UAV-Based Water Stress Mapping for Precision Irrigation Scheduling in Soybean (*Glycine max* (L.) Merr.): A Review of Thermal and Multispectral Remote Sensing Approaches

Dr. Kalen Thornford [1*], Dr. Tavin Ashmere [2]

[1-2] Faculty of Soil and Environmental Sciences, Global Agriculture Academy, Nepal

*Corresponding author: **Dr. Kalen Thornford**

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ABSTRACT

Production of soybean (*Glycine max* (L.) Merr.) has increasingly faced difficulties from erratic rains and competing freshwater needs, indicating the need for irrigation management that is accurate and spatially relevant for sustainable intensification. Platforms of unmanned aerial vehicles (UAV) fitted with buildings of thermal infrared and multispectral sensors have become common in defining the variability of the crop water conditions within fields by spatial and temporal accuracy unattainable by satellite or terrestrial solutions. The study summarizes peer-reviewed findings on the possibility of mapping water stress with the help of UAVs and integrating it into precision irrigation scheduling programs in relation to soybean and similar row crops. The principles of thermal imaging are based on the relationship between water stress indications like stomatal opening, reduction of transpiratorial cooling and increase in the air temperature above the canopy. This approach uses a geographic information system (GIS) to create irrigation management zones which leads to improved accuracy of water-status classification when compared to the use of the same sensor only. The use of GIS provides information for the implementation of variable-rate irrigation (VRI) prescriptions which help to reduce the volume of water used while providing similar yield of crops and level of water-use efficiency (WUE). The previously reported improvements depend on the timing of the flights concerning the main phenological stages of soybeans and moisture levels, atmospheric corrections, the use of soil and topographic features in the process of distinguishing zones. The limitations include high cost and sophisticated technology of thermal sensors, lack of common CWSI standards for different cultivars and places, and also low popularity of VRI technology among farmers. Therefore, we come to the conclusion that the use of thermal multispectral fusion via GIS-based software for decision making has great potential in the development of water-efficient approaches to soybean cultivation and requires further investigations to achieve desired results.

Keywords: canopy temperature depression; drone-based agronomy; evapotranspiration monitoring; site-specific irrigation; spectral vegetation indices; stomatal conductance sensing; variable-rate irrigation; within-field spatial variability

1. Introduction

Soybean is one of the most prominent grain legume crops throughout the world, supplying a large fraction of vegetable proteins and oil for food, feed, and industrial purposes. The productivity of soybean is especially sensitive to water shortage during flowering and pod-filling stages. Because water for irrigation is a limited and contested resource for agricultural, urban, and ecological needs, electing for methods of precision irrigation that supply water based on crop's requirements at specific times and regions instead of through a uniform application across an entire field has been done by agricultural scientists.

The temperature of the canopy has long been treated as an indirect marker of the plant water status, where limiting the availability of the moisture in the soil results in the closure of the stomatal holes, decrease in transpirational cooling and rise in the canopy temperature beyond the temperature of the condition of a well-watered reference surface. The phenomenon is the basis of Crop Water Stress Index that has been elaborated from ground-air-based infrared measurements to laser systems aboard UAVs. At the same time, satellites and UAVs have been developing in the field of multispectral and hyperspectral sensing methods based on vegetation

The UAV technology represents a methodological niche that sits between low-resolution satellite monitoring methods and cumbersome field sampling techniques. UAV methods provide images at the scale of centimeters, flexibility in scheduling visits at different phenological stages or irrigation events, along with possibilities to collect data simultaneously in thermal, spectral imaging and RGB (Berni *et al*., 2009) (Messina and Modica, 2020) [6] [18]. They have been applied to different crops and irrigation systems, as vineyards (Bellvert *et al*., 2014) (Bellvert *et al*., 2016) (Espinoza *et al*., 2017) [8] [9] [30], fruit orchards (Jones, 2004) (Costa *et al*., 2013) [4] [24], cereals (Zhang *et al*., 2019) (Awad and Sabbah, 2020) (Khan *et al*., 2018) (Yao *et al*., 2017) [13] [17] [23] [27] and increasingly, soybeans (Crusiol *et al*., 2020) (Morales-Santos and Nolz, 2023) (Liu *et al*., 2024) (Soybean water monitoring and water demand prediction in arid region based on UAV multispectral data, 2025) (Faseeh *et al*., 2025) (Maimaitijiang *et al*., 2017) (Bai *et al*., 2016) [10] [12] [14] [15] [16] [25] [26].

One recurrent finding from the reviewed works shows that the thermal and spectral parameters reveal partially independent aspects of plant stress physiology and their combination — usually performed through spatial analysis and interpolation — significantly increases the efficiency of hydrological status assessment in comparison to using single parameters (Mwinuka *et al*., 2021) (Liu *et al*., 2024) (Elsherbiny *et al*., 2021) [11] [14] [31]. The created maps of plant stress data can be transformed into zones of irrigation management (Haghverdi *et al*., 2015) (Miller *et al*., 2018) (Sharma *et al*., 2025) [19] [20] [21]. Nevertheless, the existing reviews of VRI implementation understate the important role of methodologies of zoning zones and information about soil properties and relief in achieving effective water-saving (Haghverdi *et al*., 2015) (Miller *et al*., 2018) (Bwambale *et al*., 2022) [19] [20] [33].

Table 1: Dual-Sensor UAV Acquisition Pipeline Specifications

System Component	Thermal Infrared (TIR) Sensor	Multispectral Sensor
Sensor Type	Long-Wave Infrared (LWIR) Camera	Multi-band Optical Camera (typically Green, Red, Red Edge, NIR)
Data Stream	Thermal Stream	Reflectance Stream
Primary Variable	Canopy Temperature (T_c, measured in Kelvin or Celsius)	Surface Reflectance (ρ, measured across specific bands)
Target Phenomenon	Transpiration & Water Stress Evaporative cooling dynamics of the soybean leaves.	Canopy Structure & Chlorophyll Biomass, leaf area index (LAI), and photosynthetic activity.
Key Derived Metrics	Crop Water Stress Index (CWSI), Stomatal Conductance	Vegetation Indices (e.g., NDVI, NDRE, EVI)
Primary Indicator	Immediate, short-term physiological response to water deficit.	Gradual, long-term structural changes and pigment degradation.

Despite this progress, soybean-specific evidence remains comparatively limited next to specialty and perennial crops. Few studies report a complete pipeline that couples UAV-derived CWSI and vegetation-index mapping with GIS-based zoning, threshold-triggered scheduling rules, and quantified agronomic and water-use outcomes specifically in soybean under field conditions (Crusiol *et al*., 2020) (Morales-Santos and Nolz, 2023) (Liu *et al*., 2024) (Soybean water monitoring and water demand prediction in arid region based on UAV multispectral data, 2025) (Faseeh *et al*., 2025) [10] [12] [14] [15] [16]. This review therefore synthesizes the current evidence base across (i) the physiological and remote-sensing principles underlying thermal and multispectral water stress detection, (ii) UAV data acquisition and geospatial processing practices, (iii) approaches to translating stress maps into irrigation scheduling decisions, and (iv) reported effects on soybean growth, yield, and water-use efficiency, with the aim of identifying research gaps that constrain operational deployment of UAV-based precision irrigation in soybean systems.

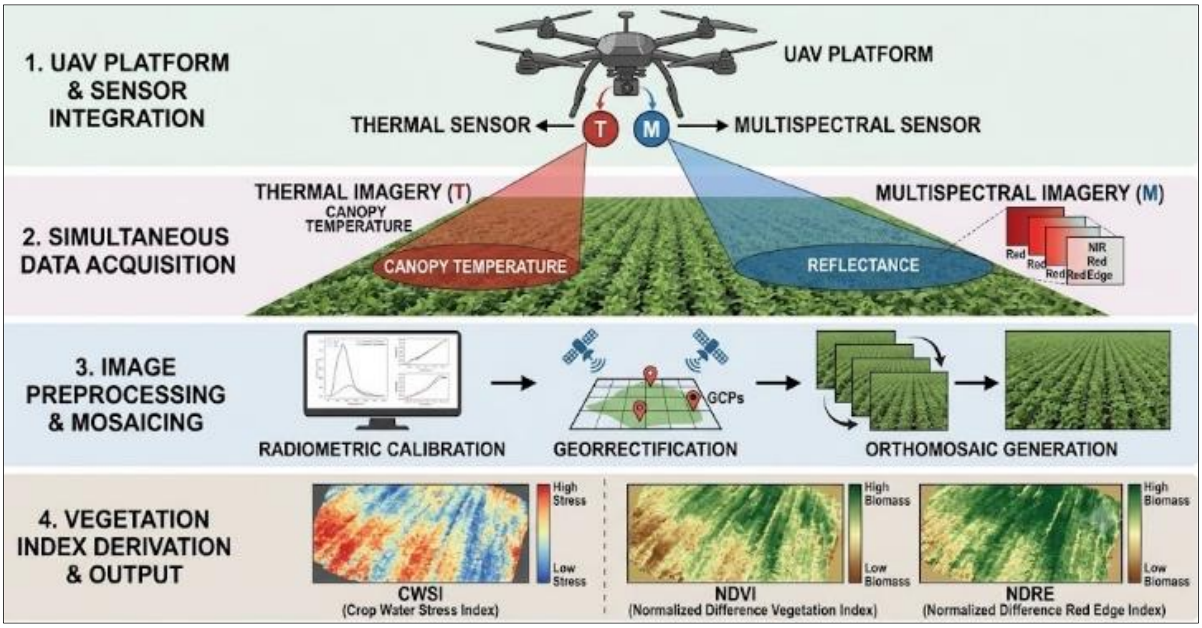

Fig 1: The UAV Data Acquisition and Processing Workflow

2. Physiological and Sensing Principles

2.1 Thermal indicators of canopy water status

The physiological basis for thermal sensing of plant water status was established well before UAV platforms existed: leaf and canopy temperature rise above ambient air temperature once stomatal closure curtails transpirational cooling (Gates, 1964) [3]. Jackson and colleagues formalized this relationship into the CWSI by normalizing canopy–air temperature differentials between theoretical non-stressed and non-transpiring baselines (Jackson *et al*., 1981) [1] (Idso *et al*., 1981) [2], and subsequent work extended stress-degree-day concepts to account for environmental variability such as vapor pressure deficit and net radiation (Idso *et al*., 1981) [2]. Reviews of thermal sensing in plant ecophysiology have repeatedly confirmed that canopy temperature depression — the difference between a well-watered reference and the observed canopy — correlates with stomatal conductance and, more variably, with leaf and stem water potential across species, though the strength of that relationship is modulated by canopy architecture, ground cover fraction, and atmospheric conditions at the time of image acquisition (Jones, 2004) [4] (Costa *et al*., 2013) [24] (Cohen *et al*., 2005) [29].

Direct evidence in soybean shows canopy temperature differences of several degrees Celsius between irrigated and water-deficit treatments, with the magnitude of separation depending on the growth stage at which stress was imposed and on atmospheric vapor pressure deficit at the time of flight (Crusiol *et al*., 2020) [10]. This is consistent with findings in other row and specialty crops, where UAV-derived canopy temperature and CWSI have distinguished irrigation treatments and, in several cases, tracked stomatal conductance and leaf water potential with useful precision (Berni *et al*., 2009) [6] (Zarco-Tejada *et al*., 2012) [7] (Bellvert *et al*., 2014) [8] (Bellvert *et al*., 2016) [9] (Cohen *et al*., 2005) [29] (Espinoza *et al*., 2017) [30].

2.2. Multispectral and structural indicators

Multispectral vegetation indices complement thermal indicators by capturing canopy structural and biochemical responses to water deficit that may precede or co-occur with detectable temperature changes. NDVI remains the most widely applied greenness index (Rouse *et al*., 1974) [5], but it saturates in dense, well-developed canopies and can be relatively insensitive to moderate water stress once the canopy is closed. Red-edge-based indices such as NDRE have shown stronger sensitivity to chlorophyll content, stomatal conductance, and photosystem II efficiency under water-deficit conditions in soybean, with correlations to physiological stress indicators reported to be considerably stronger than those for standard NDVI in some field trials (Faseeh *et al*., 2025) [16]. Similar patterns — red-edge and structural indices outperforming basic greenness indices under moderate stress — have been reported in wheat (Awad and Sabbah, 2020) [17] and in broader multispectral phenotyping reviews across crops (Liu *et al*., 2024) [14].

Table 2: Physiological Response vs. Remote Sensing Signal

Physiological Process / Indicator	Left Panel: Water-Stressed Soybean (Dry)	Right Panel: Non-Stressed Soybean (Optimal)
Stomatal State	Closed (to prevent excessive water loss via turgor pressure drop in guard cells)	Open (normal gas exchange for photosynthesis)
Transpiration Rate	Severely Reduced (minimal latent heat flux)	Active (high evaporative/latent cooling)
Canopy Temperature (Tc)	Elevated (sensible heat builds up; $T_c > T_{air}$)	Lowered (cool canopy; $T_c \leq T_{air}$)
TIR Sensor Reading	High Radiant Flux (appears as "hot" red/yellow pixels)	Low Radiant Flux (appears as "cool" blue/green pixels)
Chlorophyll & Pigments	Degrading (early-stage chlorosis, reduced light absorption)	Healthy / Dense (maximum light absorption in Blue/Red bands)
Near-Infrared (NIR) Reflectance	Decreased (leaf cell turgidity drops, reducing internal cell structure scattering)	High (healthy, turgid mesophyll cell walls scatter NIR light efficiently)
Multispectral Output	Low NDVI / Low NDRE (high Red reflectance, lowered NIR reflectance)	High NDVI / High NDRE (low Red reflectance, maximum NIR reflectance)

A separate but related body of work uses multispectral reflectance to estimate canopy or soil moisture status directly, rather than as a proxy for physiological stress. UAV-derived vegetation indices have been coupled with regression and machine-learning models to predict leaf water content and shallow soil moisture in soybean, with the strongest single-index relationships typically reported for NDVI-based nonlinear models, and further gains achieved when multispectral and thermal-infrared information are combined (Liu *et al*., 2024) [14] (2025) [15]. This convergence of physiological (thermal) and structural/biochemical (spectral) evidence is a recurring justification in the literature for multi-sensor fusion rather than reliance on either data stream alone (Mwinuka *et al*., 2021) [11] (Liu *et al*., 2024) [14] (Elsherbiny *et al*., 2021) [31].

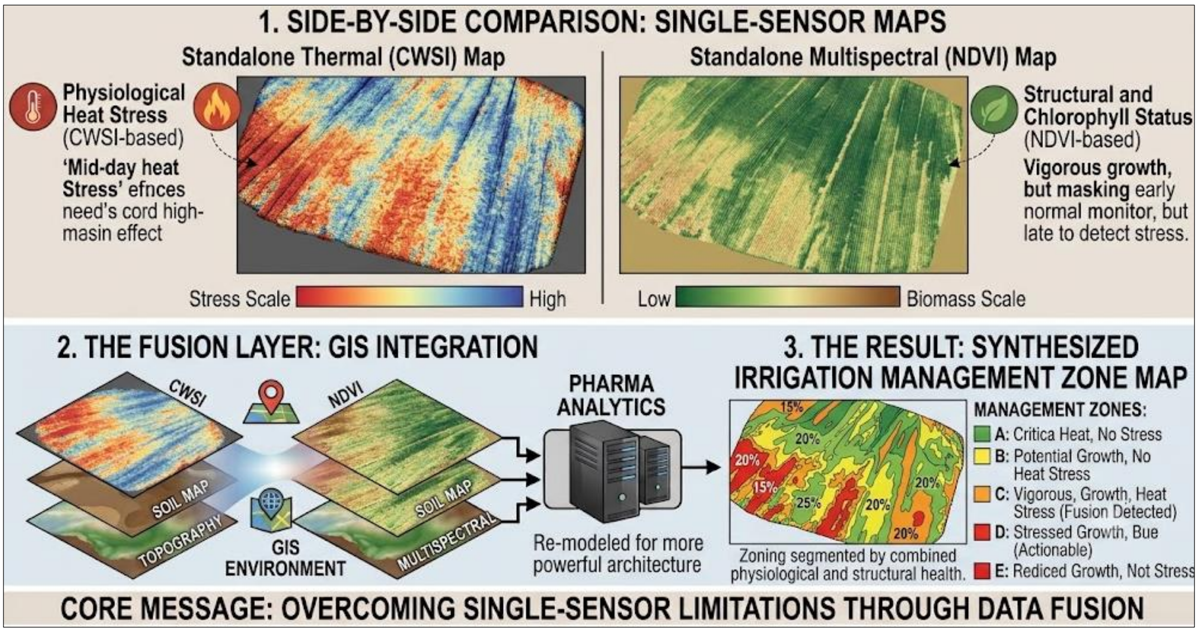

Fig 2: Conceptual Framework of Thermal–Multispectral Fusion

2.3. Sensor and data fusion

Comparative and fusion studies indicate that thermal-only classification of water status is vulnerable to confounding from wind, humidity, and canopy architecture, while spectral-only classification can be insensitive to short-term water deficits that have not yet altered pigment content or structure (Mwinuka *et al*., 2021) [11] (Liu *et al*., 2024) [14] (Elsherbiny *et al*., 2021) [31]. Studies combining UAV multispectral and thermal-infrared inputs, in some cases with machine-learning regression, report improved prediction accuracy for soil moisture and canopy water status relative to either sensor type used independently, reinforcing fusion as the emerging methodological standard for UAV-based water stress assessment (Liu *et al*., 2024) [14] (2025) [15]. A comprehensive review of UAV thermal applications in precision agriculture similarly concludes that the operational value of thermal imagery increases substantially when integrated with spectral, structural, and ancillary environmental data rather than deployed in isolation (Messina and Modica, 2020) [18].

3. UAV Platforms, Sensors, and Data Acquisition Considerations

The UAV remote sensing literature converges on several acquisition principles rather than a single prescriptive protocol, since platform choice depends on field scale, required ground sampling distance, and payload capacity. Multirotor platforms are generally favored for their acquisition flexibility and ability to fly at lower, more consistent altitudes appropriate for thermal imaging, whereas fixed-wing platforms are more efficient for larger-area multispectral or RGB surveys where absolute thermal accuracy is less critical (Berni *et al*., 2009) [6] (Messina and Modica, 2020) [18]. Radiometric thermal cameras require in-flight or near-concurrent reference targets (for example, wet and dry reference plates or canopies) to convert raw brightness temperatures into calibrated surface temperatures suitable for CWSI calculation, since uncorrected thermal imagery is highly sensitive to sensor drift, atmospheric path effects, and emissivity assumptions (Berni *et al*., 2009) [6] (Zarco-Tejada *et al*., 2012) [7] (Messina and Modica, 2020) [18].

Flight timing is treated as a first-order source of variance across the literature: thermal and CWSI measurements are most interpretable when acquired near solar noon under clear, stable-wind conditions, when canopy–air temperature differentials associated with stress are maximized and least confounded by transient boundary-layer turbulence (Jackson *et al*., 1981) [1] (Jones, 2004) [4] (Bellvert *et al*., 2014) [8] (Cohen *et al*., 2005) [29]. Multispectral flights are comparatively more tolerant of timing but still benefit from consistent illumination and, where possible, concurrent radiometric calibration panels to allow reflectance-based rather than raw digital-number-based index calculation. Real-time kinematic (RTK) or post-processed kinematic (PPK) positioning is widely used to ensure that repeat flights across a growing season are spatially co-registered to a common ground reference, which is a prerequisite for constructing time-series stress maps and for linking UAV pixels to fixed ground-truth or soil-sensor locations (Messina and Modica, 2020) [18] (Miller *et al*., 2018) [20].

Ground-truthing remains essential throughout this literature: canopy temperature, vegetation indices, and derived indices such as CWSI are consistently validated against independent measurements — infrared thermometry, porometry, stem or leaf water potential, or volumetric soil moisture sensors — before being accepted as operational stress indicators for a given field, cultivar, or season (Jackson *et al*., 1981) [1] (Bellvert *et al*., 2014) [8] (Crusiol *et al*., 2020) [10] (Cohen *et al*., 2005) [29]. This calibration step is one of the more labor-intensive components of the workflow and a recurring constraint on scaling UAV-based stress mapping to routine commercial use (Messina and Modica, 2020) [18] (Bwambale *et al*., 2022) [33].

4. From Stress Maps to Irrigation Management Zones

Translating pixel-level thermal and spectral outputs into actionable irrigation decisions requires a geospatial generalization step. Individual flight-derived rasters (orthomosaicked thermal, NDVI, NDRE, and CWSI surfaces) are typically smoothed or interpolated and then aggregated into discrete management zones using clustering or classification approaches that may also incorporate ancillary layers such as soil apparent electrical conductivity, elevation, or historical yield maps (Haghverdi *et al*., 2015) [19] (Miller *et al*., 2018) [20] (Sharma *et al*., 2025) [21]. Haghverdi and colleagues review a range of zone-delineation strategies for VRI and emphasize that the number and stability of zones, and the choice of covariates used to define them, materially affect the water-saving and yield outcomes attributable to VRI adoption (Haghverdi *et al*., 2015) [19]. Miller and colleagues demonstrate a geospatial approach that estimates root-zone available water capacity from soil survey data to evaluate candidate VRI control scenarios, illustrating how soil information is commonly fused with remotely sensed stress layers rather than used as a substitute for it (Miller *et al*., 2018) [20].

Table 3: Spatial Data Fusion Stack for Management Zone Delineation

Overlay Layer	Data Inputs & Covariates	Spatial/Temporal Nature	Role in the Fusion Model
Top Layer: Actionable Output	Prescription & Management Zone Map • Delineated zones (Optimal, Low, Moderate, Severe Stress)	Vector/Raster Output • Semi-permanent boundaries updated per flight	The Action Layer: Clusters pixels with statistically similar stress profiles to guide variable-rate irrigation, targeted scouting, or micro-fertilization.
Middle Layer B: Crop Physiology	Thermal Infrared (TIR) Raster • Surface Temperature (T_c) • Crop Water Stress Index (CWSI)	Dynamic / High-Frequency • Changes hourly based on weather and water	The Hydrological Driver: Captures real-time stomatal closure and transpiration deficits. Acts as the rapid-response indicator of the stack.
Middle Layer A: Crop Structure	Multispectral Raster • NDVI (Biomass/Chlorophyll) • NDRE (Canopy Nitrogen/Late Stress)	Moderate Frequency • Changes weekly across vegetative stages	The Structural Baseline: Captures cumulative, long-term stress impacts on leaf area index (LAI) and pigment health.
Bottom Layer: Environmental Baseline	Soil & Topographic Covariates • Digital Elevation Model (DEM) / Slope • Apparent Electrical Conductivity (EC_a)	Static / Permanent • Rarely changes season-to-season	The Environmental Foundation: Explains *why* certain areas pool water or dry out faster. Isolates soil-driven stress from disease or pest-driven stress.

Once zones are defined, scheduling logic in the literature is predominantly threshold-based: irrigation is triggered when a zone-averaged CWSI, canopy temperature depression, or vegetation index crosses a pre-established value associated with the onset of yield-limiting stress. Threshold approaches have been implemented in potato, apple, and other row and specialty crops, with thresholds calibrated against independent physiological or soil-moisture measurements for the specific cultivar and environment [28]. Reviews of variable-rate irrigation technology note that commercially available center-pivot and lateral-move systems already support zone-, sector-, or individual-sprinkler-level control, meaning the primary bottleneck for translating UAV-derived stress maps into differential water application is increasingly the decision-support and prescription-mapping layer rather than actuation hardware itself [19,21,33].

Table 4: Sensor Sensitivity and Efficacy Across Soybean Phenological Stages

Phenological Stage	Canopy Development Status	Thermal Stream (CWSI) Efficacy	Reflectance Stream (NDVI/NDRE) Efficacy	Critical Water Management Priority
Vegetative Emergence (VE to V3)	Soil background dominant; minimal row closure.	Low High risk of soil background thermal noise corrupting T_c readings.	Low Soil background reflectance interferes significantly with NDVI.	Low Low crop water demand; roots are establishing.
Rapid Vegetative (V4 to V6 / R1 Transition)	Canopy closing rapidly; inter-row gaps narrowing.	Moderate Improving as leaf area increases and masks soil background.	High NDVI peaks rapidly as green biomass expands; excellent for nitrogen/vigor tracking.	Moderate Early monitoring for baseline structural anomalies.
Flowering & Early Pod (R1 to R2)	Full row closure achieved; high transpiration demand.	High Pure canopy pixels allow highly accurate crop water stress index evaluations.	Moderate (Saturation) NDVI begins to saturate due to dense canopy closure, limiting structural insights.	High First critical window; moisture stress now can cause flower abortion.
Pod Development & Filling (R3 to R5)	Peak Peak Physiological Activity. Maximum leaf area and seed fill demand.	Maximum Sensitivity Stomata are highly reactive to soil moisture deficits. Clear, immediate thermal spikes during stress.	High (Transition to NDRE) Switching to NDRE allows tracking of early chlorophyll loss caused by prolonged water stress.	Critical / Peak Window Water stress at this stage causes irreversible yield loss (fewer pods, smaller seeds).
Physiological Maturity (R7 to R8)	Natural senescence; leaves yellow and drop.	Negligible Loss of stomatal regulation renders thermal indices uncoupled from soil moisture.	Low (Senescence Monitoring) Reflectance drops off due to natural chlorophyll degradation, not active moisture stress.	Low Crop is drying down for harvest; no irrigation or interventions applied.

5. Reported Effects on Soybean Growth, Yield, and Water-Use Efficiency

Evidence specific to soybean indicates that UAV-derived thermal and spectral indicators track physiologically meaningful water-deficit responses across vegetative and reproductive stages, with canopy temperature separating irrigation treatments more clearly during reproductive growth stages when soybean is known to be most sensitive to water limitation (Crusiol *et al.*, 2020) [10]. Studies combining spectral phenotyping with amendments intended to buffer water-deficit stress report that reduced irrigation combined with a stress-mitigating input can achieve morpho-physiological and spectral performance comparable to full irrigation, illustrating how UAV-based multispectral monitoring can be used not only to detect stress but to evaluate deficit-irrigation and input-based mitigation strategies against a full-irrigation benchmark (Faseeh *et al.*, 2025) [16]. Soil-moisture prediction models built from fused multispectral and thermal-infrared UAV data in soybean have achieved moderate-to-strong explanatory power for surface and shallow-profile moisture content, supporting their use as an indirect but non-destructive irrigation-scheduling input where direct sensor networks are impractical at field scale (Liu *et al.*, 2024) [14] (2025) [15].

Table 5: Decision Flowchart for Variable-Rate Irrigation (VRI) Scheduling

Step	Workflow Stage	Description	Expected Output
1	UAV Flight	Acquire high-resolution multispectral, thermal, and RGB images over the agricultural field at scheduled growth stages.	Raw remote sensing datasets
2	Data Fusion	Integrate multispectral, thermal infrared (TIR), RGB imagery, and ancillary field data to improve crop stress detection.	Fused geospatial dataset
3	Stress Index Generation	Calculate vegetation and thermal indices (e.g., NDVI, NDRE, CWSI, canopy temperature) to quantify crop water stress.	Spatial stress index map
4	Decision Node	Is Stress Index > Predefined Threshold?	Yes / No Decision
5A (Yes)	Generate VRI Prescription Map	Identify stressed zones and assign variable irrigation rates according to the severity of water stress.	Variable-Rate Irrigation (VRI) prescription map
6A (Yes)	Apply Variable Water	Execute irrigation using VRI-enabled equipment, supplying more water to stressed areas and less to healthy regions.	Optimized irrigation application
5B (No)	Maintain Standard Irrigation	Continue with existing irrigation schedule or postpone irrigation if soil moisture is adequate.	No change in irrigation strategy
7	Field Outcome	Evaluate crop response after irrigation by monitoring plant recovery and updating stress indices in subsequent UAV flights.	Improved crop health and optimized water management
8	Final Outcome	Assess improvements in crop productivity and irrigation efficiency.	Higher Yield, Improved Water Use Efficiency (WUE), Reduced Water Consumption, Sustainable Irrigation Management

Broader evidence from other row crops and horticultural systems, while not always directly transferable to soybean, is broadly consistent in direction: UAV-guided variable-rate or threshold-triggered irrigation has been associated with reduced total water application relative to uniform scheduling, generally without yield penalty and in some cases with improved water-use efficiency, though the magnitude of water savings is highly context-dependent on baseline irrigation practice, soil heterogeneity, and climate (Haghverdi *et al*., 2015) [19] (Miller *et al*., 2018) [20] (Sharma *et al*., 2025) [21] (Osroosh *et al*., 2015) [28] (Bwambale *et al*., 2022) [33]. Multispectral phenotyping studies in cereals similarly show that UAV-derived indices can discriminate genotypes and irrigation regimes for water-use efficiency, supporting the broader applicability of the approach to breeding and management decisions alike (Awad and Sabbah, 2020) [17].

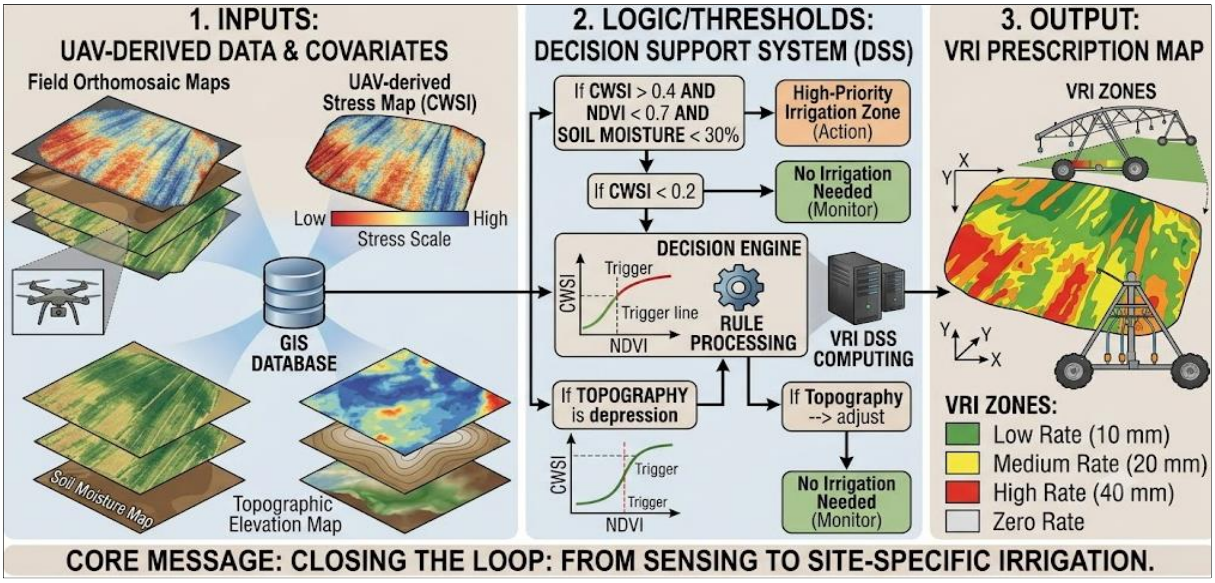

Fig 3: Decision Support System for Variable-Rate Irrigation (VRI)

6. Discussion

Taken together, the literature supports three converging conclusions. First, the physiological rationale for thermal and spectral water stress detection is well established and has been repeatedly validated from ground-based instrumentation through to UAV platforms across a wide range of crops, including soybean (Jackson *et al*., 1981) [1] (Idso *et al*., 1981) [2] (Gates, 1964) [3] (Jones, 2004) [4] (Berni *et al*., 2009) [6] (Zarco-Tejada *et al*., 2012) [7] (Bellvert *et al*., 2014) [8] (Bellvert *et al*., 2016) [9] (Crusiol *et al*., 2020) [10]. Second, sensor fusion — combining thermal, multispectral, and where available structural or soil information — consistently outperforms single-sensor approaches for water-status classification, and this pattern holds specifically within the soybean literature (Mwinuka *et al*., 2021) [11] (Liu *et al*., 2024) [14] (2025) [15]. Third, the operational translation of stress maps into irrigation decisions is comparatively less mature than the sensing science itself: zone-delineation methodology, threshold calibration, and integration with existing VRI-capable infrastructure remain more heterogeneous across studies than the underlying remote-sensing indices (Messina and Modica, 2020) [18] (Haghverdi *et al*., 2015) [19] (Miller *et al*., 2018) [20] (Sharma *et al*., 2025) [21] (Bwambale *et al*., 2022) [33].

Several limitations recur across this body of work and constrain confident generalization to commercial soybean production. CWSI and related thermal indices require careful radiometric calibration and near-noon, low-wind acquisition windows that are not always compatible with operational flight scheduling, particularly across large, multi-field operations (Jackson *et al*., 1981) [1] (Jones, 2004) [4] (Messina and Modica, 2020) [18]. Vegetation indices such as NDVI can saturate in dense canopies typical of well-developed soybean stands, motivating the use of red-edge or structural indices but also adding sensor cost and processing complexity (Liu *et al*., 2024) [14] (Awad and Sabbah, 2020) [17]. Ground-truth calibration against independent physiological or soil-moisture measurements is labor-intensive and rarely reported at a scale sufficient to establish transferable thresholds across cultivars, soil types, and climates (Crusiol *et al*., 2020) [10] (Osroosh *et al*., 2015) [28] (Cohen *et al*., 2005) [29]. Finally, while VRI actuation hardware is commercially available, its adoption remains concentrated in specific regions and larger operations, meaning UAV-derived prescriptions cannot yet be assumed to be implementable on a typical smallholder or moderate-scale soybean farm without additional capital investment (Haghverdi *et al*., 2015) [19] (Sharma *et al*., 2025) [21] (Bwambale *et al*., 2022) [33].

Economic feasibility is correspondingly under-documented. Most cited studies report technical and physiological performance metrics (correlation coefficients, classification accuracy, treatment separation) rather than direct cost–benefit analysis of UAV-based monitoring against conventional scheduling, which limits the strength of claims that can currently be made about return on investment for soybean growers specifically. Future research priorities that emerge from this synthesis include: multi-season, multi-cultivar CWSI baseline development for soybean; standardized protocols for fusing thermal and red-edge multispectral data at operational flight altitudes; integration of UAV-derived zones with lower-cost VRI retrofit technologies to broaden accessibility; and explicit economic evaluation of UAV-based precision irrigation against conventional and satellite-based alternatives under realistic farm operating conditions.

7. Conclusion

The use of UAV (Unmanned Aerial Vehicle)-mediated thermal and multispectral remote sensing offers a basis for determining the actual state of crops and provides information that allows the determination of moisture conditions accurately. It has been found that the combination of thermal canopy temperature with red-edge-sensitive vegetation indices makes it possible to assess drought more accurately than when using any type of measurement. The combination of such stress maps and GIS-based zoning and threshold scheduling allows variable rate irrigation to be performed, which in turn allows saving water and getting good harvest. The limiting factors regarding the use of technology are not that why it could be difficult for farmers to implement, but rather due to the difficulties coming from the need to standardize calibration and thresholds, perform costly ground truthing, and have access to irrigation that could implement VRI.

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