. Characteristics of the clones, species, seedling ages, and locations of the nurseries supplying the *Eucalyptus* sp. seedlings.

Clone	Age (Days) [1/]	Location of the Nurseries
AEC 0144	60–90	Jaguaré
AEC 0224	60–90	Jaguaré
BA 7346	90	Jaguaré; Linhares
CO 1407	90–120	Sooretama
TP 361	90–120	Sooretama
GG 100	90	Jaguaré

[1/] The AEC 0224 clone was evaluated in December 2016 at 60 days of age and in June and September 2017 at 90 days of age; the AEC 0144 clone was evaluated in September 2017 at 60 days of age; the CO 1407 clone was evaluated in June 2016 at 120 days of age; and the TP 361 clone was evaluated in June 2016 and June 2017 at 120 days of age. In all other assessment periods and for the remaining clones, the seedlings were evaluated at 90 days of age.

For each of the 8200 seedlings, the following traits were evaluated: plant height (PH, cm), measured with a measuring tape from the substrate surface to the insertion point of the last leaf; stem diameter (SD, mm), measured at the root collar using a digital caliper; shoot dry mass (SDM), root dry mass (RDM), and total dry mass (TDM) (g), determined using an analytical balance after drying in a forced-air oven at 60 °C until constant weight was achieved; number of leaves (NL); and leaf area (LA, cm^2), determined using ImageJ® software version 1.54k [22]. In addition to these traits, the robustness index (RI), calculated as the ratio between plant height and stem diameter (PH/SD), was also obtained [23].

The study was based on blank trials conducted in the nursery, where dispatch-ready seedlings were evaluated in continuous sequence without treatment application. To analyze the relationship between CV and PS, experimental plots of 1, 2, 4, 5, 10, 20, 25, 50, and 100 seedlings (PS) were simulated from these sequential measurements using a bootstrap resampling procedure with replacement (2000 iterations per plot size). For each simulated plot size and trait across the 41 evaluations, the corresponding CV was calculated. The

relationship between CV and PS was fitted using the power equation $CV = \beta_0 PS^{-\beta 1}$, where PS is the plot size in number of seedlings, β_0 represents the baseline CV for a single seedling, and β_1 expresses the rate of CV reduction as PS increases. The Shapiro–Wilk normality test was applied directly to individual seedling measurements for each morphological trait as a decision criterion to select the appropriate classification method [23].

Table 2. Assessment periods, numbers of evaluated seedlings, and clonal eucalyptus genotypes.

Clone	Assessment Periods	Growing Seasons	Number of Seedlings
AEC 0144	June, September 2017.	Fall; winter	400
AEC 0224	December 2015; March, June, September, December 2016; March, June, September 2017.	All	1600
BA7346	December 2015; March, June, September, December 2016; March, June, September 2017; November 2024.	All	1800
CO1407	December 2015; March, June, September, December 2016; March, June, September 2017.	All	1600
TP361	December 2015; March, June, September, December 2016; March, June, September 2017	All	1600
GG100	December 2015; March, June, September, December 2016; March 2017.	All	1200

For normally distributed data, the methodology proposed by [8], which classifies CV values based on the mean coefficient of variation (mean CV) ± standard deviation (s), was applied, as this approach is appropriate for data that satisfy the normality assumption, as presented in Table 3.

Table 3. Coefficient of variation classification limits according to Garcia [8].

Classification	Interval
Low	CV ≤ (mean CV – 1s)
Medium	(mean CV – 1s) < CV ≤ (mean CV + 1s)
High	(mean CV + 1s) < CV ≤ + (mean CV + 2s)
Very high	CV > (mean CV + 2s)

Source: Garcia [8].

For data that did not follow a normal distribution, the methodology proposed by Costa et al. [15] was applied. This approach is based on nonparametric techniques that account for data non-normality by using the median (Md) and pseudo-sigma (PSIG) (Table 4).

Table 4. Coefficient of variation classification limits according to Costa et al. [15].

Classification	Interval
Low	CV ≤ (Md – 1PSIG)
Medium	(Md – 1PSIG) < CV ≤ (Md + 1PSIG)
High	(Md + 1PSIG) < CV ≤ (Md + 2PSIG)
Very high	CV > (Md + 2PSIG)

Source: Costa et al. [15].

Where:

Md = $\frac{(Q1+Q3)}{2}$ corresponds to the median between the first (Q1) and third (Q3) quartiles of the coefficient of variation distribution, which delimit the lower and upper 25% of the distribution, respectively.

PSIG = $\frac{IQR}{1.35}$ represents the pseudo-sigma, a robust measure of dispersion calculated from the interquartile range (IQR). Unlike the standard deviation, this estimator is less influenced by outliers and describes the spread of observations around the median, providing a more reliable assessment of data variability in asymmetric distributions. This value corresponds to the standard deviation that a normal distribution would require to produce the same interquartile range as the observed data. Descriptive statistics were also computed for all 8200 seedlings to evaluate the behavior of the studied morphological traits. All data processing, bootstrap resampling simulations, power model fittings, and normality tests were performed using custom scripts developed in the R software, version 4.2.1. Artificial intelligence was used solely as a consultative tool to troubleshoot error messages and debug the original R scripts.

3. Results

Figure 2 graphically presents the distribution of plant height (PH, cm), stem diameter (SD, mm), shoot dry mass (SDM, g), root dry mass (RDM, g), total dry mass (TDM, g), number of leaves (NL), leaf area (LA, cm^2), and robustness index (RI), illustrating the measures of central tendency, dispersion, symmetry, and outliers for the *Eucalyptus* sp. clones AEC 0144, AEC 0224, BA 7346, CO 1407, GG 100, and TP 361.

Plant height exhibited the fewest outliers, with AEC 0144 and AEC 0224 presenting the lowest values and TP 361 showing the highest values. For stem diameter, TP 361 also exhibited extreme values. For SDM and RDM, the clones AEC 0224 and BA 7346 showed the highest values, respectively. Similar to SDM, AEC 0224 also presented the highest values for TDM. BA 7346 and AEC 0224 exhibited the highest values for NL, respectively. For LA, BA 7346 showed the highest values, whereas CO 1407 stood out for RI. AEC 0144 exhibited the lowest values for all evaluated traits, except for RI, for which AEC 0224 presented the lowest minimum and maximum values.

Table S1 (Supplementary Materials) presents the standard deviation (s) values obtained for all evaluated characteristics across clones and assessment periods. Overall, leaf area (LA), robustness index (RI), and plant height (PH) exhibited the highest standard deviation values. For LA, the highest dispersion was observed in clone BA7346 evaluated in November 2024 (s = 39.30 cm^2), while the lowest was recorded in clone GG100 in March 2017 (s = 9.59 cm^2). For RI, standard deviation values ranged from 10.84 (AEC 0224 in September 2017) to 28.66 (CO1407 in March 2016). For PH, s values ranged between 1.99 cm (CO1407 in December 2016) and 7.06 cm (GG100 in June 2016). Stem diameter (SD) exhibited lower and more stable standard deviation values across all clones, ranging from 0.31 mm (AEC 0224 in June 2017) to 1.17 mm (GG100 in June 2016). Regarding dry mass traits, shoot dry mass (SDM), root dry mass (RDM), and total dry mass (TDM) presented s values ranging from 0.12 g to 1.42 g, 0.10 g to 2.03 g, and 0.19 g to 2.22 g, respectively. Finally, for leaf number (NL), s values ranged between 1.35 leaves (AEC 0224 in September 2017) and 8.22 leaves (BA7346 in November 2024). Table 5 presents the coefficient of variation (CV%) values obtained for all characteristics considering only one plant per plot at each evaluation period. For PH, SD, and SDM, clone GG100 showed the highest CV values, whereas the lowest values for these same characteristics were observed in clones BA7346, GG100, and AEC 0144, respectively. For RDM, the highest CV value was observed in clone CO1407, while GG100 presented the lowest value for this characteristic. For TDM, GG100 again exhibited the highest CV value, whereas clones AEC 0224 and BA7346 showed the

lowest values. For NL and LA, clone AEC 0224 presented both the highest and lowest CV values. Finally, for RI, clone CO1407 exhibited the highest CV value, while AEC 0144 showed the lowest.

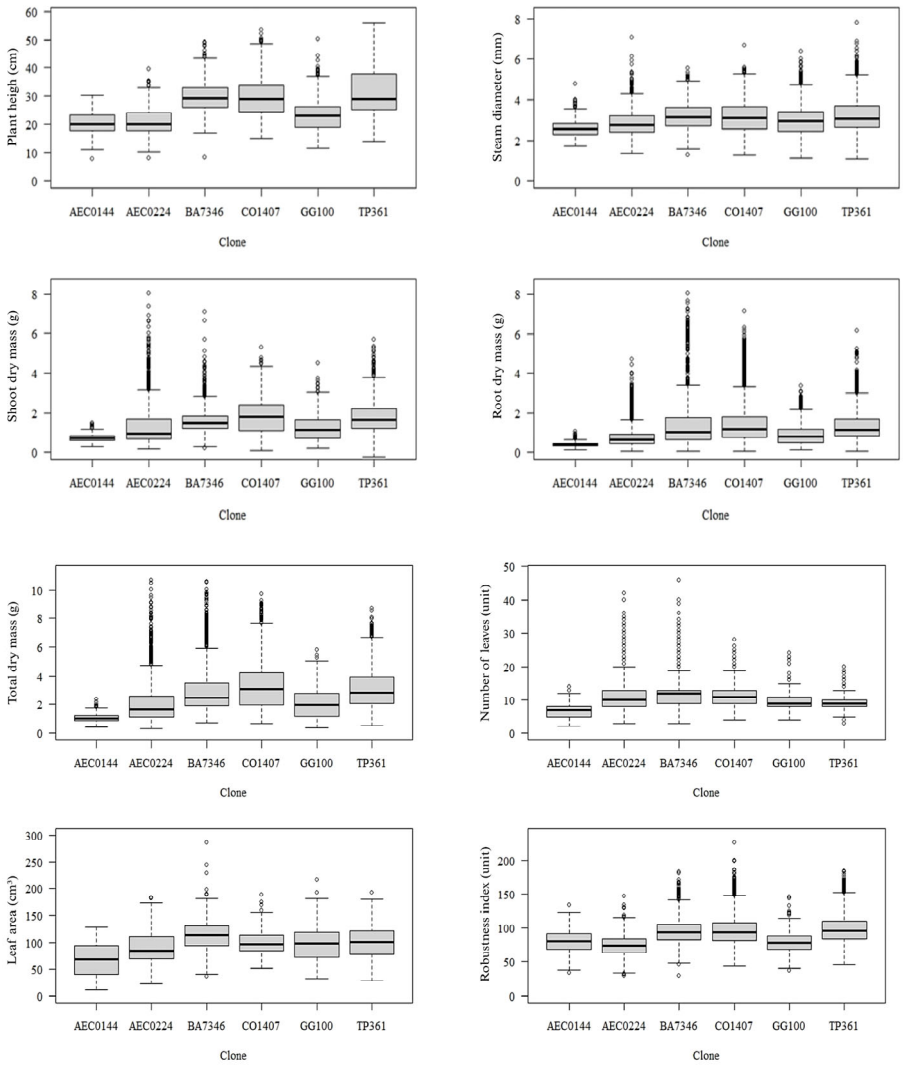


Figure 2. Boxplots showing the distributions of plant height (PH, cm), stem diameter (SD, mm), shoot dry mass (SDM, g), root dry mass (RDM, g), total dry mass (TDM, g), number of leaves (NL), leaf area (LA, cm^2), and robustness index (RI) in the *Eucalyptus* sp. clones AEC 0144, AEC 0224, BA 7346, CO 1407, GG 100, and TP 361.

Table 5. Coefficient of variation (CV%) values for the characteristics of plant height (PH, cm), stem diameter (SD, mm), shoot dry mass (SDM, g), root dry mass (RDM, g), total dry mass (TDM, g), number of leaves (NL), leaf area (LA, cm^2), and robustness index (RI) for the clonal eucalyptus genotypes AEC 0144, AEC 0224, BA7346, CO1407, GG100, and TP361 across all evaluation periods.

Clones	Assessment Periods	Coefficient of Variation (%)							
		PH	SD	SDM	RDM	TDM	NL	LA	RI
AEC 0144	June 2017	12.1	12.4	22.7	29.4	20.8	20.2	25.0	12.5
AEC 0144	September 2017	15.5	19.2	32.0	33.0	29.6	24.8	38.2	20.7
AEC 0224	December 2015	13.7	17.7	14.9	55.4	19.9	13.4	25.4	17.1
AEC 0224	December 2016	11.8	16.1	29.3	45.9	32.2	14.4	23.4	18.9
AEC 0224	June 2016	13.3	13.8	27.3	32.3	24.0	28.7	25.8	15.5
AEC 0224	June 2017	11.6	12.2	25.3	36.3	23.5	18.5	34.0	15.4

Table 5. *Cont.*

Clones	Assessment Periods	Coefficient of Variation (%)							
		PH	SD	SDM	RDM	TDM	NL	LA	RI
AEC 0224	March 2016	10.4	17.2	23.1	31.7	22.9	16.1	13.7	17.9
AEC 0224	March 2017	14.7	14.0	29.3	32.1	27.6	18.5	32.4	16.1
AEC 0224	September 2016	27.3	20.9	48.2	52.1	46.0	44.1	24.7	21.0
AEC 0224	September 2017	19.6	16.8	23.5	31.5	22.9	20.2	38.5	16.9
BA7346	December 2015	10.0	14.9	21.1	39.2	21.3	24.9	21.9	17.1
BA7346	December 2016	8.90	12.6	26.4	45.8	26.6	24.7	21.7	14.5
BA7346	June 2016	11.0	16.7	40.8	61.2	39.8	16.4	24.4	18.1
BA7346	June 2017	15.4	21.0	47.2	54.6	42.0	18.1	16.8	22.1
BA7346	March 2016	10.3	16.6	25.3	33.11	51.3	16.1	19.5	19.8
BA7346	March 2017	10.3	20.8	23.0	52.7	30.9	23.1	18.5	19.3
BA7346	November 2024	7.3	14.1	19.8	30.7	19.9	38.3	25.0	13.4
BA7346	September 2016	12.0	15.5	23.6	44.9	24.6	24.7	24.7	18.2
BA7346	September 2017	12.3	16.1	25.9	32.9	25.7	17.8	30.8	19.8
CO1407	December 2015	15.1	16.6	29.1	32.5	27.1	19.8	24.3	18.6
CO1407	December 2016	8.50	15.9	39.0	75.1	36.8	30.0	17.5	18.3
CO1407	June 2016	13.1	17.2	55.0	58.4	38.0	26.0	23.8	17.2
CO1407	June 2017	10.8	15.0	27.5	30.1	26.1	20.5	21.9	15.6
CO1407	March 2016	13.5	25.4	46.9	71.2	43.0	23.3	23.8	22.9
CO1407	March 2017	10.3	15.4	24.1	29.2	21.6	18.2	23.6	15.6
CO1407	September 2016	12.4	19.1	20.8	47.8	24.5	23.5	15.9	21.3
CO1407	September 2017	12.4	19.7	34.3	49.3	37.3	23.0	19.5	16.6
GG100	December 2015	12.3	14.1	34.4	52.0	36.8	17.3	18.9	13.9
GG100	December 2016	23.5	21.2	43.2	57.1	43.8	20.9	23.5	16.9
GG100	June 2016	31.6	36.0	53.5	72.5	58.9	23.8	32.6	19.3
GG100	March 2016	12.2	12.0	23.8	36.9	25.3	16.2	17.0	13.5
GG100	March 2017	12.0	17.2	23.9	25.7	22.0	19.9	16.5	17.7
GG100	September 2016	16.3	17.0	29.7	31.6	25.9	35.4	31.4	20.2
TP361	December 2015	10.4	14.5	24.5	44.3	27.2	17.0	16.0	16.2
TP361	December 2016	11.0	16.8	26.6	29.6	21.9	23.7	20.3	19.6
TP361	June 2016	11.3	15.9	26.1	73.5	36.3	21.3	18.2	18.5
TP361	June 2017	9.6	14.7	27.8	41.2	24.6	21.4	25.3	17.4
TP361	March 2016	9.5	18.4	34.6	69.0	36.8	17.7	24.4	21.4
TP361	March 2017	8.2	16.1	23.6	29.3	23.1	17.5	18.1	21.6
TP361	September 2016	13.9	16.4	28.3	35.2	25.5	25.4	25.6	19.9
TP361	September 2017	10.1	21.9	25.7	34.6	25.9	21.3	24.7	20.3

Tables 6 and 7 present the CV values as a function of plot size (PS) for the morphological traits plant height (PH), stem diameter (SD), shoot dry mass (SDM), root dry mass (RDM), total dry mass (TDM), number of leaves (NL), leaf area (LA), and robustness index (RI), estimated using the maximum curvature method proposed by Meier and Lessman [12] and bootstrap simulation based on the parametric data of all 8200 analyzed clones (graphical representation in Figure S1, Supplementary Material). The results showed that CV values varied according to the evaluated trait and that increasing plot size reduced CV values, thereby improving experimental precision.

Table 6. Classification of the coefficients of variation (CV), according to the methodology proposed by Costa et al. [15] for non-normal data, for the characteristics of plant height (PH), stem diameter (SD), shoot dry mass (SDM), root dry mass (RDM), total dry mass (TDM), number of leaves (NL), and leaf area (LA), considering plot sizes ranging from 1 to 10 plants.

Plants	Classification Ranges of CV (%) Values for PH			
	Low	**Medium**	**High**	**Very High**
1	CV ≤ 9.44	9.44 < CV ≤ 14.50	14.50 < CV ≤ 17.02	CV > 17.03
2	CV ≤ 6.61	6.61 < CV ≤ 10.26	10.26 < CV ≤ 12.09	CV > 12.09
3	CV ≤ 5.47	5.47 < CV ≤ 8.37	8.37 < CV ≤ 9.82	CV > 9.82
4	CV ≤ 4.74	4.74 < CV ≤ 7.25	7.25 < CV ≤ 8.50	CV > 8.50
5	CV ≤ 4.24	4.24 < CV ≤ 6.48	6.48 < CV ≤ 7.60	CV > 7.60
6	CV ≤ 3.87	3.87 < CV ≤ 5.92	5.92 < CV ≤ 9.64	CV > 9.64
7	CV ≤ 3.56	3.56 < CV ≤ 5.48	5.48 < CV ≤ 6.44	CV > 6.44
8	CV ≤ 3.35	3.35 < CV ≤ 5.12	5.12 < CV ≤ 6.00	CV > 6.00
9	CV ≤ 3.16	3.16 < CV ≤ 4.83	4.83 < CV ≤ 5.66	CV > 5.66
10	CV ≤ 3.00	3.00 < CV ≤ 4.58	4.58 < CV ≤ 5.37	CV > 5.37
Plants	**Classification Ranges of CV (%) Values for SD**			
	Low	**Medium**	**High**	**Very High**
1	CV ≤ 14.02	14.02 < CV ≤ 19.08	19.08 < CV ≤ 21.61	CV > 21.61
2	CV ≤ 9.85	9.85 < CV ≤ 13.52	13.52 < CV ≤ 15.35	CV > 15.35
3	CV ≤ 8.12	8.12 < CV ≤ 11.03	11.03 < CV ≤ 12.45	CV > 12.45
4	CV ≤ 7.04	7.04 < CV ≤ 9.55	9.55 < CV ≤ 10.82	CV > 10.82
5	CV ≤ 6.30	6.30 < CV ≤ 8.55	8.55 < CV ≤ 9.68	CV > 9.68
6	CV ≤ 5.78	5.78 < CV ≤ 7.66	7.66 < CV ≤ 8.59	CV > 8.59
7	CV ≤ 5.28	5.28 < CV ≤ 7.24	7.24 < CV ≤ 8.22	CV > 8.22
8	CV ≤ 4.99	4.99 < CV ≤ 6.77	6.77 < CV ≤ 7.65	CV > 7.65
9	CV ≤ 4.70	4.70 < CV ≤ 6.38	6.38 < CV ≤ 7.22	CV > 7.22
10	CV ≤ 4.46	4.46 < CV ≤ 6.05	6.05 < CV ≤ 6.85	CV > 6.85
Plants	**Classification Ranges of CV (%) Values for SDM**			
	Low	**Medium**	**High**	**Very High**
1	CV ≤ 21.14	21.14 < CV ≤ 36.47	36.47 < CV ≤ 44.14	CV > 44.14
2	CV ≤ 14.79	14.79 < CV ≤ 25.86	25.86 < CV ≤ 31.40	CV > 31.40
3	CV ≤ 12.17	12.17< CV ≤ 21.12	21.12 < CV ≤ 25.59	CV > 25.59
4	CV ≤ 10.53	10.53 < CV ≤ 18.30	18.30 < CV ≤ 22.19	CV > 22.19
5	CV ≤ 9.41	9.41 < CV ≤ 16.38	16.38 < CV ≤ 19.86	CV > 19.86
6	CV ≤ 8.74	8.74 < CV ≤ 14.18	14.18 < CV ≤ 16.89	CV > 16.89
7	CV ≤ 7.87	7.87 < CV ≤ 13.87	13.87 < CV ≤ 16.87	CV > 16.87
8	CV ≤ 7.43	7.43 < CV ≤ 12.96	12.96 < CV ≤ 15.73	CV > 15.73
9	CV ≤ 7.00	7.00 < CV ≤ 12.22	12.22 < CV ≤ 14.83	CV > 14.83
10	CV ≤ 6.65	6.65 < CV ≤ 11.60	11.60 < CV ≤ 14.07	CV > 14.07
Plants	**Classification Ranges of CV (%) Values for RDM**			
	Low	**Medium**	**High**	**Very High**
1	CV ≤ 26.99	26.99 < CV ≤ 49.84	49.84 < CV ≤ 76.26	CV > 76.26
2	CV ≤ 19.04	19.04 < CV ≤ 42.36	42.36 < CV ≤ 54.02	CV > 54.02
3	CV ≤ 15.53	15.53 < CV ≤ 34.61	34.61 < CV ≤ 44.16	CV > 44.16
4	CV ≤ 13.40	13.40 < CV ≤ 30.00	30.00 < CV ≤ 38.30	CV > 38.30
5	CV ≤ 11.95	11.95 < CV ≤ 26.85	26.85 < CV ≤ 34.30	CV > 34.30
6	CV ≤ 10.89	10.89 < CV ≤ 24.52	24.52 < CV ≤ 31.34	CV > 31.34
7	CV ≤ 10.05	10.05 < CV ≤ 22.71	22.71 < CV ≤ 29.04	CV > 29.04
8	CV ≤ 9.39	9.39 < CV ≤ 21.25	21.25 < CV ≤ 27.18	CV > 27.18
9	CV ≤ 8.84	8.84 < CV ≤ 20.04	20.04 < CV ≤ 25.64	CV > 25.64
10	CV ≤ 8.38	8.38 < CV ≤ 19.02	19.02 < CV ≤ 24.34	CV > 24.34

Table 6. *Cont.*

Plants	Classification Ranges of CV (%) Values for TDM			
	Low	**Medium**	**High**	**Very High**
1	CV ≤ 34.58	34.58 < CV ≤ 59.93	59.93 < CV ≤ 72.60	CV > 72.60
2	CV ≤ 14.27	14.27 < CV ≤ 27.91	27.91 < CV ≤ 34.73	CV > 34.73
3	CV ≤ 19.89	19.89 < CV ≤ 35.01	35.01 < CV ≤ 42.58	CV > 42.58
4	CV ≤ 9.99	9.99 < CV ≤ 19.83	19.83 < CV ≤ 24.74	CV > 24.74
5	CV ≤ 8.92	8.92 < CV ≤ 17.75	17.75 < CV ≤ 22.17	CV > 22.17
6	CV ≤ 8.15	8.15 < CV ≤ 16.22	16.22 < CV ≤ 20.26	CV > 20.26
7	CV ≤ 7.55	7.55 < CV ≤ 15.02	15.02 < CV ≤ 18.75	CV > 18.75
8	CV ≤ 7.06	7.06 < CV ≤ 14.04	14.04 < CV ≤ 17.53	CV > 17.53
9	CV ≤ 6.66	6.66 < CV ≤ 13.24	13.24 < CV ≤ 16.53	CV > 16.53
10	CV ≤ 6.32	6.32 < CV ≤ 12.55	12.55 < CV ≤ 15.67	CV > 15.67
Plants	**Classification Ranges of CV (%) Values for NL**			
	Low	**Medium**	**High**	**Very hgh**
1	CV ≤ 16.09	16.09 < CV ≤ 26.37	26.37 < CV ≤ 31.50	CV > 31.50
2	CV ≤ 11.16	11.16 < CV ≤ 18.75	18.75 < CV ≤ 22.55	CV > 22.55
3	CV ≤ 9.23	9.23 < CV ≤ 15.31	15.31 < CV ≤ 18.35	CV > 18.35
4	CV ≤ 7.99	7.99 < CV ≤ 13.26	13.26 < CV ≤ 15.89	CV > 15.89
5	CV ≤ 7.14	7.14 < CV ≤ 11.85	11.85 < CV ≤ 14.21	CV > 14.21
6	CV ≤ 6.60	6.60 < CV ≤ 10.34	10.34 < CV ≤ 12.21	CV > 12.21
7	CV ≤ 5.98	5.98 < CV ≤ 10.01	10.01 < CV ≤ 12.03	CV > 12.03
8	CV ≤ 5.63	5.63 < CV ≤ 9.35	9.35 < CV ≤ 11.21	CV > 11.21
9	CV ≤ 5.31	5.31 < CV ≤ 8.81	8.81 < CV ≤ 10.57	CV > 10.57
10	CV ≤ 5.04	5.04 < CV ≤ 8.36	8.36 < CV ≤ 10.02	CV > 10.02
Plants	**Classification Ranges of CV (%) Values for LA**			
	Low	**Medium**	**High**	**Very High**
1	CV ≤ 17.39	17.39 < CV ≤ 26.55	26.55 < CV ≤ 31.13	CV > 31.13
2	CV ≤ 12.26	12.26 < CV ≤ 19.10	19.10 < CV ≤ 22.53	CV > 22.53
3	CV ≤ 10.09	10.09 < CV ≤ 15.25	15.25 < CV ≤ 17.83	CV > 17.83
4	CV ≤ 8.73	8.73 < CV ≤ 13.29	13.29 < CV ≤ 15.57	CV > 15.57
5	CV ≤ 7.81	7.81 < CV ≤ 11.88	11.88 < CV ≤ 13.91	CV > 13.91
6	CV ≤ 7.14	7.14 < CV ≤ 10.83	10.83 < CV ≤12.68	CV > 12.68
7	CV ≤ 6.61	6.61 < CV ≤ 10.02	10.02 < CV ≤ 11.73	CV > 11.73
8	CV ≤ 6.19	6.19 < CV ≤ 9.37	9.37 < CV ≤ 10.96	CV > 10.96
9	CV ≤ 5.84	5.84 < CV ≤ 8.83	8.83 < CV ≤ 10.33	CV > 10.33
10	CV ≤ 5.54	5.54 < CV ≤ 8.38	8.38 < CV ≤ 9.79	CV > 9.79

Table 7. Classification of the coefficients of variation (CV), according to the methodology proposed by Garcia [8] for normally distributed data, for the robustness index (RI), considering plot sizes ranging from 1 to 10 plants.

Plants	Classification Ranges of CV (%) Values for RI			
	Low	**Medium**	**High**	**Very High**
1	CV ≤ 15.42	15.42 < CV ≤ 20.50	20.50 < CV ≤ 23.04	CV > 23.04
2	CV ≤ 10.61	10.61 < CV ≤ 15.36	15.36 < CV ≤ 17.73	CV > 17.73
3	CV ≤ 8.89	8.89 < CV ≤ 11.82	11.82 < CV ≤ 13.29	CV > 13.29
4	CV ≤ 7.70	7.70 < CV ≤ 10.24	10.24 < CV ≤ 11.51	CV > 11.51
5	CV ≤ 6.89	6.89 < CV ≤ 9.16	9.16 < CV ≤ 10.30	CV > 10.30
6	CV ≤ 6.29	6.29 < CV ≤ 8.36	8.36 < CV ≤ 9.39	CV > 9.39

Table 7. *Cont.*

Plants	Classification Ranges of CV (%) Values for RI			
	Low	**Medium**	**High**	**Very High**
7	CV ≤ 5.80	5.80 < CV ≤ 7.74	7.74 < CV 8.71	CV > 8.71
8	CV ≤ 5.44	5.44 < CV ≤ 7.24	7.24 < CV ≤ 8.14	CV > 8.14
9	CV ≤ 5.13	5.13 < CV ≤ 6.82	6.82 < CV ≤ 7.67	CV > 7.67
10	CV ≤ 4.87	4.87 < CV ≤ 6.48	6.48 < CV ≤ 7.28	CV > 7.28

4. Discussion

4.1. Morphological Performance and Data Distribution Dynamics

Morphological performance varied distinctly among the evaluated clones, reflecting expected growth patterns and age-dependent differences at the dispatch stage. Among the evaluated clones, AEC 0144 exhibited the lowest minimum and maximum values for most characteristics, except for the robustness index (RI), which aligns with literature values reported for this clone produced in tubes. By contrast, TP361, evaluated at 120 days, displayed the highest values for height (PH) and stem diameter (SD). Clone BA7346 (evaluated at 90 days) presented the highest values for shoot, root, and total dry mass, as well as leaf area (LA) and leaf number (NL), outperforming GG100 at the same evaluation age. Among all evaluated traits, stem diameter exhibited the least relative variation, whereas leaf number showed greater variation due to differences in seedling age across batches (60 to 120 days). The higher standard deviation values observed for leaf area and robustness index reflect the greater natural dispersion and individual variation of these traits within seedling batches at the dispatch stage [24]. Nevertheless, all observed variations remain within the standard ranges reported for clonal eucalyptus seedlings in forest nurseries [25]. Non-normality in morphological data highlights the limitations of traditional parametric criteria for assessing experimental precision. Regarding statistical distribution, the Shapiro–Wilk test revealed that seven of the eight evaluated characteristics did not follow a normal distribution, with the robustness index being the sole exception. This outcome demonstrates that traditional CV classification models, such as Pimentel-Gomes, which implicitly assume data normality, are inadequate for assessing experimental precision in eucalyptus seedling trials [8]. Applying generic parametric criteria to non-normal traits risks misinterpreting experimental quality. Therefore, integrating non-parametric estimators (median and pseudo-sigma) with plot size considerations provides a more appropriate and reliable framework for assessing experimental precision.

4.2. Dynamic Reclassification of Coefficients of Variation Across Plot Sizes

The proposed reclassification of CV across increasing plot sizes establishes a dynamic, trait-specific framework tailored to clonal eucalyptus seedling production. By applying the non-parametric method of Costa et al. [15] for non-normal traits (PH, SD, SDM, RDM, TDM, NL, and LA) and the parametric approach of Garcia [8] for the normally distributed robustness index (RI), this framework aligns with recommendations from Lopes et al. [10] and Braga et al. [26], who advocate for crop- and trait-specific classification scales rather than generic criteria. For smaller plot sizes, the proposed classification maintains consistency with classical criteria for traits such as PH, SD, NL, and LA. However, as the number of seedlings per plot increases, the upper limits of all CV classification ranges decrease progressively. This downward trend observed across all evaluated variables reflects the reduction in experimental error and the corresponding gain in precision, confirming the inverse relationship between plot size and relative variability reported in forest species [27]. Although some overlap exists with traditional classification limits, establishing trait-specific

reference ranges yielded greater consistency between the methodologies of Costa et al. [15] and Garcia [8], whereas substantial discrepancies were observed when compared with generic criteria [7]. As highlighted by Ferreira et al. [28], these differences underscore the necessity of accounting for both the intrinsic nature of each morphological variable and experimental plot size during CV classification.

4.3. Trait-Specific Behavior and Biomass Variability Constraints

Morphological attributes exhibited distinct baseline variabilities, requiring customized threshold limits according to the physiological nature of each trait. For traits with lower structural variation, such as SD, the proposed thresholds closely match values reported in one-plant plot evaluations using non-parametric criteria [28]. By contrast, traits such as SDM exhibited higher classification thresholds than traditional limits, which is attributable to the presence of outliers and higher natural heterogeneity inherent to biomass accumulation in eucalyptus seedlings [27]. Root dry mass displayed the highest overall baseline variability among all evaluated traits, requiring wider CV classification ranges at small plot sizes; however, as PS expanded to 10 plants, classification limits decreased sharply, bringing threshold values closer to literature ranges. Similar reclassification patterns for RDM in single-plant plots were reported by Campos et al. [29] in coffee seedlings, reinforcing that root system evaluations inherently capture greater biological heterogeneity [30].

Biomass components, foliage parameters, and derived growth indices demonstrate interdependent behavior that governs CV classification boundaries. Total dry mass (TDM) presented high classification thresholds similar to RDM, which is expected since TDM directly integrates both shoot and root biomass components. This highlights the importance of adopting trait-specific classification limits, as experiments evaluating biomass traits might otherwise be incorrectly flagged as having poor precision under generic standards. Leaf number (NL) and leaf area (LA) exhibited highly similar classification thresholds to each other, reflecting their structural interdependence in seedling canopy development. Even when traits display similar CV classification boundaries, using trait-specific threshold values is strongly recommended to maintain statistical rigor. For the robustness index (RI), the only trait displaying a normal distribution, the lower classification thresholds reflect its mathematical derivation as the ratio between height and stem diameter [23], both of which exhibited lower baseline variability.

4.4. Practical Implications for Forest Nursery Management

Adopting dynamic, plot-size-dependent thresholds provides a practical and reliable tool for evaluating experimental quality in forest research and nursery operations. Overall, the sharp decrease in CV thresholds as plot size increases demonstrates that a single, static classification scale is inadequate for evaluating experimental quality. By integrating data distribution, trait-specific variability, and PS, the proposed dynamic classification provides a more realistic and sensitive benchmark for clonal eucalyptus experiments, supporting proper PS selection and optimizing resources in forest nurseries. From a practical forestry perspective, these dynamic thresholds allow nursery managers and researchers to evaluate experimental precision based on whichever plot size they choose to adopt. For instance, if a researcher decides to use a plot size of 5 seedlings (PS = 5) to evaluate PH, traditional criteria would broadly classify any CV below 10% as low error. In contrast, our plot-size-specific framework indicates that for PS = 5, a CV of 4.24% or lower is required for a “low” classification, whereas a CV above 7.60% represents “very high” variability. This provides a more rigorous benchmark to detect microenvironmental variation across nursery benches, allowing researchers to adjust sampling effort or plot size in future trials to achieve desired statistical precision.

5. Conclusions

New coefficients of variation were obtained for the characteristics plant height, stem diameter, shoot dry mass, root dry mass, total dry mass, number of leaves, leaf area, and robustness index for eucalyptus seedlings at the dispatch stage. The results highlight the relevance of considering plot size as a central element for assessing experimental precision in studies involving eucalyptus seedlings.

The application of parametric and non-parametric reclassification methods across simulated plot sizes allowed the establishment of dynamic, plot-size-dependent CV thresholds. Rather than relying on a single static limit, this dynamic framework provides a more refined criterion for evaluating experimental precision according to the specific plot size adopted by researchers and nursery managers.

Compared to traditional rigid criteria, the proposed plot-size-specific thresholds account for the natural reduction in baseline CV as plot size expands. Therefore, this dynamic reclassification methodology offers a practical and representative alternative for forest nursery conditions, contributing to the improvement of quality assessment in *Eucalyptus* sp. seedlings at the dispatch stage.

Although the proposed dynamic CV classification provides a realistic framework for assessing experimental precision, its application is contextualized to clonal eucalyptus seedlings during the nursery production phase. Therefore, future research should focus on validating and extending this methodology to other commercial forest species, varying nursery management regimes, direct economic evaluations, and field trials to further broaden the applicability of dynamic CV classification in forestry research.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f17111275/s1, Figure S1: Trend curves of the coefficient of variation as a function of plot size for the morphological characteristics plant height (PH), stem diameter (SD), shoot dry mass (SDM), root dry mass (RDM), total dry mass (TDM), number of leaves (NL), leaf area (LA), and robustness index (RI) for the clonal eucalyptus genotypes AEC 0144, AEC 0224, BA7346, CO1407, GG100, and TP361 across all evaluation periods.; Table S1: Standard deviation (s) values for the characteristics of plant height (PH, cm), stem diameter (SD, mm), shoot dry mass (SDM, g), root dry mass (RDM, g), total dry mass (TDM, g), number of leaves (NL), leaf area (LA, cm^2), and robustness index (RI) for all clonal eucalyptus genotypes (AEC 0144, AEC 0224, BA7346, CO1407, GG100, and TP361) across all evaluation periods.

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Abbreviations

The following abbreviations are used in this manuscript:

PH	Plant height
SD	Stem diameter
SDM	Shoot dry mass
RDM	Root dry mass
TDM	Total dry mass
NL	Number of leaves
LA	Leaf area
RI	Robustness index
CV	Coefficient of variation
PS	Plot size
S	Standard deviation
Md	Median
PSIG	Pseudo-sigma
IQR	Interquartile range

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