



Spatio-temporal analysis of chickpea crop in arid environment by comparing high-resolution UAV image and LANDSAT imagery

N. Ahmad¹ · J. Iqbal¹ · A. Shaheen² · A. Ghfar³ · M. M. AL-Anazy⁴ · M. Ouladsmame³

Received: 15 April 2021 / Revised: 22 May 2021 / Accepted: 8 June 2021 / Published online: 29 June 2021
© Islamic Azad University (IAU) 2021

Abstract

Remotely sensed data play an essential role in environmental analysis and crop management. The arid agriculture region of Thal, Pakistan, is the major chickpea-growing region of the world. It was important to analyze the chickpea growth rate and yield with modern growing technology for better production in the changing climate. This study compared unmanned aerial vehicle (UAV) and Landsat imagery to monitor the crop growth and environmental parameters throughout the growing season. Twelve plots (2 × 2 m) were established in the field to monitor seven environmental parameters (plant height, number of pods and plant density, and final yield) for chickpea crop growth. A UAV drone mounted with Zenmuse X3 camera with four spectral was flown over the chickpea field on a biweekly basis to capture images with a spatial resolution of 1.86 m. The Landsat imagery (30 m spatial resolution) was also obtained, having the same UAV flight date. In spatio-temporal analysis, various vegetation indices, i.e., normalized difference vegetation index (NDVI) and soil-adjusted vegetation index (SAVI), were derived from UAV and Landsat imageries. The environmental impact parameters for crop growth were compared with the estimated final yield of chickpea crop. A coefficient of correlation ($r^2 = 0.67$; $p \leq 0.05$) between observed chickpea crop yield and UAV-derived SAVI was significant ($p \leq 0.05$). In comparison, a non-significant coefficient ($r^2 = 0.21$; $p \geq 0.05$) was found between NDVI derived from Landsat imagery with yield. The chickpea crop yield was analyzed by estimating simple linear regression between NDVI and actual yield of chickpea crop during 30–40 days before the harvesting period. The average difference between actual yield and predicted yield through SAVI-D and NDVI-L was 558.42, 553.12, 556.84 kg/ha, respectively.

Editorial Responsibility: Shahid Hussain.

✉ N. Ahmad
nahmad.ms17igis@igis.nust.edu.pk

¹ Institute of Geographical Information Systems, National University of Sciences and Technology, Islamabad 44000, Pakistan

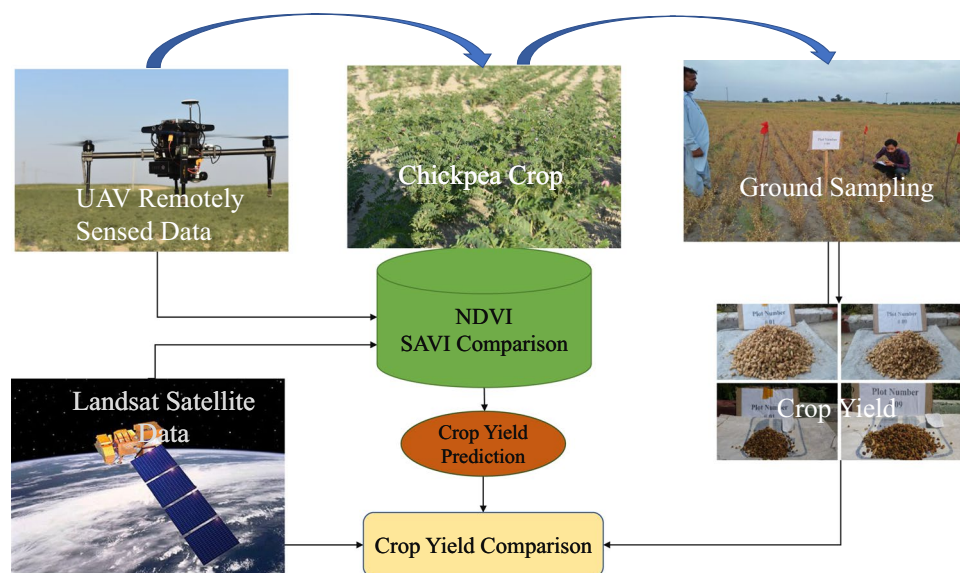
² Department of Earth Sciences, University of Sargodha, Sargodha 41000, Pakistan

³ Advanced Materials Research Chair, Chemistry Department, College of Science, King Saud University, P. O. Box 2455, Riyadh 11451, Saudi Arabia

⁴ Department of Chemistry, College of Science, Princess Nourah Bint Abdulrahman University, P. O. Box 84428, Riyadh 11671, Saudi Arabia



Graphic Abstract



Keywords Environmental impact · Vegetation indices · Crop yield · Unmanned aerial vehicle · Chickpea crop

Introduction

The remote sensing imagery (e.g., Landsat and Sentinel) has been extensively used in the agricultural analysis. However, it has temporal, spectral, and spatial resolution limitations. Crop monitoring through UAV-based sensors is now commonly used technology and an actual, fast, and beneficial method mostly in precision agriculture. Landsat satellite provides better results to estimate pre-harvesting crop yield. UAV is an emerging technology for the agriculture sector that helps to increase crop production and farm efficiency. Drones provide a quick and high-resolution image format view of crop fields to farmers for water stress, diseases, plant growth, plant health, and fertilizer monitoring. Unmanned aerial vehicle system has been recognized as an excellent tool to monitor crop temporal and spatial pattern throughout the growing season.

Satellite remote sensing using optical sensors helps to study the growth of plants and to calculate vegetation indices. NDVI calculated from different spatial resolutions (sub-5 cm to 30 m and 250 m) varies with scale. Aggregated NDVI values 30 m and 250 m were compared with Landsat 30-m products collected from a commercial vineyard in Victoria (Wang et al. 2017). Remotely sensed data provide an accurate estimation of crop yield. A comparison of two methods, (I) spatial yield estimation and (II) Landsat-based estimates, shows an error of 2.3%, while single field results show the accuracy of 13% by using satellite information.

Satellite-based method of estimating crop yield can be applied to other regions of the same crops, while hyperspectral sensors have more significant potential to show better results for early crop yield estimation (Bach 1998). Satellite-based spectral data and crop yield data of a small area of multiple variations are useful to estimate large-area crop yield estimation of any crop before its harvesting. Remote sensing satellite IRS-1B-LISS-II and crop yield data have been used for early crop yield estimation of Rohtak, District India, during 1995–1996 (Singh et al. 2002). Remotely sensed products like Landsat7 ETM+ provide a better tool to estimate pre-harvest crop yield production at a small scale, even at the district level. Crop yield estimation (rice crop) using remotely sensed Landsat7 ETM+ data was done using NDVI and RVI (ratio vegetation index) indices, and strong relationship of $R^2 = 0.92$ was found between observed and predicted values (Siyal et al. 2015). Accurate and timely information about any crop is important for farmers and policymakers. Manual collection of field data for the pre-harvesting forecast is expensive, and it takes time, whereas, by using remotely sensed data the timely and precise information was collected through efficient way. Study emphasized the use of MODIS-derived vegetation index for estimating wheat yield before 6 weeks of harvesting wheat crop in the Punjab Province of Pakistan.

The world population is increasing continuously day by day, and the agriculture sector is facing problems (labor cost, irrigation cost, diseases, applications of fertilizers) (Shaheen and Iqbal 2018). The drone is an emerging technology in



the agriculture sectors and has the potential to solve significant challenges. Bird controls, crop monitoring, irrigation, and soil analysis are the major applications of drone (UAV) technology (Ahirwar et al. 2019). Innovative technologies, especially UAV, make inordinate input in the improvements of agriculture. The study elaborates on the applications of UAV in agriculture. Using UAV DJI Phantom3 digital models, analysis and projections were derived (Hovhannisyan et al. 2018). The use of drones from the military, industry, and agriculture sectors is increasing due to the development of high-quality sensor technology in the market. Research work aimed to achieve and highlight the beneficial usage and implementation of drones in agriculture for deep observation, crop monitoring, and prevention of crop damages from any diseases or water stress (Puri et al. 2017).

The use of UAV for rapid image acquisition is rising. The workflow of the image acquisition completes in three phases: (I) preflight planning, (II) UAV flight and image acquisition, (III) image pre-processing. The image processing method was done and then NDVI was applied to the acquired images of UAV. Due to high spatial resolution, the difference between bare soil and vegetation can be efficiently observed in results (Torres-Sánchez et al. 2013). Commonly, high-resolution UAV imagery is used to study crop variations. UAV imagery provides a better solution for precision agriculture to monitor crops (Zhang and Kovacs 2012). Unmanned Aerial Imagery (UAI) is a reliable source to monitor crops and to calculate vegetation indices. UAV-based remote sensing for crop monitoring is a well-built method for crop yield prediction. High-resolution UAV imagery was used to access the vegetation traits and associate the link between yield and canopy NDVI. A high correlation ($R^2 = 0.49$) was found between UAV-NDVI and Grain Yield under full irrigation while ($R^2 = 0.14$) under limited irrigation (Hassan, 2019). UAV-based image analysis is an optimistic tool to monitor crop phenotyping at the crop's growing stage. High-resolution UAV imagery was used to access the crop emergence pattern. Results show that tomato crop emergence pattern through RGB imagery taken from UAV was highly correlated $R^2 = 0.96$ with the results of crop emergence pattern (Li et al. 2019). Drones are the best and low-cost image acquisition instruments that provide quick, high resolution for crop evaluation. A study was conducted to highlight the cheapest method of crop health monitoring and vegetation stress by accretion through UAV drone. NDVI was applied to the drone data for vegetation health monitoring (Mahajan and Bundel 2017). Using UAV for precision agriculture, ten varieties of wheat crops in the south west of France were monitored. Derived vegetation indices were relevant to vegetation analysis and established a relationship between LAI and NDVI (Lelong et al. 2008). UAV is a time-saving approach in remote sensing for crop monitoring and yield assessment. UAV technology mounted

with different sensors provides the best way to predict crop yield prediction. Rice yield estimation was done by UAV imagery, at a height of 300 m using UAV B, G, R and NIR band imagery (Zhou 2017). Real-time feedback of crops is possible through UAV providing excellent quality imagery with good spatial and temporal resolution. The present study emphasizes the potential use of UAV for crop canopy cover and NDVI during the growing season (Putra et al. 2021). Plant height, LAI, and NDVI were correlated on weekly basis. Coefficient of determination was $R^2 = 0.72$ between LAI obtained from ceptometer and canopy cover estimated from UAV imagery (Enciso, 2019). UAV technology has flexibility to capture high-resolution imagery by utilizing lesser time. Crop nutrients contamination, crop growth monitoring, diseases, and pests monitoring are carried out using UAV imagery (a wide and quick application of remote sensing). UAV technology has a wide range of perspectives in the agriculture sectors (Jia et al. 2016).

Remotely sensed data provide valuable information for crops. Using vegetation indices, comparison of Sentinel-2 imagery and UAV imagery was done for the vineyard field. NDVI results obtained from Sentinel-2 satellite and UAV imagery showed that UAV imagery showed greater variability within the fields than the Sentinel-2 dataset (Khaliq et al. 2019). Agriculture monitoring and early harvesting crop yield estimation through remote sensing are an efficient tool, and it depends upon the resolution and scale of the remotely sensed data—satellite data used especially for periodic monitoring of crops. A study was conducted to compare the crop pattern through Landsat and UAV imagery. Correlation between Landsat and UAV indices varies within a range of R^2 of 0.5–0.7. UAV imagery provides better spatial resolution results within the fields for variable rate applications (Lukas et al. 2016). Tattaris et al. (2016) used a low-flying UAV and satellite-based remote sensing techniques, to compare crop temperature and NDVI for crop improvement (Tattaris et al. 2016). Precision agriculture is a better option for the appropriate results of crop production. The study emphasizes the use of UAV for precision agriculture. Comparing Landsat8 datasets and drone imagery shows different results for both datasets because of small-scale and large-scale areas with low and high spatial resolution. However, agriculture monitoring through UAV for large-scale crops is difficult but saves time (Murugan et al. 2017). NDVI is a better tool to detect yield variations within the field. The yield compared with the NDVI coefficient of correlation obtained between NDVI and yield was 0.71 and 0.67 (Gallego et al. 2015). High-resolution UAV images were used to estimate LAI and compare it with WorldView-2 imagery (WV2). Three indices (Av, Vs, Sc) were calculated using UAV and WV2 to predict the plot level (10×10 m) LAI. Results show the highest precision of WV2 AvNDVI ($R^2 = 0.77$) whereas ScNDVI UAV ($R^2 = 0.81$) (Tian et al. 2017).



The main objective of the study was to use advanced technology (UAV imagery) in crop yield and crop health analysis during the growing season of chickpea crop. This is the pioneer study for chickpea crops using UAV (remote sensing technique), as drones provide quick use and easy access for small sections of crops with a different combination of sensors. Previously, different studies for other crops have used UAV imagery generally for yield monitoring. In agriculture, UAV images are useful for acquiring knowledge about agricultural production and tracking agricultural conditions. The visible light and near-infrared remote sensing images are captured in the experiment using a high-definition optical camera and a multi-spectral camera. UAV remote sensing is a useful tool for gathering knowledge about agricultural conditions. However, this study represents the use of UAV imagery and other real-time crops physical and climatic variables throughout the field and for different plots based on variations to monitor crop yield spatially within selected fields of chickpea, which is an innovative technique in this area. Crop yield was estimated using both UAV and Landsat imagery, and its comparison was made in the sense of yield. Vegetation indices are such that NDVI and SAVI were applied to the UAV and Landsat imagery. A detailed correlation between yield (dependent variable) and NDVI, SAVI, pH, soil temperature, number of plants, number of pods,

and plant height (independent variables) was performed to observe trend and efficiency with each independent variable. This is the first novel study of its kind for chickpea crop yield estimation using UAV (remote sensing technique) with related agro-climatic variables.

Materials and methods

Study area

The study area lies in Bhakkar district ($31^{\circ} 37' 22.8''$ N, $71^{\circ} 3' 45.36''$ E), which is part of the greater Thal desert (Fig. 1). The River Indus flows on the district's western side, but a very small area is irrigated through the canal system, while most of the area is rainfed. The majority of the soils (Shaheen et al. 2019) are sandy with dunes and rolling topography. The farmers mostly grow pulses and wheat in the Thal desert.

The climate of the area is arid with extremely hot summer ($45\text{--}50^{\circ}\text{C}$). The maximum, minimum, and average temperature of the region is 46°C , 10°C , and 28°C , respectively. The maximum, minimum, and average rainfall of the region is 186 mm, 2 mm, and 92 mm, respectively. The area receives most of the rainfall in February and March, corresponding

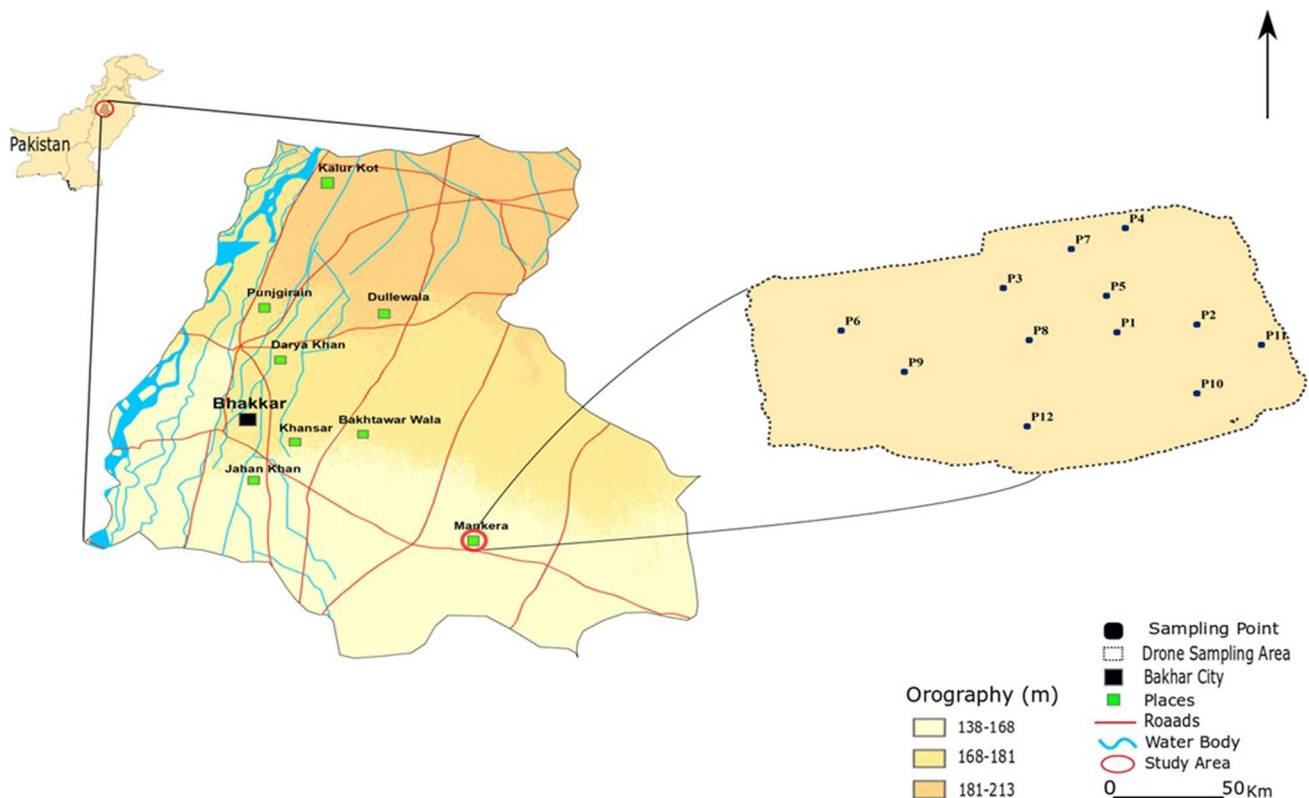


Fig. 1 Study area map showing plot areas in the Mankera district



to the pulses and wheat crops (Fig. 2). Pulses are sown in mid-November which corresponds to the driest period of the growing season. So conservation of soil moisture is one of the most critical determinants of crop success.

Chickpea crop cultivation

Chickpea is the most important crop for food and medicine (Rocchetti et al. 2020). The chickpea (*Cicer arietinum L.*) belongs to the Leguminosae family and is considered the most important region's most important economic crop. It is sown in mid of November and harvested at the end of March or early April. The chickpea has an 84.8–87.8% protein content (Boye et al. 2010; Paredes-López et al. 1991). Chickpea comes at a high rank in the worldwide production of pulse and legumes. Its starch and protein components add to nutritious and dynamic functionality. The chickpea crop young leaves and grains are used as a vegetable; the broken grain and stalks after harvest are used as fodder for animals (Bessada et al. 2019). The traditional management practices (fertilizer application, pest and insect control, etc.) were used to raise the crop throughout the growing season. The chickpea crop growth and yield are highly dependent upon the rainfall in this dry region. The average chickpea crop yield in the study area is ranged from 400 to 700 kg ha⁻¹. Annual crop yield data were collected from the Pakistan Bureau of Statistics department.

Drone and satellite imagery acquisition and processing

Aerial photographs and satellite images have proven to be successful in the efficient restoration and management of vegetation. The hybrid use of remote sensing and the drone has reduced the use of herbicides in agriculture with a challenge in improving plant health and cope with environmental threats while preserving output yield and quality of crops (Burggraaff, 2019). There were very few initiatives to reveal

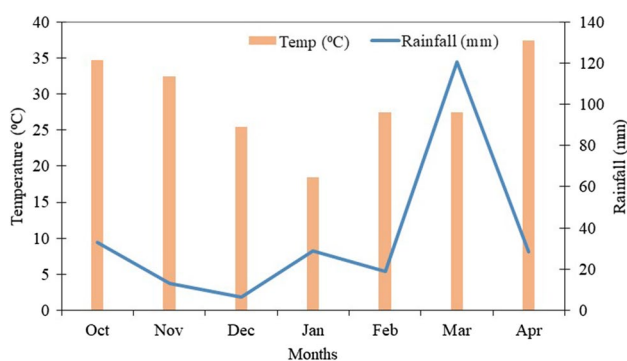


Fig. 2 Annual, monthly average temperature and rainfall in the study area

the potential of drone images. However, species-level mapping of chickpea was rarely conducted so far.

Unmanned aerial vehicle (UAV)

A DJI Matrice 100 with Zenmuse X3 camera (blue = 450 nm, green = 550 nm, red = 660 nm & near-infrared = 850 nm bands) was flown over the study area (25.5 ha) at an altitude of 53 m on February 26, 2019, to record high-resolution (1.86 m) imagery (Fig. 3). Raw images were captured around noon with no clouds with a wind speed of less than 10 km/h. The detailed specification of the drone flight is given in Table 1.

A total of 778 raw images were collected using an iPad DJI Go application (<https://apps.apple.com/us/app/dji-go/id943780750>) to conduct an automatic flight mission with an overlap of > 70%. Images were mosaic using SfM (Structure from motion) software (Maes et al. 2017). The inbuilt GPS in the UAV helps in the mosaicing of raw images. The software Structure from motion (SfM) software uses feature detection and feature matching algorithms to perfectly mosaic the images. Finally, after mosaicing, various vegetation indices were calculated. The detail of the image processing is highlighted in Fig. 4.

Satellite imagery (Landsat)

The Landsat satellite imagery with 30 m spatial resolution having was downloaded from the USGS site (<https://earthexplorer.usgs.gov/>). These images were used for comparison with the drone imageries. The acquisition time of the satellite imagery was Feb 20, 2019. The combination of two bands (red band 0.63–0.69 μm) 30 m and (near-infrared (0.77–0.90 μm) 30 m) was used in the study area for chickpea crop indices. With crop NDVI peak value for crop yield applications, they were fitted to quantify the model crop reporting difference (Roy and Yan 2020).

Three different approaches have been used in this study that includes high-resolution UAV, medium-resolution Landsat data, and field survey data. High-resolution UAV imagery has been used to check the crop variation pattern and for crop yield estimation. Landsat (30 × 30 m) dataset has been used to monitor the chickpea crop growth for the entire season. NDVI and SAVI applied to both Landsat and UAV imagery (Maddikunta et al. 2021), and correlation was applied to these NDVIs and SAVIs and the samples collected through the ground survey. Crop yield estimation was derived by using UAV-based SAVI and Landsat-based NDVI of the study area. The complete workflow of the entire study is given in Fig. 5. A modified technique was used to minimize the soil brightness effect of spectral vegetation indices using red and NIR wavelengths (Huete 1988). SAVI was calculated from the

Fig. 3 Chickpea field, DJI drone and its operation over the study area



Table 1 Drone Matrice 100 specification and other detail of data capture in the field

| S. No | UAV data specifications | Values |
|-------|-------------------------|---------------------|
| 1 | Drone type | DJI Matrice 100 |
| 2 | Camera type | Zenmuse X3 |
| 3 | Acquisition date | 20 Feb 2019 |
| 4 | Acquisition time | 1:30PM |
| 5 | Spectral bands | RGB & Converted NIR |
| 6 | Overlapping | > 70% |
| 7 | Flying altitude | 53.3(m) |
| 8 | Field of View (FOV) | 94° |
| 9 | Flight time | 60(min) |
| 10 | Coverage area | 25.5 (ha) |

reflectance measurements with values ranging from -1 to +1. SAVI as in Eq. (1). To monitor the field's vigor, SAVI was used (Messina et al. 2020).

$$SAVI = (NIR - RED) / (NIR + RED + L) \times (1 + L) \quad (1)$$

*where L is the soil brightness correction factor L = 0.5

To transform the ratio between red and NIR wavelength, NDVI was calculated using following Eq. 2. NDVI was used to assess the condition of sugarcane (Rahman et al. 2004). Basically, NDVI was calculated to compare the results of

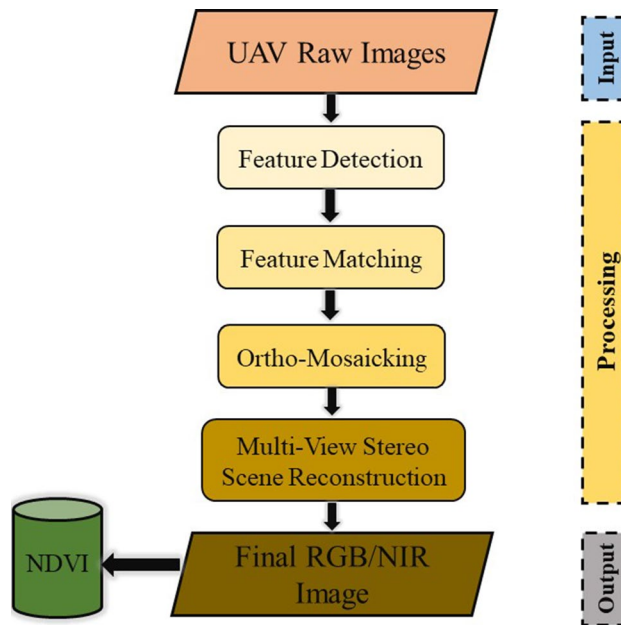
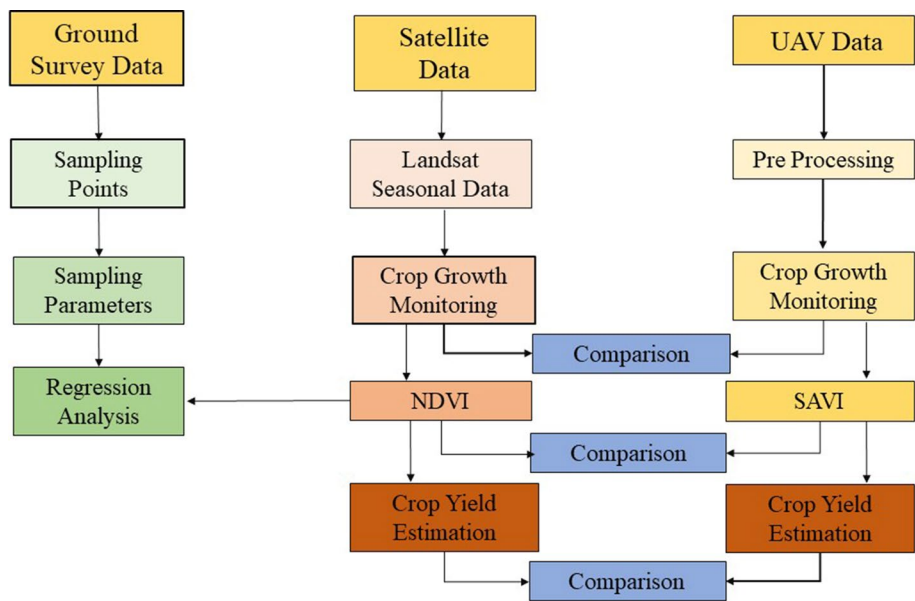


Fig. 4 Flowchart to represent pre-processing of drone imagery

SAVI obtained through UAV images. NDVI ranges from -1 to +1.

$$NDVI = (NIR - RED) / (NIR + RED) \quad (2)$$

Fig. 5 Complete methodology flowchart of the study area collected from each plot



Field survey for crop monitoring

Twelve plots with 2 × 2 m dimensions were randomly laid down in the selected field to accommodate variability in crop growth due to rolling topography. The chickpea crop growth variability may be induced by the availability of soil moisture to crop due to different aspects of the landscape (summit, shoulder, toe slope, etc.). Each plot had about 70–105 plants. Data on plant height, numbers of plants, numbers of pods, soil pH, and temperature, were recorded at the end of the growing season. Chickpea crop yield was recorded for each plot at the end of the growing season. Field survey through soil-moisture meter and GPS is shown in Fig. 6.

At the end of the growing season, data on numbers of plants, plant height, and numbers of pods per plot were collected. Chickpea crop yield was recorded per plot by taking the grains from the pods as depicted in Fig. 7.

Chickpea grain yield estimation from UAV(SAVI) and Landsat (NDVI)

Based on the combined use of a UAV and a multispectral sensor, it is determined that there is scope for yield prediction. The vegetation index, when paired with the red and near-infrared bands, was found to be a strong predictor of chickpea yield. The findings lay a theoretical foundation for using a multi-rotor UAV platform to track crop growth and investigate a scientific approach for improving yield estimation precision (Fu, 2020). The SAVI and NDVI indices stood out for their ability to forecast yield, with the highest values of these indices resulting

in the highest yield observed in the sector (Ashapure, 2020). Balaghi et al. (2008) predicted wheat yield by using NDVI, rainfall, and temperature datasets in Morocco. By using regression Eqs. (3) and (4), crop yield for the whole study area was estimated for SAVI (UAV) imagery (da Silva et al. 2020). The crop yield estimation was also analyzed using NDVI (Tiwari and Shukla 2020).

$$Y = ax + b \tag{3}$$

$$Y = (5596.1 \times Raster [SAVI]) + (93.57)$$

Predicted Yield = 1028 kg/ha.

While the actual calculated average yield for this study area is given by the following.

Actual Yield = 700 kg/ha.

Difference in Yield = Predicted Yield - Actual Yield.

1028 - 700 = 328 kg/ha.

Regression equation to predict crop yield for NDVI (Landsat) imagery is given by following

$$Y = ax + b \tag{4}$$

$$Y = (2272.9 \times Raster [NDVI]) + (223.99)$$

Predicted Yield = 711 kg/ha.

While the following gives actual calculated yield for this study area.

Actual Yield = 700 kg/ha.

Difference in Yield = Predicted Yield - Actual Yield.

711 - 700 = 11 kg/ha.



Fig. 6 Samples taken from the plots with the red color flag on the borders and collection of samples through GPS and soil-moisture meter within the field

Fig. 7 Pods collection from the bundles of chickpea plants collected from each plot and final yield



Results and discussion

Vegetation indices (NDVI, SAVI) derived from UAV and Landsat satellite imageries were used to study the chickpea crop growth variability and seasonal growth trend. Landsat image shows aggregate response, while UAV imagery

shows a single-pixel response. The high-resolution data were used to explore the vegetation biodiversity accurately. Chickpea crop variability trend within the plots using SAVI (UAV) and NDVI (Landsat) imagery is analyzed in multiple plot levels. There was a great difference between both the coefficient variation of UAV images and



that of satellite images when measuring the spectral resolution of the three spectral platforms, taking into account the bandwidth and resolution (Crusiol 2020).

Soil-adjusted vegetation index (SAVI) obtained from UAV

SAVI was analyzed to minimize the soil response in the imagery. As vegetation indices articulate the spectral response from pixels, so in this case, sand dunes affect the spectral response of vegetation due to high-resolution imagery. Both indices NDVI and SAVI were analyzed for UAV-based imagery. SAVI results were better than NDVI derived from drone imagery, so SAVI was used for relative comparison (Kopačková-Strnadová et al. 2021). The reddish and green color in the SAVI image (range 0–0.54 SAVI) analysis shows the soil and vegetation response. Higher SAVI values are generally related to the healthy plant's canopy; SAVI values will be high where plant canopy will be high and vice versa for low SAVI values. Twelve chickpea plots with SAVI indices are shown in Fig. 8. The study demonstrates successful UAV use for chickpea crop and comparison of Landsat-based calculated indices with UAV-based generated indices for chickpea crop. UAV imagery showed more accurate results than Landsat imagery because of high spatial resolution, including wavelength precision, better

spectral response, and low atmospheric interruption. UAV remote sensing advantages include minimization of labor cost, provides better results with high spatial resolution, less time consumption, and controlling operational cost. Samples of chickpea plots were selected based on their health (disease free) and height variation representation within the plots.

Normalize difference vegetation index (NDVI) obtained from Landsat

NDVI values were obtained from the Landsat imagery from plot to plot with the crop's growth stages as shown in Fig. 9. Vegetation indices show the same trend as the crop has greenery. The value of NDVI indices is high where leaves are high and it is low where plant leaves are gradually low. The highest NDVI value is 0.35 and the lowest NDVI value is 0.07 for the whole of the chickpea plot. The NDVI values of whole samples are given by above, which varies with the above, which varies with the plot to plot for UAV and Landsat imagery (Dutta and Mitra 2021). High-resolution imagery for crop monitoring is suitable for those areas which are fully covered with canopy in the field. The decametric resolution satellite imagery indicated some restrictions in presenting accurate information about the status of chickpea plots.

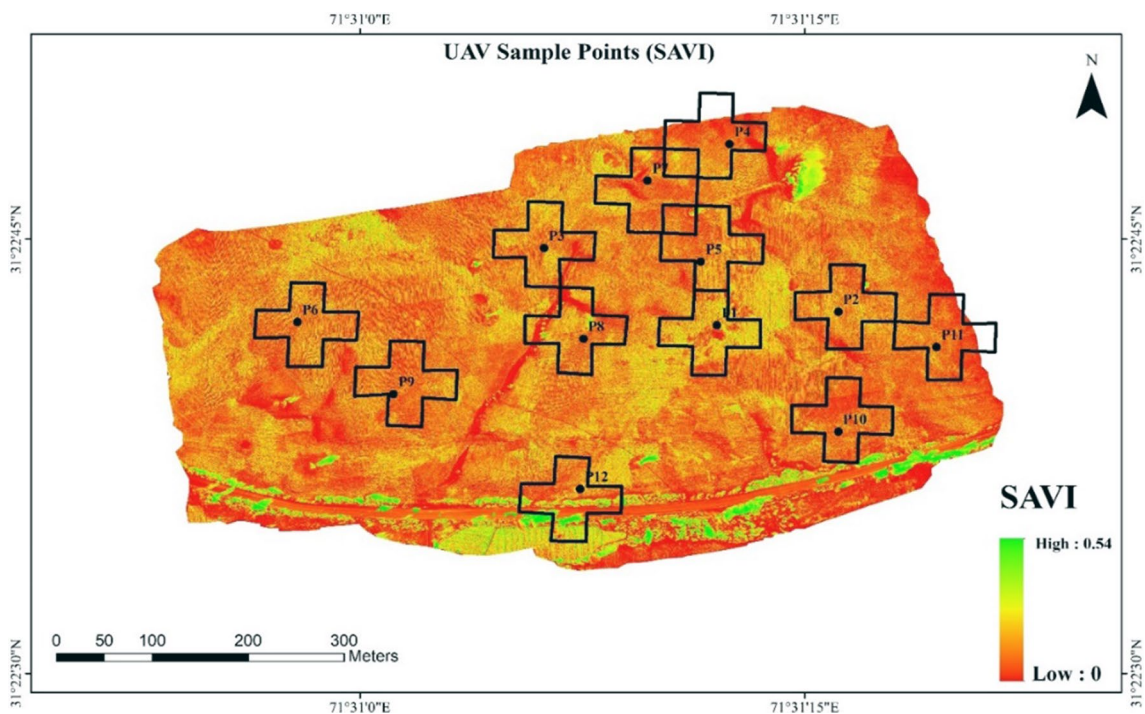


Fig. 8 Results obtained from UAV imagery along with 12 sample points showing SAVI

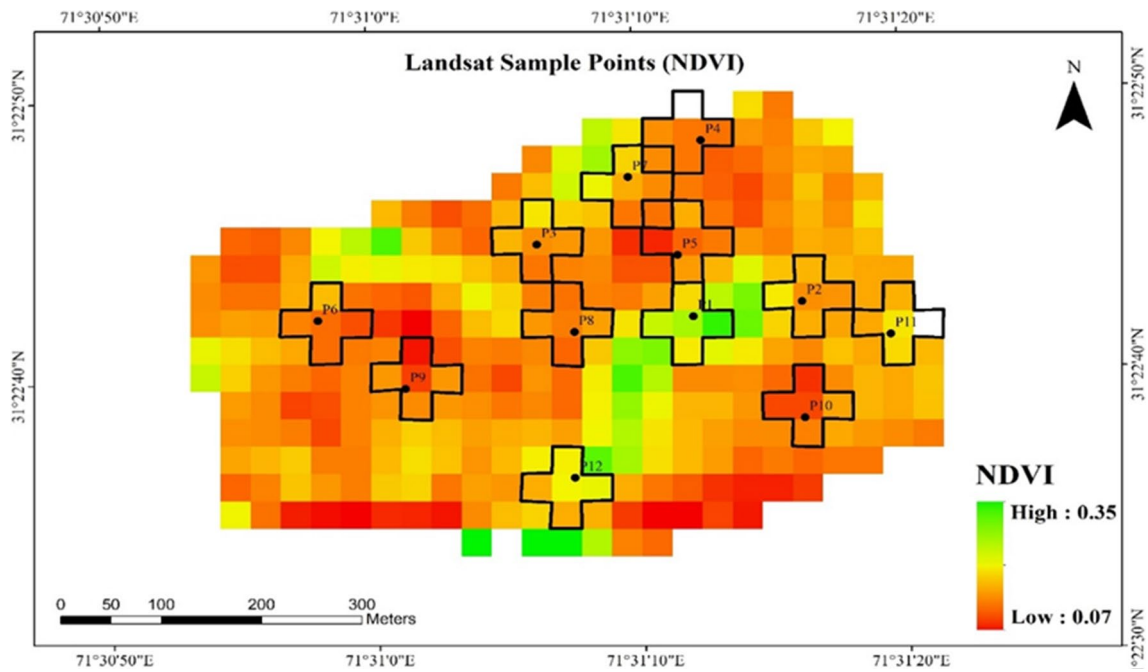


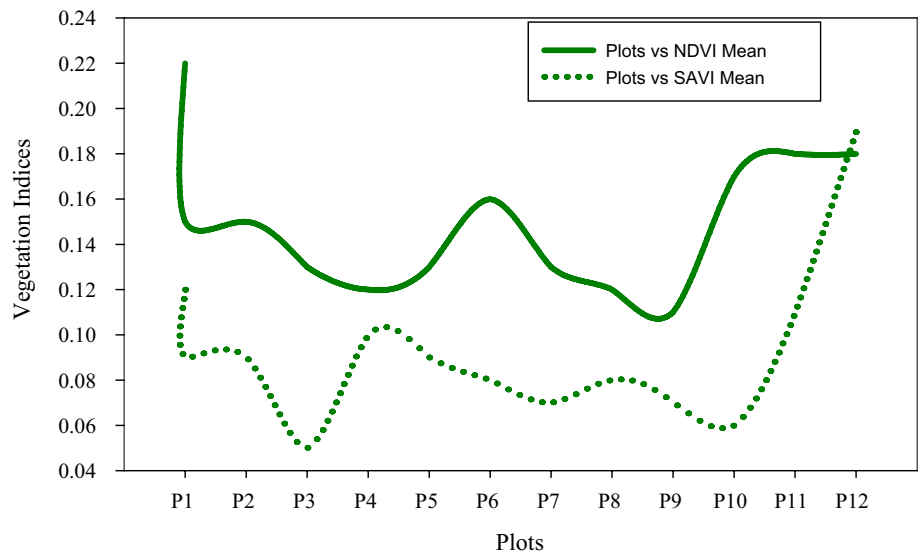
Fig. 9 Results obtained from Landsat imagery along with 12 sample points showing NDVI

Graph of (NDVI Landsat) and (SAVI) UAV

The highest SAVI value was obtained from plot number 12, while the lowest value from plot number 11. The average sum of all pixels response is very low due to dunes. The below graph represents that Points P1, P5, and P12 have the highest SAVI values. Limitations especially in spectral resolution affect the accuracy of crop growth monitoring, especially in high variation areas. The P1, P6, and P12 have the highest NDVI value. Graph of chickpea plots values derived

from NDVI and SAVI indices is given in Fig. 10. The highest correlation was found between UAV(SAVI) and actual yield ($r^2=0.6775$), while the correlation between Landsat (NDVI) and actual yield was less ($r^2=0.2126$) (Shaheen and Baig 2011). The correlation was due to different spatial resolutions between Landsat (30×30 m) and UAV(1.86 m)-based imagery. Landsat satellite image has coarse resolution and showed fewer details than the UAV image, which has very high spatial resolution with more details (the single plant was detected). Landsat images provide wall to wall coverage

Fig. 10 Graph of NDVI and SAVI values for each chickpea plot



for the large areas, while drone covers small areas with deep information (CHO et al. 2020). UAV technology is the most efficient method because of its properties and functions and it also deals with challenges, like ground-based crop reports, human errors, and many other logistical complaints regarding data collection (Meivel and Maheswari 2021).

Chickpea crop growth seasonal trend

In the arid area of Thal, chickpea is grown at the start of November in winter. The spectral response of the chickpea crop shows its peak on Feb. On Feb chickpea shows maximum greenery. The spectral response curve of chickpea increases, from Nov to Feb–March, and then starts decreasing slowly as the crop grown at its mature stage. NDVI value of chickpea is low because of the desert and rainfed area. The overall seasonal trend of chickpea crop 2019 is given in Fig. 11. Seven separate NDVI and SAVI values were computed concerning the evaluation and comparison of the effectiveness of satellite and UAV-based imagery in identifying and assessing the variation within and between chickpea plots. The close relationship between the satellite image and the map extracted from the UAV imagery, considering only the inter-row pixels, verified this effect with correlation coefficients. SAVI ranged between numerous mediums, growing the quality from higher-resolution (UAV) imagery to those with the lowest resolution. While there were different index ranges in the satellite and UAV maps (Messina et al. 2020), there were some correlations in the diffusion of vitality in the chickpea region.

Pixel-based and RGB Indices-based comparison

The pixel size of Landsat satellite imagery was 30×30 m, while the pixel size of UAV imagery was 1.83 m (Fig. 12).

To compare both results, the same area was selected for both. Within the sample points the same area with different pixel counts shows variability. Below picture on the right side shows Landsat imagery results, while on the left side it was showing results generated by UAV imagery.

True color NGB and false color NIR-GB were generated to clear visualization. Finally, the NDVI product was derived from the software SfM. Clear parallel lines showing paths of tractor and empty rows during the drill. Brownish parts in the results imagery show soil response due to dunes patches present in the field. Comparison of raster imagery with different bands combination is given in Fig. 13.

Regression analysis of crop growth variables with vegetation indices

Two vegetation indices NDVI and SAVI are used in Fig. 14. The highest $r^2 = 0.68$ was found between SAVI and yield, having SAVI as an independent variable and yield-dependent variable compared to NDVI-based $r^2 = 0.21$. $r^2 = 0.098$ was derived between elevation and yield, which means when elevation increases yield decreases. In simple, elevation and chickpea yield are inversely proportional to each other in the Thal area. Because of the desert area, the soil temperature difference was low, so $r^2 = 0.005$ was derived from soil temperature and yield. $r^2 = 0.0067$ was also low between pH and yield. Simultaneously $r^2 = 0.11, 0.36$ and 0.56 were derived from yield as a dependent variable and plant height, number of pods and number of plants as an independent variable here derived from yield as dependent variable (Fig. 15) and plant height pods and number of plants were independent variables. Regression analysis is given in graphs of all these variables (Figs. 14, 15). Chickpea canopy cover, number of plants, and plants height are also important factors to determine the relationship between SAVI, NDVI, and crop

Fig. 11 Seasonal growth trend of chickpea crop (2019)

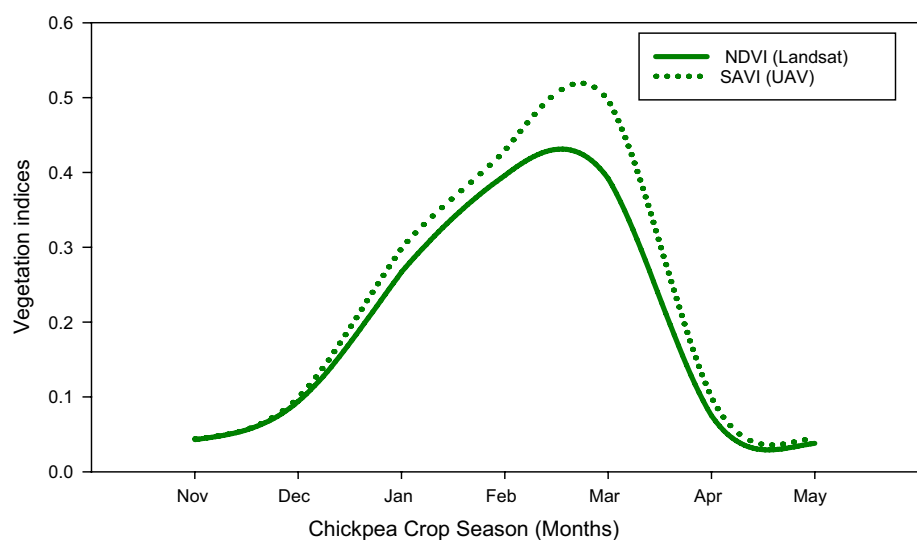


Fig. 12 Pixel-level comparison of RGB from UAV **a** and Landsat imagery, **b** with same grid size, while **c, d** representing SAVI and from UAV and NDVI from Landsat imagery simultaneously. The red box represents the boundary of plots, which is there presents the boundary of plots, which is the same for all plots, and the red dot is the center of all plot P1

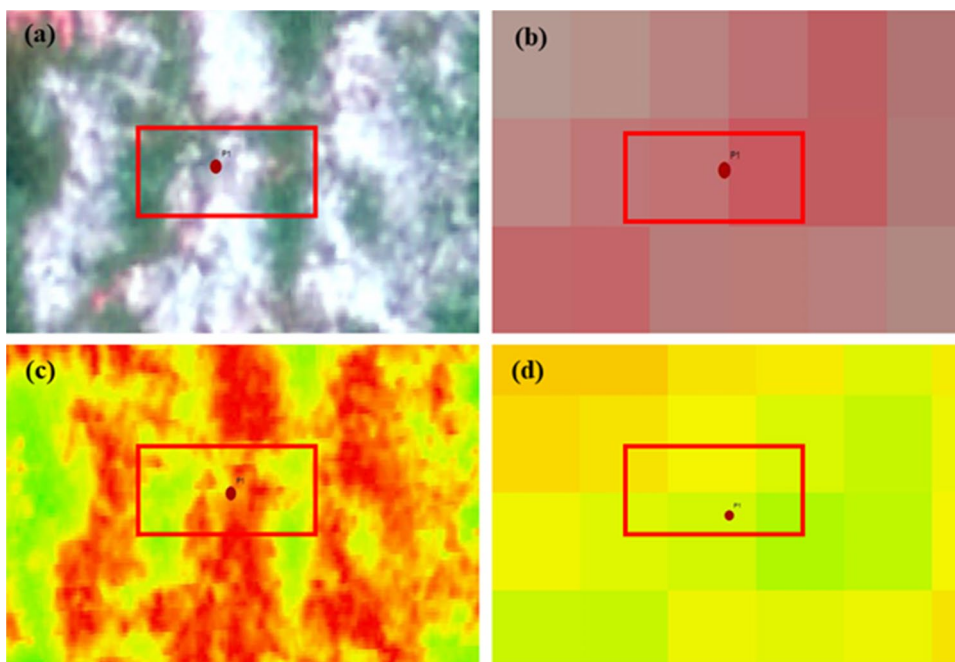
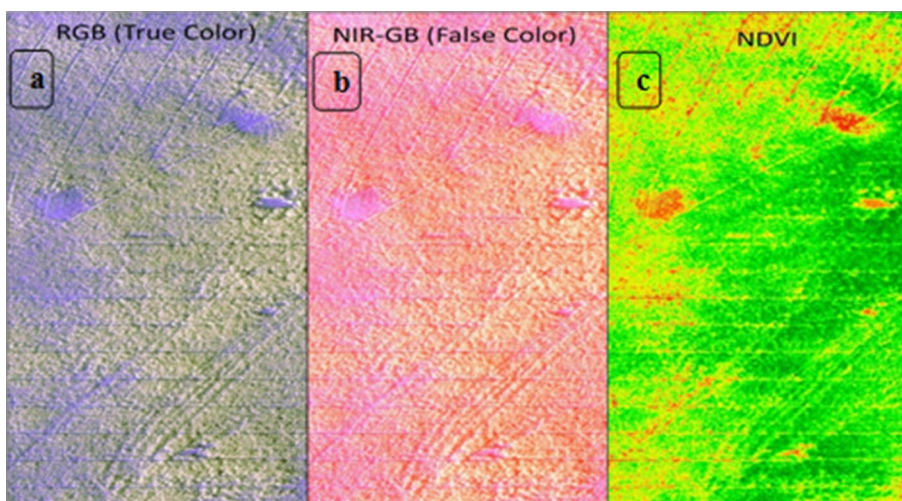


Fig. 13 Comparison of raster imagery representing composition of **a** RGB (true color), **b** NIR-GB (false color), and **c** NDVI raster imagery



yield. The maximum sand dune elevation difference is 3,4 m, which can be removed by leveling the dunes into large fields using technology “laser land leveling.”

Correlation matrix of all variables

A simple correlation matrix of all variables shows that the highest correlation coefficient was between SAVI and yield, while the lowest correlation coefficient was between elevation and yield (Guan 2019). The correlation matrix of all these variables is given in Table 2. The correlation between plant height and yield was ($r_2=0.1137$), and some pods with yield show ($r_2=0.565$). Correlation between dune elevation and yield was very low with ($r_2=0.0985$) shown in

Fig. 14c), which is a major factor for the plant growth and grain size of chickpea crop (Thapa et al. 2019). However, while there were different index ranges in the satellite and UAV maps, there were some correlations in the distribution of vigor in the chickpea region. It provides a quick and useful method to monitor crop homogeneity to check the fertilization, monitor disease, and implement irrigation techniques.

Yield estimation of chickpea grains

The final estimated yield was validated with the actual ground-based collected yield of chickpea crop of the whole study area, Fig. 16. Although UAV provides better results

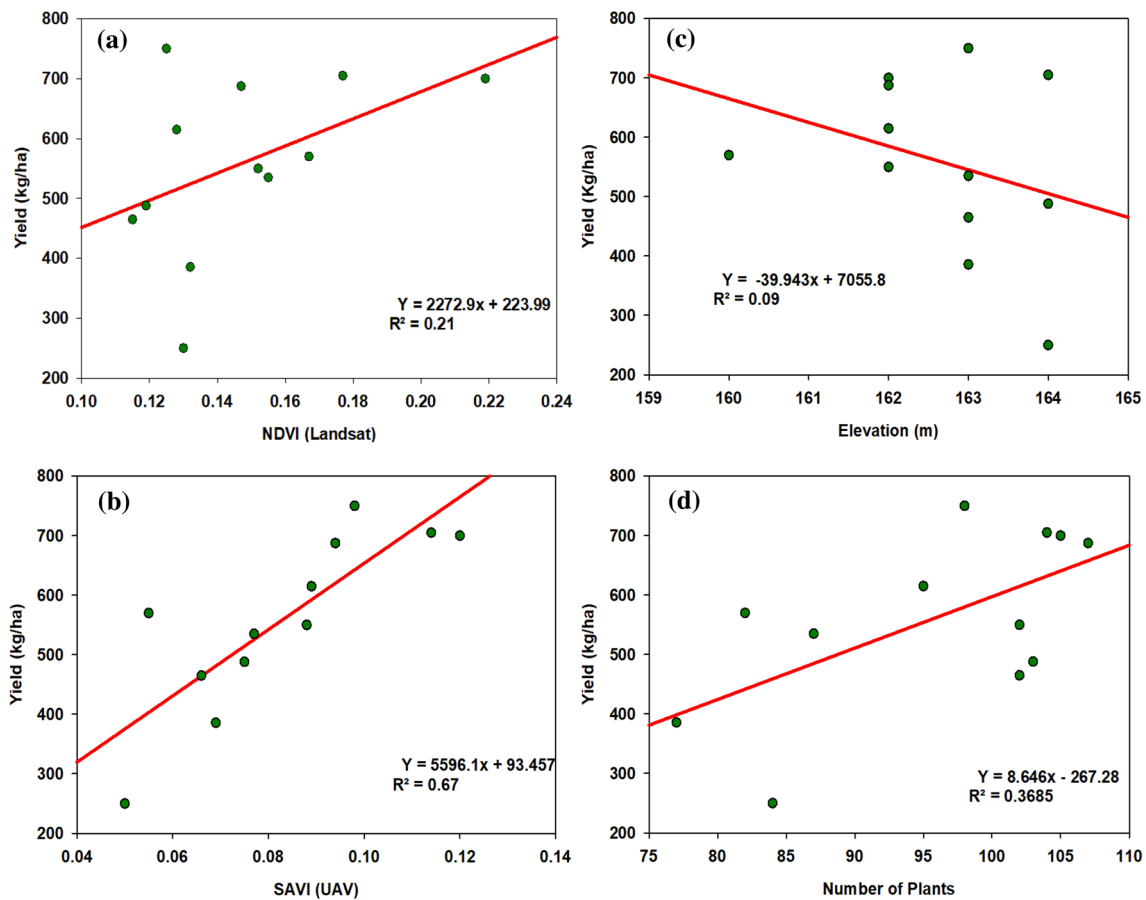


Fig. 14 The regression between **a** NDVI, **b** SAVI, **c** elevation, **d** soil temperature and yield kg/ha

and reduces labor cost, it contains some limitations, especially for extensive field coverage because monitoring phenology for large fields through UAV is difficult. High-resolution imagery can solve existing problems (Dash et al. 2017) like diseases and water stress as plot numbers 3 and 10 have a low spectral response, which is due to vegetation stress. It also has considerable potential for vegetation mapping and monitoring, crop species knowledge, plant height, bio-physical characteristics of canopies, and plant biomass. Therefore, high spatial resolution remote sensing for agriculture sectors is needed to explore the potential use of UAV imagery (Dunaeva 2017).

Crop yield comparison

The average observed yield for each plot is 554.5 kg ha^{-1} , while the average yield derived from NDVI(L) and SAVI(D) is 546.8 , 539.2 kg ha^{-1} , respectively, which are near to average observed yield value. Yield derived for each plot from NDVI(D) is very high 1266 kg ha^{-1} , while derived from indices SAVI(L) it is very low 422 kg ha^{-1} . The average observed yield for the whole of the study area

is 558 kg ha^{-1} , while yield derived from indices NDVI(D), NDVI(L), SAVI(D), SAVI(L) is 1672 , 711 , 1028 , and 463 kg ha^{-1} . Comparison of derived yield between averaged of 12 plots is shown in Fig. 16. The accurate and successful use of UAV remote sensing for agriculture is possible by carefully considering the following things: protection, safety, suitability, sensor mount, battery timing, sensor characteristics, spatial spectral resolution, a field of view, flight height, and flight time (Tassi and Vizari 2020). By increasing the use of UAV technology in the field of agriculture of Pakistan, it can be expected that it is going to be an emerging step for agriculture development. By using drone technology (UAV) future of the agriculture sector is gleaming, which is the best tool to monitor crop health, production, disease detection, and canopy cover (Martín-Béjar et al. 2020). NDVI and SAVI measured using UAV-based platforms with high-resolution imagery, which increased the accuracy of results. The most important advantage of UAV is that images are acquired according to the desired temporal and spatial demand. The acquired image has a spatial resolution of 1.86 m/pixel . UAV is a profitable and low-cost technology for big



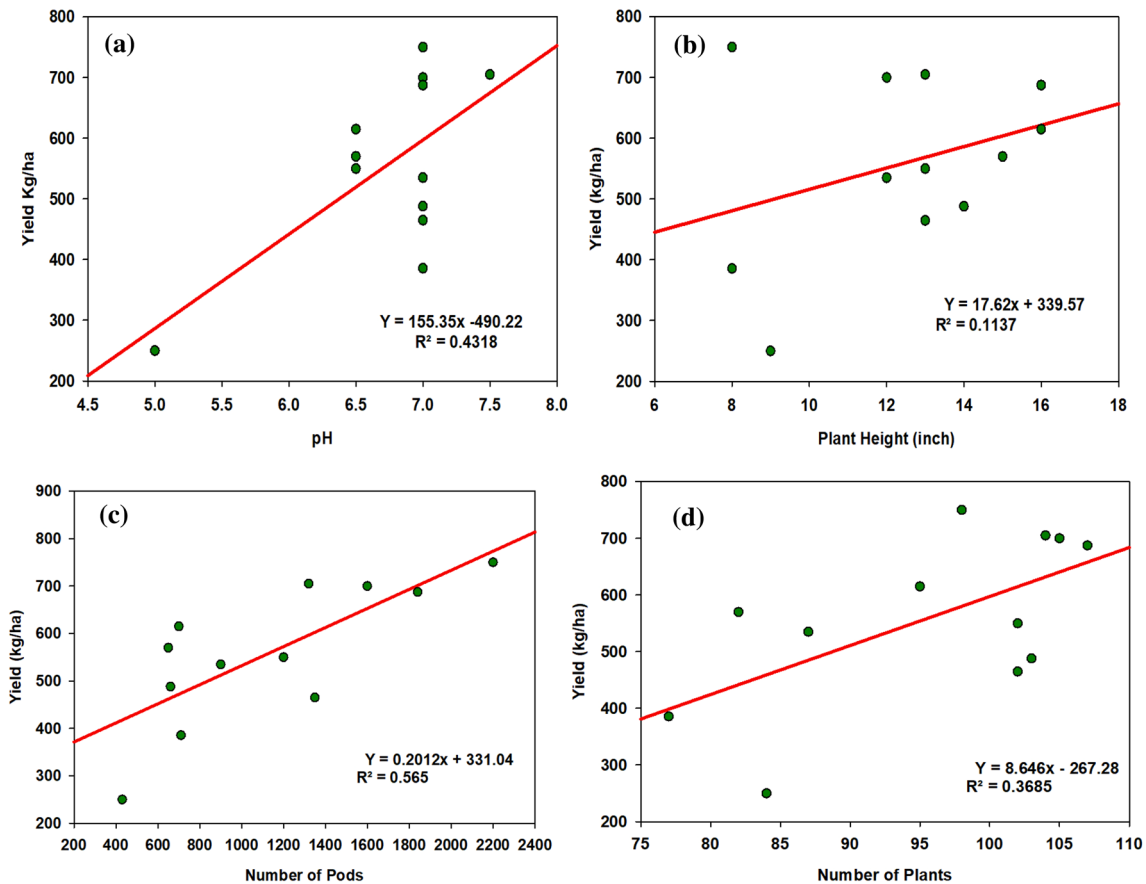


Fig. 15 Regression between **a** pH, **b** plants height, **c** number of pods, **d** number of plants and yield kg/ha

Table 2 Correlation matrix for all variables representing the highest correlation between drone-based SAVI and yield kg/ha

| | Yield (Kg/ha) | No of Plants | Plant Height | No of Pods | pH | Soil Temp(°C) | Drone SAVI | Elevation(m) |
|---------------|---------------|--------------|--------------|------------|------|---------------|------------|--------------|
| Yield (Kg/ha) | 1.00 | | | | | | | |
| No of Plants | 0.61 | 1.00 | | | | | | |
| Plant Height | 0.34 | 0.43 | 1.00 | | | | | |
| No of Pods | 0.75 | 0.64 | -0.08 | 1.00 | | | | |
| pH | -0.08 | 0.15 | -0.48 | 0.31 | 1.00 | | | |
| Soil Temp(°C) | 0.07 | 0.32 | 0.44 | 0.09 | 0.32 | 1.00 | | |
| Drone SAVI | 0.82 | 0.69 | 0.12 | 0.68 | 0.16 | 0.00 | 1.00 | |
| Elevation(m) | -0.31 | 0.14 | -0.46 | 0.05 | 0.70 | -0.31 | 0.05 | 1.00 |
| Landsat NDVI | 0.46 | 0.19 | 0.14 | 0.21 | 0.04 | 0.34 | 0.58 | -0.36 |

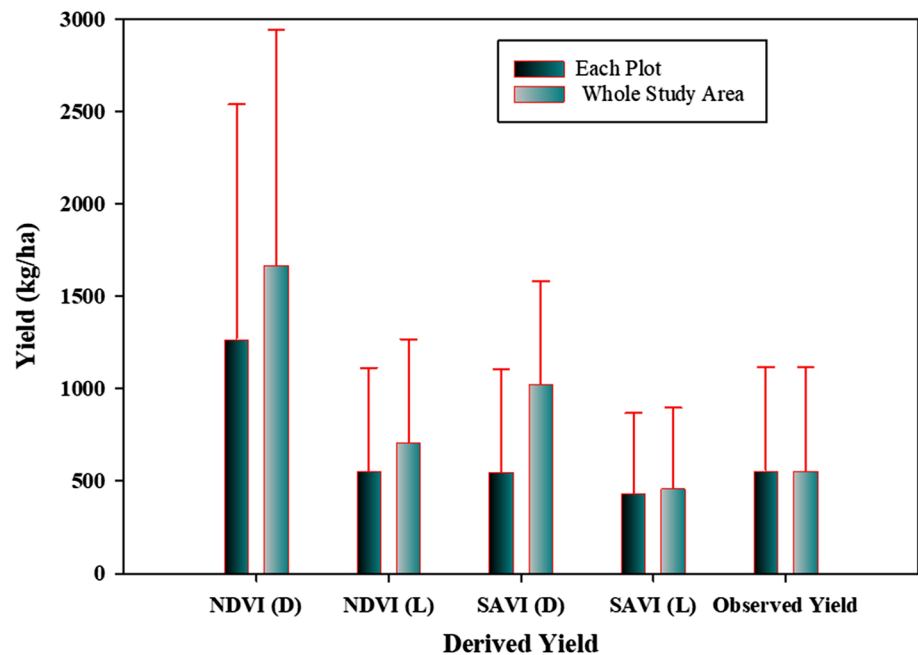
farmers, but it is not affordable and useful for small-scale farmers. SAVI ranged between various channels, increasing the quality from higher-resolution (UAV) imagery to those with the lowest resolution. Further studies can be carried out on how these datasets can be further improved and results will be used to improve the productivity of chickpea crops using modern technology. The results indicate that SAVI derived from UAV imagery is very useful as compared to the NDVI derived from Landsat imagery.

Conclusion

The results described that the UAV mounted with Zenmuse ×3 camera may be used to check crop growth at any stage of the crop and predict crop yield before harvesting. This article also describes the comparison of imagery acquired from UAV and satellite, low and high resolution. The comparison was based on the spatial resolution and the yield within each and the whole plot. Across the vegetation



Fig. 16 Comparison of observed chickpea crop yield with a predicted yield based on various indices (NDVI-D, NDVI-L, SAVI-D, SAVI-L) averaged plots (12 plots) and the whole of the study area



indices SAVI and NDVI, NDVI was positively correlated ($r^2=0.6775$) with the yield. It was concluded that UAV (with different sensors) is the best approach to monitor, detect disease, and predict yield before harvesting. It was analyzed that spatial resolution by using MicaSense Red-edge™ Sensor can be increased instead for Zenmuse X3. So, this method is recommended to check crop growth monitoring to check vegetation stress and disease. Machine learning approaches may also be used to throw out phenotyping more accurately, to draw critical decision making for field conditions and automated identification of diseases. Chickpea crop depends upon the rainfall; if there is less rainfall in the early growing season (Oct–Nov), there will be a drastic impact on chickpea crop yield. Crop yield can also be increased by introducing leveling, drip irrigation, and artificial rainfall to this rainfed area. Usage of drones for agriculture is a newly operated technology, especially in Pakistan, which can play a dynamic role in expanding the agriculture industry. High gram crop production improves the living standard of people of the “Thal Area” community because gram is the most cultivated crop in this area, especially in Bhakkar District. By increasing yield and quantity, a huge amount of revenue can be generated through exports. Gram crop production depends upon rainfall, soil temp, soil moisture, seed, and leveling of plots (dunes) in this study area.

Acknowledgements This research was supported by the Institute of Geographical Information Systems, National University of Sciences and Technology, Islamabad, Pakistan. The authors are grateful to the Deanship of Scientific Research, King Saud University, for funding through Vice Deanship of Scientific Research Chairs and thankful to the financial support funded by the Deanship of Scientific Research at Princess Nourah Bint Abdulrahman University through the Fast-track Research

Author Contributions Navid Ahmad helped in writing—original draft, data Collection, and conceptualization, Javed Iqbal supervised, formally analyzed, wrote, and funding the study. Asma Shaheen wrote the review and edited. Ayman Ghfar, Murefah mana AL-Anazy, Mohamed Ouladsmane helped in analysis and funding.

Declarations

Conflict of interest Authors declare no conflicts of interest.

References

- Ahirwar S, Swarnkar R, Bhukya S, Namwade G (2019) Application of drone in agriculture international journal curr microbiological Applied. Science 8:2500–2505
- Ashapure A et al (2020) Developing a machine learning based cotton yield estimation framework using multi-temporal UAS data. ISPRS J Photogramm Remote Sens 169:180–194
- Bach H (1998) Yield estimation of corn based on multitemporal land-sat-tm data as input for an agrometeorological model pure and applied optics. J Eur Opt Soc Part A 7:809
- Balaghi R, Tychon B, Eerens H, Jlibene M (2008) Empirical regression models using NDVI, rainfall and temperature data for the early prediction of wheat grain yields in Morocco. Int J Appl Earth Observ Geoinform 10:438–452
- Bessada SM, Barreira JC, Oliveira MBP (2019) Pulses and food security: Dietary protein, digestibility, bioactive and functional properties. Trends in Food Sci Technol 93:53–68
- Boye J, Zare F, Pletch A (2010) Pulse proteins: processing, characterization, functional properties and applications in food and feed. Food Res Int 43:414–431
- Burggraaff O et al (2019) Standardized spectral and radiometric calibration of consumer cameras. Opt Exp 27:19075–19101
- CHO S-H, LEE G-S, HWANG J-W (2020) Drone-based Vegetation Index Analysis Considering Vegetation Vitality Journal of the Korean Association of Geographic Information Studies 23:21–35

- Crusiol LGT et al (2020) UAV-based thermal imaging in the assessment of water status of soybean plants. *Int J Remote Sens* 41:3243–3265. <https://doi.org/10.1080/01431161.2019.1673914>
- da Silva EE, Baio FHR, Teodoro LPR, da Silva Junior CA, Borges RS, Teodoro PE (2020) UAV-multispectral and vegetation indices in soybean grain yield prediction based on in situ observation Remote Sensing Applications: Society and Environment 18:100318
- Dutta PK, Mitra S (2021) Application of agricultural drones and IoT to understand food supply chain during post COVID-19 agricultural informatics: automation using the IoT and machine learning:67–87
- Enciso J et al (2019) Validation of agronomic UAV and field measurements for tomato varieties. *Comput Electron Agric* 158:278–283
- Fu Z et al (2020) Wheat growth monitoring and yield estimation based on multi-rotor unmanned aerial vehicle. *Remote Sens* 12:508
- Gallego RF, Losada MHP, Martín AG, Córdoba A, Martínez LM-C, Torres CMC (2015) Using NDVI and guided sampling to develop yield prediction maps of processing tomato crop Spanish journal of agricultural research 13:204
- Guan S et al (2019) Assessing correlation of high-resolution NDVI with fertilizer application level and yield of rice and wheat crops using small UAVs. *Remote Sens* 11:112
- Hassan MA et al (2019) A rapid monitoring of NDVI across the wheat growth cycle for grain yield prediction using a multi-spectral UAV platform. *Plant Sci* 282:95–103
- Hovhannisyan T, Efendyan P, Vardanyan M (2018) Creation of a digital model of fields with application of DJI phantom 3 drone and the opportunities of its utilization in agriculture. *Ann Agrarian Sci* 16:177–180
- Huete AR (1988) A soil-adjusted vegetation index (SAVI). *Remote Sens Environ* 25:295–309
- Jia Y, Su Z, Shen W, Yuan J, Xu Z (2016) UAV Remote Sensing Image Mosaic and Its Application in Agriculture. *Int J Smart Home* 10:159–170
- Khaliq A, Comba L, Biglia A, Ricauda Aimonino D, Chiaberge M, Gay P (2019) Comparison of satellite and UAV-based multispectral imagery for vineyard variability assessment. *Remote Sens* 11:436
- Kopačková-Strnadová V, Koucká L, Jelének J, Lhotáková Z, Oulehle F (2021) Canopy top, height and photosynthetic pigment estimation using parrot sequoia multispectral imagery and the unmanned aerial vehicle (UAV). *Remote Sens* 13:705
- Lelong C, Burger P, Jubelin G, Roux B, Labbé S, Baret F (2008) Assessment of unmanned aerial vehicles imagery for quantitative monitoring of wheat crop in small plots. *Sensors* 8:3557–3585
- Li B, Xu X, Han J, Zhang L, Bian C, Jin L, Liu J (2019) The estimation of crop emergence in potatoes by UAV RGB imagery. *Plant Methods* 15:15
- Lukas V, Novák J, Neudert L, Svobodova I, Rodriguez-Moreno F, Edrees M, Kren J (2016) The combination of UAV survey and landsat imagery for monitoring of crop vigor in precision agriculture International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences 8
- Maddikunta PKR, Hakak S, Alazab M, Bhattacharya S, Gadekallu TR, Khan WZ, Pham Q-V (2021) Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges IEEE Sensors Journal
- Maes WH, Huete AR, Steppe K (2017) Optimizing the processing of UAV-based thermal imagery. *Remote Sens* 9:476
- Mahajan U, Bundel BR Drones for Normalized Difference Vegetation Index (NDVI), to Estimate Crop Health for Precision Agriculture: A Cheaper Alternative for Spatial Satellite Sensors. In: International Conference on Innovative Research in Agriculture, Food Science, Forestry, Horticulture, Aquaculture, Animal Sciences, Biodiversity, Ecological Sciences and Climate Change (AFHABEC-2016), At Jawaharlal Nehru University, 2017.
- Meivel S, Maheswari S (2021) Remote sensing analysis of agricultural drone. *J Indian Soc Remote Sens* 49:689–701
- Messina G, Peña JM, Vizzari M, Modica G (2020) A comparison of UAV and satellites multispectral imagery in monitoring onion crop. an application in the ‘cipolla rossa di tropea’ (Italy) *Remote Sensing* 12:3424
- Murugan D, Garg A, Singh D (2017) Development of an adaptive approach for precision agriculture monitoring with drone and satellite data. *IEEE J Selected Topics Appl Earth Observ Remote Sens* 10:5322–5328
- Paredes-López O, Ordorica-Falomir C, Olivares-Vazquez M (1991) Chickpea protein isolates: physicochemical, functional and nutritional characterization *Journal of Food Science* 56:726–729
- Puri V, Nayyar A, Raja L (2017) Agriculture drones: a modern breakthrough in precision agriculture. *J Statistics Manag Syst* 20:507–518
- Putra BTW, Syahputra WNH, Anam K, Darmawan T, Marhaenanto B (2021) Comprehensive Measurement and Evaluation of Modern Paddy Cultivation with a Hydrogenics System Under Different Nutrient Regimes Using WSN and Ground-based Remote Sensing Measurement:109420
- Rahman MR, Islam A, Rahman MA (2004) NDVI derived sugarcane area identification and crop condition assessment. *Plan plus* 1:1–12
- Rocchetti L et al (2020) The development of a european and mediterranean chickpea association panel (EMCAP). *Agronomy* 10:1417
- Roy DP, Yan L (2020) Robust Landsat-based crop time series modeling. *Remote Sens Environ* 238:110810. <https://doi.org/10.1016/j.rse.2018.06.038>
- Shaheen A, Baig MA (2011) Drought severity assessment in arid area of thal doab using remote sensing and GIS. *Int J Water Resour Arid Environ* 1:92–101
- Shaheen A, Iqbal J (2018) Spatial distribution and mobility assessment of carcinogenic heavy metals in soil profiles using geostatistics and random forest. *Boruta Algorithm Sustain* 10:799
- Shaheen A, Iqbal J, Hussain S (2019) Adaptive geospatial modeling of soil contamination by selected heavy metals in the industrial area of Sheikhpura. *Pakistan Int J Environ Sci Technol* 16:4447–4464
- Singh R, Semwal D, Rai A, Chhikara RS (2002) Small area estimation of crop yield using remote sensing satellite data. *Int J Remote Sens* 23:49–56
- Siyal AA, Dempewolf J, Becker-Reshef I (2015) Rice yield estimation using Landsat ETM+ Data *Journal of Applied Remote Sensing* 9:095986
- Tattaris M, Reynolds MP, Chapman SC (2016) A direct comparison of remote sensing approaches for high-throughput phenotyping in plant breeding *Frontiers in Plant. Science* 7:1131
- Tian J, Wang L, Li X, Gong H, Shi C, Zhong R, Liu X (2017) Comparison of UAV and WorldView-2 imagery for mapping leaf area index of mangrove forest. *Int J Appl Earth Observ Geoinform* 61:22–31
- Tiwari P, Shukla P (2020) Artificial Neural Network-Based Crop Yield Prediction Using NDVI, SPI, VCI Feature Vectors. In: Information and Communication Technology for Sustainable Development. Springer, pp 585–594
- Torres-Sánchez J, López-Granados F, De Castro AI, Peña-Barragán JM (2013) Configuration and specifications of an unmanned aerial vehicle (UAV) for early site specific weed management *PLoS one* 8:e58210
- Wang Y, Ryu D, Park S, Fuentes S, O’Connell M Upscaling UAV-borne high-resolution vegetation index to satellite resolutions over a vineyard. In: 2nd International Congress on Modelling and Simulation, Hobart, Tasmania, Australia, 2017.
- Zhang C, Kovacs JM (2012) The application of small unmanned aerial systems for precision agriculture: a review precision. *Agriculture* 13:693–712
- Zhou X et al (2017) Predicting grain yield in rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery. *ISPRS J Photogramm Remote Sens* 130:246–255

