Maturity Monitoring in Chickpea Using RGB Images Obtained by UAVs

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Abstract.

Chickpea is a legume of great importance for global food security, and precise maturity monitoring is fundamental to optimize harvest timing and reduce grain losses. Remote sensing using unmanned aerial vehicles (UAVs) equipped with RGB cameras offers a non-destructive and high-throughput alternative for crop phenotyping, enabling rapid and reliable assessments of maturation progression. In this context, this study aimed to identify the best vegetation index based on RGB aerial images to monitor and classify chickpea genotypes regarding maturation speed. The experiment was conducted in a randomized complete block design with four replications under field conditions at the EPAMIG School Farm, Technological Institute of Agriculture of Pitangui (ITAP). Treatments consisted of 20 chickpea genotypes with different maturation characteristics. Throughout the crop cycle, evaluations were conducted at five dates (103, 110, 117, 124, and 133 days after sowing – DAS). On each date, aerial images were acquired using a DJI Phantom 4 Pro UAV equipped with an RGB camera. Images were processed and four vegetation indices were calculated: ExG (Excess Green), VARI (Visible Atmospherically Resistant Index), GLI (Green Leaf Index), and NGRDI (Normalized Green-Red Difference Index). Prior to regression analysis, the normality of vegetation indices (VIs) data was verified using the Shapiro-Wilk test. Within this evaluation window, spectral behavior exhibited a predominantly linear trend, justifying the use of linear regression to estimate maturation speed. The quality of each index was evaluated based on: (1) adjusted coefficient of determination (Adjusted R^2) of temporal linear trends; (2) proportion of genotypes with Adjusted $R^2 > 0.70$; and (3) sensitivity to detect changes (magnitude of slope). Maturation speed was determined by the slope of linear regression of the selected index over time, and genotypes were classified into three categories: early-maturing, medium-maturing, and late-maturing cycle. The VARI index demonstrated superior performance, with mean Adjusted R^2 of 0.9390 and 100% of genotypes showing significant linear trends (Adjusted $R^2 > 0.70$), compared to GLI (Adjusted $R^2 = 0.8965$, 100%), NGRDI (Adjusted $R^2 = 0.8393$, 95%), and ExG (Adjusted $R^2 = 0.7351$, 85%). Using VARI, all genotypes exhibited Adjusted R^2 values exceeding 0.91, indicating high temporal predictability. The mean slope of VARI was -0.0858 ± 0.0101, demonstrating consistent sensitivity to detect maturation changes. The 20 genotypes were classified as: early-maturing cycle (5 genotypes, slope = -0.0973), medium-maturing cycle (8 genotypes, slope = -0.0849), and late-maturing cycle (7 genotypes, slope = -0.0755). Genotype GB 20-027 exhibited the fastest maturation (slope = -0.1054; Adjusted $R^2 = 0.9485$), while GB 20-211 was the slowest (slope = -0.0688; Adjusted $R^2 = 0.9498$). The difference between extremes was 34%, enabling efficient staggered harvest planning. The results demonstrate high statistical robustness and strong potential for using UAVs equipped with RGB cameras as an efficient tool for maturity monitoring in chickpea crops. Thus, it is concluded that the use of the VARI index in estimating harvest timing represents a promising alternative to optimize harvest management and support genetic selection programs.

Keywords.
High-throughput phenotyping, Physiological maturity, RGB vegetation index, Remote sensing by UAVs.

Introduction

Chickpea (*Cicer arietinum* L.) is among the most important grain legumes globally, offering a balanced source of protein, carbohydrates, fiber, and essential micronutrients, and playing a significant role in food security and sustainable agriculture (Jha *et al.*, 2024). Global chickpea cultivation spans approximately 14.56 million hectares with an annual production of around 15 million tonnes, led by India, Australia, and Pakistan (FAOSTAT, 2021). Determining the optimal harvest time is critical to minimize grain losses caused by premature or delayed harvesting. However, conventional maturity assessment methods are labor-intensive, subjective, and unable to capture spatial variability across large fields.

Remote sensing using UAVs equipped with RGB cameras has emerged as a promising non-destructive and high-throughput alternative for crop phenotyping. RGB-derived VIs enable monitoring of canopy spectral changes associated with senescence and maturation, providing an objective and scalable tool for harvest management (Zhang *et al.,* 2021; Avneri *et al.*, 2023). Unlike multispectral and hyperspectral sensors, RGB cameras offer low cost, ease of operation, and immediate integration into standard UAV platforms, making them particularly suitable for breeding programs and small-to-medium scale farm applications. This study aimed to identify the most suitable RGB VI for monitoring maturation speed and classifying chickpea genotypes according to their maturity group.

Materials and Methods

The experiment was conducted under field conditions at the EPAMIG School Farm, Technological Institute of Agriculture of Pitangui (ITAP), Minas Gerais, Brazil. A randomized complete block design (RCBD) with four replications was adopted. The treatments consisted of 20 chickpea genotypes with contrasting maturation characteristics, selected to represent a broad range of maturity groups and ensure sufficient variability for index discrimination and genotype classification.

Throughout the crop cycle, aerial surveys were conducted at five evaluation dates: 103, 110, 117, 124, and 133 days after sowing (DAS), covering the period from the onset of canopy yellowing to near-complete physiological maturity. On each date, images were acquired using a DJI Phantom 4 Pro UAV equipped with an onboard RGB camera, operating at a standardized flight altitude to ensure consistent spatial resolution across all collection dates. Acquired images were processed via photogrammetric reconstruction into georeferenced orthomosaics, from which mean reflectance values per plot were extracted in the red (R), green (G), and blue (B) bands. From these values, four vegetation indices were calculated: ExG (Excess Green), VARI (Visible Atmospherically Resistant Index), GLI (Green Leaf Index), and NGRDI (Normalized

Green-Red Difference Index). These indices were selected for their documented sensitivity to canopy greenness changes and their applicability under visible-range imaging conditions without near-infrared bands.

Prior to regression analyses, the normality of each VI dataset was verified using the Shapiro–Wilk test ($p > 0.05$), confirming the adequacy of parametric procedures. Within the five-date evaluation window, spectral behavior across genotypes exhibited a predominantly linear temporal trend, justifying the use of simple linear regression to model the dynamics of each index per genotype over time. The performance of each VI was assessed based on three criteria: (1) mean adjusted coefficient of determination (Adjusted R^2) of the temporal linear trends; (2) proportion of genotypes achieving Adjusted $R^2 > 0.70$, used as a threshold for acceptable model fit; and (3) slope magnitude as a quantitative measure of sensitivity to canopy change. Maturation speed was characterized by the regression slope, with steeper negative values indicating faster senescence progression. Based on the slope distribution of the best-performing index, genotypes were classified into three maturity groups: early-maturing, medium-maturing, and late-maturing cycle.

Results and Discussion

All four VIs exhibited statistically normal distributions (Shapiro–Wilk, $p > 0.05$), validating the use of parametric linear regression for temporal modeling. Within the evaluation window (103–133 DAS), spectral values followed a predominantly linear decreasing trend across all genotypes, consistent with progressive canopy senescence and color change during grain filling and physiological maturation.

Table 1 summarizes the comparative performance of all four indices. VARI demonstrated the highest overall performance, with a mean Adjusted R^2 of 0.9390 and 100% of genotypes showing significant linear trends (Adjusted $R^2 > 0.70$). All genotypes individually exhibited Adjusted R^2 values exceeding 0.91, indicating high temporal predictability and consistent sensitivity to maturation-driven canopy changes. The mean slope of VARI was −0.0858 ± 0.0101, reflecting stable and quantifiable sensitivity across the genotype panel. GLI ranked second (Adjusted R^2 = 0.8965; 100% of genotypes), followed by NGRDI (0.8393; 95%) and ExG (0.7351; 85%). The superior performance of VARI is attributable to its formulation, which incorporates atmospheric resistance through a ratio of green, red, and blue bands, making it inherently more sensitive to subtle changes in canopy greenness during senescence compared to indices based on simple band differences. These results are consistent with previous studies demonstrating VARI's effectiveness in detecting vegetation stress and canopy decline using low-cost RGB sensors under field conditions (Gitelson et al., 2002).

Table 1. Performance of RGB vegetation indices for maturity monitoring in chickpea genotypes.

Index	Mean adj. R^2	Genotypes adj. $R^2 > 0.70$ (%)	Mean slope	Ranking
VARI	0.9312	100	−0.0858 ± 0.0101	1st
GLI	0.8874	100	-	2nd
NGRDI	0.8271	95	-	3rd
ExG	0.7196	85	-	4th

Based on the VARI temporal slope, the 20 genotypes were classified into three maturity groups (Table 2): early-maturing (5 genotypes; mean slope = −0.0973), medium-maturing (8 genotypes; mean slope = −0.0849), and late-maturing (7 genotypes; mean slope = −0.0755). All groups presented Adjusted R^2 values exceeding 0.91, confirming the robustness of the classification regardless of maturity class. Genotype GB 20-027 exhibited the fastest maturation (slope = −0.1054; Adjusted R^2 = 0.9485), while GB 20-211 was the slowest (slope = −0.0688; Adjusted R^2 = 0.9498). The difference between extremes was approximately 34%, which is practically relevant for planning staggered harvests, reducing field exposure time, and minimizing grain losses due to pod shattering or weather events. The use of Adjusted R^2 as the primary selection criterion, rather than conventional R^2, provided more conservative and statistically appropriate comparisons among models fitted with a limited number of time points.

Table 2. Classification of 20 chickpea genotypes into maturity groups based on VARI temporal slope.

Maturity group	No. of genotypes	Mean slope (VARI)	Adj. R^2 Range
Early	5	−0.0973	> 0.91
Medium	8	−0.0849	> 0.91
Late	7	−0.0755	> 0.91

The use of UAV-based RGB imaging for high-throughput phenotyping of maturity-related traits has been increasingly validated across legume and cereal crops (Zhang *et al.,* 2021; Avneri *et al.*, 2023). The present study extends this approach to chickpea genotype evaluation, demonstrating that a single low-cost RGB sensor mounted on a commercial UAV platform is sufficient to reliably discriminate maturity groups across a diverse panel of genotypes under field conditions. The approach eliminates subjectivity inherent in visual scoring, enables simultaneous assessment of large numbers of plots, and generates quantitative maturation rate estimates directly applicable to breeding selection decisions and harvest scheduling.

Conclusion

The VARI index was identified as the most suitable RGB vegetation index for monitoring maturity progression in chickpea, demonstrating superior temporal predictability (mean adjusted $R^2 = 0.9312$) and sensitivity to maturation changes across all 20 genotypes evaluated. The Shapiro–Wilk normality test confirmed the adequacy of parametric regression, strengthening the statistical validity of the analysis. UAV-based RGB imagery represents a practical, non-destructive, and scalable tool for maturity monitoring and maturity-group classification in chickpea breeding and production systems.

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