Plant-level coffee yield estimation based on morphological indices

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Abstract. Yield estimation in coffee farming is traditionally conducted at aggregated spatial scales, limiting the characterization of plant-level variability and its applicability for precision management. In production systems where within-field heterogeneity affects harvesting, logistics, and crop management decisions, plant-level approaches become particularly relevant. Within this context, this study evaluates and compares coffee yield estimation approaches based on morphological indices derived from field measurements and digital image analysis. The study was conducted in three coffee plots in Viçosa, Minas Gerais, Brazil, where 60 georeferenced plants (20 per plot) were evaluated at two pre-harvest stages, approximately five and three months before harvest. For each plant, height, canopy width, and fruit load of plagiotropic branches were measured considering the average number of fruits from the first to the fifth productive internodes. These attributes were integrated into two morphological indices used as predictors in simple linear regression models to estimate individual plant yield (liters per plant). Two strategies were evaluated for fruit load quantification: manual counting at productive internodes and an automated image-based approach using smartphone photographs. In both cases, performance improved when data collected closer to harvest were used. The manual model achieved $R^2 = 0.889$, RMSE = 0.923 L/plant, and MAE = 0.635 L/plant, while the image-based model yielded lower absolute errors (RMSE = 0.374 L/plant; MAE = 0.460 L/plant), though with a lower R^2 (0.747), indicating greater plant-level accuracy despite reduced adherence to overall variability patterns. Individual plant estimates were used to generate interpolated yield maps, enabling spatial variability assessment. Pixel-by-pixel comparison between observed and model-derived maps yielded R^2 values from 0.733 to 0.944 and RMSE from 0.007 to 1.077 L/plant, confirming the models' ability to reproduce spatial yield patterns across different management zones. Overall, the results demonstrate that plant-level yield estimation based on morphological indices offers a practical and reliable alternative for early yield assessment. The image-based approach, in particular, shows strong potential for operational adoption in precision coffee farming by reducing field workload while maintaining predictive consistency at both plant and spatial scales.

Keywords. Coffee farming, Morphological variables, Digital Agriculture, Productivity prediction, Yield prediction.

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Introduction

Coffee farming constitutes one of the most important agricultural commodities in the global economy. Yield prediction models have emerged as key instruments for anticipating production trends and improving management planning (Sanou et al., 2023). Recent advances combining remote sensing and machine learning have expanded predictive capacity at the farm scale (Zanella et al., 2024; de Faria et al., 2024); however, most models still operate at broad spatial scales, limiting their capacity to capture intra-plot variability.

At the individual plant scale, morphological indices integrating structural and reproductive attributes offer a practical approach for yield estimation (Qiao et al., 2022). The integration of digital image analysis and artificial intelligence further expands the potential of such approaches by enabling automated extraction of morphological information (Barbosa et al., 2021; Eron et al., 2024; Rivera-Palacio et al., 2024). Within this context, this study aims to evaluate and compare plant-level coffee yield estimation approaches based on morphological indices derived from field measurements and digital image-based methods.

Materials and Methods

The experiment was conducted at three coffee plots at the Federal University of Viçosa (UFV), Viçosa, Minas Gerais, Brazil. Sixty plants (20 per plot) were systematically selected and georeferenced. For each plant, height, canopy width, and fruit counts from 18 plagiotropic branches were recorded at two pre-harvest periods: approximately five months (December 2023–January 2024) and three months (February–March 2024) before harvest. At harvest, individual plant yield was recorded in liters per plant.

Two morphological indices were developed based on the concept proposed by Fahl et al. (2005), which relates the productive vegetative area to the average number of fruits at productive internodes, adapted to the individual plant scale. The Productive Vegetative Area per Plant (PVAP) was computed as the product of plant height, canopy width, and a factor of two (both plant faces). For Model 1, MI_1 was obtained by multiplying PVAP by the average number of fruits manually counted at the 4th and 5th productive internodes. For Model 2, MI_2 was calculated by multiplying PVAP by the average fruit count from the 1st to the 5th internodes, obtained automatically through image analysis. Simple linear regression models were fitted between each index and observed yield, with performance evaluated using R^2, RMSE, and MAE.

The automated fruit counting model was developed using Detectron2 (v0.6; Facebook AI Research), with Faster R-CNN architecture and ResNet-50 backbone. Per collection period, 120 branch images were annotated and split into 75% training and 25% testing, with 5-fold cross-validation. Model performance was evaluated using AP, AP50, AP75, and F1-Score. After validation, the trained models were applied to all images to generate the fruit counts used as input for MI_2. Yield maps were generated for each plot using ordinary kriging, and spatial performance was assessed through pixel-by-pixel comparison between observed and model-derived maps.

Results and Discussion

Automated fruit counting model

The automated fruit counting model demonstrated consistent performance across both evaluated periods (Table 1), with test scores around 80–85% consistent with similar agricultural image analysis applications (Kim et al., 2022; Ma et al., 2023). Slightly better results were obtained for the three-months-before-harvest period, suggesting that temporal proximity to harvest provides more consistent information for accurate fruit detection.

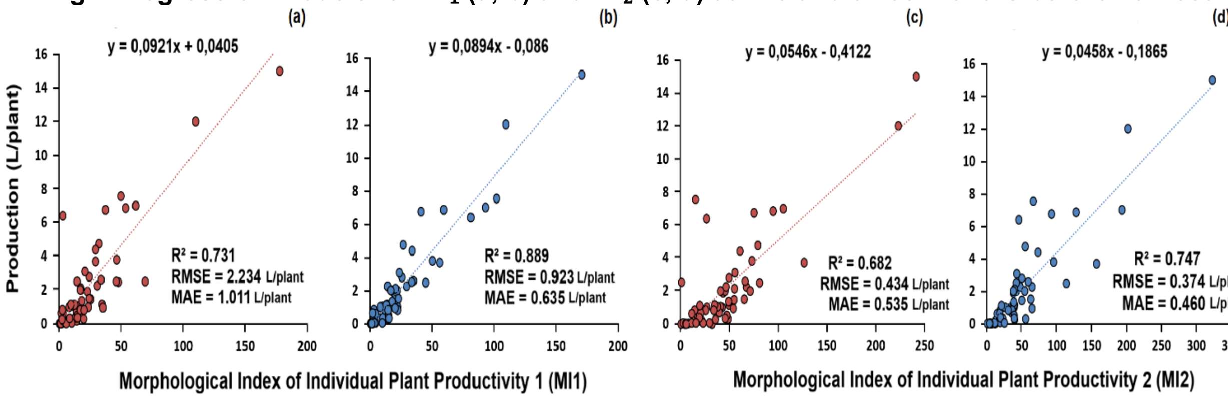
Table 1 - Performance metrics of the automated fruit counting model

Model period	Stage	AP (%)	AP50 (%)	AP75 (%)	F1-Score (%)
Five months before harvest	Training	93.24	99.01	93.24	96.04
	Cross-Validation	81.61	97.02	92.55	88.63
	Test	80.56	88.04	85.21	84.13
Three months before harvest	Training	95.69	99.99	98.98	97.79
	Cross-Validation	87.47	97.99	96.10	92.43
	Test	83.28	94.85	93.32	88.68

Yield prediction models

Both prediction models showed satisfactory performance, with notable improvement when data were collected three months before harvest (Fig. 1). All regression models were statistically significant ($p < 0.05$). The improvement observed at three months before harvest is consistent with the expected stabilization of morphological attributes at later phenological stages (Fahl et al., 2005; Alfonsi, 2008). Although Model 1 presented a higher coefficient of determination, Model 2 combined consistent predictive performance and greater operational practicality, relying entirely on automated data collection and thus being suitable for large-scale applications.

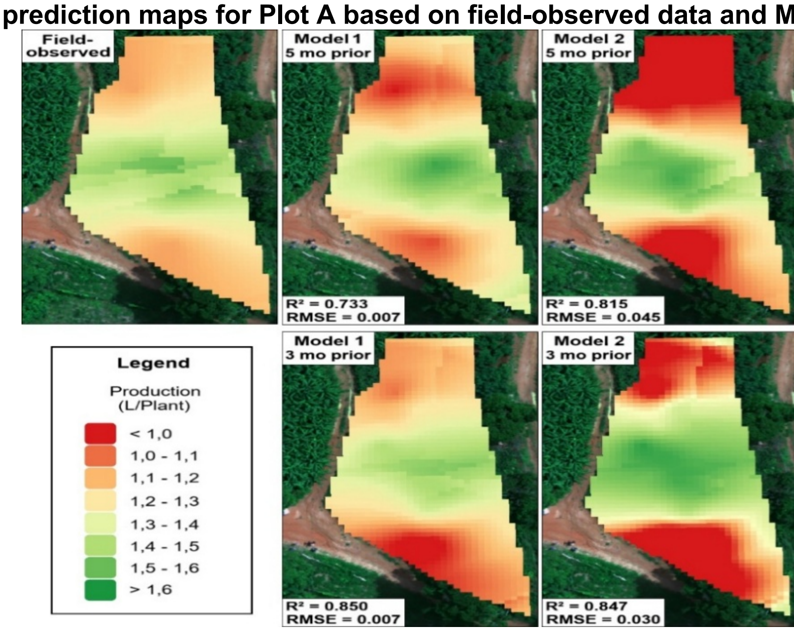
Fig. 1 Regression models for MI_1 (a, b) and MI_2 (c, d) at five and three months before harvest



Yield mapping

Yield prediction maps were generated for the three evaluated plots using ordinary kriging interpolation. Fig. 2 presents the maps for one representative plot. Both models captured the main spatial trends observed in the field-measured data. In plots with lower spatial variability, Model 2 exhibited superior spatial performance, while Model 1 performed better under higher intrinsic variability. These results reinforce the importance of data collection timing for reliable spatial predictions and highlight the practical value of these maps for early agricultural planning.

Fig. 2 Yield prediction maps for Plot A based on field-observed data and Models 1 and 2



Conclusions

The proposed morphological indices proved effective for early prediction of coffee yield at the plant level, especially when applied closer to harvest. The image-based approach, in particular, offers a scalable pathway for integrating plant-level yield information into precision agriculture workflows, supporting the development of management zones, site-specific interventions, and data-driven decision-making in coffee farming.

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