Real time estimation of leaf area index and groundnut yield using multispectral UAV

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Abstract: The use of Unmanned Aerial Vehicles (UAVs) is becoming very common for last few years for monitoring agricultural crops efficiently. Low altitude remote sensing (UAV) provides people with high temporal and spatial resolution for non-destructive, accurate and timely estimation of biophysical parameters like Leaf Area Index (LAI), crop growth, plant biomass and final crop yield. Collection of the data by UAV helps to reduce errors and it fills the biasness on an observational scale in precision agriculture. The main objective of this study was to estimate real time LAI and yield of groundnut crop based on Normalized Difference Vegetation Index (NDVI) using low cost multispectral UAV. A field experiment was set up with three different groundnut cultivars (V1= BARD-479, V2 = Chakwal-2011 and V3 = Chakwal-2016) with three replications. Field data collection regarding LAI was performed in 2019 at two different growth stages (2-3 leaf stage and Peg formation stage) of groundnut on PMAS-Arid Agriculture Research Farm (Knoot), Pakistan. Final yield was calculated at the time of crop maturity. In this study, low cost UAV platform was established with DJI Phantom 4 pro and Parrot Sequoia Sensor to develop a multispectral UAV system used as the survey platform. A Parrot Sequoia camera was mounted on the UAV used as the remote sensor. The sensor provided the information in five narrow bands including Red, Blue, Green, Near infrared (NIR) and Red Edge. The processing of UAV images was performed in the Python environment and NDVI images were created. Then regression model was performed to compare the NDVI data with the LAI and final yield of groundnut crop. The results indicated that the highest value of R^2 = 0.93 was found with NDVI and LAI at peg formation stage while value of R^2 = 0.59 was at 2-3 leaf stage. The strong and positive relationship was found between LAI and yield (R^2 = 0.97). There was also a strong and positive relationship between NDVI and yield of groundnut with value of R^2 = 0.92. The study showed that low cost multispectral UAV can be effectively used for real time estimation of LAI and groundnut yield nondestructively and accurately. The study results show that this low cost multispectral UAV platform (DJI Phantom 4 Pro with Parrot Squoia) is robust in management decisions of agriculture such as effective fertilizer application, growth monitoring, and yield estimation accurately and timely based on the vegetation indices. This study also proved the low cost multispectral UAV practicability in estimating plant biophysical parameters at a small field experiment scale reliably.

Keywords: vegetation indices, UAV, LAI, yield, multispectral camera, NDVI, groundnut, growth stages
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1 Introduction

Groundnut (*Arachis hypogaea* L.) belongs to legume or bean family and growing in the areas of warm and tropical regions of the world. Groundnut is an important edible oil crop (50 percent) and contains number of minerals (Savage and Keenan, 1994). Being a nitrogen-fixing crop, it is an important rotation crop in cropping system which usually requires a small amount of nitrogen and

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improves the soil fertility particularly under rainfed condition. India, China, and the United States are the leading producers of groundnut and grow about 70% of the world groundnut crop (Hammons, 1973). In Pakistan it is cultivated on an area of 817000 hectares with a lump sum production of 81300 tons and results in the average yield of 995 kg per hectare. Rainfed areas of Pakistan hold the cultivation of groundnut for about 70% and the main areas of cultivation include the districts of Attock, Chakwal and Rawalpindi (PARC, 2013).

Crop yield estimation plays a very important role in regional scale (Van et al., 2013). Crop yield estimation holds a profound place in economy development (Dalezios et al., 2001). Traditional methods of yield estimation are based on destructive samplings which are laborious and time consuming and labour intensive. Hence the production estimates which are based on crop acreage estimates are also not completely reliable. It is predicted that 795 million people in the world still live without sufficient supply of food (FAO, 2015). Improving food security risk and terminating hunger are primary goals in the 2030 plan of the United Nations (United Nations, 2015). It helps in the timely and vital predictions of the information that is essential for the use in effective evaluation of food security. A major challenge in addressing food security issues is yield estimation, which is the ability to accurately predict crop yields prior harvest. In developing countries agricultural monitoring and crop yield estimation can improve food production and reduce food security risks (Dodds and Bartram, 2016; Carvalho, 2006; Vermeulen et al., 2012).

Remote sensing technology is based on the multispectral cameras, which provide single bands for calculation of broadband vegetation indices (Candiago*et al*., 2015; Naqvi et al., 2018). Several studies have developed good correlation among vegetation indices and crop yield estimation surveys (Singh et al., 1992; Tahir et al., 2013; Din et al., 2019; Naqvi et al., 2019). Visible, near and thermal infrared spectral bands of remote sensing data have been used to track the phenology and infer biophysical variables of canopy (Rodriguez et al., 2004; Tahir et al., 2013; Li and Shao, 2014; Tahir et al. 2015). Vegetation Indices are algebraic arrangements of a number of spectral bands, designed to highlight vegetation vigor and vegetation properties i.e. chlorophyll content, canopy biomass absorbed radiation (Candiago et al., 2015; Tahir et al., 2015). NDVI which is based on satellite imagery is a beneficial tool for monitoring and measuring of environmental situations such as dry land, land degradation, crop simulation, yield estimation, etc. (Dutta et al., 2015; Naqvi, et al., 2019).

With the modern advances in the aircraft, computing, communication technologies; unmanned aerial vehicles (UAVs) can be used for increasing operations of extensive range of environmental and agriculture monitoring applications (Bendig*et al.*, 2014; Tahir et al., 2018). The acquisition of aerial imageries by Unmanned Aerial Vehicles (UAVs) has observed a rapid increase in the last few years. UAVs having a total weight of less than 5 kg are interesting substitutes for agricultural applications. UAVs are much more flexible and weather independent as compared to standard airborne aerial surveys. As a result, micro-UAV surveys pave the way for affordable, up to date and accurate geo-information. Reconstruction of detailed models has been ensured by high resolution imageries that have attained up to one hundred meters distance from the ground. The spectrum ranges from low cost consumer grade multispectral cameras to complex high-end multi-sensor systems. For typical photogrammetric tasks mini and micro UAVs (unmanned aerial vehicles) in combination with cost-efficient and light-weight RGB cameras have become a standard tool over the last few years. The low-altitude remote sensing acquisition method based on UAV is one of the fast and valuable agricultural parameters detection methods (Wang et al., 2019). The use of UAV low-altitude remote sensing technology to build a near-field agricultural monitoring system is a useful supplement to the traditional farmland information acquisition technology (Wang et al., 2018).

In most of the Asian and African countries, the farmland crops are planted in a complex, multi-variety and small-scale environment. In such a relatively small area, it is necessary to achieve accurate data collection of UAV-based field crop information, and multi-rotor UAVs are with capable of vertical take-off and landing. The exceptional advantages of hovering are more beneficial to obtain clear and accurate field crop information (Tahir et al., 2018; Wang et al., 2018; Wang et al., 2019). Therefore the current study is planned to use of low cost multispectral UAV (DJI Phantom4 Pro) for real time monitoring groundnut biophysical characteristics accurately and timely to manage the food security issue and to replace the conventional method for crop estimation which are time consuming, labour intensive and expensive.

2 Materials and methods

2.1 Experimental site and experiment detail

The proposed study was carried on University Research Farm (Knoot) of PMAS-Arid Agriculture University Rawalpindi, Pakistan located at the border of the District Rawalpindi and District Chakwal. The experimental site lies between 33˚11732 North, 73˚0143 East with an elevation of 521 m (Figure 1). About 70% people of these districts directly and indirectly depends on agriculture. There is no irrigation system present in this area and all agriculture is mainly depends on rainfall. These districts are famous for wheat, barley and groundnut production.

A field experiment was conducted with three different groundnut cultivars (BARD-479, Chakwal-2011 and Chakwal-2016) planted on April 17, 2019 with three replications. The experiment was laid out in randomized complete block design (RCBD) with split plot arrangement having six rows per plot. The net plot size was 4 m×2.7 m with row to row spacing 45 cm. All the cultural practices were applied uniformly in all treatments. Weeds were removed manually during vegetative growth of the groundnut crops.

2.2 Field data collection

2.2.1 Leaf Area Index measurement using BioLeaf software:

Field data collections regarding leaf area index were performed in 2019 at two different growth stages of groundnut (2-3 leaf stage and Peg formation stage) on PMAS-Arid Agriculture Research Farm (Knoot), Pakistan. In this study, groundnut canopy images were taken by DJI Phantom 4Pro UAV in RGB at two different growth stages of groundnut crop (2-3 leaf stage and Peg formation stage). Three RGB images of each plot were collected using DJI Phantom 4 Pro UAV. Then these RGB images were further processed in BioLeaf software for determining LAI of each plot. Then, mean value of LAI was calculated of each plot.

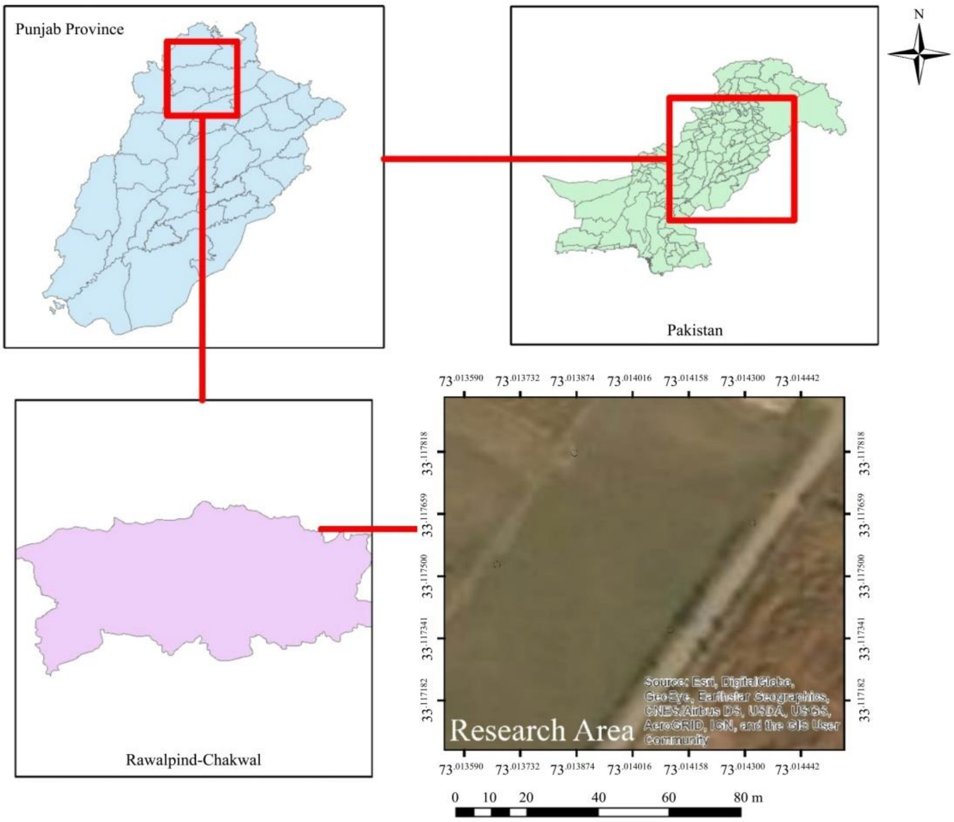

Figure 1 Map of the experimental site

BioLeaf is an open source software which is made to be compatible with android and windows to evaluate images based data for LAI and % defoliation based on the area of the image. Image obtained via any source could be processed to analyze for the strength of vegetation. Image is stored in JPG, JPEG or PNG formats. Ctrl+O short key was used to open image in software window and click the analysis icon. The image with LAI and defoliation readings as a result of processing is generated. Software is good in differentiating between green portion of plants and other image portions such as soil etc. (Machado et al., 2016).

2.2.2 Yield data

At the maturity stage of groundnut, we collected groundnut yield data of each plot and took the average. First of all we selected an area of 2 m^2 in the field, and then we uprooted all the plants of groundnut which falls in these areas of 2 m^2. After this we weighed the harvested pods of respective plants and converted the yield into kg per hectare.

3 Multispectral UAV remote sensing data

3.1 Low cost multispectral UAV (DJI Phantom 4 pro) platform for capturing images

The Unmanned Aerial System (UAS) has been transformed nowadays in affordable and flexible solutions that can provide images at a high spatial, temporal, and spectral resolution. In this study, low cost UAV platform was established with DJI Phantom 4 pro and Parrot Sequoia Sensor to develop a multispectral UAV system to use as the survey platform (Figure 2). This aircraft is an affordable small sized four-axis quadrotor aerial vehicle with a flight control system, and Wi-Fi communication capabilities. The specifications are: 1280 g of weight, 4480 mAh of battery capacity, a maximum speed of 15 m/s, and maximum flight time of around 25 minutes. A Parrot Sequoia Sensor was mounted on the DJI Phantom 4 Pro UAV used as the remote sensor (Figure 2).

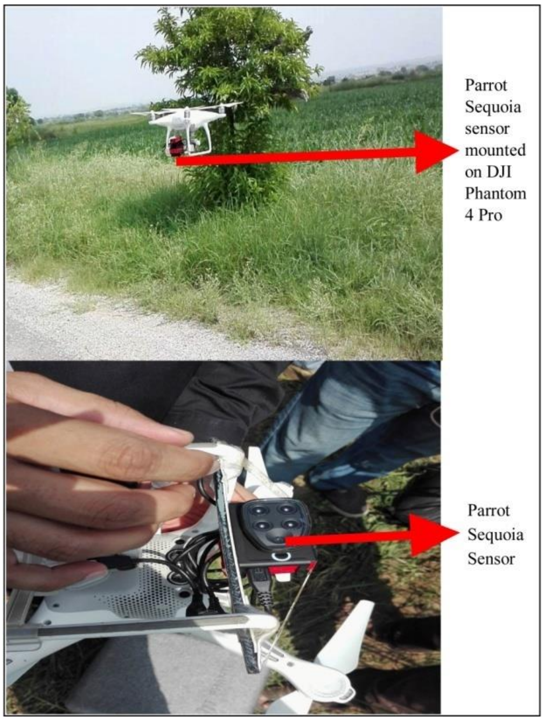

Figure 2 The DJI 4 pro UAV mounted with Parrot Sequoia Sensor

The DJI Phantom 4 Pro has 16 MP RGB sensor while parrot sequoia sensor consisted five narrowbands including green, blue, red, near infrared and red edge and synchronized 1.2 MP monochrome sensors. It provides an automatically calibrated camera because of the sunshine module and has an integrated GPS/GNSS to locate the camera when photos are being taken. In addition, it was connected with computer/smart mobile device wirelessly to the UAV and the remote camera via Wi-Fi to control the drone and to obtain real-time transmission of images and videos

(Xue et al., 2019).

3.2 UAV images processing and analysis

The images were collected in RGB and NIR bands through DJI Phantom 4 Pro UAV at two different growth stages of the crop (2-3 leaf stage and Peg formation stage) throughout the growing season. These images were processed through different software. Spyder (Scientific Python Development EnviRonment) Version 3.7, software was used to process the UAV arthomosaic images of RGB and NIR. First we stitched all the images to built the mosaic images of the whole experiment field and then to create the NDVI images at different growth stages of groundnut crop using the codes in the Spyder software. NDVI was calculated according to the equation (1) suggested by (Rouse et al., 1974). NDVI values were also derived to develop regression model with LAI and yield for the groundnut crop. ERDAS and Arc GIS software were used for image analysis and processing.

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

3.3 Statistical analysis and mapping

Statistical analysis was performed to assess and establish relationship between ground parameters and UAV derived parameters by using XLStat. Different graphs were drawn and regression models were performed to find relationship between ground-truthing data of LAI and yield with UAV derived indices of NDVI. Maps of different parameters were developed by Arc GIS software.

4 Results and discussion

4.1 Leaf Area Index measurement nondestructively using BioLeaf software

Arthomoasic RGB images were obtained from the multispectral UAV (Figure 3) of the groundnut of each experimental field.

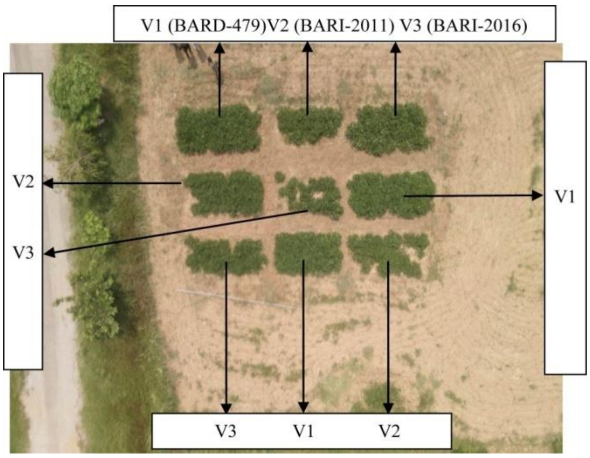

Figure 3 Arthomosaic image of the whole experiemental field with three groundnut cultivars

From these images LAI was non-destructively calculated using BioLeaf software. The images collected by the UAV were uploaded and processed cultivar wise in BioLeaf software. After processing the images in the Bioleaf software, the images were showed in black to red colour range. The black colour represents the vegetative parts while the red colour shows non-vegetative parts of the crop indicated as defoliation percentage. The results showed that highest LAI was obtained with cultivar V1 (BARD-479) with mean value of LAI was 6.0 (Figure 4), followed by cultivar V3 (Chakwal-2016) with mean value of LAI 5.2 while the lowest mean value of LAI was 4.3 in cultivar V2 (Chakwal-2011).

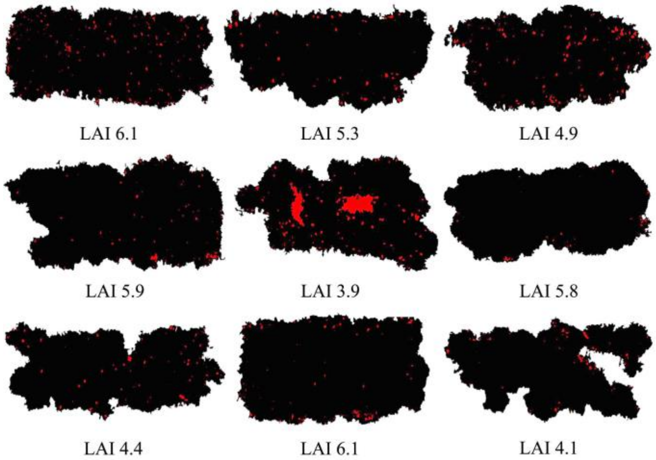

Figure 4 LAI measurements of different groundnut cultivars using BioLeaf software

4.2 NDVI map of groundnut crop

Normalized difference vegetation index values varied at different growth stages throughout the season. The NDVI value ranged from 0.029 to 0.42 at 2-3 leaf stage (Figure 5) while the NDVI value ranged from 0.3 to 0.76 at Peg formation stage (Figure 6). The highest value of NDVI 0.76 was found with cultivar V1 (BARD-479) while the lowest value of NDVI 0.31 was found with cultivar V2 (Chakwal-2011) at peg fromation stage. The lower value of NDVI of groundnut crop showed that crop was at early growth stsges, so less vegetation was present at this stage (2-3 leaf stage) and higher NDVI value correspondes that crop was at maximum vegetative atage (Peg formation stage) as shown in Figures 5 & 6.

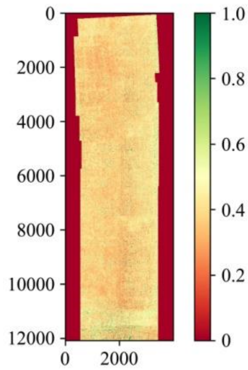

Figure 5 NDVI map of the groundnut crop at 2-3 leaf stage

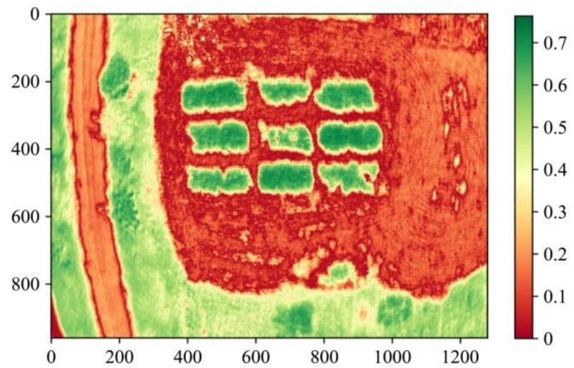

Figure 6 NDVI map of groundnut crop at Peg formation stage

4.3 Relationship between LAI and final grain yield of groundnut crop

The relationship was developed between LAI and ground truthing yield data of groundnut crop. There was a weak realionship between LAI and yield at the 2-3 leaf stage of groundnut crop with Coefficient of Determination R^2=0.33 (Figure 7). But at Peg fromation stage, there was positive and very strong linear relationship between LAI and groundnut yield with Coefficient of Determination R^2=0.97 which shown in Figure 8. The values of LAI and groundnut yield are directly proportional which gave the higher value of Coefficient of Determination R^2= 0.97. This relationship proved that LAI is strong plant biophysical charactiristic to determine the yield at Peg fromation stage in groundnut crop. We developed relationship of LAI with NDVI values derived from UAV images at different growth stages to further prove this concept.

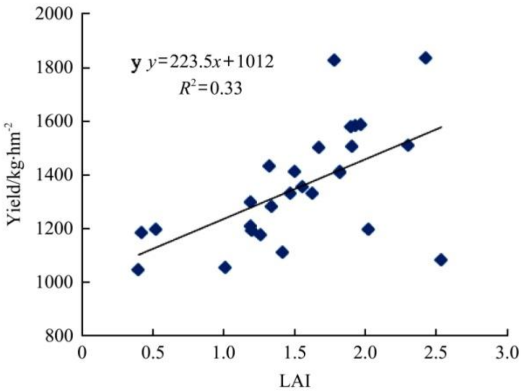

Figure 7 The Relationship between LAI and groundnut yield at 2-3 leaf stage

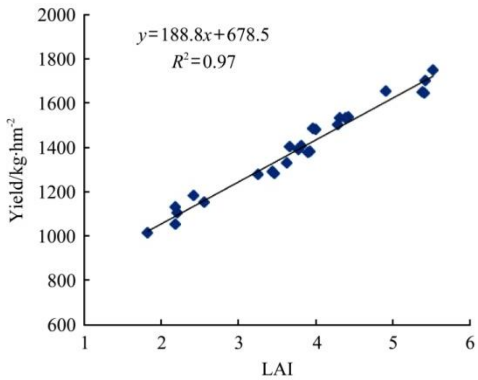

Figure 8 The Relationship between LAI and groundnut yield at Peg formation stage

4.4 Relationship between NDVI and LAI

The relationship was developed between NDVI and LAI of groundnut crop at two different growth stages. There is positive and linear relationship between NDVI and LAI at 2-3 leaf stage with Coefficient of Determination R^2 = 0.59 (Figure 9). The lower value of R^2 showed weak relationship between NDVI ad LAI at this stage. The maximum value of coefficient of determination (R^2=0.93) was found at Peg fromation stage of groundnut crop (Figure 10). This showed that there was positive and strong lear relationshp existed between NDVI and LAI. The higher value of R^2 demonstrated that groundnut crop was at its maximum vegetative stage (Peg formation stage) as shown in Figure 6. The higher R^2 value showed the fitness of model. This proved that LAI is more robust biophysical parameter of the groundnut crop to determine crop growth and yield ultimately.

4.5 Relationship between NDVI and groundnut final yield

The relationship was developed between NDVI and ground truthing yield data of groundnut crop at Peg formation stages. There is positive and strong linear relationship found between NDVI and final groundut yield data. The maximum value of coefficient of determination (R^2=0.92) was found which showed the fitness of model (Figure 11). There was weak relationship between LAI and yield at 2-3 leaf stage (Figure 7), therefore we did not develop relationship between NDVI and yield at this stage (2-3 leaf stage). The results show that yield can be determined accurately prior to harvest at Peg fromation stage in groundnut crop.

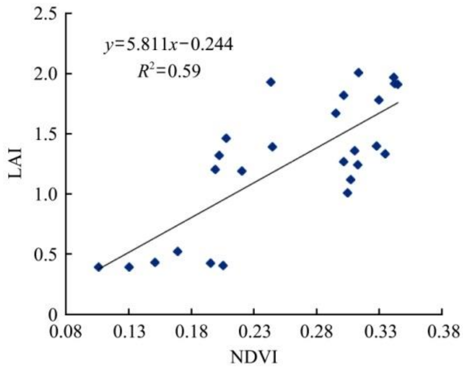

Figure 9 The Relationship between NDVI and LAI of the groundnut at 1-2 leaf stage

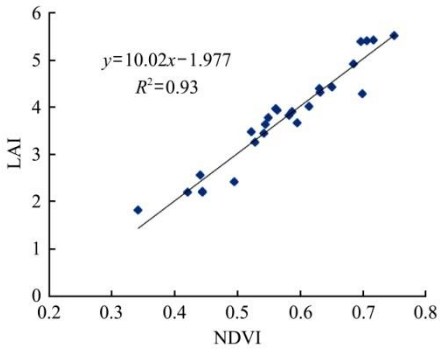

Figure 10 The relationship between NDVI and LAI of groundnut at Peg formation stage

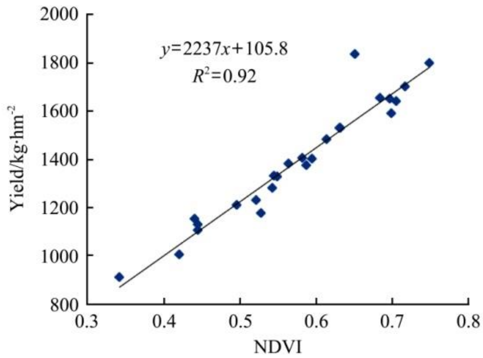

Figure 11 The relationship between NDVI and ground truthing yield data of groundnut

5 Conclusion

Low altitude remote sensing (UAV) provides us with a high temporal and spatial resolution for non-destructive, accurate and timely estimation of biophysical parameters like leaf area index (LAI), crop growth, plant biomass and final crop yield. The main objective of this study was to estimate real time LAI and yield of groundnut crop using low cost multispectral UAV based on NDVI. A field experiment was conducted with three different groundnut cultivars (V1= BARD-479, V2 = Chakwal-2011 and V3 = Chakwal-2016) with three replications. Field data collection regarding leaf area index (LAI) was performed in 2019 at two different growth stages (2-3 leaf stage and Peg formation stage) of groundnut crop. Final yield was calculated at the time of crop maturity. In this study, low cost UAV platform was established with DJI Phantom 4 pro and Parrot Sequoia sensor to develop a multispectral UAV system to use as the survey platform. This sensor provided the information in five narrow bands including Red, Blue, Green, Near infrared (NIR) and Red Edge. The processing of the UAV images was performed in the Python environment and NDVI images were created. Then regression model was performed to compare the NDVI data with the LAI and final yield of groundnut crop. The results indicated that the highest value of R^2 = 0.93 was found with NDVI and LAI at peg formation stage while value of R^2 = 0.59 was at 2-3 leaf stage. The strong and positive relationship was found between LAI and yield (R^2 = 0.97). There was also a strong and positive relationship that was found between NDVI and yield of groundnut crop with value of R^2 = 0.92. The study shows that low cost multispectral UAV can be effectively used for real time estimation of LAI and groundnut yield nondestructively and accurately. The study results show that low cost and small UAVs are robust in management decisions of agriculture such as effective fertilizer application, growth monitoring, and yield estimation accurately and timely based on the vegetation indices. This study also showed that small and low cost multispectral UAV has practicability to estimate plant biophysical parameters at small field experiment scale reliably.

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