UAV-Based NDVI Assessment for Yield Prediction in *Triticum aestivum* L.

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Received: 06 Dec 2022
Revised: 22 Dec 2022
Accepted: 09 Jan 2023
Published: 26 Jan 2023

E-ISSN: 2989-5340
DOI: https://doi.org/10.54660/jafi.2023.3.1.01-04

ABSTRACT
Background: *Triticum aestivum* L. (common wheat) is a main grain that remains significant for the overall food security across the world. Conventional ways of estimating yield involves extensive labor, destructiveness, and limitations in spatial scope. Drones equipped with multiple sensors present a non-destructive and quick alternative of monitoring crops.
Objective: The study aimed at evaluating the suitability of NDVI, derived from drones, as a representative of the growing factors of wheat as well as grain harvest.
Method: The study used randomized and complete block design of field experiment by means of multispectral equipped quadcopter flying at significant growth stages. NDVI value was obtained from orthomosaics and getting correlated with plant height, leaf area index, amount of chlorophyll, biomass, and final grain yield through regression and correlation analysis.
Results: NDVI had high temporal variability, being highest at the booting and heading stages, and was significantly associated with yield ($R^2 = 0.86$, RMSE = 0.34 t ha^{-1}). NDVI at heading stage was the most effective single-stage predictor of yield.
Conclusion: UAV-derived NDVI is an effective, scalable, and non-destructive method for wheat yield prediction which enables site-specific nutrient management and quick identification of low productivity areas in precision farming systems.

Keywords: *Triticum aestivum*; Unmanned Aerial Vehicle (UAV); Normalized Difference Vegetation Index (NDVI)

1. Introduction
Triticum aestivum L. is one of the three leading grains cultivated in the world, contributing a significant proportion of the calories and proteins consumed worldwide. Population increase, climate variations, and the decline in arable land bring about the necessity of timely and precise yield estimation. The conventional method of yield measurement is based on destructive sampling and manual measurements, which are time-consuming and geographically limited.
Precision agriculture employs spatial data acquisition together with variable-rate application technologies to enhance input efficiency. Remote sensing through drones becomes more recognized because it possesses high spatial and temporal resolution, it can be operated flexibly, and it is less costly than satellite or manned aerial applications. Drones equipped with multispectral sensors make possible the capturing of the light reflected from the vegetation in the visible and near-infrared bands for calculating vegetation indices important for determining the physiological state of crops.
The NDVI or Normalized Difference Vegetation Index is deduced from the red and near-infrared reflectances and signifies the fertility of an area or canopy by making changes due to the absorption of chlorophyll and moisture of the leaves. The higher amount of NDVI indicates the capability of canopies to absorb and photosynthesize, which is associated with the increase in biomass and yield. Therefore, the UAV imagery can effectively be used for crop monitoring and can provide early detection of stress.
The objectives of the study are: (i) analyzing the changes of NDVI from UAV across the phenological stages of wheat; (ii) estimating the correlation between NDVI and the vegetative parameters; (iii) and testing NDVI as the measures of yield.
Though RGB sensors are economical, they are subjected to changes in lighting more than multispectral sensors which use very narrow bands for reflectance measurements in index computation [6]. The concept of carrying out multispectral UAV image surveys has been explained in terms of wheat phenotyping to obtain leaf area index, biomass, and nitrogen status estimates [7, 8]. Several researchers indicate that NDVI-based variable rate technologies can be utilized to ensure accurate nutrient delivery without undue fertilizer application [9].
Currently, many digital agriculture systems continue integrating indices obtained from UAVs into GIS systems for developing prescription maps [10]. Predicting yields through machine learning techniques makes it possible to improve predictive capabilities further than those allowed by ordinary linear modeling with the help of indices obtained at different time intervals [11, 12]. Nevertheless, questions remain regarding optimal flight time, the homogeneity of calibration, and transferability of models across crop varieties [13, 14].

Therefore, this study will generate NDVI with the use of several stages of its acquisition as well as extensive ground validation.

2. Materials and Methods

2.1. Experimental Site

The field trial was conducted at an agricultural research station (28.6°N, 77.2°E) during the 2024–2025 rabi season. The site has a semi-arid subtropical climate with mean seasonal temperature of 18.5°C and total rainfall of 62 mm. Soil was sandy clay loam (pH 7.4, organic carbon 0.58%). The wheat cultivar HD-3226 was used.

2.2. Experimental Design

A Randomized Complete Block Design (RCBD) with four nitrogen-management treatments (0, 80, 120, and 160 kg N ha^{-1}) and three replications was employed, yielding 12 plots of 5 m × 4 m each, separated by 1 m buffers.

2.3. Crop Management

Land was prepared by disc harrowing and planking. Seeds were sown at 100 kg ha^{-1} using a seed drill at 20 cm row spacing. Phosphorus and potassium were applied as basal dose; nitrogen was split-applied at sowing, tillering, and jointing. Irrigation followed a critical-stage schedule (crown root initiation, tillering, jointing, flowering, grain filling). Standard integrated pest and weed management practices were followed.

2.4. UAV Platform and Sensor Specifications

A DJI Matrice 300 RTK quadcopter equipped with a MicaSense Altum-PT multispectral sensor (blue, green, red, red-edge, near-infrared, and thermal bands) was used, alongside an integrated RGB camera. Flights were conducted at 40 m altitude, 4 m s^{-1} speed, achieving a Ground Sampling Distance (GSD) of 2.1 cm $pixel^{-1}$, with 80% forward and 70% side image overlap. Flight paths were planned using DJI Pilot 2 and Pix4Dcapture software.

2.5. UAV Image Acquisition

Flights were performed at tillering, stem elongation, booting, heading, and grain-filling stages between 11:00–13:00 h under clear-sky conditions (wind < 3 m s^{-1}). Radiometric calibration was performed pre-flight using a calibrated reflectance panel. Six ground control points (GCPs) were surveyed using RTK-GNSS for geometric correction.

2.6. NDVI Calculation

NDVI was computed as:

$$NDVI = (NIR - Red) / (NIR + Red)$$

Images were preprocessed for radiometric and geometric correction, and orthomosaics were generated in Pix4Dmapper. NDVI raster layers were extracted per plot using QGIS zonal statistics.

2.7. Ground Truth Measurements

Plant height, Leaf Area Index (LAI), SPAD chlorophyll readings, aboveground biomass, spike number, grain yield, and thousand-kernel weight were recorded at corresponding growth stages using standard destructive and non-destructive sampling protocols.

2.8. Statistical Analysis

Data were analyzed using Analysis of Variance (ANOVA), linear regression, and Pearson correlation in R (v4.3). Model performance was evaluated using the coefficient of determination (R^2) and Root Mean Square Error (RMSE), with significance set at $P < 0.05$.

Table 1: Experimental design, UAV flight parameters, and image acquisition schedule.

Parameter	Specification
Design	RCBD, 4 treatments × 3 replications
Plot size	5 m × 4 m
UAV platform	DJI Matrice 300 RTK
Sensor	MicaSense Altum-PT (multispectral + thermal)
Flight altitude	40 m
GSD	2.1 cm $pixel^{-1}$
Image overlap	80% front / 70% side
Flight stages	Tillering, stem elongation, booting, heading, grain filling

4. Results

NDVI increased progressively from tillering (mean 0.42) to a peak at heading (mean 0.81), then declined during grain filling (mean 0.61) with canopy senescence. Spatial NDVI variability was greatest at booting, corresponding to differential nitrogen responses ($P < 0.05$).

Plant height, LAI, and SPAD chlorophyll readings increased significantly with nitrogen level ($P < 0.05$), with LAI showing the strongest association with NDVI ($r = 0.88$). Biomass accumulation paralleled NDVI trends across stages.

NDVI at heading showed the strongest correlation with grain yield ($r = 0.91$), outperforming earlier-stage values. Regression of yield against heading-stage NDVI produced $R^2 = 0.86$ and RMSE = 0.34 t ha^{-1} ($P < 0.001$), while tillering-stage NDVI was a weaker, non-significant predictor ($R^2 = 0.29$, $P = 0.08$).

Spatial NDVI maps identified low-productivity zones corresponding to the zero-nitrogen treatment, supporting delineation of variable-rate nutrient zones and early detection of nitrogen-deficiency stress.

Table 2: Relationships among NDVI, growth parameters, and grain yield.

Growth Stage	NDVI (mean)	Correlation with Yield (r)	R^2	RMSE (t ha^{-1})	Significance
Tillering	0.42	0.54	0.29	0.61	ns
Stem elongation	0.63	0.71	0.50	0.52	$P < 0.05$
Booting	0.76	0.85	0.72	0.41	$P < 0.01$
Heading	0.81	0.91	0.86	0.34	$P < 0.001$
Grain filling	0.61	0.68	0.46	0.55	$P < 0.05$

ns = not significant.

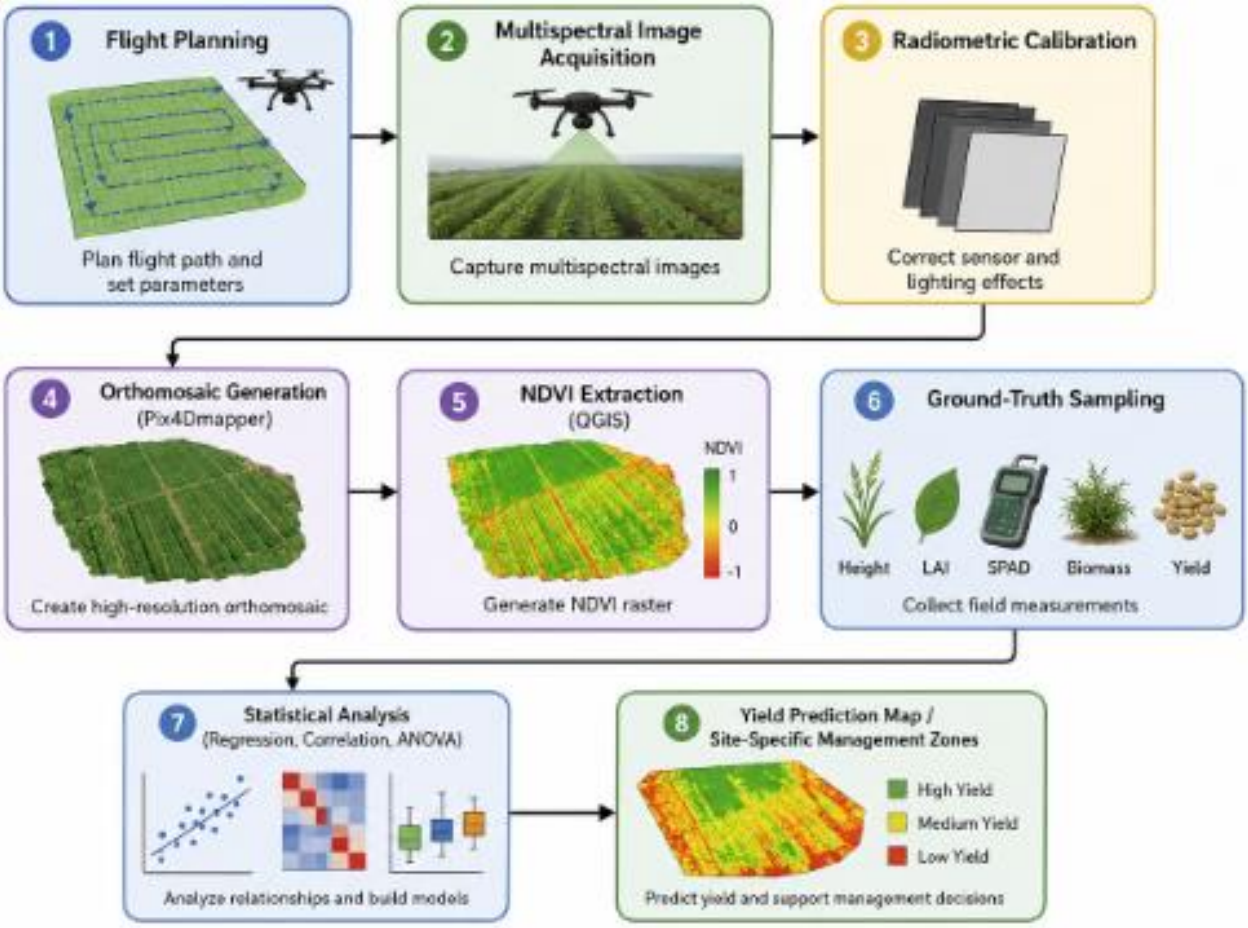

Fig 1: Workflow schematic illustrating UAV flight planning, multispectral image acquisition, orthomosaic and NDVI generation, ground-truth validation, statistical modeling, and grain yield prediction.

5. Discussion

The results confirm that UAV-derived NDVI, particularly at heading stage, is a robust predictor of wheat grain yield, consistent with the mechanistic link between canopy chlorophyll density and photosynthetic capacity reported previously [3, 4]. The weaker predictive strength of tillering-stage NDVI likely reflects incomplete canopy closure.

Compared with satellite monitoring, UAV platforms offer superior spatial resolution and flexible revisit scheduling, enabling detection of within-field variability that coarser satellite pixels cannot resolve [6, 10]. This supports integrating UAV NDVI outputs into GIS-based decision-support systems for variable-rate nitrogen and irrigation management, consistent with prior recommendations for precision nutrient stewardship [9].

These findings align with earlier multispectral UAV studies reporting R^2 values of 0.75–0.90 for heading-stage NDVI–yield relationships [5, 8], though sensitivity to cultivar and soil conditions has been noted [13].

Limitations include illumination variability, sensor calibration drift, and restriction to a single cultivar and season. Future work should explore multi-temporal machine learning models integrating multispectral, hyperspectral, thermal, and soil-moisture data to improve robustness across environments [11, 12, 14].

6. Conclusion

The research indicates that NDVI derived from UAVs (unmanned aerial vehicles) serves as a precise – non-destructive – method to forecast wheat grain yield ($R^2 = 0.86$) during the heading phase. UAV-based monitoring has distinct advantages over destructive sampling and less accurate satellite platforms: it allows for quick identification of low-productivity areas which in turn assists with the implementation of variable-rate applications of fertilizers and irrigation. Therefore, it is essential for agronomists to use UAV NDVI assessment at different crucial phenological stages. Future investigations should focus on fusion of datasets obtained from various sensors, machine-learning based predictive models, and validation during several growing seasons.

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