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Assessment of vegetation indices derived from UAV images for predicting biometric variables in bean during ripening stage

Evaluación de índices de vegetación derivados de imágenes de UAV para predecir variables biométricas en frijol durante la etapa de maduración

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ABSTRACT

Here, we report the prediction of vegetative stages variables of canary bean crop employing RGB and multispectral images obtained from UAV during the ripening stage, correlating the vegetation indices with biometric variables measured manually in the field. Results indicated a highly significant correlation of plant height with eight vegetation indices derived from UAV images from the canary bean, which were evaluated by multiple regression models, obtaining a maximum correlation of $R^2 = 0.79$. On the other hand, the estimated indices of multispectral images did not show significant correlations.
Keywords: Vegetation indices; precision agriculture; RGB images.

RESUMEN

El objetivo de este trabajo fue evaluar la predicción de las variables vegetativas del cultivo del frijol canario mediante imágenes RGB y multiespectrales obtenidas de UAV durante la etapa de maduración. Se correlacionaron los índices de vegetación con variables biométricas medidas en campo en forma manual. Los resultados indican una correlación altamente significativa de la altura de las plantas con ocho índices de vegetación derivados de imágenes de UAV de alubias, las cuales fueron evaluadas mediante múltiples modelos de regresión, obteniendo una correlación máxima de $R^2 = 0,79$. Los índices estimados de imágenes multiespectrales no mostraron correlaciones significativas.
Palabras claves: *Índices de vegetación; Agricultura de precisión; Imágenes RGB.*

Introduction

Bean (*Phaseolus vulgaris* L.) is an essential legume as a source of protein and dietary fiber for millions of people (Los *et al*., 2018). It is widely cultivated for its enormous genetic diversity. It is a nitrogen-fixing plant, highly adaptable and productive in a wide range of environments (Shamseldin & Velázquez, 2020). This crop will likely play a key role in guaranteeing food security for millions of people worldwide in the near future (Mecha *et al*., 2018). In Peru in 2019, a total of 73,298 ha of beans were cultivated, representing 0.8% of the Gross Value of Agricultural Production (GVaP) (MIDAGRI, 2020). Canary bean is the most outstanding cultivar on the Peruvian coast due to its preference in the national diet and cultural aspects. Therefore, due to the importance of this crop, it is a great challenge to monitor its development together with appropriate agronomic management in the field (Shakoor *et al*., 2017) in the context of climate change. Quantitative evaluations of biometric variables such as plant height, leaf area index, and chlorophyll content influence yield and become a high priority under precision agriculture (Eggen *et al*., 2019). Efficient and non-destructive crop growth monitoring is essential for appropriate crop management and key for digital agriculture (Wang *et al*., 2019). Determining data manually requires a significant amount of time and resources (measuring equipment, reagents, and researchers, among others). Important technological advances

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have been implemented, such as the use of unmanned aerial vehicles to increase agricultural production with limited resources (UAVs) (Khan *et al*., 2021).

UAVs are tools that provide new alternatives for monitoring crops without direct contact with them (Qi *et al*., 2020), allowing the prediction of crop development in a spatial-temporal way. The sensors coupled to a UAV allow estimating vegetative development variables with different vegetative indices (Gano *et al*., 2021). Recently, in the north of China, (Guo *et al*., 2020) used UAV images to predict yield in corn. Similarly, other researchers predicted aerial biomass in various crops such as sunflower and wheat (Du & Noguchi, 2017; Vega *et al*., 2015). In Kenya, RGB images were used to estimate cassava's growth and nutritional yield (Wasonga *et al*., 2021). Since evaluations are necessary during the development of crops and as beans are one of the main foods in the basic family basket, research must be conducted to guarantee food security under the context of climate change. Therefore, the objective of the present work was to estimate the prediction of plant height, chlorophyll content, and leaf area index through multispectral images obtained from UAV of canary bean crops during the ripening stage.

Materials and methods

Study site

The study site is located in the research field of the National Institute of Agrarian Innovation (INIA for its acronym in Spanish) (12º4'30.10''S, 76º56'33.86''W, 240 m.a.s.l) (Figure 1). The experiment was developed during the winter-spring seasons (Jun 26-Oct 2020), using commercial canary beans. An experimental field of 0.30 ha (Figure 1) with distances between plants and rows of 0.2 m and 0.9 m, respectively, was used for this research. We used drip irrigation with a distance between drippers of 0.2 m with a flow of 1.20 l h-1. The study site is arid, with an average temperature of 19.2 ºC and a total annual rainfall of 8 mm.

Field data collection

Three biometric variables were recorded on 16 plots of 7 m x 5 m at 90, 97, and 101 days after sowing (DAS). Plant height (cm) was measured manually from the soil surface to the highest stem apex. Leaf area index (LAI) was estimated from digital images taken on the canopy cover of the plant, as indicated by (Peng *et al*., 2021). was with the CCM-300 equipment (OptiSciences Hudson, NH, USA) measured Chlorophyll content (mg m^{-2}) following the methodology proposed by (Guo *et al*., 2020).

UAV RGB and multispectral image acquisition and processing

We used a Quadcopter-type UAV platform, DJI Phantom 4 Pro (Shenzhen Dajiang Baiwang Technology Co., Ltd., Shenzhen, China), with a built-in 4864 × 3648 pixel resolution RGB camera. In addition, a multispectral sensor Parrot Sequoia (Parrot SA, France), which is a synchronized array of 4 single-band multispectral cameras with 1.2 MP global shutter attached, taking images in green

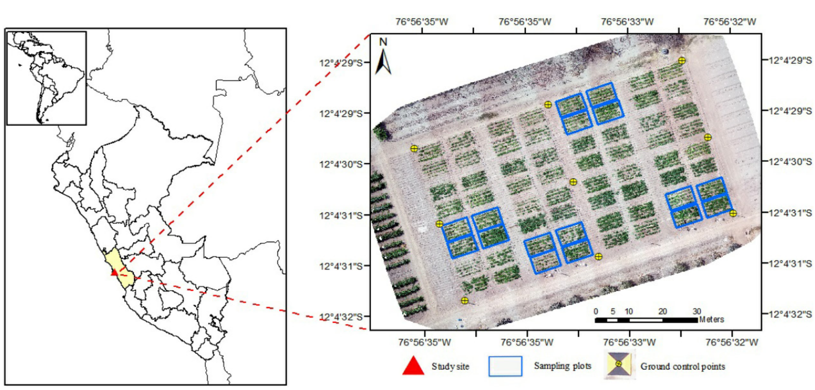

Figure 1. Location of the 64 canary bean research plots. The ground control points (GCP) are shown, and the 16 plots sampled for the estimation of vegetation indices are shown in blue rectangles.

(550 nm), red (660 nm), red edge (735 nm) and near infrared (790 nm). The images were collected at 90, 97, and 101 DAS during sunny days with wind speeds lower than 12 m s-1, from 11:00 to 13:00 hours approximately on the 16 research plots, as detailed in Figure 1. The flight plan was established with the Pix4Dcapture software (v. 4.12.1, Pix4D SA, Prilly, Switzerland), considering a frontal and lateral overlap of 80%, the height of 30 m, speed of 2.8 m s-1, and the camera focused at nadir position (perpendicular to the ground surface), allowing to obtain a resolution of 0.8 cm and 2.5 cm for RGB and multispectral images, respectively. Figure 2 shows a flow chart for data acquisition from the UAV platform to image processing. Image processing was performed with Pix4Dmapper Pro software (v. 4.3.33, Pix4D SA, Prilly, Switzerland), according to the following steps: (i) alignment of geolocated images, (ii) generation of point clouds and geometric correction, and (iii) generation of the digital surface and orthomosaic model using the inverse distance weighting method. The geometric correction was performed considering nine ground control points (GCP) (Figure 1) previously installed and registered with differential GNSS (Global Navigation Satellite System) (South Galaxy G1 model, South Surveying & Mapping Instrument Co. Ltd, Guangdong, China).

Calculation of vegetation indices

The vegetation indices were calculated from RGB images and were carried out prior to bands normalization (R = red, G = green, and B = blue) in the Pix4Dmapper software. In addition, the multispectral bands were obtained (R = red, G = green, RE = red border, and NIR = near infrared). In this research, 19 vegetation indices were estimated to assess biometric parameters (Table 1).

Statistical analysis: Biometric variables (plant height, leaf area index, and chlorophyll content) and vegetation indices were correlated using the following statistical indicators: Pearson's correlation coefficient (r) and coefficient of determination (R^2); both were calculated with R software v. 4.1.0 (R Core Team, 2021).

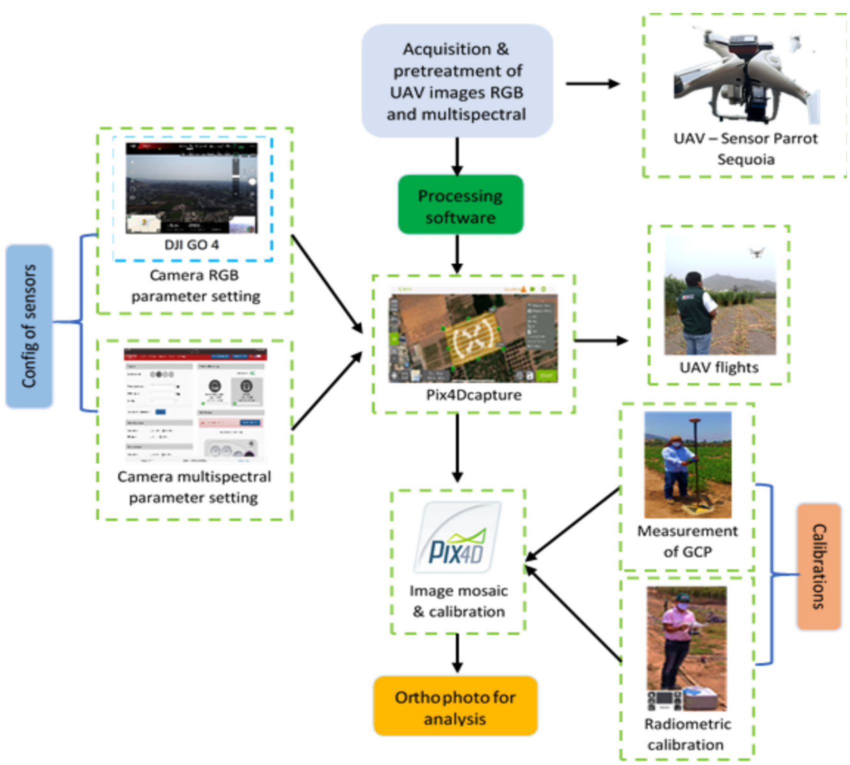

Figure 2. Flowchart for the acquisition and processing of images for the calculation of the vegetation indices of a canary bean crop.

Table 1. Vegetation index calculations from Red-Green-Blue and Multispectral images.

Abbrev	Definition	type	Reference
NGRDI	(G - R)/(G + R)	RGB	(Han *et al.*, 2019)
ExG	2xG-R-B		(Han *et al.*, 2019)
ExR	1.4xR– G		(Bendig *et al.*, 2015)
ExB	1.4xB – G		(Ballesteros *et al.*, 2018; Guo *et al.*, 2020)
IKAW	(R – B)/(R + B)		(Du & Noguchi, 2017)
GRRI	G/R		(Beniaich *et al.*, 2019)
ExGR	ExG – ExR		(Lussem *et al.*, 2018)
GBDI	G-B		(Bendig *et al.*, 2015; Lussem *et al.*, 2018)
MGRVI	(G x G-R x R)/(G x G x R x R)		(Wan *et al.*, 2018)
RGBVI	(G x G - B x R)/(G x G + B x R)		(Lussem *et al.*, 2018)
VDVI	(2 x G - R -B)/(2 x G + R +B)		(Wan *et al.*, 2018)
VARI	(G – R)/(G + R – B)		(Beniaich *et al.*, 2019)
RGRI	R/G		
NGBDI	(G - B)/(G + B)		
CIVE	(0.441 x R - 0.8818 xG + 0.385 x B + 18.787)		
NDVI	(NIR – r)/(NIR + r)	Multiespectral	(Ranjan *et al.*, 2019; Wasonga *et al.*, 2021)
GNDVI	(NIR – g)/(NIR + g)		(Sankaran *et al.*, 2019)
SAVI	[(NIR – r)/(NIR + r+L)](1+L)		(Ranjan *et al.*, 2019)
NDREI	(NIR – re)/(NIR + re)		(Hassan *et al.*, 2018; Ranjan *et al.*, 2019)

Results and discussion

Correlation between spectral indices and growth variables

The correlation analysis between the vegetation indices and growth variables was carried out for 90, 97, and 101 DAS, finding significant correlations (p-value < 0.05) at 97 DAS for plant height. According to (Schirrmann *et al.*, 2016), the plant height and coverage derived from the UAV images became important because chlorophyll content decreases in the wheat leaves with further propagation of senescence. In contrast, the other variables (chlorophyll content and leaf area index) did not register significant correlations, so we decided not to consider them for the multiple linear regression model. Plant height is an important variable since it depends on the growth rate of crops (Rai *et al.*, 2020). In Table 2, 19 vegetation indices correlated to plant height are detailed. Four indices (RGBVI, VDVI, ExGR, and ExB) presented high significance (p-value <0.01), eight indices (ExR, GBDI, NGBDI, NGRDI, MGRVI, VARI, CRRI, and RGRI) showed significance (p-value <0.05), and four indices (ExB, ExR, IKAW, and ExG) were inversely proportional. No multispectral index presented significant correlations (NDVI, SAVI, GNDVI, and NDREI).

Table 2. Vegetation indices correlated with plant height recorded at 97 DAS.

Indice	plant height	
	r Pearson	*p-value*
NDVI	0.39	0.135 ns
SAVI	0.40	0.125 ns
GNDVI	0.33	0.215 ns
NDREI	0.37	0.156 ns
CIVE	0.22	0.418 ns
RGBVI	0.64	0.008 **
ExR	–0.62	0.011 *
GBDI	0.63	0.010 *
VDVI	0.64	0.007 **
NGBDI	0.60	0.014 *
NGRDI	0.61	0.011 *
MGRVI	0.61	0.012 *
IKAW	–0.18	0.502 ns
VARI	0.59	0.017 *
ExGR	0.63	0.009 **
ExG	–0.32	0.223 ns
CRRI	0.62	0.010 *
RGRI	0.60	0.014 *
ExB	–0.66	0.005 **

**Altamente significativos, * Significativo, ns: No significativo.

Our results agree with those of (Hassan *et al.*, 2018), who stated that the vegetation indices decrease after flowering in wheat, causing fluctuations during senescence.

Prediction model for estimating plant height.

Multiple linear regression analyzes were performed for three prediction models after correlating the vegetation indices and plant height at 97 DAS, as detailed in Table 3. Figure 3 shows the three prediction models for the measured plant height and its predicted values: (i) for model I, 10 vegetation indices were used (RGBVI, GBDI, VDVI, NGBDI, NGRDI, MGRVI, VARI, ExGR, CRRI, RGRI) with significant correlations $0.59 < r < 0.64$ (p-value < 0.05), generating a predictive model with an $R^2 = 0.79$ (p-value < 0.01), (ii) in model II four vegetation indices were considered (RGBVI, GBDI, VDVI, ExGR) with significant correlations of $0.63 < r < 0.64$, (p-value < 0.01), obtaining a predictive model with $R^2 = 0.60$, and (iii) to generate the prediction model III, three vegetation indices were considered (ExR, ExG, ExB) with negative correlations $-0.66 < r < -0.32$, generating a predictive model with an $R^2 = 0.46$. Although for model II, four vegetation indices with high correlation values were chosen, their prediction decreases because it presents an R^2 lower than model I but higher than that of model III. As we add a greater number of indices to the predictive model, it is more reliable. However, model II with four indices also predicts high significance; we would use it for data analysis if we had fewer resources. (Bendig *et al.*, 2015) reported plant height estimation with two vegetative indices (GRVI and

Table 3. Multivariate linear regression models between vegetation indices and plant height recorded during ripening stage for canary bean.

Prediction model	Spectral Index	Regression Coefficient	Intercept	Model R^2
I	RGBVI	–2893.1	5934.9	0.79
	GBDI	21228.7		
	VDVI	5500.7		
	NGBDI	–8715.3		
	NGRDI	5934.9		
	MGRVI	–9715.4		
	VARI	3526.0		
	EXGR	–5071.7		
	CRRI	–139.1		
	RGRI	1657.0		
II	RGBVI	–3556	2709	0.60
	GBDI	4832		
	VDVI	–1332		
	EXGR	–3179		
III	EXR	–91.31	51.45	0.46
	EXG	210		
	EXB	–216.05		

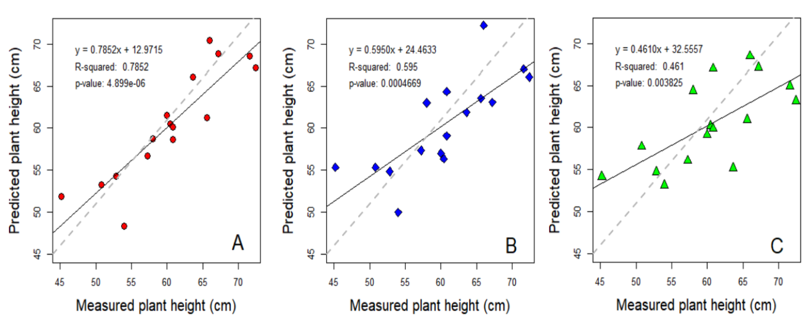

Figure 3. Correlation between the estimated data and plant height recorded for three models, A) Model I is based on ten vegetation indices, B) Model II is based on four vegetation indices, and C) Model III is based on three vegetation indices with inverse correlation.

RGBVI) evaluated during different stages of barley through the use of multiple linear regression models.

To our best knowledge, this is the first research work in Peru using technology such as UAV for agronomic monitoring of canary beans. A highly significant correlation for plant height was obtained from eight estimated vegetation indices from RGB images in this crop at the ripening stage. It was possible to predict the size of this crop with high performance (R^2 = 0.79) using model I. Recent studies (Parker *et al.*, 2020; Wasonga *et al.*, 2021) reported similar results for beans and cassava crops, demonstrating the utility of UAVs and vegetation indices to compile biometric variables.

Conclusions

A highly significant correlation was obtained for plant height with eight RGB image vegetation indices in the commercial canary bean crop. The obtained indices from multispectral images did not show significant correlations. The predictive model I with R^2 = 0.79 predicts plant height with good accuracy. The use of these tools is important due to the need to conduct more agronomic evaluations promptly in crops and mainly in those that are cultivated in arid environments such as the Peruvian coast. We are currently conducting experiments with new technologies using remote sensors such as UAV to predict biometric variables estimated from vegetative indices obtained from RGB and multispectral images in bean crops and others of national importance. In addition, images from the PeruSat-1 (Peru) and Kompsat 3 (South Korea) satellites will be used, allowing timely monitoring and prediction of crop development under different agronomic management scenarios (irrigation, fertilization, among others) on a larger scale.

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