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Dual UAV sensing and variable rate fertigation for climate resilient sugarcane cultivation in Northern India

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Abstract

Sugarcane (*Saccharum officinarum* L.) is a vital cash crop and a cornerstone of rural economies in South Asia, yet its cultivation remains highly resource-intensive, with heavy demands for irrigation and nitrogen fertilizer. Conventional practices such as flood irrigation and blanket fertilizer application often result in poor water productivity, low nutrient-use efficiency, and significant environmental losses. Precision farming tools, particularly unmanned aerial vehicles (UAVs), provide opportunities to address these challenges by enabling site-specific monitoring and targeted input management. In this study, a dual-UAV workflow was developed for sugarcane cultivation under subtropical conditions in northern India. A lightweight sensing drone equipped with a multispectral camera was used to monitor canopy vigor through NDVI and NDRE vegetation indices at key growth stages. Stress maps generated from these indices were processed into management grids and translated into fertigation schedules, which were executed by a small-class UAV equipped with variable-rate spraying capability. Compared with conventional farmer practice, the sensor-guided treatments demonstrated substantial improvements in input-use efficiency and crop performance while lowering water and nitrogen requirements. The approach highlights the potential of UAV-based sensing-to-actuation pipelines as a scalable, low-cost strategy for tall-stature crops, indicating potential pathways to enhance climate resilience, farm profitability, and environmental sustainability under the conditions tested. Beyond sugarcane, the workflow provides a replicable template for precision nutrient and water management in other resource-intensive cropping systems.

Keywords Precision agriculture, UAV, Remote sensing, Variable-rate fertigation, Sugarcane, Site-specific management

1 Introduction

Sugarcane (*Saccharum officinarum* L.) is one of the world's most important industrial crops, providing raw material for sugar, ethanol, bioenergy, and several agro-industrial products. Globally, sugarcane is cultivated on more than 26 million hectares, producing over 1.9 billion tonnes annually, with India and Brazil together accounting for nearly



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60% of total production [1]. In India alone, the crop occupies approximately 5 million hectares and supports millions of farmers as well as large processing industries, making it a critical component of rural livelihoods and the national bioeconomy [2].

Despite its economic importance, sugarcane cultivation is highly resource intensive. The crop requires substantial irrigation inputs, often exceeding 20,000–25,000 m³ ha⁻¹ under conventional flood irrigation systems, along with large nitrogen (N) fertilizer applications ranging between 200 and 300 kg ha⁻¹ [3, 4]. Such input-intensive management frequently results in inefficient resource utilization. Nitrogen-use efficiency (NUE) in many Indian sugarcane systems is reported to be as low as 30–35%, indicating that a significant proportion of applied nitrogen is lost through leaching, volatilization, or denitrification processes [5]. Similarly, flood irrigation practices often lead to poor water-use efficiency (WUE), with considerable losses through runoff and deep percolation [6]. These inefficiencies not only reduce farm profitability but also contribute to environmental concerns, including groundwater depletion, nutrient contamination, and greenhouse gas emissions [7].

Traditional management practices in sugarcane cultivation further exacerbate these challenges. Fertilizers and irrigation water are typically applied using uniform, calendar-based schedules that do not account for spatial variability in soil conditions, crop vigor, or nutrient demand [8]. As a result, some portions of the field receive excess inputs while others remain under-supplied, leading to uneven crop growth and reduced overall efficiency. Although technologies such as drip irrigation and split fertilizer applications have shown potential to improve resource use efficiency, their adoption in many parts of India remains limited due to infrastructure costs, operational complexity, and limited technical awareness among farmers [9]. These constraints highlight the need for innovative management approaches capable of dynamically monitoring crop conditions and enabling site-specific input application.

Recent advances in precision agriculture have provided new opportunities to address these challenges through the integration of remote sensing technologies and digital decision-support tools. Among these technologies, unmanned aerial vehicles (UAVs) have emerged as a highly flexible platform for high-resolution crop monitoring. Compared with satellite imagery, UAV-based sensing offers superior spatial resolution and greater temporal flexibility, enabling detailed assessment of crop conditions throughout the growing season [10]. When equipped with multispectral sensors, UAVs can generate vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Red Edge Index (NDRE), which are widely used indicators of canopy vigor, chlorophyll content, and nitrogen status [11].

Numerous studies have demonstrated the effectiveness of UAV-derived vegetation indices for monitoring crop growth and guiding nutrient management in major crops such as wheat, rice, and maize [12–14]. In sugarcane systems, UAV applications have primarily focused on biomass estimation, crop health monitoring, and stress detection [15, 16]. However, most existing studies remain limited to diagnostic monitoring, where vegetation indices are used primarily to identify crop stress rather than to guide operational management decisions. The translation of UAV-derived data into actionable field interventions—such as variable-rate fertilization or irrigation—remains relatively under-explored, particularly in tall-stature crops where ground-based machinery faces operational constraints.

The concept of integrating UAV sensing with automated input delivery offers a promising pathway to overcome these limitations. By converting vegetation index maps into spatially explicit management prescriptions, UAV-based systems can enable real-time adjustment of fertilizer and water applications according to crop needs. While several international studies have explored UAV-based prescription mapping for variable-rate fertilizer application, these systems often rely on ground-based machinery for implementation [3, 17, 18]. Such approaches may be less suitable for sugarcane cultivation, where dense canopy structure and field conditions can limit the accessibility of conventional equipment during mid-to-late growth stages.

A dual-UAV system—combining one platform for multispectral sensing and another for targeted input delivery—offers a potential solution to this challenge [19, 20, 21, 22, 23]. In such a system, UAV-derived vegetation indices can be used to dynamically identify crop stress zones, while a second UAV executes variable-rate fertigation or foliar treatments based on these spatial prescriptions. Despite the rapid growth of UAV technologies in agriculture, fully integrated sensing-to-actuation workflows remain relatively rare, particularly in developing-country contexts and in high-biomass crops such as sugarcane.

Against this backdrop, the present study investigates the potential of a dual-UAV sensing and actuation system for precision nutrient and water management in sugarcane cultivation under subtropical conditions in northern India. The study aims to develop and evaluate an operational workflow that links UAV-based crop monitoring with site-specific fertigation decisions.

Specifically, the objectives of this research were:

- (i) to develop a UAV-based sensing-to-actuation pipeline integrating multispectral crop monitoring with variable-rate fertigation delivery;
- (ii) to evaluate the impact of this approach on water-use efficiency (WUE), nitrogen-use efficiency (NUE), crop yield, and economic return compared with conventional farmer practices; and
- (iii) to assess the feasibility of UAV-enabled fertigation as a scalable strategy for improving resource-use efficiency in sugarcane production systems.

It is hypothesized that integrating UAV-derived vegetation indices (NDVI and NDRE) with automated variable-rate fertigation will significantly improve input-use efficiency and crop productivity while reducing water and nitrogen requirements relative to conventional uniform management practices [24]. By demonstrating an end-to-end UAV sensing-to-actuation framework under real-world field conditions, this study contributes to advancing climate-resilient and resource-efficient agricultural management strategies for high-input cropping systems.

2 Materials and methods

2.1 Study area and crop details

The field experiment was conducted during the 2023–2024 growing season at Nanauta block, Saharanpur district, Uttar Pradesh, India (29°42'N, 77°24'E; WGS84 geographic coordinate system; 270 m a.s.l.). A satellite view of the experimental site and surrounding agricultural landscape is shown in Fig. 1. This region falls under the Upper Gangetic Plains agro-climatic zone, which is characterized by semi-arid to sub-humid conditions,



Fig. 1 Satellite view of the experimental field located in Nanauta block, Saharanpur district, Uttar Pradesh, India (29°42'N, 77°24'E; WGS84 coordinate system). The image shows the agricultural landscape surrounding the study site within the Upper Gangetic Plains agro-climatic zone. The experimental field is indicated by the location marker, and grid coordinates are displayed to illustrate spatial reference. Source: Google Earth imagery (Google LLC)

alluvial soils, and intensive irrigation agriculture [25]. The site experiences a mean seasonal temperature range of 23–35 °C, with an annual rainfall of ~1,100 mm, primarily concentrated during the monsoon months (July–September).

The soils at the study site are classified as sandy-loam to loam Inceptisols, with a near-neutral pH (7.4) and moderate organic carbon content (0.65%).

The commercial variety Co-0238 was selected for this trial. Co-0238 is a widely adopted cultivar in northern India due to its high yield potential, superior sucrose recovery, and tolerance to major pests and diseases [26, 27, 28].

Sugarcane was planted on 12 February 2023 in furrow rows at 90 cm × 120 cm spacing, following regional agronomic recommendations [14]. The crop was harvested in mid-December 2023, corresponding to an approximately 10-month crop duration under sub-tropical conditions.

2.2 Experimental treatments and design

The field trial was laid out in a Randomized Complete Block Design (RCBD) with three treatments and three replications [29, 30], each plot measuring approximately 0.11 ha, as given in Table 1, and the schematic representation of the RCBD has been shown in Fig. 2.

- T1 (Control – Farmer Practice): Conventional flood irrigation combined with blanket nitrogen application of 250 kg N ha⁻¹, delivered in two equal splits (basal and mid-season) [4].
- T2 (Sensor-Guided Fertigation): UAV-monitored fertigation using a rule-based engine that adjusted irrigation and N application in response to vegetation index thresholds (NDVI < 0.52). Nitrogen was applied in three splits, with variable rates based on canopy vigor zones.
- T3 (Sensor-Guided Fertigation + Biostimulant): Same as T2, but supplemented with foliar application of a seaweed extract biostimulant when NDRE < 0.30 persisted after fertigation. Biostimulants have been shown to enhance nutrient uptake and stress tolerance in sugarcane and other crops [31, 32].

The NDVI threshold (<0.52) was selected based on global trait datasets and sugarcane-specific UAV studies that associate values below this cutoff with moderate-to-severe nitrogen deficiency [24, 33]. Similarly, the NDRE threshold (<0.30) was chosen for its higher sensitivity to leaf nitrogen status under dense canopies, as established in sugarcane and maize monitoring studies [20, 21].

Each plot was bordered by guard rows to minimize edge effects and irrigated using subsurface hose connections linked to the actuation UAV. Fertilizer inputs were delivered as urea–ammonium nitrate solution (18% N), a formulation commonly used in fertigation trials for its rapid plant availability [14].

2.3 UAV platforms and sensor specifications

Two UAV platforms were employed in this study: a micro-class sensing UAV for canopy monitoring and a small-class actuation UAV for variable-rate fertigation, as shown in Fig. 3.

Sensing UAV: A custom-built quadrotor micro-UAV (<2 kg MTOW) was equipped with the MicaSense RedEdge-MX multispectral camera [34]. The sensor captures five

Table 1 Experimental block design for sugarcane

Treatment	Description	Decision trigger
T1	Farmer-practice flood irrigation + blanket N (250 kg ha ⁻¹)	Fixed calendar
T2	UAV-monitored fertigation (split N, variable irrigation)	NDVI-based canopy stress detection
T3	UAV-monitored fertigation + biostimulant foliar spray	NDVI–NDRE combined canopy stress detection

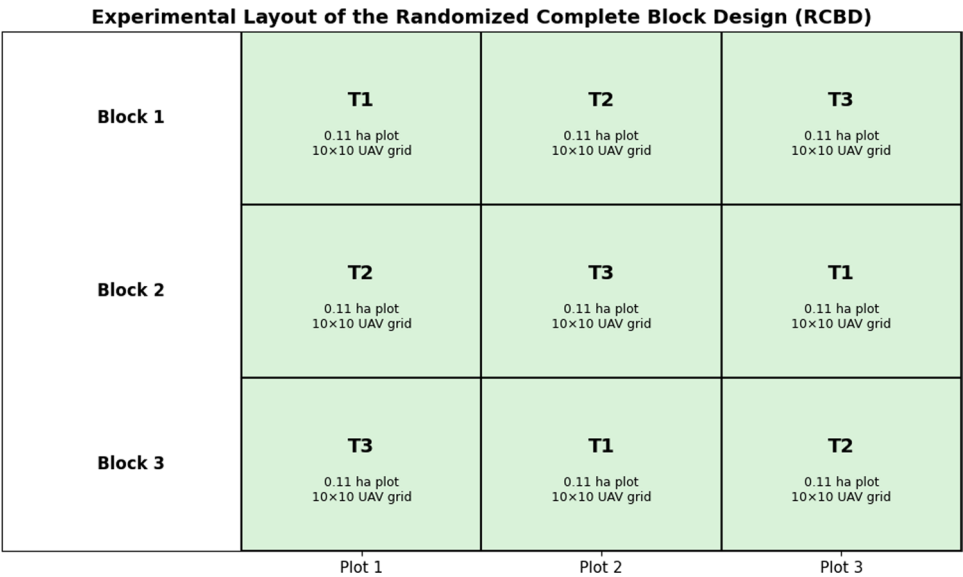


Fig. 2 Schematic representation of the randomized complete block design (RCBD) used in the experiment. Three treatments (T1: farmer practice; T2: UAV-guided fertigation; T3: UAV-guided fertigation + biostimulant) were arranged across three replicated blocks. Each plot covered approximately 0.11 ha and was further subdivided into 10 × 10 UAV management grids used for vegetation index mapping and spatial analysis

UAV-GUIDED VARIABLE FERTIGATION IN SUGARCANE

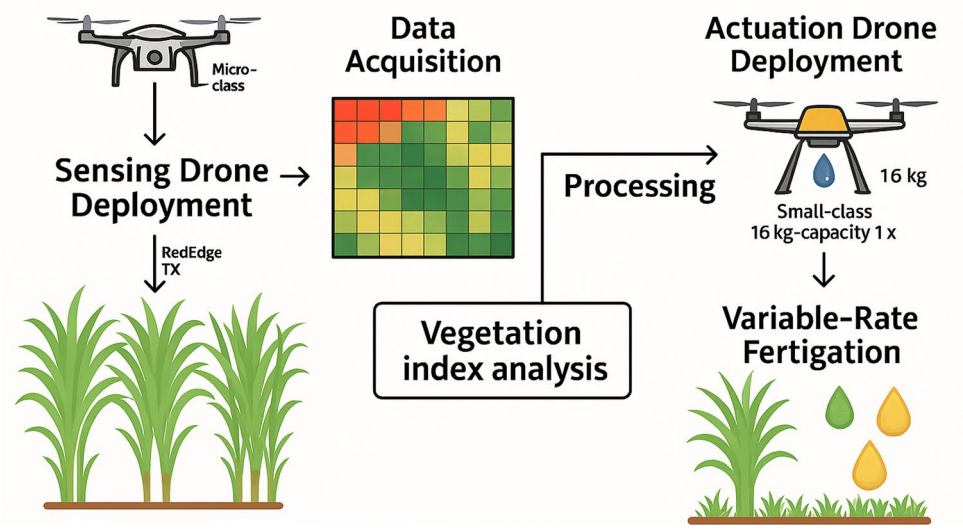


Fig. 3 Workflow of the dual-UAV, vegetation-index-guided variable-rate fertigation protocol used in this sugarcane study. A micro-class sensing drone equipped with a RedEdge-MX sensor acquires multispectral imagery; vegetation indices (NDVI, NDRE) are processed to generate stress maps, which trigger site-specific fertigation by a small-class 16 kg payload drone

discrete spectral bands: Blue (475 nm, FWHM 20 nm), Green (560 nm, 20 nm), Red (668 nm, 10 nm), Red Edge (717 nm, 10 nm), and Near-Infrared (840 nm, 40 nm), producing ~5 cm GSD at 45 m flight altitude [16, 21]. Radiometric calibration was performed before each flight using the manufacturer's reflectance calibration panel and incident light sensor [34].

Captured multispectral images were stitched into orthomosaics using the OpenDroneMap (ODM) toolkit, an open-source photogrammetry software widely used in UAV-based agricultural research [35, 36]. Vegetation indices (NDVI, NDRE) were subsequently processed using a custom Python 3.10 pipeline (NumPy, Rasterio, and GeoPandas libraries), which allowed automated raster extraction, thresholding, and conversion into management grids.

Actuation UAV: Variable-rate fertigation was performed using a hexacopter UAV (24 kg MTOW) built on a carbon-fiber frame with a payload capacity of 16 L. The UAV was equipped with dual ultra-low volume (ULV) rotary atomizer nozzles, delivering droplets in the 80–100 μm range, suitable for foliar applications with high canopy penetration and reduced drift [37]. The flight control system was based on Pixhawk open-source autopilot hardware, running ArduPilot firmware. Variable-rate task files (GeoJSON format) generated by the Python pipeline were ingested into Mission Planner, an open-source ground-control software compatible with Pixhawk, to execute site-specific fertigation missions.

Both UAVs operated under India's Drone Rules, 2022 experimental category for agricultural research [38]. Differential GPS (DGPS) correction was employed to improve flight accuracy, and autonomous missions were flown with a pre-programmed grid pattern to ensure uniform image acquisition and treatment coverage.

Flight positioning was achieved using the onboard GNSS receiver integrated with the Pixhawk autopilot system, providing horizontal positional accuracy of approximately $\pm 1\text{--}2$ m under open-sky conditions. Each sensing mission acquired approximately 220–230 overlapping multispectral images per flight at 45 m altitude with 80% forward and 70% side overlap. Across the five growth-stage monitoring missions, a total of approximately 1,120 multispectral images were processed for orthomosaic generation.

Image georeferencing was performed using the UAV's onboard GNSS positioning embedded in the image metadata. Ground control points (GCPs) were not deployed because the experimental plots were relatively small and the positional accuracy provided by the onboard GNSS was sufficient for grid-based spatial analysis. Orthomosaics were generated using structure-from-motion photogrammetry in OpenDroneMap (ODM), resulting in an estimated positional accuracy of approximately $\pm 1\text{--}2$ m, which was adequate for delineating the 10×10 management grids used for vegetation index mapping and fertigation decision-making.

2.4 Vegetation-index calculation and image processing

Multispectral images were acquired by the RedEdge-MX sensor mounted on the sensing UAV during five key phenological stages of sugarcane growth: Establishment (~30 days after planting, DAP), Tillering (~60 DAP), Grand Growth (~120 DAP), Elongation (~180 DAP), and Maturity (~270 DAP).

Radiometric calibration was performed before each flight using the MicaSense reflectance calibration panel and the downwelling light sensor integrated with the

RedEdge-MX [34]. Calibration ensured that spectral reflectance values were normalized against solar irradiance variations, enabling inter-flight comparability [39]. Dark current correction and vignetting correction were automatically applied through the RedEdge firmware.

The acquired images were stitched into orthomosaics using OpenDroneMap (ODM), an open-source photogrammetry engine validated for agricultural UAV applications [35, 36]. GeoTIFF outputs were then processed in a custom Python pipeline (NumPy, Rasterio, and GeoPandas libraries) to generate vegetation indices. Two primary indices were computed for this study:

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}$$

$$\text{NDRE} = \frac{\text{NIR} - \text{RedEdge}}{\text{NIR} + \text{RedEdge}}$$

where NIR corresponds to the 840 nm band, Red to the 668 nm band, and RedEdge to the 717 nm band [40].

The orthomosaics were divided into 10×10 management grids (0.1 ha per cell) to enable site-specific analysis. Grid-level mean NDVI and NDRE values were extracted, and threshold values were applied to classify each cell as “Low,” “Medium,” or “High” vigor. The thresholds adopted were NDVI < 0.52 and NDRE < 0.30 [41, 42]. These thresholds were based on previous sugarcane and cereal studies linking vegetation indices to leaf nitrogen status [20, 24].

The resulting stress maps were exported as GeoJSON shapefiles and served as direct input to the variable-rate fertigation engine. This sensing-to-decision workflow allowed UAV-based indices to be operationalized into actionable management prescriptions within the same season [43].

2.5 Variable-rate fertigation and foliar protocol

The UAV-based sensing workflow was directly integrated with a rule-based fertigation engine written in Python (v3.10). Stress maps derived from NDVI and NDRE (Sect. 2.4) were converted into GeoJSON task files defining site-specific nitrogen application rates for each 0.1-ha management cell. These prescriptions were uploaded to the Pixhawk-based actuation UAV via Mission Planner, enabling execution of variable-rate fertigation flights.

Fertigation logic: Nitrogen was applied in the form of a urea–ammonium nitrate (UAN) solution (18% N), delivered through the UAV spraying system using variable-rate aerial application. Targeted fertigation rates were defined as 70, 50, and 40 kg N ha^{−1} for Low, Medium, and High NDRE zones, respectively. The rule-based thresholds (NDVI < 0.52; NDRE < 0.30) were drawn from global nitrogen trait datasets and validated against sugarcane-specific UAV studies [24, 33]. In Treatments T2 and T3, the actuation UAV was used to apply the variable-rate fertigation prescriptions derived from the vegetation-index maps.

Spraying system: The actuation UAV employed flights that were conducted at 3–4 m above canopy height and a ground speed of approximately 4 m s^{−1}, which helped reduce drift risk while maintaining uniform coverage across the crop canopy [44, 45].

Foliar Biostimulant Protocol: Treatment T3 combined UAV-guided variable-rate fertigation with foliar application of a seaweed extract biostimulant (3 mL L^{-1} , 60 L ha^{-1}) applied using the same actuation UAV platform at the Grand Growth and Elongation stages [31, 46].

Pulse-drip scheduling: To reduce leaching and volatilization, fertigation was delivered in pulse-drip cycles (two pulses per day), following the principles of deficit and precision irrigation management [47]. This approach enabled synchronization of N supply with crop uptake patterns, improving both NUE and WUE.

2.6 Agronomic measurements

To evaluate the effects of UAV-guided fertigation, a range of morphological, physiological, and yield parameters were measured at key phenological stages of sugarcane.

Growth and morphological traits: Plant height (from soil surface to the tallest fully expanded leaf) and tiller density (number of shoots per meter row length) were recorded at each growth stage [48].

Chlorophyll content (SPAD Readings): Leaf chlorophyll status was assessed using a SPAD-502 Plus chlorophyll meter (Konica Minolta, Japan). For each plot, 30 readings were collected from the top visible dewlap (TVD) leaves (the first fully expanded leaf with a visible collar), which are widely accepted as the diagnostic leaves for nutrient assessment in sugarcane [49, 50].

Yield determination: At harvest, cane yield (t ha^{-1}) was estimated by cutting and weighing all stalks within each plot. Subsamples were used for determining commercial cane sugar (CCS%), following the Bureau of Sugar Standards (BSS) protocols and procedures recommended by the Indian Sugarcane Breeding Institute [51].

2.7 Water and nutrient efficiency measurements

- **Water-Use Efficiency (WUE):** Calculated as the ratio of cane yield (kg) to total irrigation water applied (m^3), following Richards (1993) [52].
- **Nitrogen-Use Efficiency (NUE):** Computed as the ratio of yield gain due to applied nitrogen over the amount of N supplied, based on the framework of Moll et al. (1982) [53].

Economic assessment: Net economic return (₹ ha^{-1}) was calculated by accounting for input costs (fertilizer, water, energy, UAV operation, and biostimulant application) against the gross return from cane yield. UAV operation costs were estimated using prevailing service rates for agricultural drones in India, adjusted for research settings.

WUE and NUE are globally recognized sustainability indicators under the FAO's Water Productivity Framework and the International Plant Nutrition Institute (IPNI)'s 4R Nutrient Stewardship program [54]. In sugarcane, improving WUE and NUE is particularly important, as baseline efficiencies remain low ($< 35\%$ for NUE; $< 10 \text{ kg cane m}^{-3}$ water in many regions) [55]. By adopting UAV-guided, site-specific fertigation, this study aimed to demonstrate measurable improvements in these global benchmark indicators. By combining physiological indices (SPAD, NDVI/NDRE), yield attributes, and efficiency calculations, the measurement framework provided a holistic evaluation of the UAV-based fertigation protocol.

2.8 Statistical analysis

Data collected on yield, water-use efficiency (WUE), nitrogen-use efficiency (NUE), and economic return were subjected to one-way analysis of variance (ANOVA) to test for treatment effects [30, 56, 57]. When significant treatment effects were detected ($p < 0.05$), Tukey's HSD test was used for post-hoc comparison of means.

All statistical analyses were performed in R software version 4.3.0 [58], using the stats and agricolae packages. Assumptions of ANOVA (normality and homogeneity of variance) were tested using Shapiro–Wilk and Levene's tests, respectively. In addition to agronomic metrics, spatial analyses of NDVI and NDRE layers were performed using Python 3.10 with the NumPy and GeoPandas libraries. Grid-level data were extracted from UAV orthomosaics, and stress zones were classified using rule-based thresholds (Sect. 2.4). Effect sizes (η^2 for ANOVA) were also reported where relevant, to provide an estimate of the magnitude of treatment effects beyond statistical significance [59, 60].

3 Results

All results reported correspond to a single-season field experiment and should be interpreted within this experimental scope.

3.1 Spatial distribution of vegetation indices

Figure 4 shows a ten panel composite of NDVI heatmaps for Treatments T2 and T3 across the five growth stages (Establishment → Maturity). In both treatments high-vigor zones ($\text{NDVI} > 0.60$) expanded from Stage 1 to Stage 3, then plateaued. Stress patches ($\text{NDVI} < 0.52$) persisted at grid cells (3, 4) and (6, 7) in both seasons, but their areal extent during the Grand Growth stage declined from 18% (T2) to 9% (T3) after the first fertigation/biostimulant cycle.

Figure 5 shows a ten-pane composite of NDRE heat-maps for Treatments T2 and T3 across the five growth stages (Establishment → Maturity). At Grand-Growth mean NDRE reached 0.47, indicating adequate canopy N; however, grids < 0.30 covered 7% of the plot, triggering site-specific N correction. These spatial layers validated the threshold values adopted from Li et al. [7] and provided the georeferenced shapefiles used by the actuation drone.

3.2 Fertigation response generated from UAV sensing

Figure 6 overlays the NDRE stress mask on the 10×10 management grid and classifies each cell as Low, Medium or High fertigation demand. In T3, only 30 of 100 cells required the highest N rate, reducing total applied N by approximately 24% compared to T1. Two follow-up flights further shrank the High-demand area to 11 cells (11%). The rule-based engine therefore shifted ~70% of the field to Medium or Low N.

3.3 -Water- and nitrogen-use efficiency

Table 2 summarizes irrigation, N applied, and derived efficiencies. Relative to farmer practice (T1), water use fell by 17% in T2 and 30% in T3, mainly because stress-free grids were skipped during pulse-drip events. Nitrogen-use efficiency (NUE) improved from 31% (T1) to 40% (T2) and 48% (T3), comparable to gains reported by Suman et al. [2] with biologically fixed N but achieved here with sensor guidance.

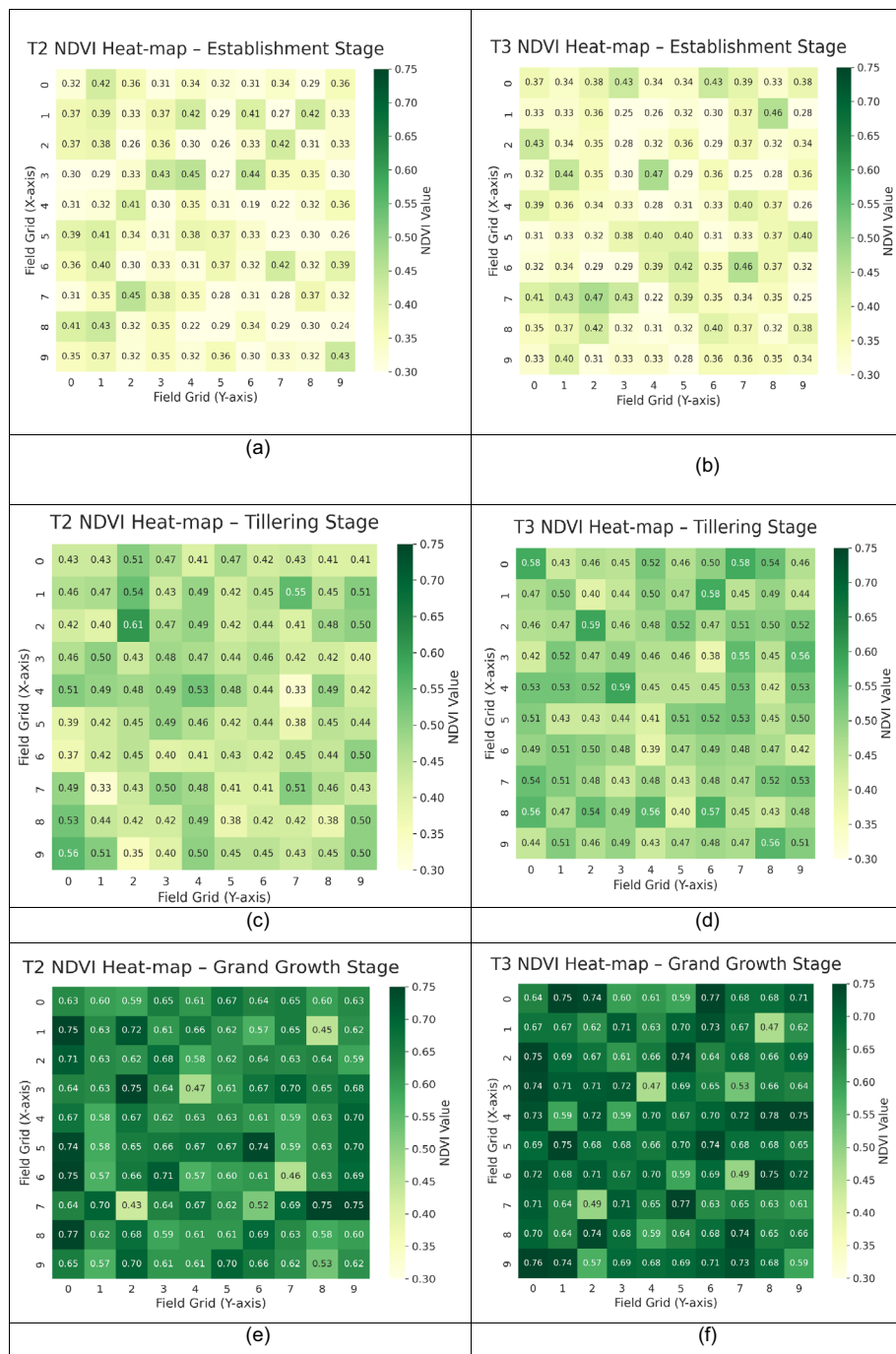


Fig. 4 Spatial Normalized Difference Vegetation Index (NDVI) heat-maps for sugarcane under Treatment T2 (sensor-guided fertigation) and Treatment T3 (sensor-guided fertigation + biostimulant) at the five phenological stages monitored in 2023. The common colour bar (0.30 → 0.75) uses the YIGn palette: light yellow (NDVI ≤ 0.40) marks low-vigour or sparsely covered pixels, while dark green (NDVI ≥ 0.70) marks dense, healthy canopy. **a** Establishment (~30 DAP)—T2; **b** Establishment—T3; **c** Tillering (~60 DAP)—T2; **d** Tillering—T3; **e** Grand Growth (~120 DAP)—T2; **f** Grand Growth—T3; **g** Elongation (~180 DAP)—T2; **h** Elongation—T3; **i** Maturity (~270 DAP)—T2; **j** Maturity—T3. Grid orientation follows the internal field coordinate system used during UAV data processing, where the X and Y axes correspond to row and column indices of the management grid rather than geographic coordinates

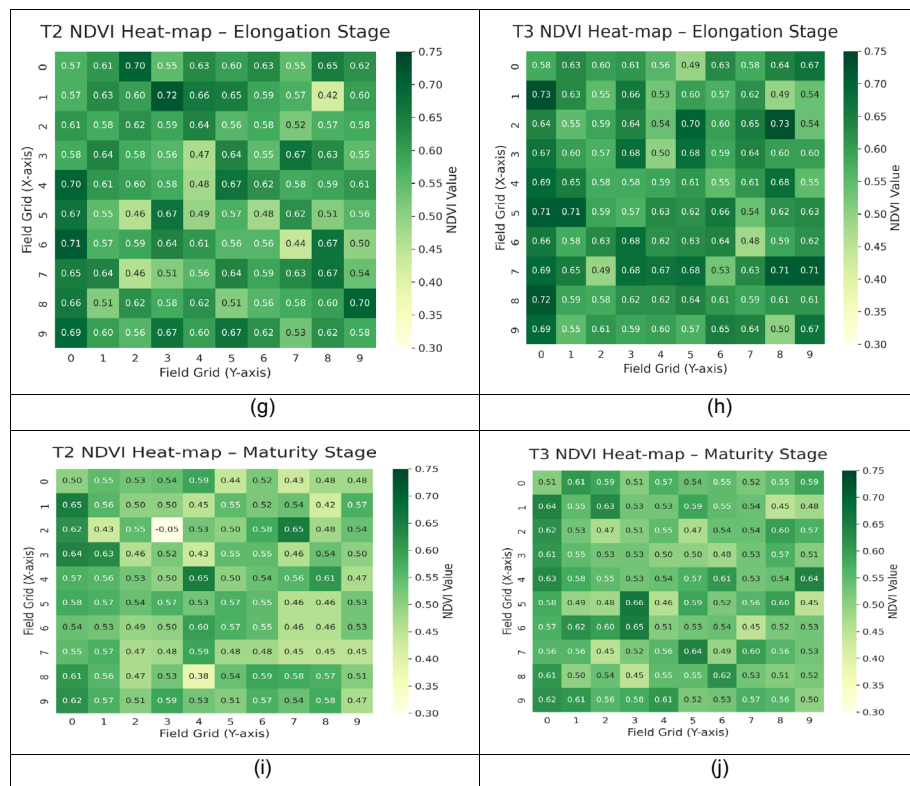


Fig. 4 (continued)

3.4 Yield and profitability outcomes

Table 3 lists yield and net economic return. Monetary values are expressed in Indian Rupees (₹); for international reference, ₹1 ≈ USD 0.012 (≈ €0.011) at the average 2023 exchange rate. Variable-rate management increased yield by 8% (T2) and 17% (T3) over T1, largely because mid-season N stress was corrected rapidly. After accounting for drone-operation and biostimulant costs, net return rose by ₹17,000 ha⁻¹ in T2 and ₹29,200 ha⁻¹ in T3. These gains corroborate water-savings studies in drip-irrigated cane (Menezes et al. [3]) but are achieved here through an entirely aerial decision pipeline.

3.5 Statistical validation of treatment effects

One-way ANOVA revealed significant treatment effects for cane yield ($F_{2,6} = 125.2$, $p = 1.3 \times 10^{-5}$), water-use efficiency ($F_{2,6} = 4453.8$, $p < 1 \times 10^{-9}$) and nitrogen-use efficiency ($F_{2,6} = 921.6$, $p = 3.4 \times 10^{-8}$). Tukey's HSD separated the treatments into three distinct groups (T3 a > T2 b > T1 c) for all variables (Table 2). Net economic return followed the same ranking, with T3 exceeding T1 by 56 % ([3]). These results confirm that sensor-guided fertigation saved inputs while significantly enhancing productivity. Treatment effects on yield were very large, with $\eta^2 = 0.976$ and $\omega^2 = 0.965$, indicating that over 96% of yield variability was explained by UAV-guided management, as shown in Table 4. Pairwise Hedges' g values confirmed strong differences, particularly between T1 (farmer practice) and T3 (sensor-guided fertigation + biostimulant), where $g = -9.44$, reflecting an extremely large effect size. WUE showed near-perfect treatment differentiation ($\eta^2 = 0.999$; $\omega^2 = 0.999$). Pairwise comparisons revealed extremely large effect sizes, with T1 vs T3 yielding Hedges' $g = -81.85$, underscoring the substantial impact of UAV-guided

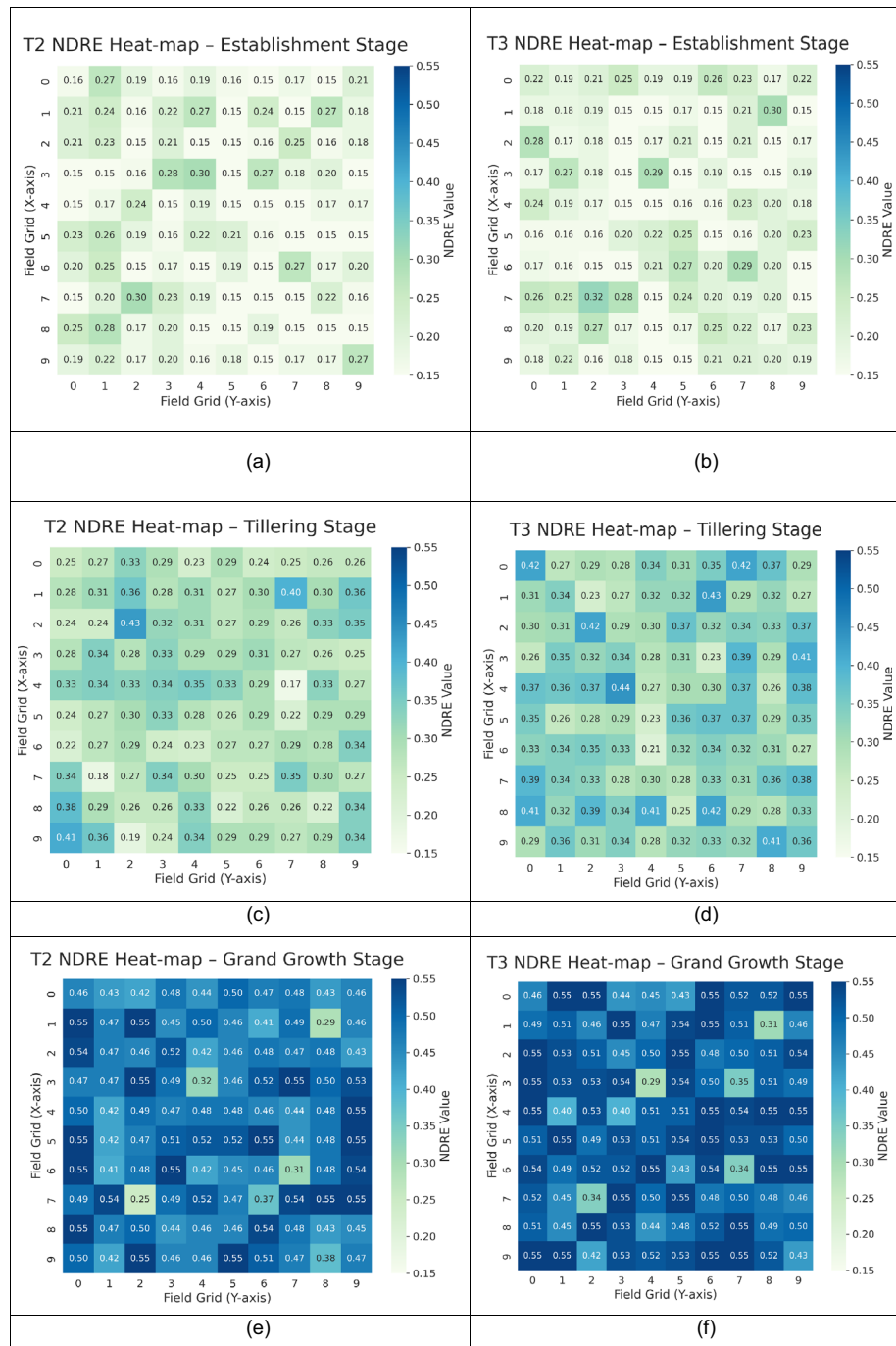


Fig. 5 Spatial Normalized Difference Red Edge (NDRE) heat-maps for sugarcane under Treatment T2 (sensor-guided fertigation) and Treatment T3 (sensor-guided fertigation + biostimulant) at the five phenological stages monitored in 2023. The common colour bar (0.15 → 0.55) uses the GnBu palette: very light green (NDRE ≤ 0.25) indicates bare soil or low-chlorophyll pixels, whereas dark blue (NDRE ≥ 0.50) denotes high leaf-nitrogen/chlorophyll and vigorous canopy. **a** Establishment—T2; **b** Establishment—T3; **c** Tillering—T2; **d** Tillering—T3; **e** Grand Growth—T2; **f** Grand Growth—T3; **g** Elongation—T2; **h** Elongation—T3; **i** Maturity—T2; **j** Maturity—T3. Grid orientation follows the internal field coordinate system used during UAV data processing, where the X and Y axes correspond to row and column indices of the management grid rather than geographic coordinates

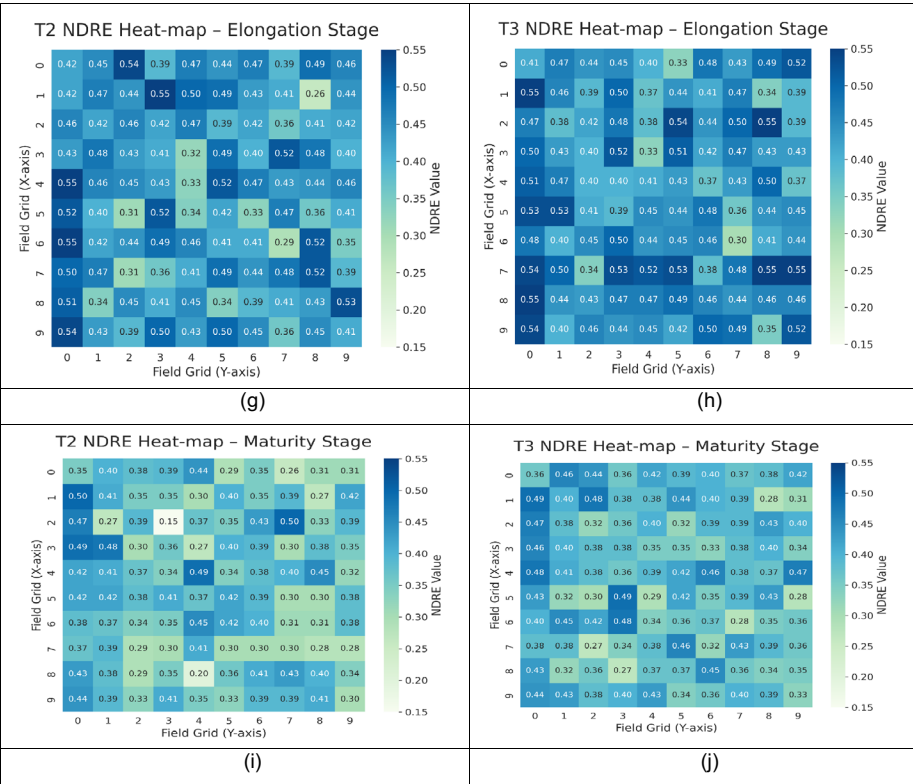


Fig. 5 (continued)

fertiligation on water productivity (Table 5). NUE also displayed near-total variance explanation by treatments ($\eta^2 = 0.997$; $\omega^2 = 0.995$). Pairwise Hedges’ g values exceeded –26 between T1 and T3, confirming that UAV monitoring and variable-rate fertiligation substantially improved nitrogen recovery efficiency compared to conventional management, as shown in the Forest Plot in Figure 7.

4 Conclusion

Beyond the regional benefits in northern India, this dual-UAV fertiligation workflow offers a potentially scalable template, although further validation across diverse agro-ecological conditions is required. By integrating low-cost multispectral sensing with open-source, UAV-enabled variable-rate spraying, the approach demonstrates the potential to improve yield while reducing fertilizer and water inputs under the conditions tested.

The study provides indicative pathways for advancing climate-smart agricultural practices: improving nitrogen recovery efficiency, reducing irrigation demand, and delivering higher economic returns to farmers. These outcomes directly contribute to the United Nations Sustainable Development Goals (SDG 2: Zero Hunger and SDG 12: Responsible Consumption and Production), while also supporting SDG 6 (Clean Water and Sanitation) and SDG 13 (Climate Action) by reducing nutrient leaching and greenhouse gas emissions.

Looking ahead, coupling UAV workflows with AI-driven decision support and expanding validation across diverse agro-ecologies will be critical steps toward mainstreaming this technology. If integrated with service-provider models and farmer cooperatives,

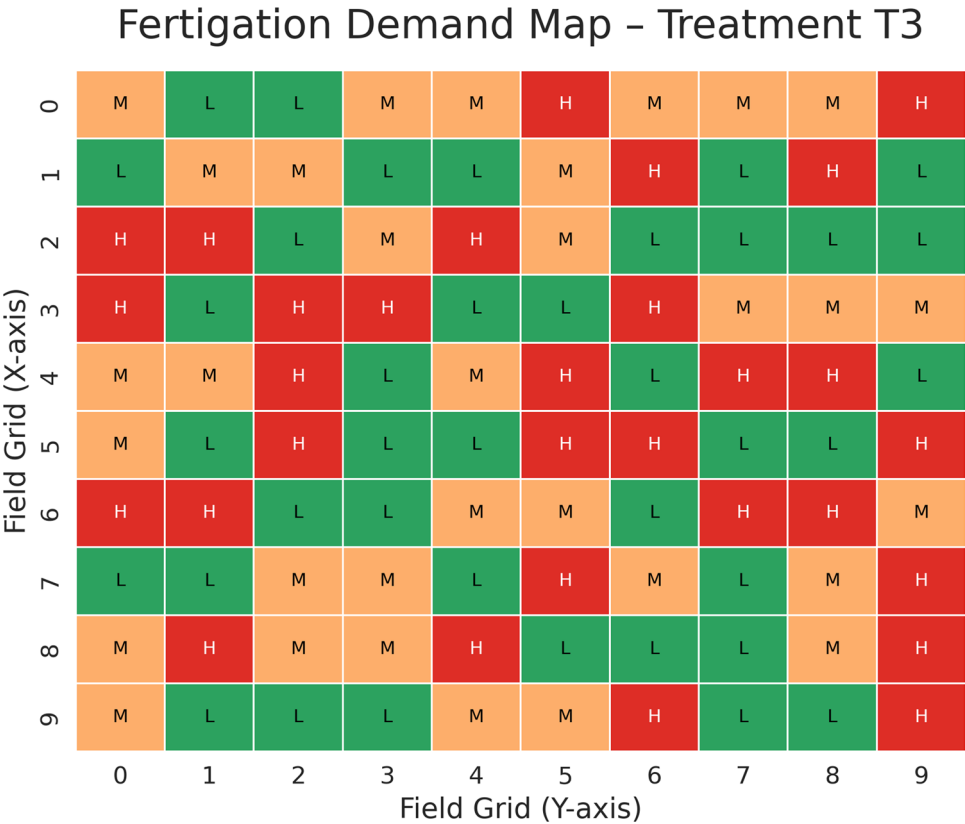


Fig. 6 Rule-based fertigation-demand classification derived from UAV NDRE maps for Treatment T3. Each 10×10 management cell is labelled Low (green), Medium (orange), or High (red) nitrogen demand. The initial sensing flight identified High demand in 30% of cells; subsequent adaptive flights reduced this area to 11%, shifting the majority of the field to Medium or Low application rates and cutting total applied N by 24% relative to the blanket-application control (T1). Grid orientation follows the internal field coordinate system used during UAV data processing, where the X and Y axes correspond to row and column indices of the management grid rather than geographic coordinates

Table 2 Water and nitrogen inputs, water-use efficiency (WUE), and nitrogen-use efficiency (NUE) for the three treatments (mean ± SD, *n* = 3)

Treatment	Water (m ³ ha ⁻¹)	N applied (kg ha ⁻¹)	WUE (kg m ⁻³)	NUE (%)
T1	8900 ± 87 ^c	250	8.78 ± 0.06 ^c	31.3 ± 0.46 ^c
T2	7400 ± 50 ^b	210	11.44 ± 0.11 ^b	40.3 ± 0.38 ^b
T3	6200 ± 50 ^a	190	14.72 ± 0.06 ^a	48.0 ± 0.56 ^a

^{c,b,a}Different superscript letters within a column indicate significant differences at *p* < 0.05 (Tukey's HSD)

Table 3 Cane yield, percentage gain over T1, and net economic return for the three treatments (mean ± SD, *n* = 3)

Treatment	Yield (t ha ⁻¹)	Δ Yield vs T1	Net return (₹ ha ⁻¹ , Indian Rupees)
T1	78.2 ± 1.1 ^c	-	52,000 ± 800 ^c
T2	84.6 ± 0.8 ^b	+ 8%	69,300 ± 650 ^b
T3	91.3 ± 1.0 ^a	+ 16.8%	81,200 ± 1050 ^a

^{c,b,a}Different superscript letters within a column indicate significant differences at *p* < 0.05 (Tukey's HSD)

Table 4 ANOVA effect sizes

Metric	η^2	ω^2
Yield (t ha ⁻¹)	0.976	0.965
WUE (kg m ⁻³)	0.999	0.999
NUE (%)	0.997	0.995

Table 5 Pairwise effect sizes (Hedges' g)

Metric	Comparison	Hedges' g
Yield (t ha ⁻¹)	T1 vs T2	-5.18
	T1 vs T3	-9.44
	T2 vs T3	-5.63
WUE (kg m ⁻³)	T1 vs T2	-24.40
	T1 vs T3	-81.85
	T2 vs T3	-30.88
NUE (%)	T1 vs T2	-16.99
	T1 vs T3	-26.23
	T2 vs T3	-12.97

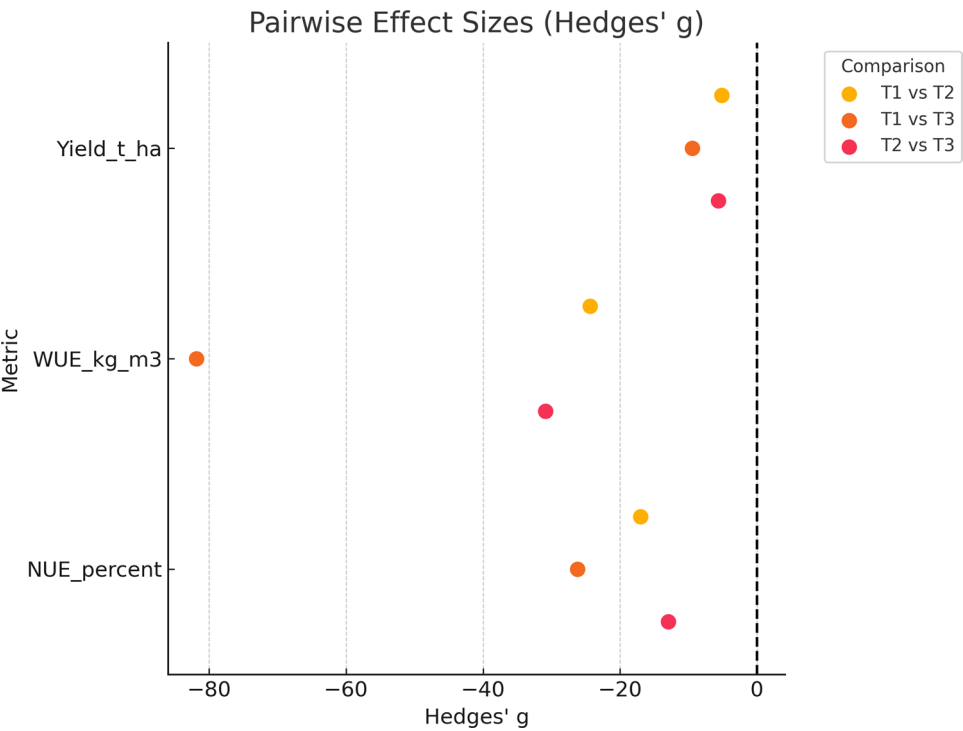


Fig. 7 Forest plot of pairwise effect sizes (Hedges' g) for yield, water-use efficiency (WUE), and nitrogen-use efficiency (NUE) across treatments (T1 =farmer practice; T2= UAV-monitored fertigation; T3=UAV-monitored fertigation+biostimulant). Negative values indicate superior performance of UAV-guided treatments relative to conventional practice. All comparisons showed extremely large effect sizes, highlighting the strong impact of UAV-based site-specific management

UAV-based precision fertigation could accelerate the transition to sustainable intensification, ensuring food security while safeguarding environmental resources.

5 Discussion

The results of this study confirm that integrating UAV-based canopy monitoring with automated variable-rate fertigation significantly improved yield, nitrogen-use efficiency (NUE), and water-use efficiency (WUE) in sugarcane. Compared with farmer practice, UAV-monitored treatments reduced nitrogen inputs by nearly one-quarter and irrigation water use by up to one-third, while delivering yield gains of 8–17%. These findings are consistent with earlier reports demonstrating that site-specific nutrient management can enhance both productivity and resource-use efficiency in high-input cropping systems [3, 14].

The pronounced improvements in WUE observed here align with studies in drip- and pulse-irrigated sugarcane, where precision water delivery minimized percolation losses [6]. However, unlike ground-based drip systems, the UAV-enabled fertigation workflow is non-invasive, scalable, and adaptable to smallholder plots. This makes it particularly suitable for regions where landholdings are fragmented, as is typical in India and much of sub-Saharan Africa [61].

NUE improvements in this study (31% → 48%) are notable, considering that sugarcane systems often suffer from poor nitrogen recovery (<35%) under blanket fertilization [5]. Comparable increases have been reported in Australian trials where variable-rate fertilizer application was implemented using ground-based sensors [13]. Our results extend this evidence base by showing that UAVs can operationalize sensing-to-application pipelines even in tall-stature crops where ground machinery is impractical.

The incorporation of biostimulant foliar sprays (Treatment T3) further enhanced yield and NUE. Seaweed extract application has been shown to improve nutrient uptake, photosynthetic activity, and abiotic stress tolerance in several crops, including sugarcane [31, 46]. The synergistic gains observed here suggest that UAV-based delivery could serve as an efficient mode for precision application of biostimulants in addition to fertilizers.

From a socio-economic perspective, UAV-guided fertigation increased net economic return by ₹17,000–29,200 ha⁻¹ relative to farmer practice. While the initial investment in UAV systems can be high, the availability of drone service providers and open-source autopilot platforms (Pixhawk/ArduPilot) lowers barriers to adoption. Similar arguments have been made in Brazil, where UAV spraying services have expanded rapidly due to their cost-effectiveness in sugarcane and maize systems [62].

Despite strong results, this study was conducted over a single season and site, with one sugarcane cultivar (Co-0238). Multi-location trials across diverse agro-climatic zones are needed to validate robustness. Additionally, while the rule-based engine effectively operationalized vegetation index thresholds, future research could incorporate machine learning models that adapt prescriptions dynamically, as demonstrated by UAV-ML studies in Sri Lanka and China [19, 63]. Integration of UAV workflows with IoT soil moisture sensors and cloud-based decision support systems could further strengthen adoption under real-world farming conditions [64].

Overall, these findings highlight that UAV-based sensing-to-actuation pipelines are not just a technological innovation but also a socio-ecological intervention, capable of reducing agrochemical footprints while improving farmer profitability.

This study has certain limitations that should be acknowledged. The field experiment was conducted at a single location and over one cropping season, which may limit the generalizability of the findings across diverse agro-climatic conditions. The evaluation was restricted to a single sugarcane cultivar (Co-0238), and responses may vary across genotypes. Additionally, the rule-based fertigation thresholds (NDVI and NDRE) were derived from literature and may require local calibration for broader applicability. While UAV-based operations were demonstrated under controlled research conditions, operational scalability in smallholder farming systems may depend on service accessibility, cost structures, and regulatory frameworks. Future research should focus on multi-location, multi-season validation, integration with machine learning-based adaptive decision systems, and economic feasibility under real-world farming scenarios.

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Authors contribution

SVR conceived the study, designed the experimental framework, conducted the field experiments, developed the UAV-based sensing-to-actuation workflow, performed data curation and analysis, prepared figures and visualizations, and wrote the original manuscript draft. PKV supervised the research design and methodology, provided guidance on statistical analysis, validated the experimental framework, contributed to interpretation of results, and critically reviewed and edited the manuscript. VT contributed to co-supervision of the research, provided guidance on experimental planning and economic analysis, assisted in methodological refinement, and contributed to manuscript review and editing. All authors reviewed and approved the final version of the manuscript.

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Data availability

The datasets generated and analyzed during the current study are part of ongoing research efforts of CHIRAG TECHNOLOGIES and are not publicly available at this time but may be made available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

This study involved field experiments on cultivated sugarcane (*Saccharum officinarum* L.) and did not involve human participants or animals requiring ethical approval. All experimental procedures complied with institutional and national guidelines for agricultural research.

Consent for publication

Not applicable.

Plant material compliance statement

The plant material used in this study consisted of commercially cultivated sugarcane (variety Co-0238) grown under standard agricultural practices at a cooperating farm site. No wild, endangered, or protected plant species were collected. The study complied with all relevant local and national guidelines governing agricultural research. No specific permits or licences were required.

Competing interest

The authors declare no competing interests.

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