Estimating okra leaf area index using unmanned aerial vehicle imagery

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Abstract: The study aimed at estimating the leaf area index of okra using vegetation indices obtained by analysing image data from a low-cost Unmanned Aerial Vehicle (UAV). Additionally, the work also assessed which of the two indices commonly used (excess green (ExG) and normalized green-red difference index (NGRDI)) could give a better estimation of leaf area indices. The study was conducted in Cape Coast in southern Ghana at an experimental site located at the University of Cape Coast's Teaching and Research Farm. The experiment was arranged in a randomised complete block design (RCBD) with four treatments (2 cm, 3 cm, 5 cm and 7 cm sowing depths) and four replicate blocks. This resulted in sixteen plots each measuring 3 m by 3 m. Overall, it was realised that sowing okra seeds at 3cm depth gave the best prediction of leaf area index (R^2>0.76 for both indices). Also, comparing the vegetation indices, the ExG gave a better estimation (R^2>0.65) compared to NGRDI (R^2>0.43). This study suggests a recommended sowing depth of 3 cm for okra and ExG vegetation index for estimating leaf area index of okra.

Keywords: unmanned aerial vehicle, geographic information system, vegetative index, leaf area, Okra

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1 Introduction

In Ghana, agriculture contributes about 19.2% of the gross domestic product(GSS, 2018). Among the key vegetable crops cultivated in the country include okra (*Abelmoschus esculentus* L) which is largely consumed by the citizenry due to its high composition of essential vitamins and minerals (Agyare et al., 2017). The weather conditions in the country largely favour the production of the crop all-year-round. It is therefore important to increase the production of okra for the country's economic benefit.

In the face of projected rapid change in population growth with corresponding food demand, there is the need to focus on research related to the monitoring of agronomic parameters that promote the development of okra. Leaf area index (LAI) is one important parameter that could be used to assess crop health status, canopy physiology and nutritional supply (Kalisperakis et al., 2015). The method of determining LAIs manually tends to be laborious and time consuming.

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Consequently, the modern trend of research in precision agriculture shows that using unmanned aerial vehicle imagery data (drone technology) is rapidly gaining attention for crop phenotype studies and surveillance purposes. UAV imagery data have been employed to predict leaf area indices with varying degrees of accuracies (Yuan et al., 2017; Apolo et al., 2018). Yuan et al. (2017) successfully retrieved the leaf area indices of soybean plants from UAV imagery data models. Apolo et al. (2018) confirmed that images of UAV flying at low altitude could be used to successfully estimate LAIs of maize. Other works have also attempted using vegetation indices (VIs) from UAV images for predicting the vegetative growth of plants, especially LAI and biomass (Bendig et al., 2014; Kalisperakis et al., 2015). Zhou et al. (2017) showed that VIs can as well be used to predict other growth parameters including yield.

However, for developing countries in sub-Saharan Africa such as Ghana, the use of UAV technology in precision agriculture research has rarely been explored. Researchers continue to study crop growth parameters by manual means with its associated drudgery. Hence, the need to explore the potential of UAV technology estimate in-field growth parameters.

Our literature search so far shows that little focus has been given to estimating the okra LAI using VIs from UAV images in Ghana and other sub-Saharan countries. However, two common vegetative indices (Excess Green (ExG) and Normalized Green-Red Difference Index (NGRDI)) obtained from UAV flying at low altitude have been widely used for predicting plant biomass (Xue and Su, 2017; Tumlisan, 2017; Wan et al., 2018). In addition to this, Singh et al. (2013) reported that sowing depth influences the LAI of plants.

Hence, the study aimed at estimating the LAI of okra cultivated under varying sowing depths using UAV-based VIs.

2 Materials and methods

2.1 Experimental Setting

The study field was located at the University of Cape Coast's School of Agriculture's Teaching and Research Farm in the Central Region of Ghana. According to Owusu-Sekyere et al. (2011), the area is characterized by an annual temperature range of 23.2ºC -33.2ºC with an annual mean of 27.6ºC and a relative humidity range of 81.3%-84.4%. It usually experiences two rainy seasons namely the major season which usually starts from May and ends in July/August and a minor season that starts around September and ends around November/December. The soil type at the experimental site is loamy sand. The study was done under rainfed conditions from June 12, 2018, to August 23, 2018.

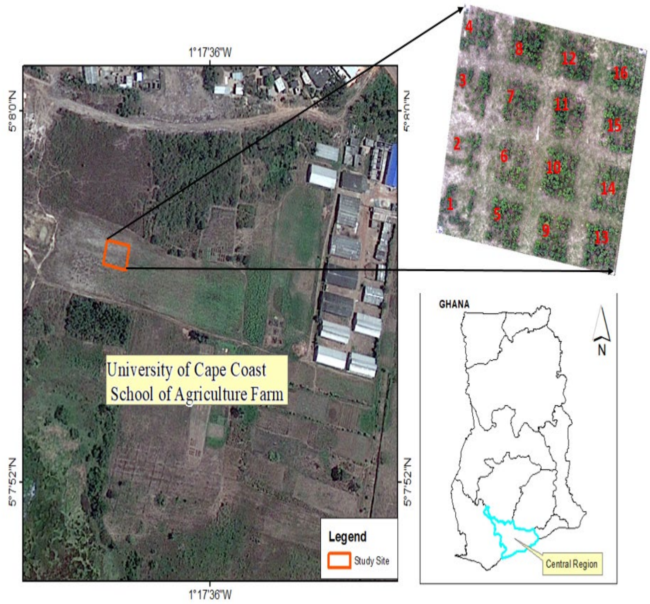


Figure 1 Location of study site on the University of Cape Coast's School of Agriculture Teaching and Research Farm

Figure 1 shows the experimental area indicating the location of the 16 plots. The latitude and longitude of the study area were 5° 07' 57.13" and 1° 17" 48.28" respectively. A randomised complete block design with four replicate blocks was used in this study. The treatments were sowing depths at 2 cm, 3 cm, 5 cm and 7 cm. In each block, the treatments were randomly administered to the plots. Prior to this, the field was ploughed and harrowed and the plot sizes demarcated to a dimension of 3 m by 3 m square size. It was laid out in such a way that 1.5 m spacing between blocks and 1 m spacing between plots in a block were used as buffer zones. Seeds of Kirikou F1 okra variety were sown using a dibbler. A 50 cm by 50 cm planting spacing was used.

2.2 UAV Imaging system, flight planning and data collection.

In this study, our main surveying device was a quad-copter UAV for the acquisition of high-resolution aerial images. The imaging system used was a low-cost Phantom 3 Professional UAV (DJI, Shenzhen, China) made up of a platform and a red, green and blue (RGB) camera equipped with a 1/ 2.3” Complementary Metal Oxide Semiconductor (CMOS) sensor and 12.4 effective megapixels. The camera has a resolution of 4000×3000. The lens has a 94° of the angle of view with 20 mm f2.8 focus. Even though similar studies have used UAV with a multispectral camera (Zhou et al., 2017), the purpose of this study was to opt for a low-cost device that is affordable to most farmers in developing countries. Map Pilot v2.7 software was used for monitoring the UAV, as well as for setting up the flight paths. The images were captured at nadir in every 3.5 s at a flying height of 20 m above ground level (AGL). The average ground sample distance or the resolution of the images was 0.86 cm. The images were also captured at a frontal and side overlap of 80%.

Prior to the flights, black and white Ground Control Points (GCP) targets were placed at vantage points on the ground and their geographical locations measured using Dual Frequency Geographic Positioning System (GPS) with an accuracy of 2cm. The size of all the targets was 42 cm × 29.7 cm (A3 size). The visibility of these targets in the images was then used during the image processing to geo-rectify the orthophoto. The images were collected between day time hours of 10 am to 12 pm starting on the day of sowing (12^{th} June 2018) and subsequently on 26^{th} June (okra seedling stage), 12^{th} July (okra crop initial stage), 26^{th} June (okra crop development stage), 9^{th} August (mid-stage or early maturity stage of okra) and 23^{rd} August (Late maturity stage of okra).

2.3 Generation of spectral vegetation indices

Based on the UAV images of RGB spectral bands, VIs were calculated using band math tool in ENVI 5.2. Two (2) VIs, ExG and NGRDI, were used. Details of the indices formulae are presented in Table 1.

At each date, average VIs for each plot were calculated using zonal statistics tool in ArcMap 10.5.

Table 1 Vegetation indices used in the study

Vegetation Index	Equation
ExG	$2G-R-B$
NGRDI	$\frac{G-R}{G+R}$

Note: *R, G and B represent the spectral reflectance values acquired in the Red, Green and Blue portion of the electromagnetic spectrum, respectively.

2.4 Field measurement

Manual measurements of the plant height of six tagged plants per plot were taken using a tape measure two days after flying the UAV on the experimental plot. Specifically, the leaf length along the mid-rib (from petiole to the tip) and maximum width were measured for leaves of the tagged plants for average length and width to be noted per the specific growth stage. The number of leaves was also recorded. The following equation was used to calculate the leaf area (LA) of each leaf:

$$LA\ (m^2) = L \times W \times k \qquad (1)$$

Where,

L =leaf length (m)

W = leaf width (m).

k= 0.62 for okra (Musa and Usman, 2016)

To obtain the total leaf area per plant, the specific leaf area was multiplied by the number of leaves counted. The LAI was then determined by dividing the leaf area by the ground area of the plant (Tunca et al., 2018).

2.5 Statistical analyses

All data collected were subjected to the analyses of variance procedure using Minitab statistical software version 17. Where significant difference exists, the Tukey comparison test was done at a probability level of 5%. Multiple linear regression was also conducted to investigate the relationship between the LAI and VIs. Graphs were plotted using Microsoft Excel 2010.

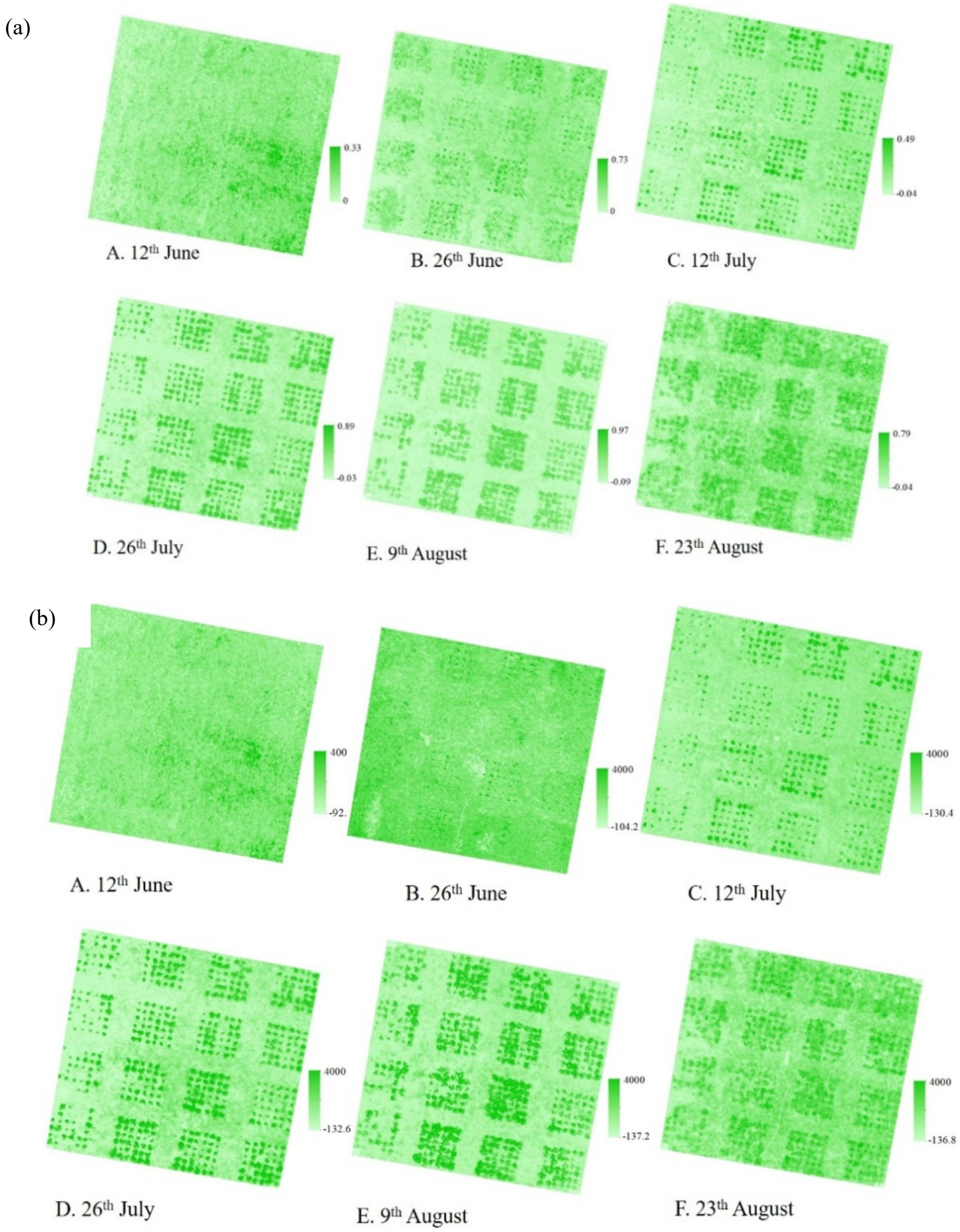
3 Results and discussion

3.1 Change of VIs and LAI sat different growth stages under varied sowing depths

The NGRDI and ExG maps of the fields were generated for each flight date (or okra growth stage) from UAV images obtained (Figure 2). Generally, a similar trend of increasing vegetation over time was observed on both maps.

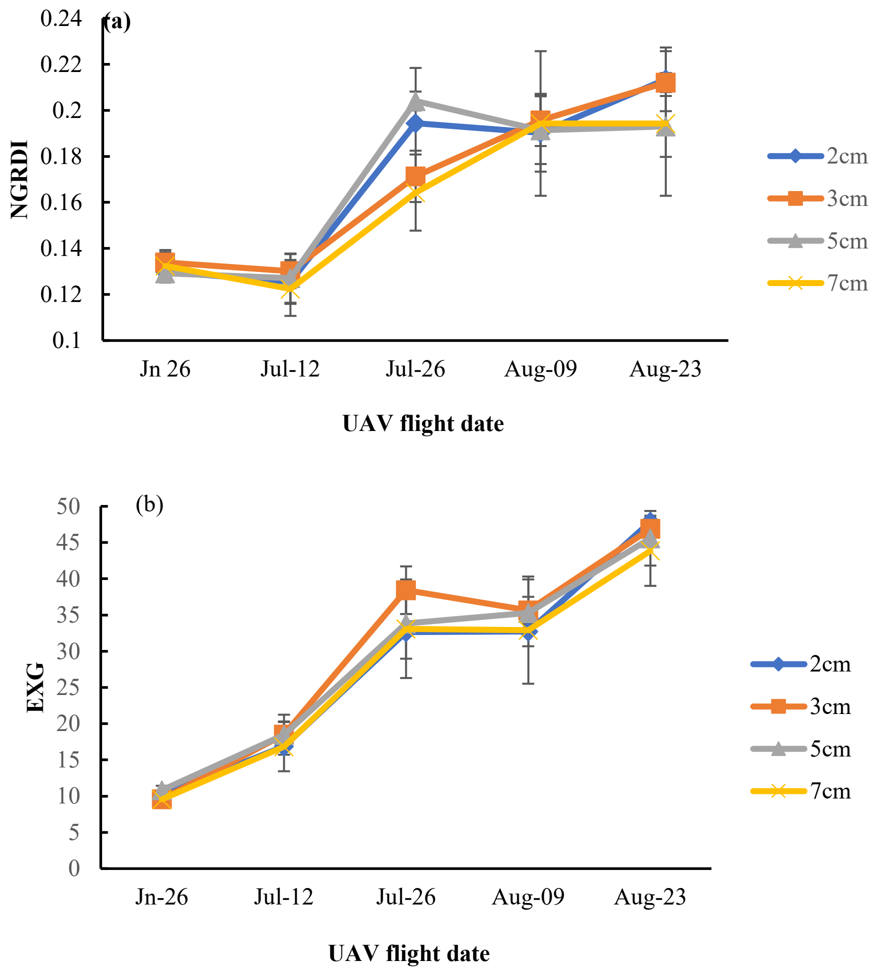
This observation was in accordance with what was generally observed in the okra field. However, from the generated data (Figure 3), for some experimental treatments, especially, 2 cm - ExG and 5 cm – NGRDI, there was little drop in the pattern of growth at the early maturity stage of the plant (9th August). This could be attributed to some pest attack on the plants some days prior to the date of flight (or growth stage). It was observed that the leaves had some pests boring holes in some leaves and this might have affected the estimation of the VIs.

The analysis of variance conducted showed that there were no significant differences among the treatments ($p>0.05$) for both indices at all stages of growth presented for the image-based data in this study. Nevertheless, it could generally be observed that at 2 cm and 3 cm sowing depths, there were generally gave better leaf growth. It was also observed that, sowing at the deepest treatment of 7 cm gave the lowest VIs.



(a) NGRDI and (b) ExG at various growth stages

Figure 2 Maps of vegetation indices



(a) NGRDI (b) ExG

Figure 3 Vegetation indices at different growth stages under varying sowing depths

Table 2 shows the mean LAIs at the growth stages for the plants sown at different depths. The analysis of variance results for the ground truth LAI data showed significant differences among the treatments on the 26th July (*p*=0.047), 9th August (*p*=0.00) and 23rd August (*p*=0.00) which represent the crop development, early maturity and late maturity stages of the plant respectively. The results from the pooled analyse indicates a similar trend for the VIs except for the 5 cm depth of sowing at the early and late maturity stages where the trend changed, making the highest recording to be observed in 5 cm treatment instead of 3 cm depth of sowing. Zhou et al. (2017) reported a strong relationship between observed image-based UAV values and ground-based data for estimating LAI at the early and mid-stages of crop development. This could account for the differences observed in UAV based data and ground-truth LAI at the early and late maturity stages.

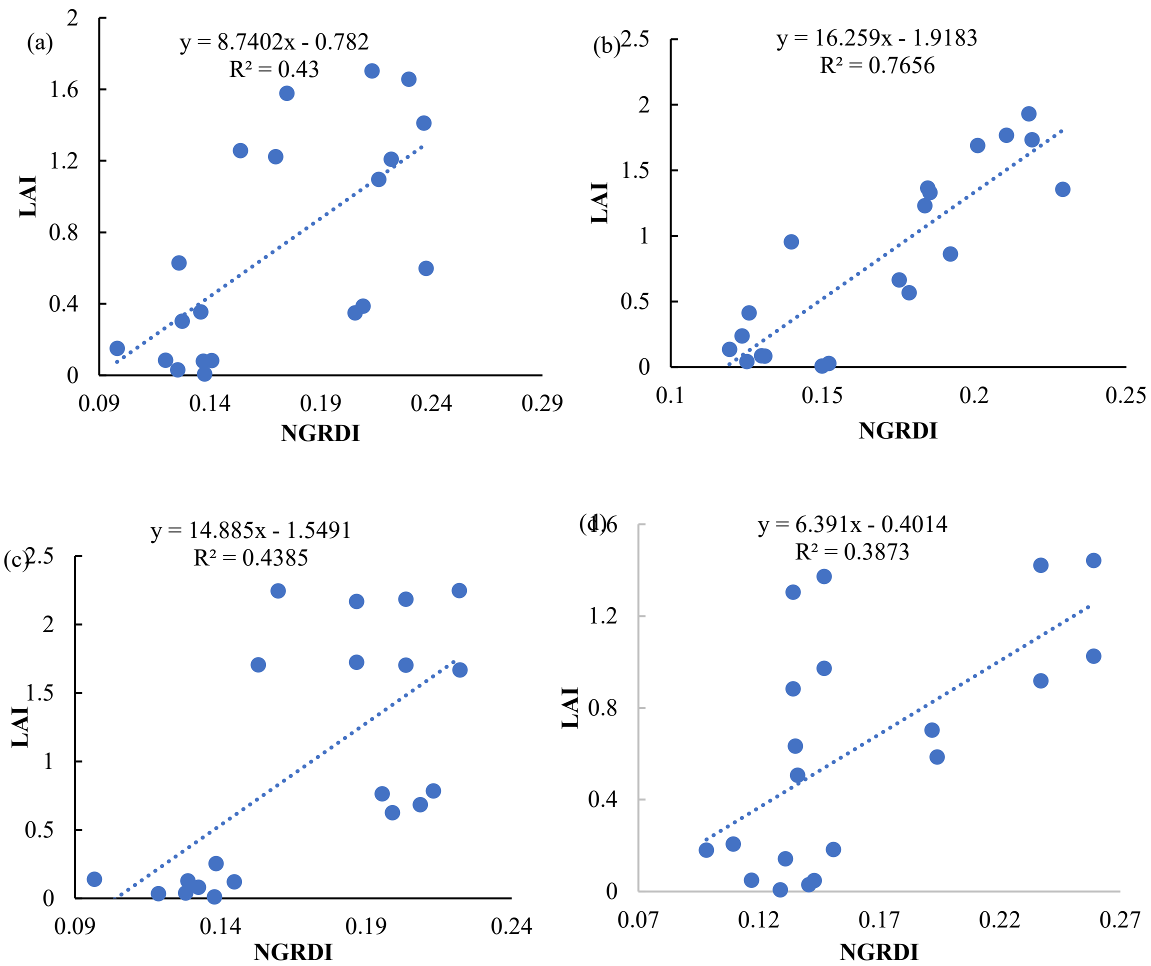
Table 2 The variation of LAI at different growth stages under varying sowing depths

Growth Stage	LAI at 2cm	LAI at 3cm	LAI at 5cm	LAI at 7 cm
Seedling stage(June 26)	0.051±0.037	0.054±0.054	0.041±0.030	0.033±0.020
Crop initial stage (July 12)	0.223±0.127	0.202±0.164	0.161±0.062	0.179±0.026
Crop Development stage (July 26)	0.492±0.142	0.761±0.178	0.714±0.073	0.608±0.083
Mid-stage/Early maturity stage (August 9)	1.197±0.070	1.320±0.061	1.700±0.023	0.950±0.062
Late maturity stage (August 23)	1.588±0.129	1.779±0.106	2.212±0.041	1.385±0.062

Note: Values represent mean ± standard deviation

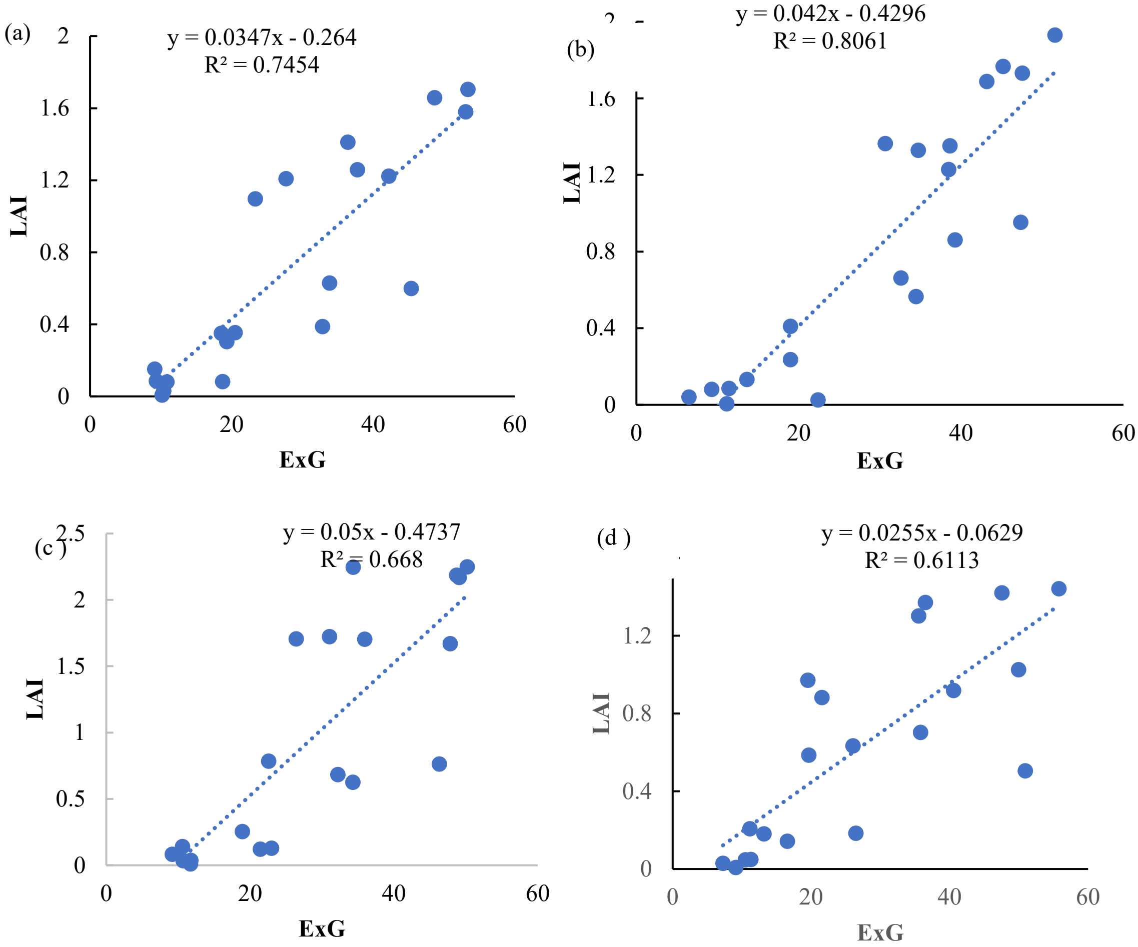
3.2 Relationship between VIs and LAI for different sowing depths

Figures 4 and 5 present the relationship between the UAV image-based VIs and the manually determined LAIs over the whole period of growth for the respective treatments (2 cm, 3 cm, 5 cm and 7 cm depths). Thus, all the experimental tests were combined into one data for each of the treatments separately for the two indices. It consistently showed that at 3cm depth of sowing okra seeds, a strong regression (R^2=0.77 for NGRDI and R^2=0.81 for ExG) was established for predicting the LAI from the imaged based data. Again, the weakest regression was observed for 7cm sowing depth (R^2=0.39 for NGRDI and R^2 = 0.61). According to Aikins et al. (2011), sowing depth significantly affect the leaf growth of soybean. This could influence the photosynthetic activities of the plants and general crop productivity and yield. The authors reported that sowing seeds too deep in the soil negatively influence the development of the crop. Other work by Singh et al. (2013) also confirmed that increasing sowing depth influences the LAI of wheat. They reported that at a sowing depth of 2 cm, the highest mean LAI was 2.87 while the lowest (2.66) was recorded for a greater depth of 6 cm. They further reported a similar trend for the yield of the crop. The reason for crop doing better in moderate depths could be that it ensures good germination, rapid emergence and good performance as the seeds must be planted in an environment that ensures the availability of nutrients and water from the soil. Opande et al. (2017) also buttressed the need to sow seeds at a moderate depth for better plant leaf growth and general performance.



(a) 2cm, (b) 3cm, (c) 5cm, (d) 7cm

Figure 4 Relationship between NGRDI and LAI for sowing different depths of throughout the growth period

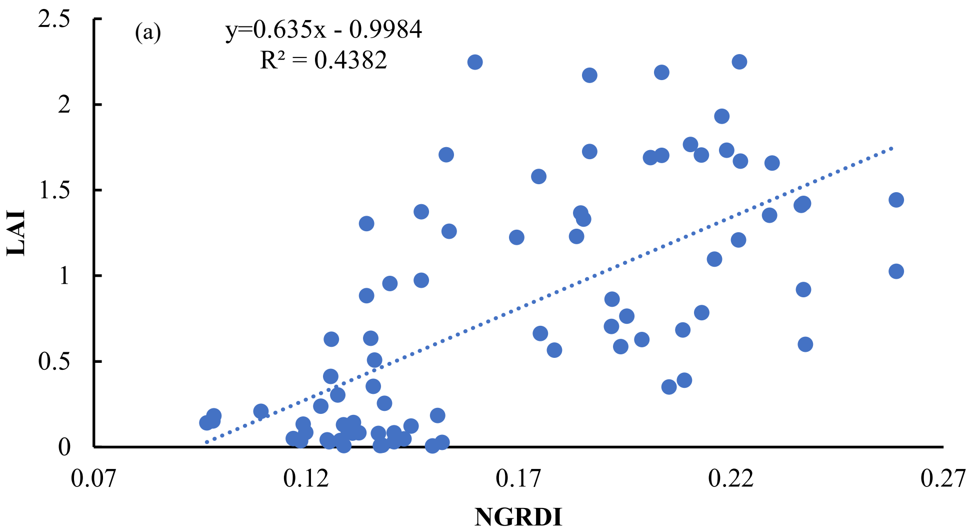


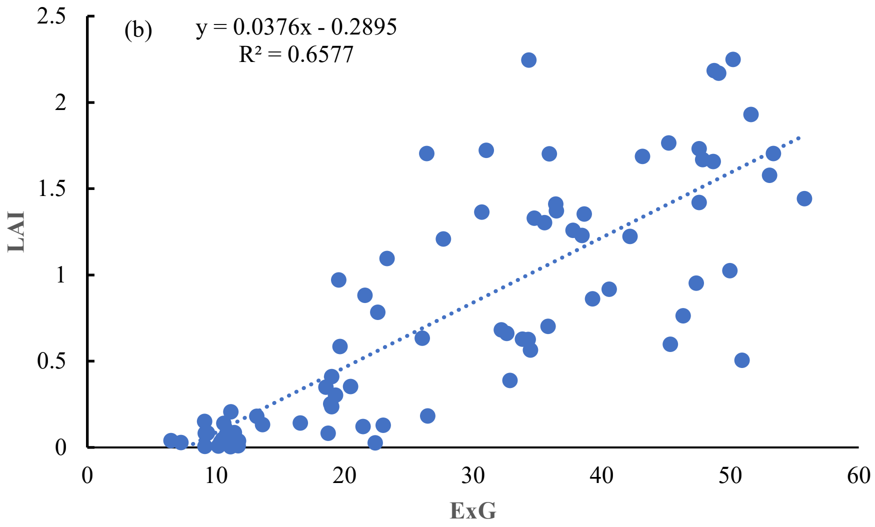
(a) 2cm, (b) 3cm, (c) 5cm, (d) 7cm

Figure 5 Relationship between ExG and LAI for sowing different depths throughout the growth period

3.3 Comparative assessment of the VIs in predicting LAI

An overall regression graph was plotted to assess how the indices effectively or otherwise predict the LAI of okra in the pooled data. From Figure 6, a strong relationship was found for ExG-LAI (R^2=0.68) while a relatively weaker one was observed for NGRDI (R^2=0.44). This gives an indication that the ExG index predicts the LAI better than NGRDI.





(a) NGRDI - LAI (b) ExG-LAI

Figure 6 Comparison of VIs and LAI

Multiple linear regression was carried out to investigate whether the VIs could predict LAI. The results showed that more than 65% of the variation in LAI can be explained by the predictor variables ExG and NGRDI. Overall, the regression model was found be significant (p=0.000). On the other hand, it was found that the ExG was statistically significant (p=0.000) whiles the NGRDI was not (p=0.197) The final predictive model was:

LAI = -0.509 +0.03317ExG +2.07NGRDI

Since LAI plays a key role in the biological and physical processes of plants (Yao et al., 2017), in this work, it is more likely to predict it using the ExG than NGRDI for okra plants. This confirms that between the two, ExG is a better option. From the works of Yang et al. (2015) and Hamuda et al. (2016), the ExG is often able to better extract plant green features against the bare soil especially in the presence of other residues on the surface of the soil. This is explaining the reason behind this observation and hence, ExG, may be a good index for estimating okra plant parameters from aerial view.

3 Conclusion

Overall, the study has demonstrated the possibility of estimating the LAI of okra using VIs obtained from a low-cost UAV imagery under four sowing depths. It could be concluded from the study that sowing the okra seeds at 3 cm depth resulted in the best vegetation growth and LAI determination. The poorest observation was with sowing okra seeds at 7 cm depth. Also, comparing the two VIs data extracted from the UAV imagery, the ExG showed a better potential for estimating the LAI compared to NGRDI. Future work could look into assessing their efficiencies in predicting okra yield.

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