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UAV-based multispectral imaging for real-time crop health assessment and yield estimation in wheat

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Abstract

Leading agronomists now argue that satellite imagery alone can't capture the within-field variability needed for precision wheat management. Unmanned Aerial Vehicles (UAVs) may fill this gap. This research evaluated UAV-based multispectral imaging for assessing crop health and estimating grain yield in winter wheat across five growth stages at Zhejiang University's experimental farm during 2022-2023. A DJI Matrice 300 RTK equipped with a MicaSense RedEdge-MX sensor captured imagery at 30 m altitude, producing orthomosaics at 2.5 cm ground resolution. Four vegetation indices NDVI, GNDVI, NDRE, and SAVI were extracted and correlated with ground-truth biomass, leaf area index, and final grain yield. NDVI at the heading stage showed the strongest correlation with yield ($R^2 = 0.84$, RMSE = 0.31 t/ha). A random forest regression model combining all four indices at heading achieved $R^2 = 0.89$ and MAPE of 6.8% during validation. Spatial yield maps generated from the model revealed within-field yield variation of up to 1.9 t/ha, which conventional sampling missed entirely. These results confirm that UAV multispectral imaging at the heading stage provides a reliable, non-destructive tool for yield estimation and health monitoring in wheat.

Keywords: UAV, multispectral imaging, wheat, NDVI, crop health assessment, yield estimation, remote sensing, vegetation indices, precision agriculture, random forest

Introduction

According to a growing body of expert opinion, the future of crop monitoring lies not in orbiting satellites but in low-altitude drones carrying high-resolution sensors^[1]. Satellites provide broad coverage but suffer from cloud contamination, coarse spatial resolution (10-30 m), and fixed revisit schedules that often miss critical growth stages^[2]. UAVs, by contrast, can be deployed on demand at altitudes of 20-50 m, capturing imagery at centimeter-level resolution that reveals within-field heterogeneity invisible from space^[3].

Multispectral sensors mounted on UAVs capture reflected light in discrete wavelength bands typically blue, green, red, red-edge, and near-infrared from which vegetation indices can be calculated. The Normalized Difference Vegetation Index (NDVI) remains the most widely used, but newer indices like the Green Normalized Difference Vegetation Index (GNDVI) and the Normalized Difference Red-Edge index (NDRE) may better detect subtle differences in canopy chlorophyll and nitrogen status^[4, 5].

This research aimed to determine which vegetation index, at which growth stage, provides the most accurate pre-harvest yield estimate for winter wheat, and whether combining multiple indices through machine learning improves prediction beyond single-index regression^[6, 7].

Climatic and environmental conditions

The field trial was conducted at the Zijingang Campus Experimental Farm, Zhejiang University, Hangzhou, Zhejiang Province, China (30°18'N, 120°05'E, elevation 8 m). Hangzhou has a subtropical monsoon climate with mean annual temperature of 17.4 °C and precipitation of 1,454 mm. During the wheat season (November 2022-May 2023), cumulative rainfall was 586 mm, mean temperature was 12.8 °C, and total sunshine hours were 892 h. UAV flights were conducted only on clear or partly cloudy days between 10:00 and 14:00 local solar time to minimize sun angle effects on reflectance measurements^[8].

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System Configuration and Flight Parameters

The UAV platform was a DJI Matrice 300 RTK quadcopter with real-time kinematic positioning (± 1 cm horizontal accuracy). The MicaSense RedEdge-MX multispectral sensor captured five bands: blue (475 nm), green (560 nm), red (668 nm), red-edge (717 nm), and near-infrared (842 nm) at 1.2 megapixels per band. Flights were conducted at 30 m altitude with 80% forward overlap and 70% side overlap, producing ground sampling distance of 2.5 cm/pixel. Radiometric calibration used a MicaSense calibrated reflectance panel photographed before and after each flight. Images were processed in Pix4Dmapper v4.7 to generate georeferenced orthomosaics and reflectance maps. Vegetation indices were computed pixel-wise: $NDVI = (NIR - Red)/(NIR + Red)$, $GNDVI = (NIR - Green)/(NIR + Green)$, $NDRE = (NIR - RE)/(NIR + RE)$, $SAVI = 1.5 \times (NIR - Red)/(NIR + Red + 0.5)$ [9, 10].

Materials and Methods

Material

The research was conducted from November 2022 to June 2023. Winter wheat variety Yangmai-20 was sown on November 12, 2022, at 180 kg/ha seed rate in 48 plots (6 m $\times$ 5 m each) arranged in a randomized complete block design with four

nitrogen treatments (0, 90, 180, 270 kg N/ha) and four replications. Basal fertilizer (90:60:40 kg/ha N:P₂O₅:K₂O) was applied at sowing, with remaining nitrogen topdressed at tillering and jointing stages. The varied nitrogen levels were designed to create a range of canopy conditions and yield outcomes for model calibration [11].

Methods

UAV flights were conducted at five growth stages: tillering (Z25), jointing (Z32), heading (Z55), grain filling (Z75), and maturity (Z91) according to Zadoks’ decimal code. Ground-truth measurements included leaf area index (LAI, using an AccuPAR LP-80), above-ground biomass (destructive sampling of 0.5 m² quadrats), and SPAD chlorophyll readings. At harvest, grain yield was measured per plot at 13% moisture. Plot-average vegetation indices were extracted from orthomosaics using QGIS zonal statistics. Simple linear and multiple regression models were built for each index-stage combination. A random forest regression (500 trees, 3 variables per split) combining all four indices at heading was also trained using 70% of data and validated on 30%. Model accuracy was assessed by R², RMSE, and MAPE [12].

Results

Table 1. Correlation (R²) between vegetation indices and wheat grain yield at five growth stages

Growth Stage	NDVI	GNDVI	NDRE	SAVI	Best Single Index
Tillering (Z25)	0.41	0.38	0.29	0.43	SAVI
Jointing (Z32)	0.62	0.58	0.54	0.61	NDVI
Heading (Z55)	0.84	0.79	0.76	0.81	NDVI
Grain Fill (Z75)	0.73	0.71	0.68	0.72	NDVI
Maturity (Z91)	0.31	0.28	0.24	0.33	SAVI

All R² values significant at $p < 0.01$ except maturity-stage NDRE ($p < 0.05$)

NDVI at heading provided the strongest single-index yield prediction ($R^2 = 0.84$). All indices peaked in predictive power at heading, then declined through grain filling and maturity as canopy senescence reduced spectral contrast between treatments.

Table 2. Performance of yield estimation models at the heading stage

Model	R ²	RMSE (t/ha)	MAPE (%)
NDVI linear regression	0.84	0.31	8.4
GNDVI linear regression	0.79	0.37	9.7
Multiple regression (4 indices)	0.86	0.28	7.6
Random forest (4 indices)	0.89	0.24	6.8

Validation set: n = 14 plots (30% holdout).

The random forest model outperformed all linear approaches, achieving $R^2 = 0.89$ and MAPE of 6.8%. Spatial yield maps generated from this model revealed within-field variation of up to 1.9 t/ha between the highest and lowest yielding zones within a single nitrogen treatment block.

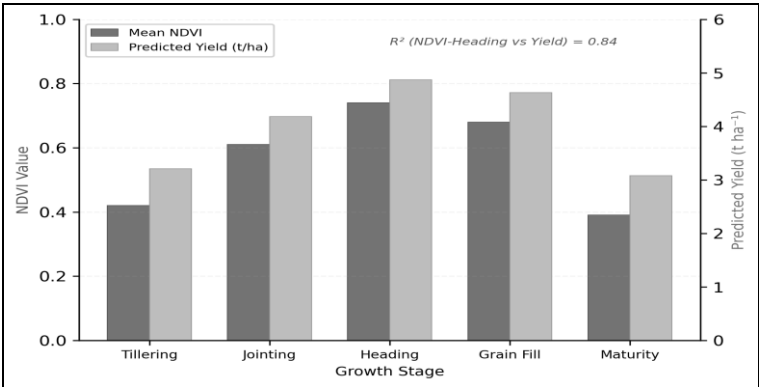


Fig 1: Mean NDVI values and predicted yields across five wheat growth stages. NDVI peaked at heading (0.74) and declined sharply by maturity (0.3)

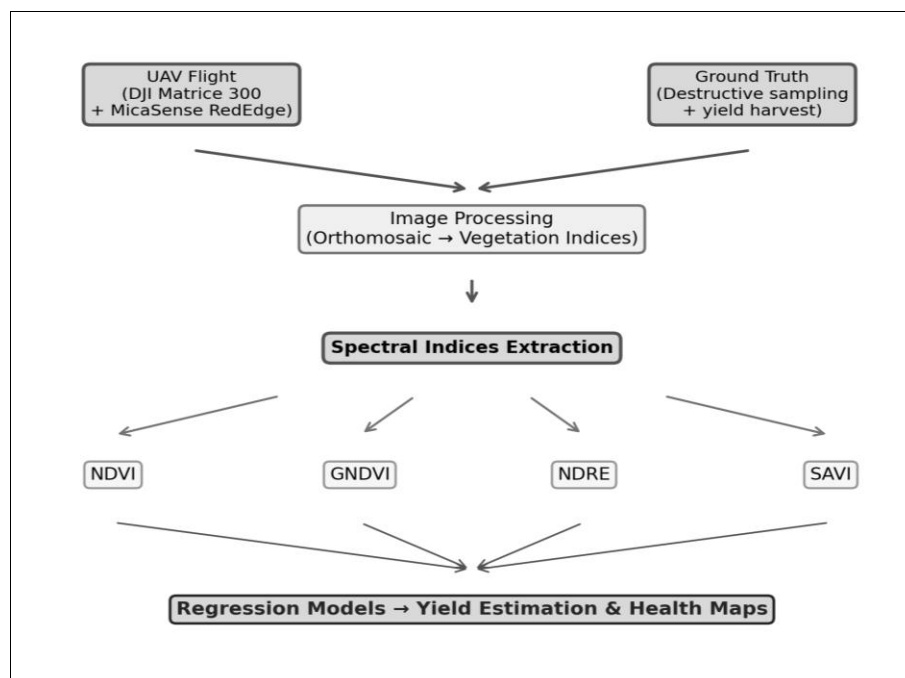


Fig 2: Workflow for UAV-based multispectral crop health assessment and yield estimation in wheat, from data acquisition through vegetation index extraction to regression modelling

Comprehensive interpretation

Heading emerged as the optimal imaging window for yield prediction. At this stage, canopy closure is complete but senescence hasn't begun, maximizing spectral separation between well-nourished and stressed canopies. The random forest model's advantage over linear regression likely reflects its ability to capture nonlinear interactions among indices.

Discussion

The R^2 of 0.84 for NDVI at heading is consistent with results from Zhao *et al.* [4], who reported R^2 values of 0.80-0.87 for UAV-derived NDVI and wheat yield in the North China Plain. The improvement offered by random forest ($R^2 = 0.89$) aligns with the broader trend in precision agriculture toward machine learning for yield mapping [13]. The within-field variation of 1.9 t/ha underscores the limitation of plot-average sampling spatial yield maps can guide variable-rate nitrogen application, potentially saving 15-20% of fertilizer input while maintaining yields [14].

The decline in predictive power after heading deserves discussion. During grain filling, the canopy begins senescing from the lower leaves upward, reducing the spectral contrast between nitrogen treatments. By maturity, most leaves are dead and spectral variation reflects straw color rather than photosynthetic activity. This temporal window effect means that timing the UAV flight correctly is as important as choosing the right sensor or index. For operational use, a single well-timed flight at heading could replace multiple flights across the season, reducing costs and data processing burden.

NDRE, which targets the red-edge band, was expected to outperform NDVI for nitrogen stress detection based on its reported sensitivity to chlorophyll variation [5]. However, in this research, NDRE consistently ranked third or fourth. This may reflect the fact that nitrogen differences in our trial were large enough to be captured by any index; NDRE's advantage may only appear at finer levels of nitrogen variation. Future research with more closely spaced nitrogen rates could test this hypothesis.

Limitations

This research was conducted at a single site with one wheat variety, limiting generalizability. Cloud cover restricted UAV flights to clear days, which may miss time-sensitive stress events. The random forest model requires retraining for different varieties and environments. Additionally, the 2.5 cm resolution generates very large datasets that demand substantial computing resources for processing a practical constraint for real-time application on large farms. The economic cost of the UAV system (approximately USD 15,000) may also limit adoption by smallholders [14].

Conclusion

UAV-based multispectral imaging at the heading stage provides reliable, non-destructive wheat yield estimation with R^2 up to 0.89 using random forest regression. NDVI was the best single-index predictor. The technology reveals within-field yield variability invisible to conventional sampling, supporting precision nutrient management. Future work should test the approach across multiple sites, varieties, and seasons to build robust, transferable prediction models.

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