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Estimation of optimal plot size for chickpea experiments using Bayesian approach with prior information

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ABSTRACT. Heterogeneity among experimental units can introduce experimental errors, necessitating the use of techniques that enhance statistical inferences to address this issue. One effective approach is determining the optimal plot size, which can reduce experimental error. While frequentist methods are commonly employed for this purpose, Bayesian approaches offer distinct advantages. Therefore, our objective was to estimate the optimal plot size for chickpea experiments using the Bayesian approach and compare the results with those from the frequentist approach. We conducted two control experiments (with no treatments) involving eight cultivation rows, each spanning seven meters in length, with 50 cm spacing between rows and 10 cm spacing between plants. We evaluated the central six rows, totaling 60 plants per cultivation row. At the end of the growth cycle, we assessed seed count, seed weight, harvest index, and shoot dry mass. Data collection was conducted at the individual plant level. We determined the optimal number of plots using both the frequentist approach (modified maximum curvature method) and Bayesian approach, employing informative and uninformative prior distributions. The optimal plot size varied depending on the specific experiments and the variables under analysis. However, there was consensus in the estimation of the optimal experimental plot size between the two approaches. We recommend using 15 plants as the optimal plot size for chickpea cultivation.

Keywords: *Cicer arietinum*; agricultural experimentation; legume; Bayes' theorem.

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Introduction

In the realm of research, the precise determination of experimental unit size holds paramount importance. This step significantly enhances the precision of experiments, a crucial aspect of experimental design. The presence of heterogeneity among experimental units poses a challenge to experimental accuracy. Storck, Garcia, Lopes, and Estefanel (2011) attributed this to various factors, including variations in soil fertility, drainage, leveling, texture, and structure, among others.

To address the issue of such variations, it becomes imperative, among other measures, to establish the appropriate plot size. Zimmermann (2014) notes that while we cannot entirely eliminate errors, procedures such as standardizing experimental units and selecting suitable plot sizes are essential steps in minimizing them. However, studies focused on determining optimal plot sizes for chickpea cultivation remain scarce in the literature.

Chickpea (*Cicer arietinum* L.) stands as a legume of immense global economic significance (Bidyarani, Prasanna, Babu, Hossain, & Saxena 2016). Cultivated in over 50 countries, particularly in India, which boasts the largest production and consumption rates (FAO, 2017), chickpea exhibits adaptability to various climatic conditions. It thrives in poorly fertile soil, arid regions with dry and mild climates, and irrigated arid areas (Nascimento, Silva, Artiaga, & Suinaga 2016). Nevertheless, chickpea research remains relatively limited, with a notable lack of investigations into the adaptability of its varieties across different regions and management practices.

The literature describes numerous methods for estimating the optimal plot size, often grounded in various principles. One widely adopted approach involves regressing the variability associated with the response variable against plot size. This method identifies a point of stabilization in variability, which can be determined visually or through algebraic techniques (Lessman & Atkins, 1963). Within this context, the modified maximum curvature method, as proposed by Méier and Lessman (1971), emerges as a prominent technique.

While these methodologies primarily adhere to the frequentist approach, Bayesian inference presents a compelling alternative (Azevedo et al., 2017; Valadares et al., 2022). Bayesian inference allows for the incorporation of *a priori* information, potentially enhancing the accuracy of estimations. As noted by Carvalho, Beijo, and Muniz (2017), using informative prior distributions can improve inference precision by harnessing existing knowledge from prior experiments. Thus, this study aims to estimate the optimal plot size for chickpea cultivation using the Bayesian approach with informative priors and subsequently compare the results with those obtained through the frequentist approach.

Material and methods

Location and characterization of the experimental area

The experiments were conducted between May and September 2019 at the Federal University of Minas Gerais, Montes Claros Campus, situated at latitude 16°40'59.15" S and longitude 43°50'17.81" W. The region falls under the *Aw* climate classification, characterized by dry winters and rainy summers (Alvares, Stape, Sentelhas, Moraes Gonçalves, & Sparovek, 2013). To prepare for the experiments, soil samples were collected from the 0-20 cm layer to assess the chemical and physical properties of the soil, following the methods outlined by Teixeira, Donagemma, Fontana, and Teixeira (2017).

The experiments were conducted using Haplic Cambisol soil. The results for the soil's granulometric composition were as follows: sand = 220 g kg^{-1}, silt = 460 g kg^{-1}, and clay = 320 g kg^{-1}. For the chemical properties, the results were: organic matter = 30.3 g kg^{-1}, pH (H_20) = 6.70, P (Mehlich-1) = 13.74 mg dm^{-3}, K (Mehlich-1) = 152 mg dm^{-3}, Ca = 7.85 $cmol_c$ dm^{-3}, Mg = 1.41 $cmol_c$ dm^{-3}, Al (KCl) = 0.00 $cmol_c$ dm^{-3}, H + Al = 1.19 $cmol_c$ dm^{-3}, sum of bases = 9.50 $cmol_c$ dm^{-3}, effective cation exchange capacity = 9.50 $cmol_c$ dm^{-3}, potential cation exchange capacity = 10.84 $cmol_c$ dm^{-3}, and base saturation = 89%.

Experiment setup

The cultivar used belonged to the desi group, with the code CNPH 003. We conducted two control experiments (without any treatments) in May 2019, with the following sowing dates: May 15^{th} and May 22^{nd}. Each experiment consisted of eight cultivation rows, each seven meters in length. For evaluation purposes, we considered the central six rows as the usable areas, excluding 0.5 meters from each end of every crop row (border). The spacing between crop rows was 0.5 meters, and the spacing between plants within the crop row was 0.1 meters.

We pre-treated the seeds with the fungicide Protreat (Carbendazim + Thiram) at a concentration of 5 mL kg^{-1}. Planting was carried out manually, with two seeds sown per furrow, and thinning was performed 30 days after emergence, maintaining a density of 10 plants per linear meter.

Fertilization during planting involved the application of 300 kg ha^{-1} of simple superphosphate, 160 kg ha^{-1} of potassium chloride, and 300 kg ha^{-1} of ammonium sulfate. For topdressing, 25 days after emergence, we applied 56 kg ha^{-1} of ammonium sulfate, following the recommendations of Nascimento et al. (2016).

Phytosanitary treatments and irrigation were administered based on crop requirements and regional technical guidelines (Nascimento et al., 2016). Manual weed control was conducted as needed. The irrigation system employed was a micro-sprinkler system with a four-day irrigation schedule.

Analyzed characteristics

The plots were evaluated on an individual plant basis, defined as the basic unit (BU). The following characteristics were assessed: seed weight (SW), number of seeds (NS), harvest index (HI), and shoot dry mass (SDM). SW was determined by drying the seeds in an oven at 105°C for 24 hours to ascertain moisture content, which was subsequently adjusted to 13%. NS was determined by counting the seeds. HI, expressed as a percentage (%), was calculated using the formula [(seed weight/shoot biomass) x 100]. Lastly, to determine SDW in grams per plant (g $plant^{-1}$), a forced air circulation oven was used at 65°C until a constant weight was achieved. All assessments were conducted at the conclusion of the 120-day crop cycle following sowing.

Statistical analysis

The optimal plot size was determined using the modified maximum curvature method as proposed by Lessman and Atkins (1963) through Equation 1, as follows:

$$CV_i = \frac{a}{X_i^b} + e_i \quad (1)$$

where: CV_i represents the coefficient of variation between the plots associated with the i-th number of basic units (BUs), X_i is the i-th number of BUs used to form the plot, a is the intercept, and b is the regression coefficient. To estimate parameters a and b via the least squares method, the equation was logarithmized, resulting in Equation 2:

$$log(CV_i) = log(a) - b.log(X) \quad (2)$$

In a generalized form, the model is given by Equation 3:

$$Y_i = \beta_0 + \beta_1 X_i + e_i \quad (3)$$

where: Y_i is the logarithm of the coefficient of variation associated with the i-th BU, β_0 is the logarithm of the intercept a, β_1 is the regression coefficient, X_i is the logarithm of the number of BUs, and e_i is the random errors.

The optimal plot size was determined using the modified maximum curvature method proposed by Meier and Lessman (1971) in Equation 4:

$$X_o = \left\{\frac{a^2 b^2 (2b+1)}{b+2}\right\}^{\frac{1}{2b+2}} \quad (4)$$

where: X_o represents the optimal plot size, and a and b are parameters estimated in the previous function. For the frequentist approach, the regression coefficients were obtained using the *lm* function of the R software (R Core Team, 2019) for both experiments, and the optimal plot size was determined programmatically.

In the Bayesian approach, assuming that each observation Y_i follows a distribution as $Y_i \sim N(\beta_0 + \beta_1 x_i; \sigma^2)$, the likelihood function for each plot size i is given by Equation 5:

$$L_i(\beta_0, \beta_1, \sigma^2, Y_i) = \prod_{i=1}^{a} \frac{1}{\sqrt{2\pi\sigma^2}} exp\left\{-\frac{1}{2\sigma^2}[y_i - (\beta_0 + \beta_1 x_i)]^2\right\}$$

$$= \frac{1}{(\sqrt{2\pi\sigma^2})^a} exp\left\{-\frac{1}{2\sigma^2}\sum_{i=1}^{a} [y_i - (\beta_0 + \beta_1 x_i)]^2\right\}, \forall_i \quad (5)$$

For estimating the model parameters, prior distributions need to be assigned. For β_0, β_1, and σ^2, the following distributions were considered: $\beta_0 \sim N(\mu_0, \sigma_0^2), \beta_1 \sim N(\mu_1, \sigma_1^2)$ and $\sigma^2 \sim gamaInv(\alpha{:}\beta)$, the latter an inverse range with mean and variances equal to $\beta/(\alpha-1)$ and $\beta^2/[(\alpha-1)^2 (\alpha-2)]$ respectively.

Assuming independence between the parameters in these distributions, the joint posterior distribution for each plot size is given by Equation 6:

$$P_i(\beta_0, \beta_1, \sigma^2, Y_i) = \frac{1}{\sqrt{2\pi\sigma_0^2}} exp\left\{-\frac{1}{2\sigma_0^2}[(\beta_0, \mu_0)^2]\right\} \times$$

$$\frac{1}{\sqrt{2\pi\sigma_1^2}} exp\left\{-\frac{1}{2\sigma_1^2}[(\beta_1, \mu_1)^2]\right\} \times \frac{1}{[\beta^\alpha G(\alpha)]}\left(\frac{1}{\sigma^2}\right)^{\alpha+1}$$

$$exp\left\{-\frac{1}{\beta\sigma^2}\right\} \propto exp\left[-\frac{1}{2\sigma^2}(\beta_0, \mu_0)^2\right] \times \frac{1}{\sqrt{2\pi\sigma_1^2}}$$

$$exp\left[-\frac{1}{2\sigma_1^2}(\beta_1, \mu_1)^2\right] \times \left(\frac{1}{\sigma^2}\right)^{\alpha+1} exp\left\{-\frac{1}{\beta\sigma^2}\right\} \quad (6)$$

To make inferences about the parameters of interest, their posterior marginal distributions should be obtained. By denoting the vector of parameters by $\theta p = (\beta 1, \beta 2, \sigma^2 3)$, where: p = 1, 2, 3; the posterior marginal distribution for the parameter θ_p was obtained by the following integral: $P(\theta_p|x) = \int P(\theta_p|x)\, d\theta_p$, that is, the integral regarding all parameters of the vector except the p-th component.

Most of these integrals are complex and lack exact solutions. To address this, Markov chains were employed using the Monte Carlo method to determine the moments of interest of the marginal distributions.

In this study, the Bayesian approach was implemented in the R program (R Core Team, 2019) using the rJags package (Plummer, 2019).

In the first experiment, an uninformative prior was adopted for the Bayesian approach. Thus, the following distributions were used: $\beta_0 \sim N(\mu_0 = 0, \sigma_0^2 = 1{,}000{,}000), \beta_1 \sim N(\mu_1 = 0, \sigma_1^2 = 1{,}000{,}000)$, and $\sigma^2 \sim GamaInv(\alpha = 0.0001, \beta = 5{,}000)$. In the second experiment, the means and variances of the posterior distributions from the first experiment were considered as prior information. This was incorporated through the values assumed for the parameters of the prior distributions, referred to as hyperparameters. This resulted in the distributions: $\beta_0 \sim N(\mu_0 = \overline{\beta_0}, \sigma_0^2 = Var(\overline{\beta_0})), \beta_1 \sim N(\mu_1 = \overline{\beta_1}, \sigma_1^2 = Var(\overline{\beta_1}))$, and $\sigma^2 \sim GamaInv(\alpha, \beta)$, Where: $\overline{\beta_0}$ stands for the mean of the posterior distribution of β_0 obtained in the first experiment, $\overline{\beta_1}$ is the mean of the posterior distribution of β_1 obtained in the first experiment, $Var(\overline{\beta_0})$ is the variance of the posterior distribution of β_0 obtained in the first experiment, $Var(\overline{\beta_1})$ is the variance of the posterior distribution of β_1 obtained in the first experiment, and α and β are the values obtained considering the posterior distribution of the mean square of the residue obtained in the first experiment by solving the system composed of Equation 7 and Equation 8.

$$\bar{\sigma}^2 = \beta/(\alpha - 1) \quad (7)$$

$Var(\sigma^2) = \beta^2/[(\alpha - 1)^2(\alpha - 2)]$ which was

$$\alpha = \frac{(\sigma^2)^2}{var(\bar{\sigma}^2)} + 2\ ;\ \beta = \frac{(\sigma^2)^3}{var(\bar{\sigma}^2)} + 1 \quad (8)$$

In the Bayesian analysis, 110,000 iterations were considered in the Gibbs algorithm for each parameter of the regression model, with a burn-in period of 10,000 iterations. To obtain an uncorrelated sample, a thinning interval of 10 iterations was used, as in studies from other fields of knowledge (Nascimento et al., 2011; Teodoro, Nascimento, Torres, Barroso, & Sagrilo, 2015; Euzébio et al., 2018).

In both approaches, the optimal plot size is estimated algebraically, resulting in non-integer values. As the plots consist of plants in this study, the values were rounded to the nearest whole number in the discussion of results, rounding up to avoid underestimating the optimal number of plots.

Results

In the study, various variables were analyzed, including the number of seeds (NS), seed weight (SW), harvest index (HI), and shoot dry mass (SDM). The mean squared residues (MSR) for Experiment I were higher than those for Experiment II, except for the variable NS, which had a higher estimate in Experiment II (Figure 1).

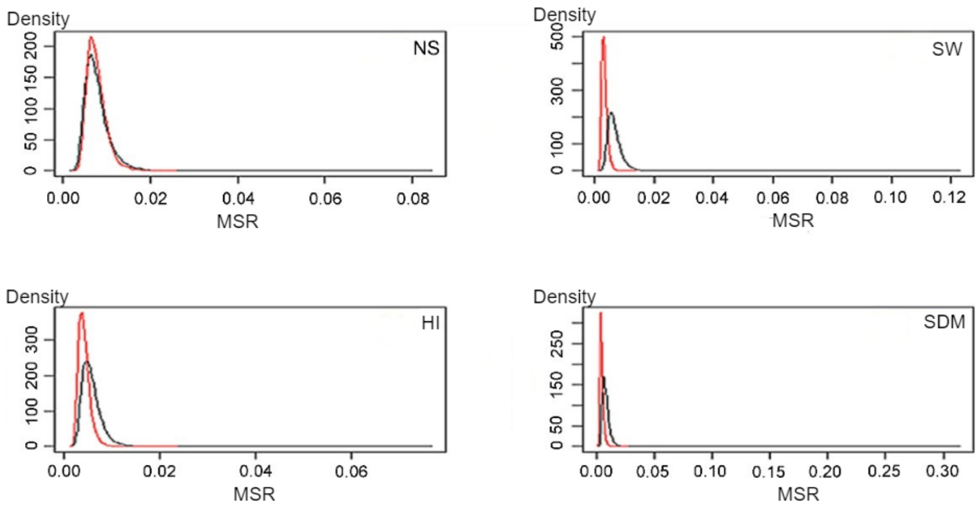

Figure 1. A posteriori distribution of the mean squared residues (MSR) for experiment I (—) and experiment II (—) with informative prior of the variables number of seeds (NS), seed weight (SW), harvest index (HI), and shoot dry mass (SDM) of chickpea.

The coefficient "a" (intercept) was higher in Experiment I for all variables. Among the analyzed variables, HI had the highest value for Experiment I and the lowest for Experiment II. For Experiment I, the estimates of coefficient "a" decreased in the following order: HI, SW, NS, and SDM. For Experiment II, it decreased in the order: NS, SW, SDM, and HI (Figure 2).

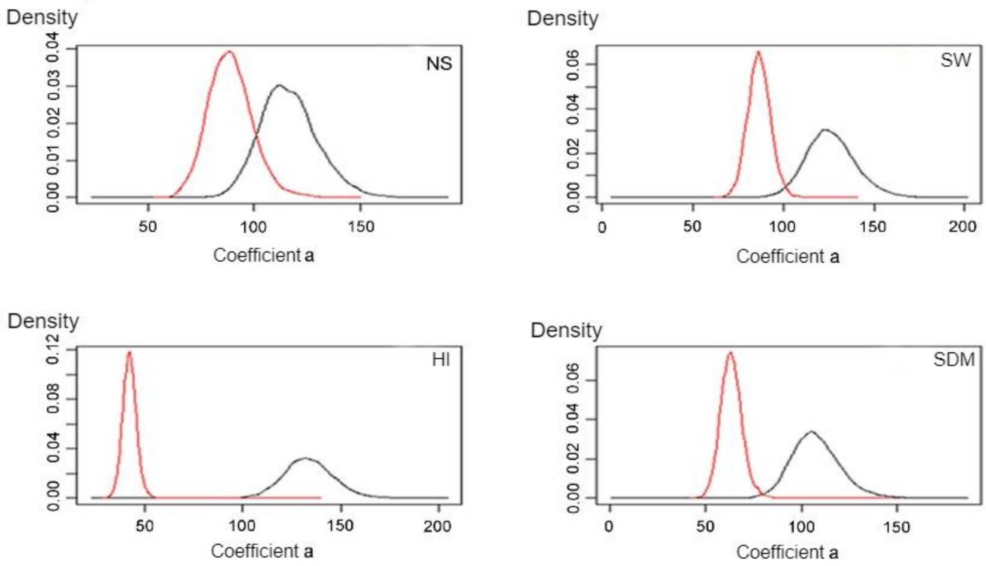

Figure 2. A posteriori distribution of coefficient "a" (intercept) for experiment I (——) and experiment II (——) with informative prior of the variables number of seeds (NS), seed weight (SW), harvest index (HI), and shoot dry mass (SDM) of chickpea.

Coefficient "b" showed similar results for all variables in Experiment I. In contrast, the values of "b" in Experiment II were lower than those in Experiment I for all variables, with HI having the lowest value (Figure 3). As for the other variables, coefficient "b" varied differently between experiments. For experiment I, it decreased in the following order: SW, HI, SDM, and NS. And, for experiment II, the order was NS, SW, SDM, and HI. Moreover, we noted that, as the values of coefficients "a" and "b" increased, the estimated optimal plot sizes also showed an increase.

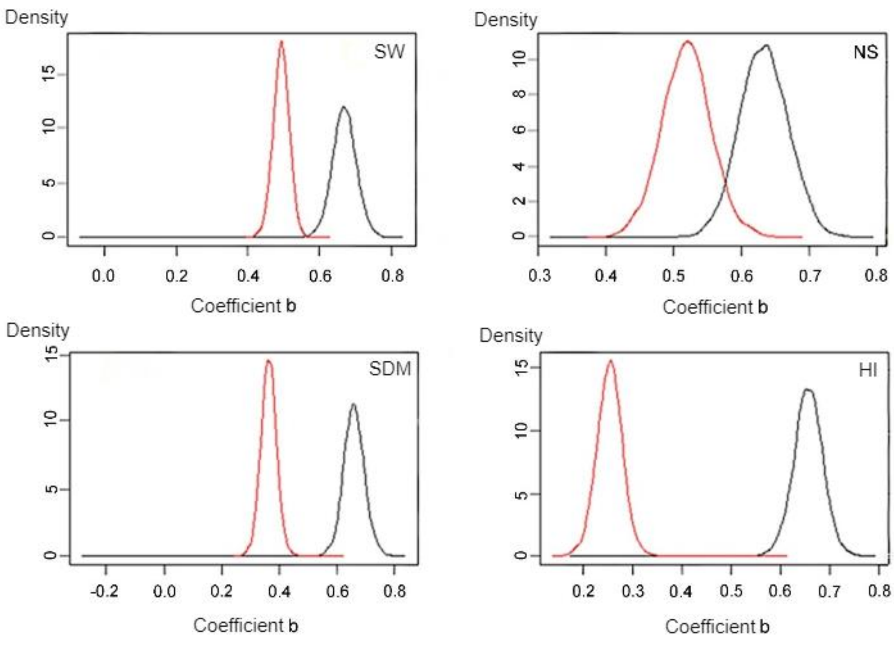

Figure 3. A posteriori distribution of coefficient "b" (regression coefficient) for experiment I (——) and experiment II (——) with informative prior of the variables number of seeds (NS), seed weight (SW), harvest index (HI), and shoot dry mass (SDM) of chickpea.

The optimal plot size varied depending on the variables analyzed and the experiments conducted. In the Bayesian approach, for the variable number of seeds, using an informative prior in the second experiment led to a lower estimate of the coefficient of variation compared to the uninformative prior, reducing from 38.55 to 29.62%, respectively (Table 1).

For the variable number of seeds and seed weight, the optimal plot size was 14 BUs in the first experiment for both the frequentist and Bayesian approaches. In the second experiment, 12 BUs were recommended for different approaches, considering informative or uninformative *a priori* distributions (Table 1).

Table 1. Residual variance (σ^2), coefficient "a," coefficient "b," optimal number of base units (BUs) by frequentist and Bayesian approaches, mode, coefficient of variation (CV), limit inferior (LI), and limit superior (LS) by Bayesian approach for the variable number of chickpea seeds (NS).

Variable	Experiment	Approach	Estimate	σ^2	a	b	BUs
Number of seeds	Exp. 1	Frequentist		0.00695	115.347	0.63211	13.2225
		Bayesian	Mode	0.00649	115.835	0.63219	13.2158
			CV	44.8183	352.227	5.87350	5.73139
			LI	0.00360	91.8050	0.55857	11.6958
			LS	0.01353	145.171	0.70228	14.6278
	Exp. 2	Frequentist		0.00729	88.2208	0.51903	11.5616
		Bayesian (Uninformative)	Mode	0.00667	87.9170	0.52337	11.5168
			CV	38.5498	462.289	7.21485	7.35899
			LI	0.00366	69.8821	0.44150	9.86551
			LS	0.01388	111.219	0.58857	13.1867
		Bayesian (Informative)	Mode	0.00688	88.6602	0.52416	11.6042
			CV	29.6174	331.522	6.79942	6.95345
			LI	0.00401	69.8027	0.44974	9.93040
			LS	0.01198	109.257	0.59002	13.1003

Exp. 1: Experiment I; Exp. 2: Experiment II.

For the variable seed weight, similar to the variable number of seeds, in the first experiment, the recommended optimal plot size was 14 BUs, whether using the frequentist or Bayesian approaches. In the second experiment, 12 BUs were recommended for various approaches, regardless of whether informative or uninformative *a priori* distributions were considered (Table 2).

Table 2. Residual variance (σ^2), coefficient "a," coefficient "b," optimal number of base units (BUs) by frequentist and Bayesian approaches, mode, coefficient of variation (CV), limit inferior (LI), and limit superior (LS) by Bayesian approach for the variable weight of chickpea seed (SW).

Variable	Experiment	Approach	Estimate	σ^2	a	b	BUs
Seed weight	Exp. 1	Frequentist		0.00583	125.194	0.66843	13.6488
		Bayesian	Mode	0.00529	128.004	0.65995	13.5831
			CV	46.8124	211.333	5.25432	5.09285
			LI	0.00294	101.967	0.60107	12.3365
			LS	0.01138	155.718	0.73525	14.9482
	Exp. 2	Frequentist		0.00195	86.4697	0.49382	11.4412
		Bayesian (Uninformative)	Mode	0.00186	86.0716	0.49076	11.4003
			CV	51.1435	30.7896	4.11980	4.24251
			LI	0.001027	76.4643	0.45374	10.5238
			LS	0.00385	97.4370	0.53012	12.3228
		Bayesian (Informative)	Mode	0.00288	87.7736	0.48408	11.5389
			CV	30.0186	41.7114	4.60626	4.68540
			LI	0.00158	74.8673	0.44979	10.3656
			LS	0.00490	99.0859	0.53836	12.4475

Exp. 1: Experiment I; Exp. 2: Experiment II.

Regarding the harvest index, the estimated optimal plot size differed from the previously mentioned variables. In the first experiment, both approaches indicated an optimal plot size of 15 BUs. However, in the second experiment, it significantly reduced to six BUs for both approaches, whether considering informative or uninformative *a priori* distributions (Table 3).

For shoot dry mass, in the first experiment, both the frequentist and Bayesian approaches recommended a 13 BU optimal plot size. However, in the second experiment, the optimal plot size decreased to nine BUs for both approaches without informative prior information. When an informative prior was used, the optimal plot size increased to 10 BUs, slightly higher than the Bayesian approach with an uninformative prior. It is important to note that shoot dry mass was the only variable with differing results between the two methodologies (Table 4).

In summary, when considering informative prior distributions, the Bayesian approach consistently yielded lower coefficient of variation estimates and narrower credible intervals for all analyzed variables. Among these variables, shoot dry mass (Table 4) had the lowest coefficient of variation at 28.23%, while harvest index (Table 3) had the highest at 30.29%.

Table 3. Residual variance (σ^2), coefficient "a," coefficient "b," optimal number of base units (BUs) by frequentist and Bayesian approaches, mode, coefficient of variation (CV), limit inferior (LI), and limit superior (LS) by Bayesian approach for the variable harvest index (HI) of chickpea.

Variable	Experiment	Approach	Estimate	σ^2	a	b	BUs
Harvest index	Exp. 1	Frequentist		0.00503	133.044	0.65556	14.2546
		Bayesian	Mode	0.00454	138.124	0.65553	14.1658
			CV	43.4579	125.808	4.87104	4.68621
			LI	0.00262	108.869	0.59506	12.9053
			LS	0.00966	159.794	0.71622	15.3865
	Exp. 2	Frequentist		0.00340	41.9277	0.25315	5.60878
		Bayesian (Uninformative)	Mode	0.00300	41.9230	0.25269	5.69638
			CV	81.8720	176.747	10.2124	11.8035
			LI	0.00176	35.7469	0.20378	4.36143
			LS	0.00663	49.1380	0.30420	6.92078
		Bayesian (Informative)	Mode	0.00362	41.8106	0.25125	5.67957
			CV	30.2875	192.4855	10.6133	12.2886
			LI	0.00217	35.5053	0.20119	4.30459
			LS	0.00654	49.2424	0.30328	6.94197

Exp. 1: Experiment I; Exp. 2: Experiment II.

Table 4. Residual variance (σ^2), coefficient "a," coefficient "b," optimal number of base units (BUs) by frequentist and Bayesian approaches, mode, coefficient of variation (CV), limit inferior (LI), and limit superior (LS) by Bayesian approach for the variable shoot dry mass (SDM) of chickpea.

Variable	Experiment	Approach	Estimate	σ^2	a	b	BUs
Shoot dry mass	Exp. 1	Frequentist		0.00737	106.343	0.65884	12.4320
		Bayesian	Mode	0.00711	105.250	0.65258	12.4414
			CV	35.6417	365.794	5.70754	5.67514
			LI	0.00390	83.2787	0.58280	11.0129
			LS	0.01413	133.481	0.73321	13.7797
	Exp. 2	Frequentist		0.00395	63.2767	0.36458	8.89337
		Bayesian (Uninformative)	Mode	0.00354	63.1185	0.35785	8.93527
			CV	39.3837	114.220	7.35117	7.97789
			LI	0.00215	53.4872	0.31127	7.47220
			LS	0.00767	74.5377	0.41640	10.2454
		Bayesian (Informative)	Mode	0.00474	63.1395	0.36569	9.02325
			CV	28.2299	206.013	8.24029	8.91865
			LI	0.00291	52.5786	0.307031	7.39396
			LS	0.00847	76.3052	0.42441	10.4777

Exp. 1: Experiment I; Exp. 2: Experiment II.

In Experiment I, the choice of approach did not significantly impact the recommended optimal number of BUs. However, there was a slight variation depending on the analyzed variable, ranging from 13 BUs for shoot dry mass to 15 BUs for harvest index. In Experiment II, when informative prior information was used, the estimated optimal plot size for all analyzed variables was consistent with the other approaches. The only exception was shoot dry mass, where seed weight and number of seeds suggested a higher optimal size of 12 BUs. In situations where the optimal plot size varies depending on the analyzed variables, it is advisable to choose the larger plot size, which is 15 BUs.

Discussion

Defining the optimal plot size plays a crucial role in crop planning, contributing to enhanced statistical inference precision while reducing resource costs. The literature offers a range of methods for this purpose, and as shown in this study, the selection of a method can lead to divergent outcomes based on the chosen parameters. In this research, a plot size of 15 Basic Units (BUs) for chickpeas was found to be suitable across all variables and approaches studied, ensuring that it does not underestimate plot size under any circumstance.

The optimal plot size for chickpeas remains a topic of debate, with studies in the literature proposing different sizes. For instance, Hoskem et al. (2017) and Avelar, Costa, Brandão Junior, Paraíso, and Nascimento (2018) used 10-m² plots with eight plants per plot, while Khaitov and Abdiev (2018) examined 10 plants within 28.8-m² plots. In contrast, Almeida Neta et al. (2020) conducted their research with plots totaling 4 m² and using 10 representative plants. Although the number of plants evaluated in these studies is relatively close to the number of BUs recommended in our study, it falls short of the BUs required for achieving greater experimental precision.

The modified maximum curvature method is commonly employed to determine the optimal plot size for various crops. However, in the context of chickpea, there is a scarcity of studies in the existing literature. An example of such a study can be found in Egypt, where Bayoumi and El-Demardash (2008) estimated optimal plot sizes under normal and water-stressed conditions. They suggested 5 m² (equivalent to 200 plants) for normal irrigation conditions and 8 m² (equivalent to 320 plants) for water-stress conditions. These values differ significantly from those obtained in the present study. The disparities in results may be attributed to the different methods employed by the authors, with Bayoumi and El-Demardash (2008) using the maximum curvature method and the comparison of variances method. Additionally, variations in environmental conditions can lead to different outcomes due to the influence of soil heterogeneity.

Magalhães et al. (2023) employed the Hatheway method to determine the optimal plot size for chickpeas and suggested plots consisting of 25 BUs for the conditions they investigated, which included the evaluation of variables such as the number of seeds, seed weight, and shoot dry mass. Santos, Haesbaert, Lúcio, Storck, and Cargnelutti Filho (2012) emphasized the importance of determining plot sizes for an entire crop, even in situations where the crop may be exposed to different conditions than those initially considered.

In practical terms, it is crucial to use whole numbers when defining the optimal plot size to avoid underestimating it. In this regard, the frequentist approach in this study revealed that for Experiment I, the estimated optimal plot size ranged from 13 to 15 basic units, while in Experiment II, it varied from 6 to 12 basic units. This variability in estimates depending on the analyzed variables is consistent with findings from previous studies, such as those by Schmildt, Schmildt, Cruz, Cattaneo, and Ferreguetti (2016) on papaya and Guimarães, Donato, Aspiazú, Azevedo, and Carvalho (2019) on forage cactus. When such variability exists, it is recommended to choose the largest plot size to avoid underestimation (Lúcio, Haesbaert, Santos, & Benz, 2011), particularly since multiple characteristics are often analyzed simultaneously (Guimarães et al., 2019).

Experiment II displayed a greater discrepancy in recommended plot sizes among the variables analyzed, with a notable difference between the estimates for the harvest index and shoot dry mass compared to Experiment I. This discrepancy can be attributed to the lower estimates of coefficients "a" and "b" for these variables. In this context, there is a strong association between these coefficients and plot size, as larger plot sizes tend to result from higher values of coefficients "a" and "b". A similar relationship was observed in a study on potato crops conducted by Oliveira, Storck, Lúcio, Lopes, and Martini (2006).

In the quest to determine the optimal plot size, it is noteworthy that using *a priori* information in the Bayesian approach yielded results similar to the frequentist approach. However, the Bayesian approach offered the advantage of achieving lower coefficients of variation for all the variables analyzed. A reduction in the coefficient of variation signifies gains in experimental accuracy, which is a crucial aspect in agricultural research (Lorentz & Lúcio, 2009).

The use of Bayesian inference has been increasingly applied in various fields of plant breeding, resulting in more accurate results when informative priors are available. This approach has been employed in studies such as the analysis of adaptability and stability of alfalfa genotypes (Nascimento et al., 2011), the selection of cowpea genotypes (Teodoro et al., 2015), the selection of carioca bean genotypes (Euzebio et al., 2018), the determination of the optimal number of evaluations in kale half-sib progenies (Azevedo et al., 2021), and the estimation of genetic parameters and selection of sweet potato half-sib progenies (Valadares et al., 2022).

Martins Filho, Silva, Carneiro, and Muniz (2008) highlighted that employing Bayesian inference in small sample sizes helps minimize estimation bias, leading to more accurate credible intervals for the parameters. Additionally, this approach is efficient in predicting future values compared to frequentist inference (Azevedo et al., 2017). Teodoro et al. (2015) emphasized that the use of informative priors in Bayesian analysis contributes to obtaining more accurate results when compared to the frequentist approach. Furthermore, it is expected that the accuracy of Bayesian inference increases as more *a priori* information becomes available.

Conclusion

Our findings suggest that the optimal plot size for chickpea field experiments is 15 plants. Both the frequentist and Bayesian approaches yielded similar results for estimating the optimal plot size, even when informative priors were incorporated into the Bayesian analysis.

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