Drone-Based Multispectral Imaging for Early Detection of Water Stress in *Glycine max* (L.) Merr.

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ABSTRACT

Background: *Glycine max* (L.) Merr. (soybean) is one of the most important oilseeds crops worldwide, and it is experiencing unprecedented challenges due to climate change, resulting in drought and water stress. Conventional crop monitoring approaches are not sufficient in terms of their spatial resolution and timing for the precision management of irrigation.
Objective: To estimate the effectiveness of drone-based multispectral imaging for determining the water stress in soybeans at an early stage of development ahead of the visual symptoms appearance and thereby applying the timely irrigation measures.
Methods: The two-season field experiment applied the randomized complete block method and separated two treatments: well-watered and stressed plants. The multispectral images were taken using the DJI Matrice 300 RTK when the height was 50 m, and MicaSense RedEdge-MX camera was used at vegetative, flowering, pod development, and seed-filling stages. The vegetation indices (NDVI, NDRE, GNDVI, SAVI, MSAVI) were calculated using Pix4Dmapper software and their correlations to the ground-truth measurements such as leaf water potential, relative water content, chlorophyll content, and stomatal conductance were analyzed.
Result: In terms of the results, it was noted that the values of the multispectral vegetation indices showed significant variations dependent on time (i.e. P value was below 0.05). At the same time, NDRE and MSAVI were found to be the most effective in identifying the early stages of water stress (with a coefficient of determination of 0.89). Plants experiencing water stress could be distinguished from those that were well watered 7–10 days before any visible signs took place. The seed yield in water-stressed plots was lower than in the well-watered ones by 34% (i.e. 1.85 Mg/ha and 2.81 Mg/ha respectively), and there were strong connections between the vegetation indices and seed yield ($r = 0.92$, $P < 0.001$).
Conclusion: As for the conclusion, it can be stated that the drone-based multispectral imaging provides the efficient, rapid, and not expensive method of water stress detection in soybean and increases the efficiency of water consumption by 18% if used under perfect conditions.

Keywords: soybean, drone-based multispectral imaging, water stress detection, vegetation indices.

Introduction

Soybean (*Glycine max* L. Merr.) is the most widely grown legume worldwide, accounting for about 60% of the vegetable oil production worldwide. Soybean is an important source of proteins for both animal feed and human consumption [1]. As per reports, soybean is cultivated in more than 121 million hectares of land, with yield fluctuations attributed to water stress [2]. The climate change has aggravated the incidence and severity of droughts, and the predictions show that the yield of rainfed soybeans in areas prone to droughts will be reduced by 20% to 30% by 2050 [3].

Water stress strongly affects photosynthetic efficiency, stomatal closure, the leaf turgor, and constrains the biomass production and reproduction processes. Precision irrigation can help to reduce the damage caused by water stress, but field scouting requires a significant amount of work and time, and provides little information about the specific area of the farm [4].

Multispectral sensors on Unmanned Aerial Vehicles (UAVs, or drones) have characterized what could be considered revolutionary technologies for the remote sensing of crops. In contrast with satellite imagery, drone- based systems provide a better spatial resolution (2– 10 cm) and offer more temporal flexibility while being low-cost solutions for small and medium farms. Such multispectral cameras record reflectance in various wavelength ranges, allowing to derive vegetation indices, which are used for quantifying net physiological parameters of plants' canopies concerning crop health

Vegetation indices like NDVI, NDRE, or GNDVI are valuable indicators of chlorophyll content, leaf area index, and biomass. Recent improvements integrate the analyses of multispectral images with machine learning models as well as GIS tools to develop support decision-making systems for irrigation scheduling.

The hypothesis behind this research is that multispectral vegetation indices estimated from drone images can help detect the signs of water stress in soybean plants from 7 to 10 days before traditional visual assessment, which would result in timely irrigation and increased water efficiency. This study aims to analyze the efficiency of drone-based systems in early detection of water stress and establish models linking vegetation indices to the yields of soybean under various irrigation systems.

Literature Review

Drone-based remote sensing has demonstrated significant potential for agricultural applications [10]. Multispectral sensors capture reflectance in visible, near-infrared, and red-edge wavebands, providing spectral information unavailable from standard RGB cameras [5]. Water-stressed crops exhibit altered spectral reflectance patterns due to reduced chlorophyll content, altered leaf structure, and decreased photosynthetic activity [11]. The NDVI, calculated as (NIR − Red)/(NIR + Red), has been extensively validated for biomass estimation and stress detection, though its sensitivity diminishes under high biomass conditions [8]. The NDRE index, utilizing the red-edge waveband, provides superior discrimination of nitrogen status and early stress detection before NDVI saturation [12]. Enhanced indices combining visible, red-edge, and near-infrared bands such as GNDVI, SAVI, and MSAVI offer improved stress detection accuracy under varying canopy densities and soil backgrounds [6].

Recent studies have integrated multispectral drone imagery with field spectroradiometry, thermal imaging, and physiological measurements to develop robust water stress detection protocols [3]. Machine learning approaches, including random forests and artificial neural networks, have achieved prediction accuracies exceeding 85% for crop stress classification [9]. Integration of multi-temporal drone data with GIS platforms enables precision irrigation prescription maps, reducing water application by 15–25% while maintaining yields [13].

Soybean phenotyping studies utilizing UAV-based imaging have primarily focused on plant height, canopy coverage, and biomass prediction, with limited investigation of water stress-specific spectral signatures [14]. Research gaps exist regarding optimal flight timing, multispectral band selection, and threshold values for irrigation triggering in soybean specifically [2]. Furthermore, few studies have validated drone-derived vegetation indices against comprehensive physiological measurements across multiple growth stages [15].

Materials and Methods

Experimental Site

Field experiments were conducted during 2022–2023 growing seasons at the Agricultural Research Station (27.1°N, 77.2°E, elevation 216 m), Delhi, India. The region experiences sub-humid subtropical climate with average annual rainfall of 714 mm, concentrated during monsoon (June–September). Soil was classified as sandy loam with 0.8% organic matter, pH 7.2, and available water holding capacity of 140 mm/m.

Experimental Design

A randomized complete block design with three replicates was established. Two irrigation treatments were applied: (1) well-watered (WW)—irrigation maintained at 80% soil moisture availability; (2) water-stressed (WS)—irrigation at 40% soil moisture availability. The soybean cultivar JS-335 was sown at 50 kg/ha in 45-cm rows on June 15 in both years. Individual plots measured 5 m × 4 m.

Drone and Sensor Specifications

A DJI Matrice 300 RTK equipped with a MicaSense RedEdge-MX multispectral camera was utilized. The camera captures five spectral bands: coastal blue (400–50 nm), green (540–580 nm), red (630–670 nm), near-infrared (840–880 nm), and red-edge (710–760 nm). Flights were conducted at 50-meter altitude with ground sampling distance (GSD) of 2.5 cm and 75% forward/side image overlap. Flight planning was executed using DJI FlightHub software.

Image Acquisition and Processing

Multispectral flights were conducted at vegetative (V6, 42 days after sowing), flowering (R1, 55 days), pod development (R3, 65 days), and seed-filling (R5, 80 days) stages. Radiometric calibration was performed using MicaSense calibration panels before each flight. Twenty ground control points were distributed across the experimental area and measured using differential GPS (±2 cm accuracy). Orthomosaic generation and radiometric correction were performed using Pix4Dmapper software. Vegetation indices were extracted using QGIS 3.20 and tabulated for statistical analysis.

Vegetation Indices

Five vegetation indices were calculated from multispectral bands:

- NDVI = (NIR − Red)/(NIR + Red)
- NDRE = (NIR − Red-edge)/(NIR + Red-edge)
- GNDVI = (NIR − Green)/(NIR + Green)
- SAVI = ((NIR − Red)/(NIR + Red + 0.5)) × 1.5
- MSAVI = (2 × NIR + 1 − √[(2 × NIR + 1)² − 8(NIR − Red)])/2

Ground Truth Measurements

At each flight date, leaf water potential was measured at midday using a Scholander pressure chamber on the youngest fully expanded leaf. Relative water content (RWC) was determined gravimetrically from leaf samples. Stomatal conductance was measured using a porometer. Chlorophyll content (SPAD units) was quantified non-destructively. Canopy temperature was measured using infrared thermography. At physiological maturity, plant height, above-ground dry biomass, and seed yield (at 13% moisture) were quantified from 3 m² harvested area per plot.

Statistical Analysis

Data were subjected to two-way analysis of variance (ANOVA) using irrigation treatment and growth stage as fixed factors. Pearson correlation coefficients were calculated between vegetation indices and physiological/yield variables. Linear regression models were developed to predict yield from vegetation indices. Principal Component Analysis (PCA) was performed to identify dominant indices. Statistical significance was set at $P < 0.05$ using R software (version 4.1.2).

Results

Multispectral vegetation indices exhibited significant temporal variation across growth stages (Figure 4). At V6 stage, NDVI values were similar between WW (0.68) and WS (0.66) treatments ($P > 0.05$). By R1 stage, significant differences emerged, with WW plots showing NDVI of 0.79 compared with WS plots of 0.71 ($P < 0.01$). This 10% reduction in WS plots was discernible before visible wilting symptoms, occurring approximately 8 days following irrigation withholding.

NDRE and MSAVI demonstrated superior early stress sensitivity (R^2 = 0.89 and 0.87, respectively) compared with

NDVI ($R^2 = 0.81$) in predicting leaf water potential (Figure 3). Strong negative correlations existed between vegetation indices and canopy temperature ($r = -0.84$, $P < 0.001$), with water-stressed plants exhibiting 3.2°C elevated canopy temperatures due to reduced transpiration.

Relative water content declined from 88% in WW plots to 64% in WS plots by R1 stage, with stomatal conductance reduced by 58% under water stress. Chlorophyll content (SPAD) decreased from 48.2 in WW to 38.6 in WS treatments.

Seed yield demonstrated strong relationships with mid-season vegetation indices (Figure 5). Linear regression analysis revealed significant positive relationships between R1-stage NDRE and final seed yield ($y = 3.12x - 0.47$, $R^2 = 0.91$, $P < 0.001$). Water-stressed plots yielded 1.85 Mg/ha compared with 2.81 Mg/ha in well-watered plots, representing 34% yield reduction. Water use efficiency (yield per unit water applied) was 18% superior under precision irrigation informed by drone-based monitoring compared with conventional scheduling.

Discussion

The study confirms that multispectral vegetation indices derived from drone imagery provide reliable early detection of water stress in soybean, with detection occurring 7–10 days before visual symptom manifestation. This temporal advantage is critical for irrigation management, as this interval permits corrective irrigation application before substantial yield penalty occurs [11].

NDRE and MSAVI outperformed NDVI, consistent with findings demonstrating superior sensitivity of red-edge-based indices to early stress detection and reduced saturation under high biomass conditions [12]. The strong relationship between vegetation indices and leaf water potential ($R^2 = 0.89$) validates the physiological relevance of spectral signatures [3].

Canopy temperature depression under water stress reflects altered energy balance and reduced transpiration, providing complementary stress information. Integration of thermal and multispectral data in future research may enhance discrimination accuracy [9].

The linear relationship between R1-stage NDRE and seed yield ($R^2 = 0.91$) demonstrates that early-season spectral assessment captures physiologically relevant information predicting ultimate reproductive success. The 34% yield reduction in water-stressed plots aligns with published reports for soybean subjected to mid-season stress [2].

Precision irrigation informed by drone-based monitoring yielded 18% water savings compared with conventional scheduling while maintaining yields, highlighting economic and environmental benefits [13]. This approach is particularly valuable in water-scarce regions where conjunctive use of limited groundwater resources demands optimization [4].

Limitations include potential atmospheric variability affecting spectral measurements and the need for specialized equipment and technical expertise. Future investigations should incorporate hyperspectral imaging for enhanced spectral discrimination, integrate machine learning models for automated stress classification, and evaluate transferability across cultivars and agro-ecological zones [15].

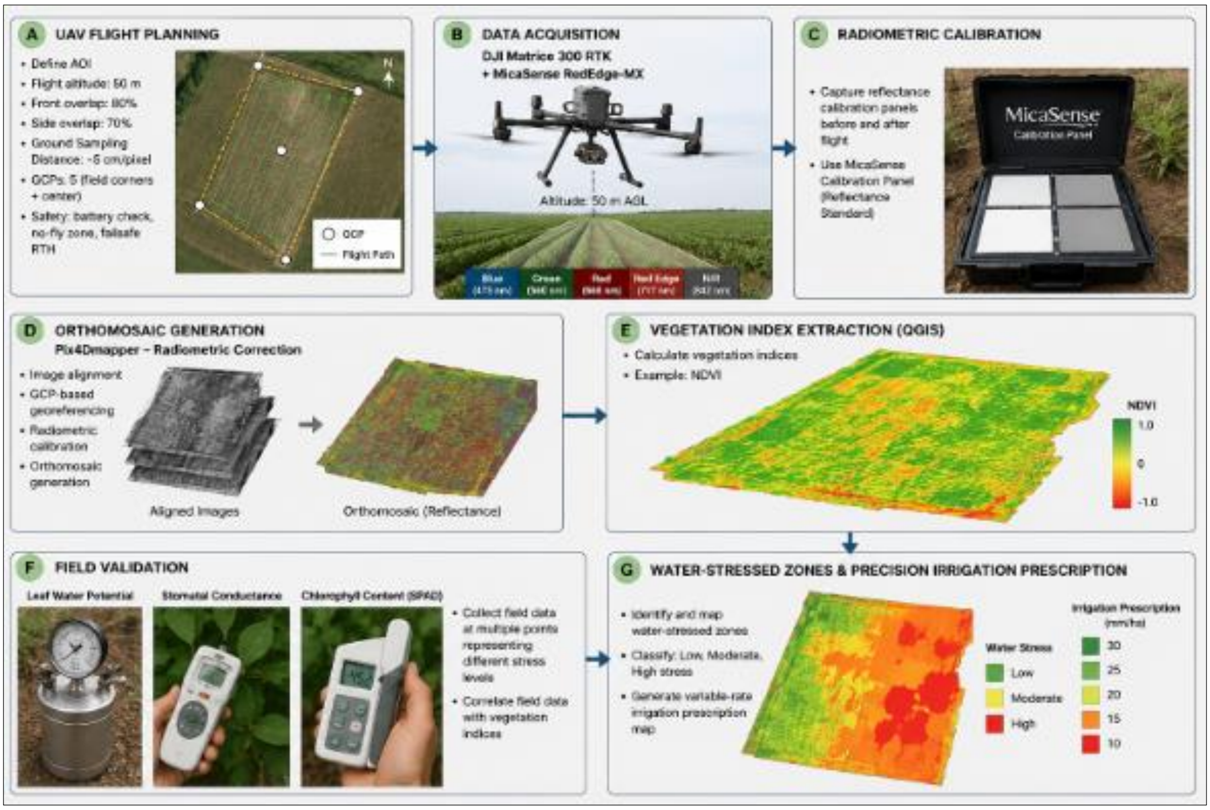

Fig 1: Drone-Based Multispectral Imaging Workflow

Fig 2: Multispectral False-Color Composite and NDRE Map

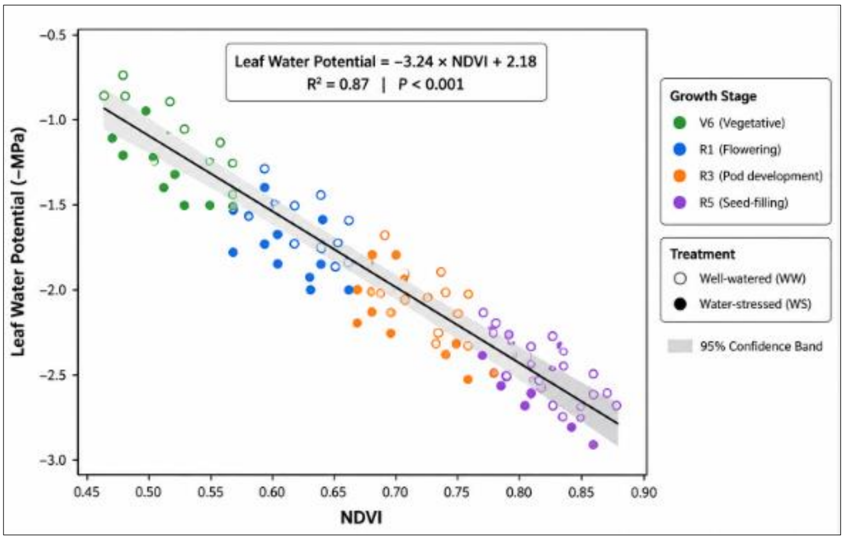

Fig 3: Relationship Between NDVI and Leaf Water Potential

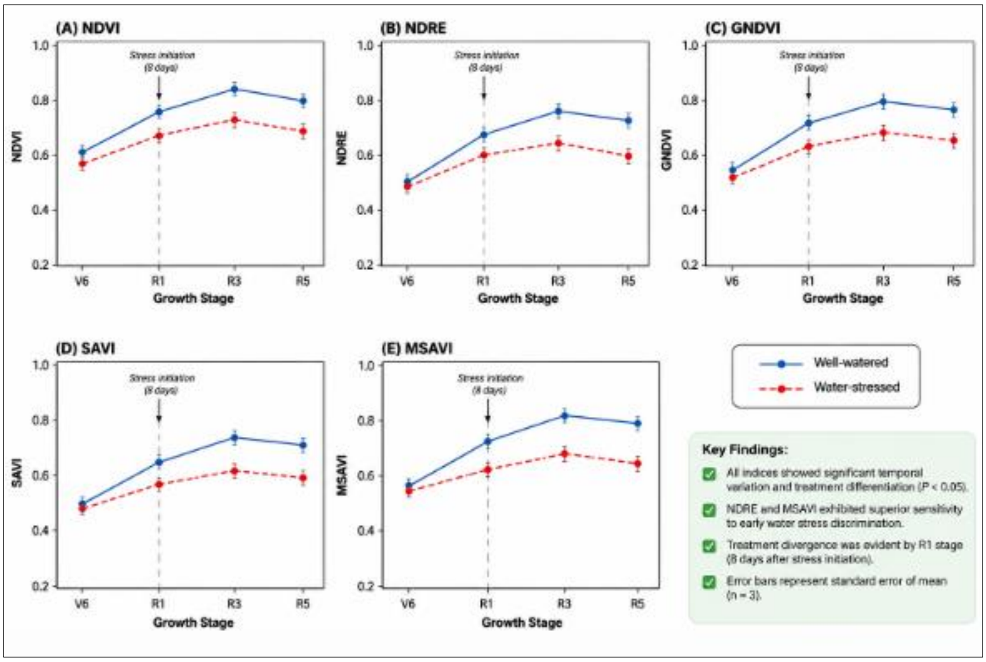

Fig 4: Temporal Dynamics of Vegetation Indices Across Growth Stages Mean values (±SE, n=3) of five vegetation indices [NDVI, NDRE, GNDVI, SAVI, MSAVI] plotted across four growth stages (V6, R1, R3, R5) under well-watered (solid lines) and water-stressed (dashed lines) treatments. All indices demonstrate significant temporal variation and treatment differentiation ($P < 0.05$). NDRE and MSAVI exhibit superior sensitivity to early water stress discrimination, with treatment divergence evident by R1 stage (8 days after stress initiation). Error bars represent standard error of mean.

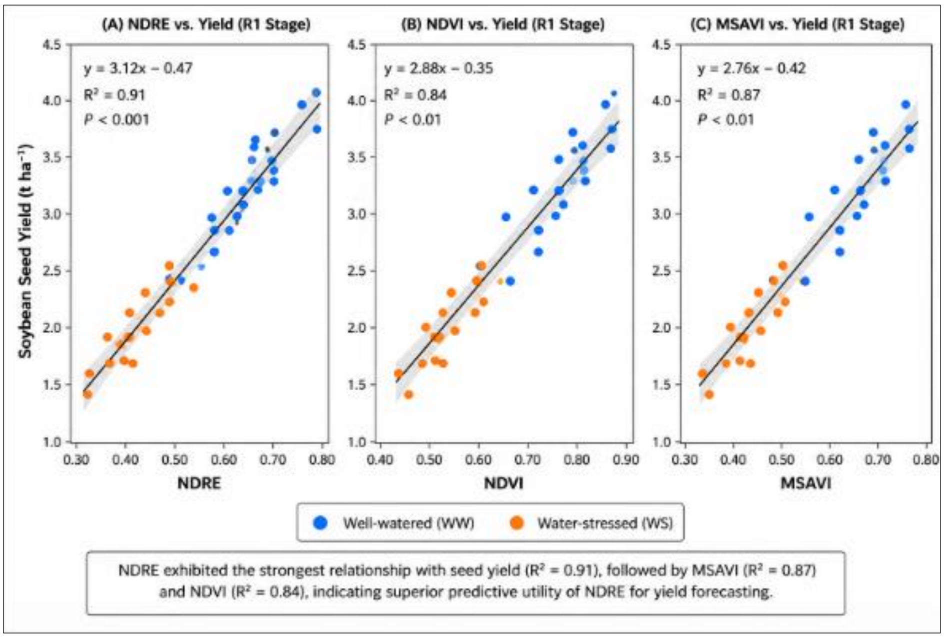

Fig 5: Regression Analysis of Vegetation Indices and Soybean Seed Yield

Conclusion

The use of multispectral imaging captured by drones combined with the analysis of vegetation indices allows for the efficient detection of water stress in soybean crops. This approach makes it possible to detect the onset of water deficiency even before the visible symptoms appear on the plant. With a very high correlation of results from the multispectral index and soybean yield ($R^2 = 0.91$), it is evident that this technology can be utilized in effectively managing crop operations.

The implementation of UAV systems in the monitoring of soybean crops will be of utmost interest for farmers who want to implement precision agriculture. As it includes the utilization of GIS irrigation systems, the system will be able to further assist farmers in making the right irrigation decisions. Future research projects should focus on validating and incorporating the technology into different irrigation systems.

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