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ORIGINAL ARTICLE

Visual assessment of leaf area index in coffee (*Coffea arabica* L.) fields[1]

Avaliação visual do índice de área foliar em campos de café (*Coffea arabica* L.)

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HIGHLIGHTS:

Current techniques to estimate leaf area index (LAI) are unsuitable for heterogeneous coffee fields.
Trained field workers are able to estimate LAI of coffee fields.
Visual evaluations are more accurate and precise than specialized on-ground equipment LAI estimations.

ABSTRACT: The application of leaf area index (LAI) in coffee crop management depends on the availability of methodologies for proper estimation. The objective of this study was to develop a methodology for the visual assessment of LAI in coffee fields and to establish a protocol for training, evaluation, and feedback for evaluators. Four rounds of LAI measurements were conducted using visual estimates, two instruments (LAI 2200-C and AccuPAR LP-80), and defoliation of coffee hedgerows in Poás, Costa Rica. In each round, five workers visually estimated the LAI values on two occasions separated by 15 days, and feedback reinforcement was provided to each worker at the end of each round. Visual assessments showed high repeatability and reproducibility and the estimates were adjusted to the linear regression model in most cases. Evaluators improved their capacity to visually assess the LAI throughout the rounds, as the value of R^2 increased consistently for most workers, with values as high as 0.87. Instrumentation evaluation of LAI produced R^2 values of 0.5-0.6, with significant underestimation bias. The performance of the different methods is discussed in the context of widely spaced hedgerows. The proposed visual methodology constitutes a statistically sound, rapid, simple, and reliable method for determining the LAI of coffee fields to aid in decision-making for crop management.

Key words: canopy analyzer, visual estimation, repeatability and reproducibility analysis

RESUMO: A aplicação do índice de área foliar (IAF) na gestão da cultura do cafeeiro depende da disponibilidade de metodologias para sua estimativa correta. É proposta aqui uma metodologia para a avaliação visual do IAF em plantas de café, por tanto se estabelece um protocolo para o treinamento dos avaliadores. Foram feitas quatro rodadas de medições do IAF utilizando estimativas visuais, dois instrumentos (LAI 2200-C e AccuPAR LP-80), e desfolhações de sebes de café na Costa Rica. A cada rodada, cinco trabalhadores estimaram visualmente os valores do IAF em duas ocasiões e separados por 15 dias. Ao final de cada rodada, foi dada uma retroalimentação a cada trabalhador. A avaliação visual mostrou alta repetibilidade e reprodutibilidade, e as estimativas foram ajustadas para o modelo de regressão linear na maioria dos casos. Os avaliadores melhoraram sua capacidade de avaliar visualmente o IAF ao longo das rodadas, e o valor de R^2 aumentou consistentemente para a maioria dos trabalhadores, com valores tão altos quanto 0,87. A avaliação do IAF por instrumentos produziu valores de R^2 de 0,5-0,6, com significativa tendência de subestimação, e não se ajustou ao modelo de regressão linear. O desempenho dos diferentes métodos é discutido no contexto de coberturas com amplo espaço. A metodologia visual proposta constitui uma determinação sólida, rápida, simples e confiável do IAF na lavoura do café e considera-se uma ajuda na tomada de decisões para a gestão da safra.

Palavras-chave: analisadores de copa, estimativa visual, análise de repetibilidade e reprodutibilidade

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Introduction

The leaf area index (LAI) is a quantitative dimensionless parameter obtained by dividing the leaf area by the soil (or surface) area corresponding to that foliage (Watson, 1947). In coffee (*Coffea arabica* L.), the LAI is related to yield (Montoya et al., 2017; Barbosa et al., 2021), evapotranspiration, irrigation requirements (Gutiérrez & Meinzer, 1994; Costa et al., 2019; Santos et al., 2020), susceptibility to foliar diseases (Garedew et al., 2019), optimum foliar spray (Siegfried et al., 2007), and ecological services (Taugourdeau et al., 2014).

Monitoring the LAI can provide valuable information for decision-making in coffee crops; however, reliable and accessible methods for its estimation are scarce. The use of instruments that depend on light transmittance through the canopy to estimate the LAI (such as the AccuPAR LP-80 Ceptometer or the LAI 2200-C) may be unreliable, as the underlying models assume canopies with uniform foliar distribution; thus, they are not adequate for crops grown at wide spacing (such as hedgerows) or with shading (Bréda, 2003; Fang et al., 2019). Utilizing remote images (obtained from satellites or unmanned aerial vehicles) for LAI estimation in coffee production can also be a viable option, but at a potentially high cost and with complex implementation (Taugourdeau et al., 2014; Jaramillo-Giraldo et al., 2019; Dos Santos et al., 2020; Bento et al., 2022). Simple and inexpensive methods have also been proposed, such as smartphone apps that estimate LAI through image analysis; however, their precision is still lower than that of instrumentation (Hong et al., 2023).

Direct methods, such as defoliating a sample plot and measuring the leaf area with a planimeter, can be very precise, but destructive and time-consuming (Montoya et al., 2017). Allometric models based on tree diameter, height, and branch length measurements are also available for coffee; but they are often limited to a single variety or cropping system (Gonçalves et al., 2020; Estrada et al., 2022).

In that context, one option is visual estimation, which offers a practical and low-cost alternative for assessing the LAI of coffee fields. These evaluations can be performed by training farm staff and periodically reinforcing methods in the field, as supported by statistically validated estimates (Gallegos-Torell & Glimskär, 2009). This approach has been successfully tested in the forestry context (Hakamada et al., 2016). In this study, our objective was to develop a methodology for visual LAI assessment in coffee fields and to establish a protocol for estimator training, evaluation, and feedback.

Material and Methods

The research was conducted at La Hilda Estate Farm in San Pedro de Poás, Alajuela (10.0893” N-84.235088” O), Costa Rica. The farm comprises 450 ha situated along an elevation gradient from 1000 to 1500 m. The climate is seasonal with well-defined dry (December-April) and rainy (May-November) seasons. The average total annual rainfall is 2,400 mm; the driest month is January (< 15 mm), and the month with the most rain is October (> 500 mm). Average temperature is 18-19 °C with little seasonal variation. The soils are mostly deep and fertile Andosols with a high-moisture regime. The most common coffee varieties planted are Catuaí, Caturra, Costa Rica-95 and Obatá. Planting arrangement is usually 1.8 m between rows and 1 m between plants (5,555 plants ha^{-1}), although arrangements with lower densities are being increasingly implemented, using 0.8 m between plants and 3.6 m between rows (2,777 plants ha^{-1}). Variations of these two arrangements are observed throughout the farm. Approximately 70% of the fields have sparse shade provided by a variety of local trees.

Four different field surveys (rounds) were conducted to measure LAI. For each round, 20 points were sampled, with each point corresponding to three continuous plants in a hedgerow segment. Thus, 80 sampling points (20 points in each round) were selected to represent the diversity of crop conditions, such as varying LAI, coffee varieties (Catuaí, Obatá, Caturra, CR-95 and Geisha), planting densities (from 2,774 up to 6,994 plants ha^{-1}), and three pruning systems: mechanized hedging, scheduled pruning cycles, and no pruning. For each round, 20 sampling points were obtained from four to six fields. A summary of the characteristics of all fields and sampling points is presented in Table 1. These rounds were performed over four days (March 26, April 7, July 4, and July 18, 2019) by the same crew members. The LAI increased consistently from early May, when the rainy season began. The maximum LAI of most fields was reached between rounds 3 and 4 in July (~4.6, Taugourdeau et al., 2014). Flower anthesis occurred between rounds 1 and 2 because of the early rains in March.

Each round included: 1) training of workers for visual LAI estimation, 2) selection of sampling points, 3) visual LAI estimation, 4) determination of LAI with AccuPAR LP-80 (Meter Group, Pullman, WA, USA) and LAI-2200C (LI-COR, Lincoln, NE, USA), and 5) determination of LAI by the defoliation of coffee trees. Visual estimates were performed by a group of five male field workers from Finca La Hilda of different

Table 1. Main characteristics of the selected fields and sampling points in each round, including planting density, variety, pruning type and respective leaf area index (LAI) value range

Round	Field	Sampling points	Density (plants ha^{-1})	Variety	LAI range (by defoliation)
1	1	1-4	4545	Obatá	2.3-3.6
	2	5-8	2778	Catuaí	1.7-2.9
	3	9-10	6173	Obatá	0.1-0.2
	4	11-14	5556	Catuaí	1.0-4.4
	5	15	5556	CR-95	5.5
	6	16-20	5556	Catuaí	2.7-4.3
2	7	1-4	6173	Catuaí	3.8-6.1
	8	5-8	4785	Caturra	3.0-4.6
	9	9-12	3636	Obatá	1.5-3.6
	10	13-16	3086	Catuaí	3.4-4.0
	11	17-20	2070	Geisha	3-3.8
3	12	1-4	5556	Catuaí	4.4-7.6
	13	5-8	5556	Caturra	3.1-6.5
	15	9-12	3953	Catuaí	5.1-6.3
	16	13-16	5000	Catuaí	4.0-6.2
	17	17-20	5000	Obatá	1.8-3.0
4	18	1-4	3086	Catuaí	4.9-6.8
	19	5-8	6173	Catuaí	2.9-6.3
	20	9-12	6173	Catuaí	3.5-8.3
	21	13-16	3086	Catuaí	1.0-5.4
	22	17-20	5000	Obatá	1.2-3.2

ages (25-42 years), levels of schooling (3rd-11th grade), and years of work at the farm (2-20 years). The evaluators received a short course to introduce the concept and importance of measuring LAI, including photographs of coffee fields with their respective LAI. During the training for LAI visual estimation, three factors were emphasized to be considered by evaluators: crop density, plant size, and degree of defoliation.

At the sampling points selected in each field, the workers visually estimated the LAI within the ranges provided on a semi-quantitative scale (Table 2). This estimate was expressed verbally by each worker and recorded, thereby preventing other workers from overhearing their estimates. Two weeks later, the workers were taken to the same fields and sampling points, visited in a different sequence, and asked to re-estimate the LAI (visual estimations I and II, respectively).

At the end of each round and at the beginning of the next round, feedback and further training were provided to each worker, considering: 1) performance in the previous visual estimation round in relation to actual LAI of each field, 2) results of the two visual estimates made at each sampling point, 3) a scatter plot comparing their responses in both assessments with actual LAI, 4) the value of the determination coefficient (R^2) for their estimates and whether there were biases in the visual assessment, and 5) photographs of the fields where the estimate was further from the actual value, in order to identify and correct possible causes of error.

Once the workers performed the two visual estimations, the LAI of the same sampling points was determined using a LAI 2200-C plant canopy analyzer and an AccuPAR LP-80 ceptometer. The LAI-2200C calculates LAI from diffuse blue light incident above and below the canopy using a lens that perceives this radiation at five different zenith angles (LI-COR, 2016). The AccuPAR LP-80 ceptometer uses a single photosynthetically active radiation (PAR) sensor above the canopy and a bar with 80 aligned PAR sensors for below-canopy measurements (Decagon Devices, 2016). The protocols employed followed the recommendations for crop hedgerows with high separation (LI-COR, 2016). Light extinction coefficients were selected to minimize the effect of light scattering.

LAI measurements were performed at each sampling point following a V-shaped transect that produced nine readings for each sampled hedgerow segment (Figure 1A). The LAI 2200-C was used with a lens restriction cover that allowed light to enter at an angle of 90°. Each transect was repeated twice, with the light input oriented parallel or perpendicular to the hedgerow (R1 and R2, respectively). Each repetition in the transect included four reference measurements above the canopy with the opening angle oriented in the same direction (T1 and T2). The AccuPAR LP-80 ceptometer transect was repeated only once, with the instrument oriented perpendicular to the hedgerows (Figure 1B), as suggested by the manufacturer (Decagon Devices, 2006). In both cases, start and end points of each transect were exactly half the distance between the two rows.

Table 2. Estimation ranges by LAI estimators for coffee fields at La Hilda, San Pedro de Poás, Costa Rica

Range	LAI values
0	0.0-0.9
1	1.0-1.9
2	2.0-2.9
3	3.0-3.9
4	4.0-4.9
5	5.0-5.9
6	6.0-6.9
7	7.0-7.9

For direct LAI estimation through defoliation, the leaf area of coffee trees was related to foliar fresh weight by linear regression (Y = 3.2298X + 0.0212; R^2 = 0.995). This regression was previously constructed by manually removing all the leaves of 10 coffee plants (in different growth stages and conditions) and obtaining their fresh weight in the field, the leaf area was then obtained using a LI-3000 Area Meter (LI-COR, Lincoln, NE, USA). Once the visual estimations and instrumental evaluations (using the LAI 2200-C and AccuPAR LP-80) were performed, the LAI was determined at each sampling point by removing and determining the fresh weight of all foliage from that point (that is, the same hedgerow segments for all three plants). The actual LAI was calculated by extrapolating the average tree leaf area to field plant density.

The statistical analysis consisted of 1) adjustment to the simple linear regression model (identity function) of visual and instrumentation estimates with respect to the actual LAI, and 2) repeatability and reproducibility analysis of visual estimates. The first part of the analysis tested the adjustment of the visual or instrument estimates to the following simple linear regression:

$$\text{Defoliation LAI value} = \beta_0 + \beta_1 \times \text{LAI estimate} + \text{Error}$$

where:

LAI - leaf area index;
β_0 - intercept; and,
β_1 - slope of the equation.

The estimators of β_0 and β_1 are b_0 and b_1, respectively. The null hypotheses (H_0) in this case are $\beta_0 = 0$ and $\beta_1 = 1$ (which are the identity function parameters), while the alternative hypotheses (H_1) are $\beta_0 \neq 0$ and $\beta_1 \neq 1$. The Student t test on

White circles show the LAI-2200C lens and the opening angle direction, parallel (T1) or perpendicular (T2) to the hedgerow. The circles marked R1 and R² indicate the reference PAR measurements taken above the canopy. Black bars with gray circles in B indicate ceptometer bar positions at the same sampling points

Figure 1. LAI sampling transects using an LAI 2200-C canopy analyzer (A), and an AccuPAR LP-80 ceptometer in coffee hedgerows (B)

H_0 was conducted at $p \leq 0.05$. In each case, the coefficient of determination (R^2) was calculated to determine the predictive power of the estimate for assessing the actual LAI. This process was repeated independently for each worker and instrument during each evaluation round.

The second part consisted of an analysis of variance with two random factors: the worker and estimation event (I or II). The first is associated with reproducibility and the second is associated with repeatability. Reproducibility refers to concordance between evaluators, whereas repeatability refers to agreement between independent assessment events. The percentage variance attributable to each of these factors was calculated over the total variance to proportionally estimate the amount of repeatability and reproducibility in the measurement method because the total variance corresponds to the sum of the evaluator variance between estimates, the variance between evaluators, and the error. Analyses were performed using JMP statistical software (SAS Institute, Cary, NC, USA). Figures were constructed using RStudio version 4.1.3 (R Core Team, Boston, MA, USA).

Results and Discussion

A wide spectrum of LAI values was sampled throughout the evaluation rounds, ranging from 0.1 to 7.8 (Figure 2). The overall mean LAI values were higher in the last two cycles than those in the first two, corresponding to the onset of the rainy season. However, because the sampling points were chosen to represent varying LAI conditions, each individual round of 20 points encompassed defoliation LAI values spanning at least four units. Differences were observed among the different estimation methods, particularly in rounds 2 and 3, in which both instruments showed lower median LAI values than those obtained using the defoliation method.

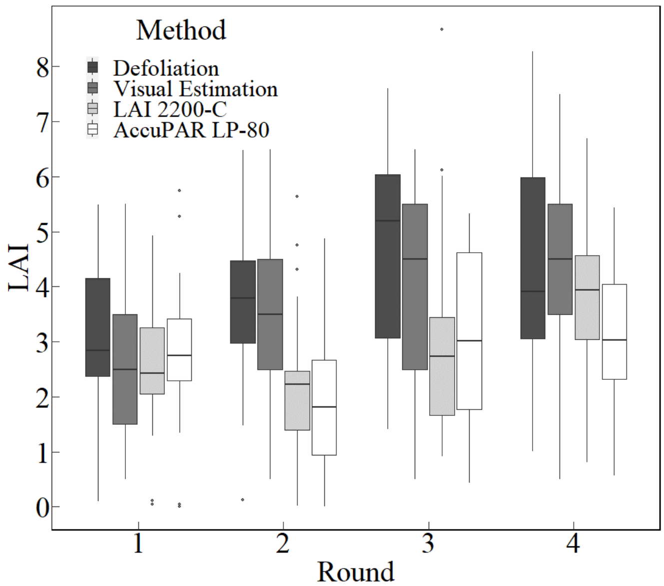

Figure 2. Leaf area index (LAI) values measured through four evaluation rounds via defoliation, visual estimation by five different estimators, and instrumentation (LAI 2200-C and AccuPAR LP-80) in coffee fields (March 26, April 7, July 4, and July 18, 2019) at La Hilda, San Pedro de Poás, Costa Rica

The linear regression analyses to compare each estimation method (visual assessment or instrumentation) with the defoliation LAI values (considered as the actual LAI) show variable R^2 values but are significant at $\alpha = 0.01$ for all cases (Figure 3). This variation was highly dependent on the method and evaluation round. For visual assessments, adjustment to the linear regression depended strongly on the evaluator and evaluation round. Nonetheless, the evolution of the R^2 determination coefficient shows that most evaluators consistently improved their ability to visually estimate the LAI as the training process advanced. As the outcome of this training is a key element in this research, the values of R^2, as well as the estimated intercept (β_0) and slope (β_1), were plotted for both instrumentation and evaluators over the four rounds (Figure 3). Evaluators 1 and 3 showed a sustained increase in R^2, that reached values of 0.87 and 0.82 in rounds 3 and 4, respectively (Figure 3A). For evaluators 2 and 4, R^2 did not increase in rounds 1 and 2, but showed significant improvement in rounds 3 and 4. Regarding evaluator 5, R^2 increased between rounds 1 and 2, decreased in round 3, and increased again to 0.75 in round 4. Both instruments (LAI 2200-C and AccuPAR LP-80) presented R^2 values between 0.5-0.6 in rounds 1, 2, and 3, with the only exception being the AccuPAR LP-80 in round 3 ($R^2 = 0.76$). In this case, the coefficient of determination did not exhibit a clear evolution pattern throughout the four rounds. As a result, in round 4, the R^2 coefficient of determination for every worker was higher than that for any instrument.

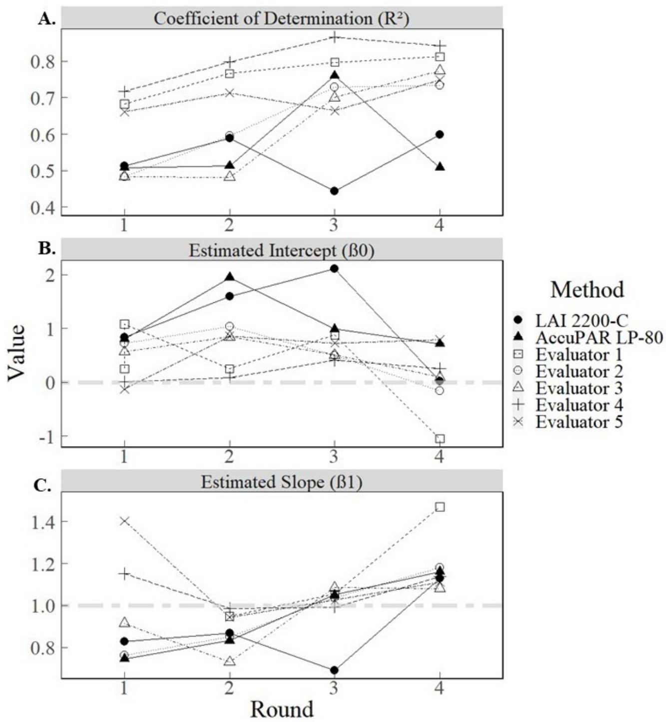

Figure 3. Coefficient of determination (R^2) (A), estimated intercept value (β_0) (B) and estimated slope value (β_1) (C) of the visual estimation simple linear regression model (by five evaluators; dashed lines) or via instrumentation (LAI 2200-C and AccuPAR LP-80; solid lines) with respect to actual LAI, in coffee fields in four evaluation rounds (March 26, April 7, July 4, and July 18, 2019). The gray dashed lines mark the expected values

The slope value (β_1) was statistically equal to 1 in all rounds for all the visual evaluators (Table 3 and Figure 3B), except for evaluators 5 and 1, in rounds 1 and 4, respectively (as the *t* probability value was less than the 0.05 significance level). A slope different from 1 would indicate that the estimation error changes with the actual LAI values, which is difficult to correct with training. Regarding the instrumentation, the values of β_1 were close to 1 in all rounds (Table 3 and Figure 3 B) and under no circumstances was the hypothesis of $\beta_1 = 1$ rejected, which indicates that instrumental estimation changed correspondingly with the actual LAI.

Regarding the intercept (β_0) estimate values, two evaluators (3 and 4) had estimates that were statistically equal to zero in all rounds (Table 3); one evaluator (2) had a nonzero intercept in one of the rounds and two evaluators (1 and 2) had a nonzero intercept in two of the rounds (Table 3 and Figure 3C). Unlike the slope, the intercept value did not show a clear trend and was not consistently close to zero throughout the training rounds for the evaluators. These data indicate that despite the ability of the evaluators to identify and quantify differences in LAI (expressed in the slope), some still had an underestimation bias. However, this is more easily correctable through training, as a deviation below zero indicates overestimation, and a deviation above zero indicates underestimation. Regarding the intercept (β_0) estimate values for the instruments, they were different than zero in rounds 2 and 3 for the AccuPAR LP-80 and in round 2 for the LAI 2200-C (Table 3 and Figure 3C) which also indicates an important underestimation of the actual LAI values.

Finally, repeatability and reproducibility analyses were applied to verify the reliability of the visual estimation method and revealed only a minor effect of the evaluator and estimation event on the total variance of the LAI visual assessments (Table 4). The highest effect of an evaluator on the variance was 4.6% in round 2, which decreased to 0.3% in round 3. The effect of the estimation event was low in the first two rounds and increased slightly in the third round. In both cases, the effect of the evaluator or estimation event was not significant. Altogether, the low percentages in the four estimation rounds indicated that the visual measurement method was robust and had high repeatability (for the same worker) and reproducibility (among workers).

Table 3. Probabilities of t for $\beta_1 = 1$ (slope) and for β_0 (intercept) of the visual estimation simple linear regression model (by five evaluators) or through instrumentation (LAI 2200-C and AccuPAR LP-80) with respect to actual LAI, in coffee fields

Method	Round			
	1	2	3	4
	Probability of t for $\beta_1 = 1$			
Evaluator 1	0.70	0.66	0.69	0.02*
Evaluator 2	0.15	0.33	0.74	0.28
Evaluator 3	0.60	0.13	0.60	0.59
Evaluator 4	0.21	0.91	0.93	0.29
Evaluator 5	<0.01*	0.66	0.88	0.50
LAI 2200-C	0.49	0.56	0.14	0.66
AccuPAR LP-80	0.27	0.50	0.81	0.63
	Probability of t for $\beta_0 = 0$			
Evaluator 1	0.43	0.44	0.01*	0.02*
Evaluator 2	0.07	0.01*	0.24	0.72
Evaluator 3	0.18	0.09	0.26	0.81
Evaluator 4	0.97	0.77	0.16	0.41
Evaluator 5	0.73	0.01*	0.13	0.04*
LAI 2200-C	0.17	<0.01*	0.31	0.99
AccuPAR LP-80	0.14	<0.01*	0.04*	0.43

*Significant at $p \leq 0.05$

Previous studies validating visual evaluation methods for agriculture have yielded diverse results. Hakamada et al. (2016) demonstrated that, in the context of eucalyptus plantations, visual assessments outperformed instrumentation (LAI 2000 and AccuPAR LP-80) and hemispherical photographs in terms of similarity to actual values. In their study, the R^2 for the visual assessment was 0.9, which was slightly lower than the LAI 2000 correlation ($R^2 = 0.99$) but considerably higher than that of the AccuPAR LP-80 ($R^2 = 0.18$). Büchi et al. (2018) conducted a similar study comparing visual assessments with image analysis to estimate the canopy cover on cover crops. Despite the visual assessments slightly underestimating canopy cover, both studies identified several benefits, such as faster evaluation time, ease of use, and reduced total time required.

Variability in intrinsic observer capacity is arguably the most influential factor in the success of visual estimation methodologies. The analysis conducted in this study showed high reproducibility (concordance between evaluators) using the visual method, but the coefficient of determination of the estimates differed for individual observers. The oldest and most experienced workers showed a higher predictive capacity for the actual LAI. This is consistent with phytopathological research, in which the most experienced evaluators have displayed greater accuracy in visual estimation (Bardsley et al., 2013). Nonetheless, other studies in disease visual assessments have also suggested that even experienced evaluators can present low repeatability if not properly trained (Bock et al., 2010).

The feedback process employed in this study reinforced led, with a few exceptions, to all workers consistently improving the R^2 values of their estimates throughout the four rounds. This is in line with the results obtained for canopy cover estimates (Gallegos-Torell & Glimskär, 2009). The case of evaluator 1 warrants further discussion. Despite having high R^2 values, his estimates showed a significant underestimation bias during round 3 ($\beta_0 = 0.88$). During the next feedback session, the trainer explained to evaluator 1 that his estimates captured variations in LAI well, but with consistent underestimation. It seems plausible that Evaluator 1 possibly tried not to underestimate in round 4, provoking the opposite bias and overestimation LAI (the estimated intercept value was −1.05). Evaluator 1 also presented an estimated slope value other

Table 4. Magnitude and percentage of the variance components in the visual estimation of leaf area index (LAI) of coffee fields

Round	Variance component	Magnitude of variance	Percentage of variance
1	Evaluator	0.03	2.8
	Estimation event	0.01	0.7
2	Evaluator	0.09	4.6
	Estimation event	0.00	0.0
3	Evaluator	0.01	0.3
	Estimation event	0.01	3.4
4	Evaluator	0.02	0.8
	Estimation event	0.04	1.64

than one (β_1 = 1.47), but R^2 remained relatively high (0.81). This situation draws attention to the scope and limitations of visual measurement methods, the importance of selecting workers trained to visually assess LAI, the type of feedback given, and the acceptable error for each specific use of the data generated. If this information is used to calibrate foliar spray applications, pre-calibration should first be performed to establish a relationship between the product dose, application volume, and LAI (Siegfried et al., 2007). An additional question concerns the frequency of the training reinforcement sessions with the evaluators, as they may lose accuracy and precision over time; however, no antecedents were found regarding this issue. Several authors suggest that field training should be combined with image visually aided training (Gallegos-Torell & Glimskär, 2009; Bock et al., 2010) which can significantly increase the reproducibility of the measurement system.

Regarding the use of instrumentation, this study confirmed the trend observed in the literature regarding underestimation of LAI by these tools (Bréda, 2003). In our study, fluctuations of the estimated intercept values (β_0) between instruments observed over the four rounds can be explained by the high heterogeneity of the coffee field canopy distribution, which differed in hedgerow spacing and LAI distribution (Table 1). It has been widely reported that the underlying mechanisms of these instruments face important limitations when dealing with leaf clumping, woody components, non-uniform foliage and heterogeneous leaf angle distribution (Bréda, 2003; Fang et al., 2014; Zhu et al., 2018; Yan et al., 2019). In terms of leaf angle distribution, although some models may provide the ability to parameterize the appropriate crop distribution, this factor varies considerably among coffee varieties and developmental stages, resulting in increased complexity (Unigarro et al., 2021). Altogether, this illustrates the importance of using adapted methods for accurate estimations of the LAI in situations where instrument performance is compromised, such as highly spaced hedgerows in coffee, which are increasingly popular as they facilitate labor, machinery circulation and enhance light and water use efficiency.

Two other factors may have negatively affected the accuracy of LAI measurements using these instruments. First, environmental conditions during the evaluation can affect instrument performance. In particular, the LAI 2200-C operates best under homogeneous overcast conditions without sudden changes in radiation (LI-COR, 2016), and the conditions at the field site do not always meet ideal weather conditions. Although the correction was made by the dispersion (using the “K records” as described in the user’s manual), the weather may have significantly impacted the accuracy of the instrument. In contrast, the AccuPAR LP-80 ceptometer is known to be less affected by weather conditions, but its predictive capacity for actual LAI was not significantly higher than that of LAI 2200-C, except for the results obtained in round 3.

The second factor is the light extinction coefficient (*k*) required for LAI calculation. While the instruments used the *k* values reported in the literature, variations in the *k* coefficient have been identified among different coffee varieties, and they depend strongly on the size, inclination, color, and grouping of leaves, among other factors (Unigarro et al., 2021). Finally, the choice of lens restriction cap could also affect LAI 2200-C performance. The results shown here were taken with lens restriction covers of 90°, but restriction covers of 10°, 45°, 180 °, and 270° did not improve instrument performance (data not shown).

Conclusions

1. Quick and accurate visual estimation of coffee field LAI can be achieved using the simple training protocol described in this study. This protocol consisted of successive rounds of pre-evaluation guidance and post-evaluation feedback for a group of fieldworkers who performed the assessments.

2. This protocol is particularly suitable in situations where specialized equipment is either unavailable or performs inadequately.

3. However, visual estimation accuracy is highly dependent on evaluator capacity and the quality of training received.

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