



REVIEW ARTICLE

Recent trends in crop water stress monitoring using remote sensing technologies: A review

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Received: 04 December 2025; Accepted: 10 April 2026; Available online: Version 1.0: 04 June 2026

Cite this article: Gokul S, Manivannan V, Thirukumaran K, Boominathan P, Jagadeeswaran R, Raja R, Prabukumar G, Asritha M, Surya K. Recent trends in crop water stress monitoring using remote sensing technologies: A review. Plant Science Today. 2026; 13(sp2): 1-18.
<https://doi.org/10.14719/pst.13057>

Abstract

Unmanned aerial vehicle (UAV) based remote sensing has emerged as a disruptive technology for detecting crop water stress (CWS) in real time, precisely and at low cost offering significant advancements over conventional approaches. The study examined the red green blue (RGB), multispectral (MSP), hyperspectral (HSP), thermal image sensors integrated with UAVs, which offers a high-spatial and temporal resolution of physiological indicators such as chlorophyll content and canopy cover, canopy temperature, stomatal conductance. The study highlights that in spring maize, random forest (RF) models using UAV-derived MSP and thermal indices with leaf area index (LAI) performed well ($R^2 > 0.575$, root mean square error (RMSE) < 0.073) with accurate detection of crop water content at the 9th leaf and milking stages, as well as stomatal conductance at tasseling and silking stages. Combining UAV-derived spectral and textural features enhanced model accuracy in cotton, with extreme gradient boosting (XGBoost) showing the highest performance for canopy equivalent water thickness (CEWT) ($R^2 = 0.75$) and crop water stress index (CWSI) ($R^2 = 0.90$). Despite significant advances, problems remain in standardising data acquisition procedures, decreasing fluctuations due to environmental variability and combining UAV-derived data into reliable decision-support systems for precise irrigation management. The review emphasises key research gaps, such as the demand for strong cross-regional validation, real-time monitoring and the development of compatible systems linking UAV imagery data with ground sensors and crop models. Overall, advances in UAV-based remote sensing technology are altering crop water stress (CWS) detection, creating new potential to enhance agricultural resilience, boost resource-efficient management and focusing on increasing concerns with respect to climate-induced water stress.

Keywords: canopy temperature; multispectral; spectral indices; thermal sensor; unmanned aerial vehicle

Introduction

The global population is anticipated to reach almost 10 billion by 2050 (1). As a result, food production must increase rapidly in the face of input shortages (water), climatic uncertainty and environmental sustainability (2). At present, 80–90 % of the freshwater resource is used globally in agriculture and roughly two-third of the freshwater is used for agricultural irrigation (3). In contrast, the availability of agricultural water supplies is being threatened by climate change, raising global water shortages, frequent dry spells and global warming. The world's dryland area has grown substantially over the past decade and there has been a significant increase in the frequency, possibility and extent of droughts. As a result, there has been a \$30 billion global loss in crop production (4).

Plant abiotic stress, which includes water stress, generally referred to as drought stress, poses a major constraint for crop production if it persists for a prolonged period (5). Water stress negatively affects the physiological growth and developmental

processes of crops, significantly impacting crop production and quality (6). A lack of water availability causes physiological and biochemical alterations that affect photosynthetic rate and development processes, indicating crop water stress (CWS) (7). Crops subjected to moisture stress result in stomatal closure, which lowers transpiration and evaporation, resulting in increased canopy temperature. Leaf temperature, stomatal conductance, soil moisture content, canopy water content and evapotranspiration (ET) are some of the biochemical and biophysical metrics identified as possible indicators of crop water status (8). A change in irrigation frequency is expected to result in a 10–27 % reduction in maize yield (9). Conventional techniques for assessing agricultural water stress include measuring the soil moisture content, examining meteorological factors and monitoring various physiological indicators, including stomatal conductivity and water potential (10). Even though these techniques can provide precise information regarding the degree of CWS, they are destructive, time-consuming and labour-intensive (11).

To overcome these restrictions, quick and non-destructive CWS sensors have been developed. For rapid acquisition of digital data, remote sensing is combined with a variety of optical sensors like red green blue (RGB), multispectral (MSP), hyperspectral (HSP) and thermal images. The platforms are employed using satellites, airplanes, unmanned aerial vehicles (UAVs) and handheld devices. Artificial intelligence (AI) systems can be used to analyse these digital data and assess the physical and chemical characteristics of crops (12). Crop classification, yield forecasting, disease and pest identification and management and CWS assessment all have been performed using remote sensing technology (13–16). Recently, UAVs evolved into modern field phenotyping platforms supplying high spatio-temporal resolution data for crop water status monitoring and are less expensive, flexible and less dependent on climatic factors (17).

Despite rapid developments in remote sensing technologies for estimating CWS, current studies are scattered across multiple crucial aspects. Most prior studies typically focus on single-sensor techniques, such as MSP or HSP data and thermal and were limited to specific methodological frameworks, unable to provide an integrated representation across platforms. Additionally, there is a distinct gap in the detailed analysis on the integrated use of UAV-based high-resolution data and satellite observations, notably for large-scale stress monitoring under various agro-climatic conditions. Furthermore, recent advances in machine learning (ML) and AI approaches for CWS monitoring have not been extensively investigated in conjunction with conventional biophysical and spectral indices. In addition, important operational limitations like as data fusion, scalability, cost-effectiveness and real-time applicability in precision irrigation management have received inadequate critical attention.

In order to address these gaps, the current review delivers an extensive analysis of the recent trends in CWS assessment using remote sensing technologies, integrating findings from MSP, HSP and thermal sensing platforms, including satellite and UAV-based systems. To assesses the role of recent analytical methodologies, such as ML and data-driven models, while also aiming at the multi-scale feasibility and constraints of existing techniques. The paper also identifies significant research gaps and provides future prospective for establishing strong, scalable and decision-support frameworks for precision agriculture.

Importance of crop water stress assessment

Drought stress is a critical abiotic stress that induces dehydration in plants, preventing cells from maintaining acceptable water concentrations, which ultimately limiting plant growth and crop production (18). Therefore, assessing CWS is essential for optimising crop production, particularly through precision irrigation (19). The availability of timely irrigation information is vital in agriculture for enhancing the crop yield but also contributes to ensuring food security. Detailed studies of crop responses to water stress are required to determine drought-tolerant crop species and maintain the ideal balance between irrigation and yield.

Crop water stress (CWS) assessment plays a major role in defining the environmental interaction of crops and is critical for effective irrigation scheduling (10). By enabling early identification and adequate measures routine water stress monitoring can reduce the risk of economic loss. Further, to minimise yield loss and respond with proper agrotechnical solutions, it is essential to evaluate CWS before the occurrence of unrecoverable damage. Understanding

CWS evaluation methods is essential for effective irrigation control and eliminating irrelevant crop stress (20).

Different methods of crop water stress assessment

Ground-truth measurements

Soil-based approaches: Traditional soil-based methods for detecting CWS rely on *in situ* soil moisture assessment and atmospheric variables to evaluate the loss of moisture from the soil-plant system (21). Different methods based on soil analysis are summarised in Table 1.

Table 1. Various soil-based approaches for detecting crop water stress

Technique	Advantages	Disadvantages	Reference
Direct method			
Gravimetric	Very accurate	Slow, destructive, lab needed	(22)
Indirect methods			
Neutron scattering	Accurate, fast	Costly, not for shallow soil, radiation	(23)
Gamma-ray	High resolution	Expensive, hazardous	(24)
Time domain reflectometry	Stable, non-invasive	Costly, errors in saline/wet soil	(25)
Capacitance sensor	Cheaper, site-specific	Needs frequent calibration	(26)
Frequency domain reflectometry	Better in dry soil, precise	Less accurate when wet, calibration	(27)
Tensiometer	Cheap, good for deep soil	Limited range, not for dry/saline soil	(28)
Resistive (Gypsum)	Very low cost	Low accuracy, frequent calibration	(29)

Evapotranspiration-based measures: Evapotranspiration based measures play a crucial role in monitoring CWS and its relationship with yield. Various indicators, including precipitation, soil moisture, vegetation indices like normalised difference vegetation index (NDVI) and ET, are employed to quantify CWS. Initially, a significant correlation between crop production and the ratio of actual to reference ET (fRET) was demonstrated, which serves as a substitute for water stress (30). Later, established a correlation between relative yield losses and water stress at different phases of crop growth (31).

Plant based approaches

Plant based approaches for detecting CWS are often more susceptible than soil moisture content techniques. Several plant-based measures are outlined in Table 2.

Table 2. Plant-based methods for evaluating crop water stress

Approach	Method	Advantages	Disadvantages	Reference
Stem water potential (Ψ stem)	Pressure chamber, non-transpiring leaf	Accurate, good for drought studies	Laborious, discrete data, time-consuming	(32)
Relative water content (RWC)	Fresh/dry weight ratio	Direct water status, scalable with remote sensing	Destructive, intensive sampling	(33)
Leaf water potential (Ψ leaf)	Scholander chamber	Good for stress detection	Affected by environment, time-consuming	(34)
Stomatal conductance (Gs)	Infrared porometer	Indicates gas exchange, scalable with remote sensing	Costly, individual leaf data, needs skill	(35)
Sap flow	Thermal sensors measure sap rate	Real-time, irrigation planning	Complex, expensive, influenced by temp.	(36)

Canopy temperature: Canopy temperature has been widely studied as an indicator of plant water stress. It can be measured using thermal imagery or infrared thermometers (37, 38). The significance of foliar temperature variations in detecting water deficit was established, highlighting the complex relationship between foliar temperature, moisture availability and plant water status (21). Infrared thermal images can derive canopy temperature, which has been found to correlate well with stomatal conductance (39) and stem water potential (40). However, accurately isolating leaf temperature from the full image is essential to avoid erroneous estimates of canopy temperature due to non-leaf material (39). The measurement of canopy temperature is based on the principle that leaf temperature is influenced by transpiration rates, which are in turn governed by stomatal conductance. A decrease in plant water status leads to a reduction in transpiration due to stomatal closure, which increases in leaf temperature. However, relying solely on canopy temperature as a proxy for plant water stress has limitations. It cannot directly estimate the physiological status of crops under varying conditions.

Vegetation indices for crop water stress monitoring

Vegetation indices (VIs) are increasingly utilised for monitoring crop water levels and enhancing irrigation schedules at the canopy and

landscape levels (40). These indices have been applied to estimate CWS in various crops, including wheat, cotton and maize (41–43). Structure, chlorophyll, lutein and moisture indices are the four main categories of vegetation indices (VI) (44). Structure indices like NDVI, renormalised difference vegetation index (RDVI) and soil-adjusted vegetation index (SAVI), are frequently employed to monitor vegetative cover and canopy structure, both of which are significantly influenced by water stress (45). Chlorophyll indices, including the transformed chlorophyll absorption in reflectance index (TCARI) and optimised SAVI combinations, are especially useful for detecting water stress since chlorophyll content declines under water-limited conditions. The various VIs are presented in Table 3. These indices effectively track physiological changes due to water stress, particularly in crops like maize, where TCARI/RDVI and TCARI/SAVI combinations showed strong correlations with crop water stress index (CWSI) resulting in R^2 values of 0.47 and 0.50 at reproductive and final stages, respectively and 0.81 and 0.80 for TCARI/RDVI and TCARI/SAVI at the late reproductive and final stages, respectively (17).

Crop water stress index

An important factor of crop-atmospheric interactions, CWS is "an index of water stress using leaf scale and plant temperature analysis

Table 3. Detection of plant water stress utilising reflectance indices

Spectral indices	Formula	Crop stress indicators	References
Transformed chlorophyll absorption in reflectance index (TCARI)	$3 [(R700 - R670) - 0.2(R700 - R7550) \times (R700/R670)]$	Leaf water potential and stomatal conductance	(46)
Optimised soil adjusted vegetation index (OSAVI)	$\frac{(1+0.16) (R700 - R 550)}{(R800 + R670) + 0.16}$	Stomatal conductance, leaf water potential	(46)
Normalised difference vegetation (NDVI)	$\frac{R800 - R 670}{R800 + R 670}$	Stomatal conductance, leaf water potential	(47)
Photochemical reflectance index (PRI)	$\frac{R570 - R531}{R570 + R 531}$	Chlorophyll fluorescence, stomatal conductance	(48)
Renormalised difference vegetation index (RDVI)	$\frac{R800 - R670}{\sqrt{R800 - R670}}$	Stomatal conductance, leaf water potential	(49)
Normalised photochemical reflectance index (NPRI)	$\frac{PRI}{RDI \times \frac{R700}{R670}}$	Stomatal conductance, chlorophyll fluorescence	(50)
OSAVI/TCARI	$\frac{3(R700 - R670) - 0.2(R700 - R550) \times \frac{R700}{R670}}{(1 + 0.16)(R700 - R550) + 0.316}$	Stomatal conductance, leaf water potential	(46)
Simple ratio water index (SRWI)	$\frac{R860}{R1240}$	Leaf water potential	(51)
Water index (WI)	$\frac{R860}{R1240}$	Leaf water potential	(51)
Normalised difference water index (NDWI)	$\frac{R860 - R1240}{R860 + R 1240}$	Leaf water potential	(52)

approaches" and is essential for efficient irrigation. To measure the water deficit level of crops utilising canopy temperature (T_c), air temperature (T_a) and vapor pressure deficit (VPD). The empirical CWSI was initially proposed and followed by the development of theoretical method for calculating the CWSI based on upper and lower limits (T_{max} and T_{min}) by combining formulas of the Penman-Monteith and energy balance theory (53, 54). However, the application of this method may be limited due to the number of parameters required for obtaining the CWSI baseline. Previous study suggested a method that uses wet and dry reference surfaces to make estimation simple (Eqn. 1) (55).

$$\text{CWSI} = \frac{T_c - T_{\text{wet}}}{T_{\text{dry}} - T_{\text{wet}}} \quad (\text{Eqn. 1})$$

where, T_c = Canopy temperature, T_{wet} = Temperature of a well-watered leaf, T_{dry} = Temperature of a leaf with fully closed stomata.

The CWSI index ranges from 0–1, where 0 or lower baselines indicate no stress and plant transpiration at its maximum rate, while 1 or upper baselines indicate severe water stress (56). To get around this constraint, the hybrid CWSI an empirical upper limit coupled with a theoretical lower limit has been proposed as a way to lower the demand for complex atmospheric observations with greater accuracy.

Additionally, the water deficit index (WDI), derived from the CWSI, uses similar principles but is specifically designed to account for composite plant-soil surfaces under various micrometeorological conditions (Eqn. 2) (57).

$$\text{WDI} = 1 - \frac{\lambda \text{Eact}}{\lambda \text{Epot}} \quad (\text{Eqn. 2})$$

where, λEact = Actual latent heat flux density and λEpot = Potential latent heat flux density.

Recent works have reviewed alternative indices based on infrared thermometers that involve lower data than CWSI for predicting CWS. The canopy temperature ratio (T_c ratio) measured over completely irrigated and water-deficit can serve as alternate for the water stress coefficient (K_s) used in the reference ET-crop coefficient (58). The results indicate that the T_c ratio is a suitable empirical measure of K_s for assessing crop ET under water deficit conditions and facilitates the application of crop coefficient method for scheduling deficit irrigation. Deficit-irrigated sunflowers grown under arid/semi-arid conditions responded well to irrigation scheduling and water stress monitoring using T_c based the degrees above non-stressed (DANS) approach (59). In addition, a single measurement T_c metric degree above canopy threshold (DACT) was used for detecting water stress in maize (60). Among four thermal remote sensing indices-based approaches (CWSI, DANS, DACT and T_c ratio), DANS and DACT are sensitive to CWS as compared to CWSI, although it requires more data for computing crop ET coefficients (61).

Remote sensing approaches for assessing crop water stress

Remote sensing provides a time-efficient, non-destructive and precise method for assessing CWS, addressing the challenges of traditional field measurements, which are labour-intensive and disruptive (62). It offers insights into spatial and temporal crop variability, enabling more comprehensive analysis and forecasting. Crop water stress is mostly assessed with RGB, HSP, MSP and thermal

infrared (TIR) sensors using ground vehicles, satellites and UAV. Red green blue sensors collect the visible spectrum, whereas MSP and HSP sensors acquire infrared bands for more detailed plant analysis (63, 64). Infrared cameras are particularly useful for determining water stress by measuring T_c and transpiration rates (65).

These technologies facilitate data collection without direct physical interaction, enabling precise crop temperature measurements and specific information crucial for irrigation scheduling (66). Remote sensing systems, which include both active (backscatter-based) and passive (reflectance-based) sensors, are deployed on various platforms such as ground vehicles, satellites and aircraft (67). Radio detection and ranging (RADAR) and light detection and ranging (LiDAR) are examples of active sensors, whereas affordable RGB, MSP, HSP and TIR are examples of passive sensors (68). Remote sensing techniques, by examining regions of the electromagnetic spectrum including ultraviolet (10–380 nm), visible (400–700 nm) and near-infrared spectra (850–1700 nm), provide indirect indicators of water stress through leaf biochemical attributes (69). This technology is especially effective for monitoring drought stress and provides early detection for efficient irrigation scheduling and scaling information from the leaf to the field level (40).

Ground-truth measurements

Infrared thermometer: An efficient technique for determining specific plant water stress, infrared thermometry is frequently used to schedule irrigation for a wide range of crops. This approach, which focuses on T_c measurement was demonstrated earlier and further studies have used spectral indices based on T_c and its variation to detect CWS (21, 70, 71). Water stressed and non-water stressed baselines for irrigated maize in Colorado, USA, were established by combining infrared thermometry with relevant meteorological data (72).

Canopy temperature is precisely estimated by infrared sensors since they can detect emitted radiation. This makes it a valuable tool for assessing crop water status (73). The SI-111 infrared radiometer (IRR) sensor, which measures surface temperature by converting thermal energy from surfaces, is commonly used for this purpose, offering a measurement range from - 60–110 °C, with a manufacturer accuracy of ± 0.5 °C (74).

Infrared thermography has been employed for quantitative estimation of crop stress using both index-based and physically based approaches. One common method to quantify water stress is the CWSI derived from infrared thermometry (54, 75). This technique has been used successfully for satellite and drone-based remote sensing applications.

Satellite-based remote sensing

The solar or optical-spectral domain of the electromagnetic range (0.4–2.5 μm ; visible and near infrared (VNIR)/shortwave infrared (SWIR)) has been the primary focus of remote sensing of vegetation for the past 40 years. Various MSP and HSP cameras have been developed as a result of this approach and are currently being utilised on the ground (like ASD FieldSpec and Spectral Evolution PSR+), in the air (such as AVIRIS, HyMap, HySpex and Aisa FENIX) and space (such as Landsat, SPOT, MODIS, IKONOS and HYPERION). These optical-reflective systems depend on the spectral reflectance characteristics of plant leaves, the canopy and the soil background (76).

Satellite-based systems, such as TIR imagery from AVIRIS and MODIS, have shown promise in studying thermal variability and water stress over large agricultural areas. Landsat images, primarily the near infrared (NIR) and SWIR bands, have been used in empirical methods like the reflectance trapezoid to estimate water stress in crops (77). Additionally, the NIR and Red-Edge bands from WorldView-2 data have been correlated with crop biophysical and biochemical quality characteristics, such as those found in grapevines, achieving R^2 values ranging from 0.70–0.95 (78). MODIS data, particularly the ET product (MOD16), has been used to create models like the ET warning index (ETWI), which tracks water-stress trends globally (79). Combining MOD16 with Landsat data has also been successful in monitoring ET and detecting water stress at the field level (80).

The Sentinel-2 satellites, with their rich spectral information, are highly effective for CWS estimation. With spatial resolutions ranging from 10–60 m and a 5 day revisit frequency, Sentinel-2 offers better spatial and temporal resolution compared to Landsat 8 (which has a 30 m spatial resolution and 16 day revisit frequency). This makes Sentinel-2 particularly useful for monitoring crops like grapevines (81). However, while Sentinel-2 lacks thermal bands for land surface temperature, Landsat 8's thermal bands remain valuable, especially for estimating stem water potential in crops like cotton (82). For estimating soil water potential, linear regression methods using Sentinel-2 reflectance bands and VIs (such as the normalised difference index (NDI) 45) have proven effective, with R^2 values of 0.6269 and root mean square error (RMSE) of 3.6802. In precision agriculture, satellite platforms with resolutions below 30 m are preferred for detailed analysis (83). Frequently used platforms include Sentinel-2 for optical data and the Landsat satellite for thermal data.

Radio detection and ranging remote sensing

Radio detection and ranging technology (RADAR), offers an alternative to optical sensors by utilising a higher frequency band and wider bandwidth to significantly enhance resolution capabilities (84). It is an active remote sensing system that operates in the microwave spectrum (0.3–300 GHz), similar to LiDAR, but with RADAR echo returns, called backscattered signals, measured in amplitude and phase. These backscattered signals are related to the physical (geometry, roughness) and electrical (permittivity) properties of a target.

In the field of plant phenotyping, radar represents a promising new frontier that has not yet been explored extensively. Most RADAR applications in phenotyping have come from satellite-based systems (85), piloted aircraft and ground penetrating RADAR (86). Recent advances in RADAR instrumentation and UAV design have opened up new opportunities to integrate these technologies, although they are still in the early stages of commercial application. RADAR data, depending on the frequency and polarisation used, presents significant potential for various plant phenotyping applications, including the measurement of soil moisture, root characteristics and plant architecture (87). However, more research is needed to fully realise the potential of UAV-mounted RADAR systems for robust and effective plant phenotyping.

Light detection and ranging remote sensing

Light detection and ranging (LiDAR) is a dynamic remote sensing system that provides accurate three dimensional (3D) data by measuring the time it takes for laser pulses to travel from the sensor

to the target and return. This method delivers precise data about the target object, including crop canopies. Light detection and ranging has significant potential for CWS estimation due to its ability to analyse field conditions quickly and efficiently. The directed short-band laser light used in LiDAR easily infiltrates the crop canopy and is less affected by the light it encounters, making it effective for measuring CWS in a non-destructive manner (88).

Recent advancements in LiDAR technology, including the integration of 3D imagery with natural colour, chlorophyll fluorescence, the photochemical reflectance index and leaf temperature data, have further enhanced its ability to assess CWS. The system has been tested in various crops and the results have exhibited a strong correlation between leaf water status and the number of LiDAR values acquired (65). The LiDAR system's ability to capture high-resolution data has led to the development of advanced algorithms designed to extract CWS information more accurately. Techniques combining LiDAR data with geometric regulations have shown promise in analysing the relationship between CWS and crop parameters (89).

Some limitations include vulnerabilities and inefficiencies in acquiring physiological traits and a partial representation of CWS. Additionally, while LiDAR offers a quick and cost-effective way to gather data, its application to CWS remains less developed (90). To address these limitations, future studies are exploring the integration of LiDAR with other technologies to enhance its effectiveness and reliability.

Thermal remote sensing

Thermal infrared remote sensing systems have become an effective tool for monitoring CWS by detecting crop temperature and identifying differences in stomatal conductance, which is directly related to the plant's water status and transpiration rate (91). These systems are valuable because they correlate well with moisture content proxies, such as temperature and stomatal conductance and provide non-destructive, low-labour methods for assessing water stress in crops (9). The thermal infrared portion of the electromagnetic spectrum, ranging from 8–14 μm , is particularly useful for detecting water stress in plants because it responds to changes in transpiration rates, which decrease under water deficit conditions.

Several studies have shown the potential of thermal infrared systems in CWS monitoring, highlighting the use of satellite-based thermal sensors such as Landsat TM, MODIS, ECOSTRESS and VIIRS (92). These tools are commonly used to monitor crop water status across large areas. A method to calculate the CWSI using hot and cold pixels from Landsat 8 satellite data, demonstrating the method's effectiveness in irrigation scheduling for sugarcane during the growing season (93). Their results showed a strong correlation between the new CWSI based on Landsat 8 satellite and the computed CWSI based on field measurement with a RMSE between 0.12–0.29 for multiple images and a coefficient of determination around 0.49–0.85 and also observed a strong negative relationship between CWSI and vegetation water content (WVC), with R^2 values ranging from 0.42–0.78, confirming the utility of thermal infrared data for assessing water stress and managing irrigation. However, despite their utility, these satellite systems have limitations, including coarse spatial resolution and low temporal frequency, which hinder their ability to capture the fine-scale variability in water stress across smallholder farms. Vegetation indices, like normalised difference water index (NDWI) and NDVI, can be combined with thermal images to quantify water stress directly or indirectly by analysing canopy cover, vigour and growth (94).

Advanced remote sensing techniques, such as UAV-mounted thermal infrared sensors, have been employed to measure stomatal conductance and physiological parameters in crops under varying water regimes. The UAV systems can achieve high accuracy in estimating water stress, with models demonstrating coefficients of determination (R^2) ranging from 0.73–0.93.

Multispectral remote sensing

The Landsat program has long been an important source for MSP data analysis, particularly for monitoring CWS (95). This program, along with other systems like Sentinel-1, Landsat-8 and combination methods, has yielded significant results in terms of monitoring CWS. For instance, the RMSE values were recorded as 0.89, 0.24 and 0.31 (mm day^{-1}) for Sentinel-1, Landsat-8 and combined methods, respectively (96). These values demonstrate the potential accuracy and usefulness of these sensors for assessing CWS. Recent advancements in spaceborne imaging spectroscopy, such as those provided by the GeoEye system (OrbView and IKONOS) and the Digital Globe system (WorldView and QuickBird), allow for high-resolution MSP data collection. These systems are commercially available at more affordable prices, providing significant opportunities for widespread use in crop monitoring. The study tested MSP sensors, which included spatial and spectral resampling techniques for more accurate CWS analysis (97). The synergistic use of VIS-NIR and SWIR sensors, along with a multi-camera NIR+SWIR array, is particularly efficient in assessing crop leaf water status and nitrogen concentration, crucial indicators of crop health and stress (98).

Unmanned aerial vehicles-based remote sensing system

Unlike space-borne satellites, handheld spectroradiometers and UAVs enable local mapping with significantly higher spatial and temporal resolutions. These are advantageous for monitoring plant water status and optimising irrigation scheduling.

Unmanned aerial vehicles equipped with very high resolution (VHR) sensors offer the latest crop image analytics,

effectively addressing the limitations of satellite imagery. Unmanned aerial vehicles images can also be acquired frequently under user-defined ground sampling points and temporal range, minimising environmental disruptions such as cloud cover (99). The reliability of VIs produced from remotely sensed data from RGB, MSP and HSP sensors for estimating crop growth, plant height, canopy cover, moisture and nutrient status, biomass, leaf area index and yield (Fig. 1) (100).

The high-resolution imagery from UAVs can be further analysed using advanced image analysis methods to extract valuable insights into crop stress variability. This includes identifying both biotic stressors (e.g., diseases and pests) and abiotic stressors (e.g., water and nutrient deficiencies) (17, 101). Additionally, UAV platforms with sensors have become indispensable tools in precision agriculture research, providing ultra-high spatial and temporal resolutions (102). Unlike satellites, UAVs deliver on-demand, high-resolution datasets under a variety of atmospheric conditions, making them highly flexible for agricultural applications (103).

Recent research highlights the utility of UAV-mounted sensors in water stress assessment. To assess the water stress in cotton fields and estimate fiber quality, the potential of using spectral indices obtained from UAV data was examined with the green-red vegetation index (GRVI) against commonly used indices like the NDVI and CWSI (101). The results indicated that GRVI was effective in detecting variations in water content under mild stress but was less reliable under prolonged stress conditions, limiting its capability to reflect the actual water status of soil and crops. Similarly, the effectiveness of UAV-based MSP and thermal cameras in evaluating cotton canopy water stress was demonstrated, highlighting the strong potential of UAV technology for real-time water stress monitoring (104). The surface soil moisture in maize was determined using machine learning algorithms integrated with UAV-based MSP, thermal and RGB data obtaining an accuracy of 9.6–11.2% (RMSE) (8).

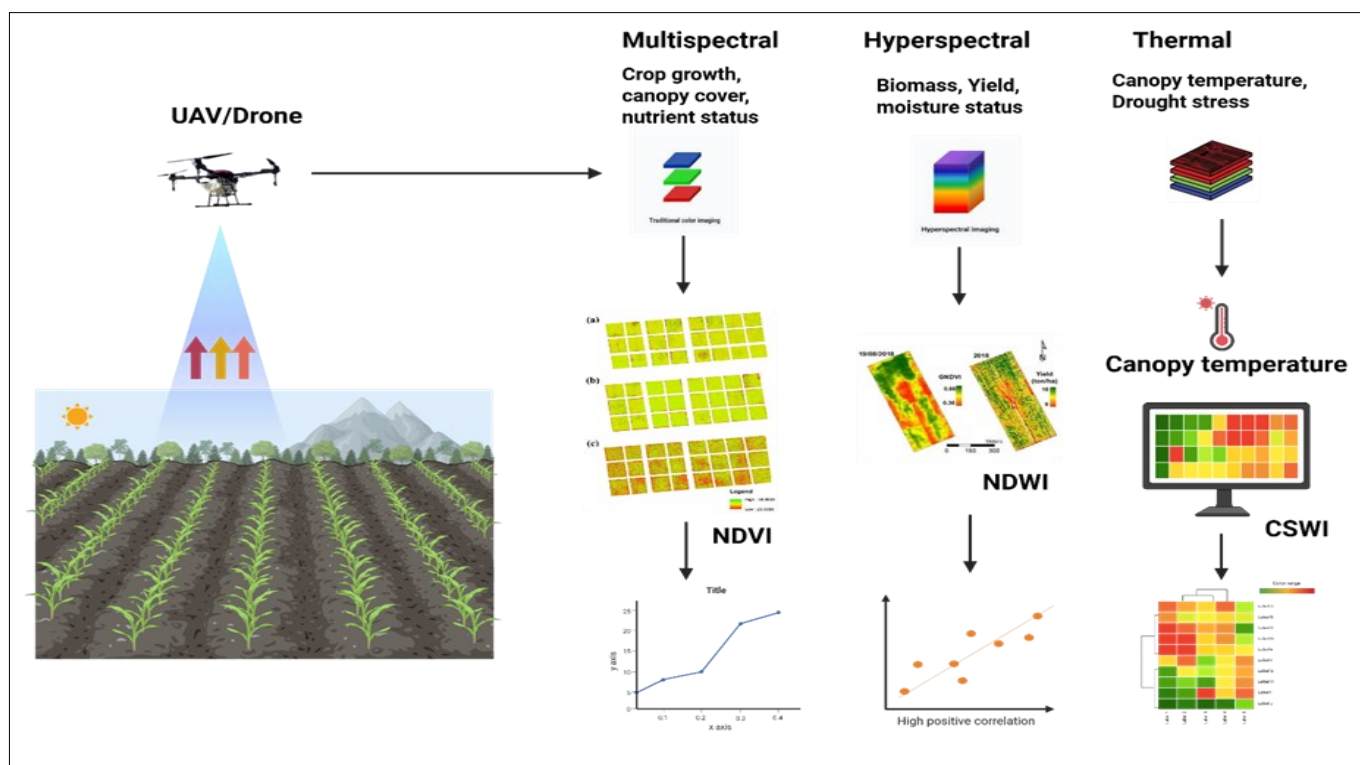


Fig. 1. Different unmanned aerial vehicle based remote sensing sensors in crop monitoring for calculating different stress indices.

Red green blue imagery

Red green blue sensors are widely used in phenotyping due to their simplicity, minimal requirements for specialised data collection methods and ease of processing. These sensors are also commercially available at relatively low costs (105). Meanwhile, the use of actual UAV RGB images with two resolutions of 2.7 and 14.7 mm were utilised in maize crop, the lower resolution exhibited lower water stress prediction accuracy with R^2 of 0.62 and RMSE of $0.12 \text{ mol m}^{-2} \text{ s}^{-1}$ with stomatal conductance (Gs) (106). However, their use for monitoring crop water content in the field is limited due to certain constraints. Effective application of RGB imaging for assessing moisture content requires controlled lighting conditions and specific leaf orientations relative to the camera. This dependence on pre-set conditions restricts its practicality for field-scale assessments, especially in dynamic outdoor environments (107). Consequently, RGB imaging for CWS assessment is often combined with thermal imaging techniques, which provide complementary data to enhance accuracy and reliability in stress detection (17).

Hyperspectral imaging

Hyperspectral remote sensing, also known as imaging spectroscopy is a powerful tool in agriculture. It captures light within a broad range of wavelengths (400–2500 nm) that span the visible, NIR and SWIR frequency bands. Unlike traditional MSP remote sensing, imaging spectroscopy provides hundreds of narrow spectral bands, making it sensitive to unique biophysical and biochemical properties (108). This enables a more detailed understanding of plant conditions, including structural and physiological traits, crop varieties, pests, diseases and water stress. Hyperspectral imaging has been widely utilised for CWS evaluation, offering higher accuracy than MSP imaging. This is particularly critical for detecting early signs of stress, such as nutrient deficiencies and crop diseases, which MSP sensors often fail to capture due to their limited spectral resolution (109). Hyperspectral imaging is becoming increasingly popular as a reliable tool, both in proximity and from a distance, to detect drought stress in agriculture (110).

Starting from remote sensing studies on vegetation, HSP imaging has become integral to crop phenotyping. Applications include extracting structural and physiological plant information, developing sensitive spectral indices and detecting plant stress and health (111). Hyperspectral imaging is also used to estimate soil moisture over large areas. For example, the use of temperature, precipitation, radiation and NDVI data to predict soil moisture (SM) and its spatiotemporal variability in Tibetan grasslands, achieving a prediction efficiency of 94 % using random forest models (112).

Thermal imaging

Unmanned aerial vehicles-based thermal imaging platforms have been widely used in precision agriculture, resulting in a high possibility of detecting crop diseases and water stress (113). High-resolution thermal imaging sensors, operating in the spectral range of 3–14 μm (commonly 3–5 μm or 7–14 μm), have proven highly effective for analysing CWS due to their ability to penetrate plant tissues and detect changes in moisture content more reliably and sensitively than RGB imaging (107, 114). The integration of thermal cameras with UAS has revolutionised agricultural monitoring by providing cost-effective, high spatial resolution data, enabling widespread adoption of remote sensing technologies. Thermal

imaging is especially useful for determining T_c , an important physiological parameter related to transpiration, leaf water potential and stomatal conductance (Gs) (115), which is frequently used to compute CWSI using equation 1 (Fig. 2).

Many studies highlight its effectiveness across crops, such as maize, where UAV thermal imagery showed strong correlations with in-field IRR sensors ($R^2 = 0.94$) during growth stages. The maize T_c was optimally calculated during the mid-vegetative stage (RMSE = 0.59°C , $R^2 = 0.81$, RMSE = 2.9 %) based on thermal infrared data, followed by indices such as NIR, normalised green red difference index (NGRBI), enhanced vegetation index (EVI) and NDVI. Similarly, stomatal conductance was ideally forecasted during the early reproductive stage (RMSE = $25.9 \text{ m mol m}^{-2} \text{ s}^{-1}$, $R^2 = 0.85$, RMSE = 11.5 %) using the red-edge band, followed by NIR, green, OSAVI and blue bands also playing vital roles (101). In cotton fields, water stress was evaluated by daily revisits, with high spatiotemporal resolution in Yangling, China (116). Similar applications were observed for sugar beet and soybean crops under different irrigation regimes (117).

Thermal imaging has also been successfully integrated with UAVs carrying MSP sensors (RGB, VNIR), enabling enhanced stress detection for precision agriculture, particularly in viticulture and broader crop monitoring (118). It is integral to plant phenotyping by measuring leaf surface temperature, which correlates with stomatal conductance and evaporation rates, especially during critical growth (107). A positive correlation was also found between thermal images and NDVI and the ratio between TCARI and OSAVI as indices highly correlated with ($R^2 = 0.68$ for g_s and $R^2 = 0.50$ for Ψ_{stem}) in Tempranillo vineyards (119). Beyond agriculture, thermal imaging holds potential for climate change research, vegetation analysis and drought stress studies in non-crop species. Furthermore, ongoing efforts to integrate thermal, NIR and red-edge spectral data aim to enhance its applications.

Multispectral imaging

Unmanned aerial vehicle MSP imaging systems, paired with high-resolution pixel sensors, are cost-effective, accessible and efficient tools for monitoring CWS (65). These systems simultaneously capture three colour bands red, green and blue offering natural colour imagery while enabling precise analysis of crop water status. Their lower cost and ease of operation make them attractive options for large-scale agricultural applications. Studies have demonstrated the potential of these systems in various crops. For example, the spatial variability of water content in Tempranillo vineyards using a UAV-integrated MSP sensor. The findings highlighted strong correlations between NDVI and the ratio of TCARI to optimised soil adjusted vegetation index (OSAVI) with stomatal conductance (g_s , $R^2 = 0.84$) and stem water potential (Ψ_{stem} , $R^2 = 0.68$). Further, TCARI ($R^2 = 0.45$) and TCARI/OSAVI ($R^2 = 0.58$) were specifically correlated with the stem water potential of rain-fed Tempranillo grapevines in Spain (119). However, using single vegetation indices like TCARI for general water stress (GWS) showed limited capability in capturing variance ($R^2 = 0.35$), where the high performance of all VIs was an R^2 of 0.42 which is similar to an observation from a previous study (118). Better correlations, such as those observed between GNDVI and stem water potential (Ψ_{stem}), were reported in studies on Carménère grapevines in Chile ($R^2 = 0.58$ and 0.31) respectively (119).

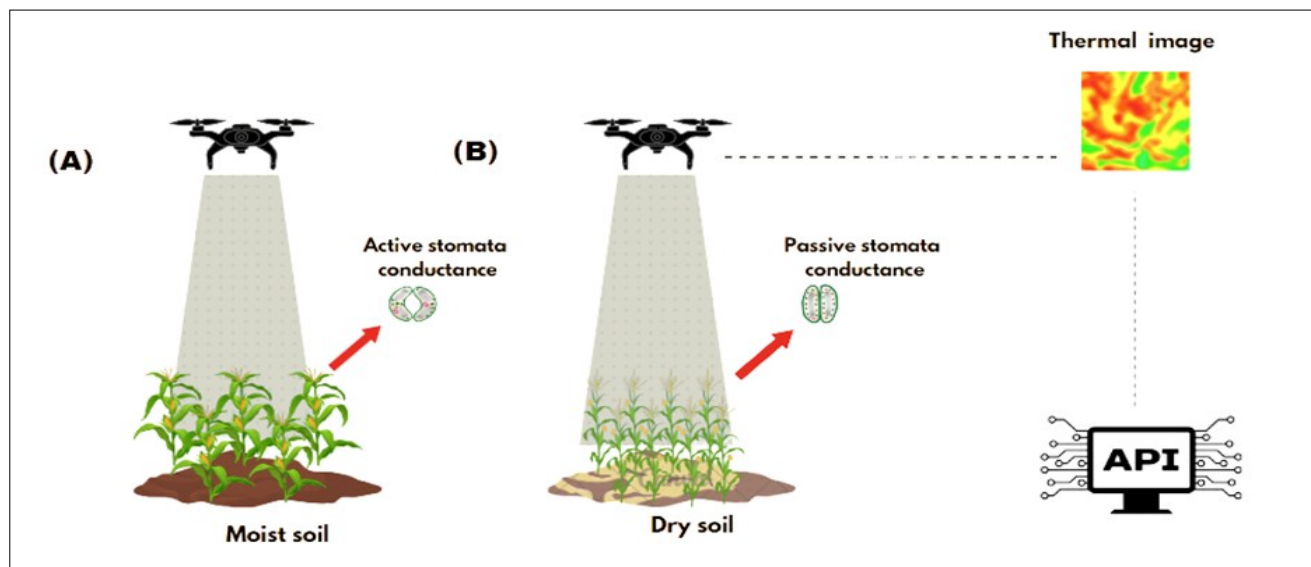


Fig. 2. Measuring canopy temperature using unmanned aerial vehicle based thermal imaging: (A) without stress and (B) under stress conditions.

In maize, the feasibility of mapping crop water status at reproductive and maturation stages using regression models based on vegetation indices (e.g., NDVI, soil-adjusted vegetation index). These UAV-derived indices achieved a strong correlation with ground-based data ($R^2 = 0.81$), underscoring the effectiveness of UAV MSP imagery for water stress monitoring (120). Similarly, relationships between specific VIs, such as structural and chlorophyll and CWSI further validated the potential of UAV-based water status mapping in maize. UAV multi-spectral imaging provides high resolution NDVI maps have become cost-effective and widely used by farmers, whereas UAV thermal imaging requires significant financial expenditures that presently limit widespread adoption (121). The sensors employed for CWS detection are summarised in Table 4.

Machine learning and deep learning algorithm for stress detection

Machine learning

Vegetation indices integrated with ML algorithms, such as NDVI and TCARI, have proven effective for water stress characterisation (94). Unmanned aerial vehicle thermal imagery, processed through edge detection and Gaussian mixture models, has been used to calculate species-specific water stress indices. The use of optical multisensory data fusion coupled with an support vector machine (SVM) classifier was suggested for CWS assessment, whereas artificial neural network (ANN) based systems determined water potential and evapotranspiration with high precision (122). These systems integrated wireless sensor networks and data from infrared

Table 4. Various sensor types are employed in characterising plant phenotypes

Sensor type	Crop	Key Indicators	Strengths	Limitations	Reference
Thermal remote sensing (satellite-based)	Sugarcane	CWSI, VWC	- Effective for large-scale monitoring - Strong correlation with vegetation water content ($R^2 = 0.42-0.78$) - Useful for irrigation scheduling	- Coarse spatial resolution - Low temporal frequency - Limited field-scale variability detection	(94)
Thermal imaging (UAV-based)	Maize	Canopy temperature (T_c), CWSI	- High spatial resolution - Strong correlation with ground sensors ($R^2 = 0.81-0.94$) - Accurate estimation of physiological traits	- Sensitive to environmental conditions - Requires radiometric correction	(115)
Thermal imaging (UAV-based)	Cotton	Canopy temperature, water stress indices	- Simplified CWSI (CWSIsi) showed higher correlation with stomatal conductance (g_s, $R^2 = 0.660$) and transpiration rate (tr, $R^2 = 0.592$) compared to empirical CWSI and spectral indices	- High operational cost - Data processing complexity	(116)
Thermal + multispectral integration	Vineyard	NDVI, TCARI/OSAVI, canopy temperature	- Improved stress detection accuracy - Strong correlation with stomatal conductance ($R^2 = 0.68$)	- Increased system complexity - Higher cost	(118)
Multispectral imaging (UAV-based)	Vineyard	NDVI, GNDVI, TCARI, OSAVI	- Strong correlation with stomatal conductance ($R^2 = 0.84$) - Cost-effective and flexible	- Limited performance with single indices (low $R^2 \sim 0.35-0.42$)	(119)
Multispectral imaging (UAV-based)	Maize	NDVI, SAVI, structural & chlorophyll indices	- Strong agreement with ground data ($R^2 = 0.81$) - Effective at reproductive and maturation stages	- Less sensitive to early stress - Requires model calibration	(120)

CWSI: crop water stress index; VWC: vegetation water content; NDVI: normalised difference vegetation index; GNDVI: green normalised difference vegetation index; TCARI: transformed chlorophyll absorption in reflectance index; OSAVI: optimised soil adjusted vegetation index; SAVI: soil adjusted vegetation index.

thermometers (IRTs) to generate crop and soil stress analyses (65). Random forest has been widely used to address data overfitting. For e.g., HSP vegetation indices (NIR, WI and D1) with RF and SVM to model predawn leaf water potential in grapevines (123).

Random forest, ANN and multiple linear regression were used to estimate Gs values using NDVI and TCARI derived from UAV based MSP images in the vineyard (118). Including neural networks for estimating relative water content (RWC) in rice genotypes under deficit water stress using existing water band indices and newly proposed ones like the normalised difference ratio index (NDRI) and ratio index (RI) achieving high accuracy (109). Multispectral vegetation indices, texture features (TFs) and texture indices (TIs) derived from UAV data were employed to assess the efficacy of SVM, back-propagation neural network (BPNN) and extreme gradient boosting (XGBoost) in estimating canopy equivalent water thickness (CEWT) and CWSI in cotton. The findings indicated that the integration of spectral and textural data enhanced accuracy; specifically, XGBoost VIs + TFs model obtained the highest value for CEWT ($R^2 = 0.75$), whereas XGBoost VIs + TFs + TIs model attained more accuracy for CWSI prediction ($R^2 = 0.90$) (124). In spring maize, RF models integrating UAV derived MSP and thermal indices with LAI produced the best results ($R^2 > 0.575$, RMSE < 0.073). Plant water content was examined more precisely at the 9th leaf and milking stages and normalised stomatal conductance at tasseling and silking stages (125). In maize, MSP cameras provided more robust input data than thermal (TH) cameras with ($R^2 = 0.97$ and 0.71) and mean-normalised root mean square errors (nRMSE) were 10 and 25 %, respectively. In the case of MS cameras, the RF ($R^2 = 0.97$) and elastic net regression (ENR) ($R^2 = 0.88$) provided the best models. The correlation between soil water content (SWC) and thermal data was exponential, which was inaccurately handled by the general linear model (GLM) (> 40 % nRMSE; additionally, the robust linear model (RLM) and ENR failed to work with only one variable), so TH data was only acceptable with the RF (24.4 % nRMSE) (126). The agronomical

use of the RF model for determining SWC may provide an effective tool for calculating the optimal irrigation water requirement in precision agriculture, as one of the main objectives of irrigation is to determine an adequate water requirement for arable crops (127).

Deep learning

Deep learning (DL), an advanced subset of ML, has received substantial attention in recent years for big data analysis, particularly in remote sensing and computer vision applications (128, 129). While DL has made notable progress in the agricultural field especially in areas like plant disease detection and yield prediction its application in CWS estimation is relatively advanced, with research in this area still being limited. Several review papers have explored the potential of DL for plant stress phenotyping, highlighting the technique's promising future (130). The superiority of DL over conventional ML was first indicated (131). Deep learning can be defined as a non-linear processing model consisting of different layers of ANN, which may use supervised or unsupervised learning methods and high-level abstractions for feature representation (132).

In terms of plant water stress assessment, various deep-learning models have been applied. For instance, the convolutional neural network (CNN) based regression model was proposed to estimate SM levels from thermal images obtained from airborne systems over three distinct farm locations (133). This model demonstrated superior performance compared to the basic deep neural network (DNN) model. Deep neural networks were used to enhance *in situ* soil moisture assessment with raw data obtained from the visible infrared imaging radiometer suite (VIIRS) (134). The DL model displaced the global land data assimilation system (GLDAS) and soil moisture active passive (SMAP) products in terms of reliability. Convolutional neural network models were found to outperform other models including RF, XGBoost and ANN in estimating daily reference evapotranspiration (ET) using limited hourly meteorological data (135). Various deep learning models applied over various crops are given in Table 5.

Table 5. Role of deep learning in assessing crop water stress

Crop/Plant	Input	DL Model	Comparison	Key Findings	Reference
Maize	Image	AlexNet, Gabor filter	AlexNet, ResNet50, ResNet101	5 class of drought stress categorisation; 98.8 % accuracy	(136)
Corn	Image	ResNet120, ResNet50	Gradient Boosting (GBDT)	2 class: 98 % accuracy; treatment class: 96 %	(137)
Maize	Image	VGG16	NA	Treatment (3 class): 98 %; Severity (5 class): 85 % accuracy	(138)
Ornamental plants	Image	CNN	NA	Treatment (3 class): 94 %; Area: 0.9884	(139)
Maize	Image	SVM + CNN	VGG16, ResNet50, Xception, SqueezeNet	Monitoring (2 class): 94 %; Treatment (3 class): 88.4 %	(140)
Maize, jowar	Image	BiLSTM	CNN, LSTM, RNN	80 % accuracy for 3 class detection	(141)
Maize, soybean, bhendi	Image	GoogLeNet, Inception V3, Alexnet	NA	Maize (3 class): 98.3 %; Soybean (2 class): 94.1 %; okra 97.5 % accuracy	(116)

BiLSTM: bidirectional long short-term memory; CNN: convolutional neural network; GBDT: gradient boosting decision tree; LSTM: long short-term memory; NA: not applicable; RNN: recurrent neural network; SVM: support vector machine; VGG16: visual geometry group 16-layer network.

The use of long short-term memory (LSTM) and bidirectional long short-term memory (BiLSTM) models for evaluating ETo based on relative humidity and air temperature, while three DL methods DNN, temporal convolution network (TCN) and LSTM evaluated for reference ETo estimation (104, 142). Applying the temperature surface-vegetation index (TSVI) model, an integrated approach was proposed to enable the continuous estimation of daily actual ETo at the regional scale with the TSVI-DNN model and showed a high correlation with ground-based observations (143).

The use of pre-trained CNN models, specifically ResNet50 and ResNet120, to classify maize water stress under three different treatments (optimum moisture, light drought and moderate drought) (137). Their models achieved accuracy rates between 91–98 % with training times as short as 8 min. This performance was superior to that of conventional methods, such as the gradient boosting decision tree (GBDT) model and demonstrated the efficiency of CNN models in plant water stress classification. A comparative analysis of deep convolutional neural network (DCNN) models revealed their high potential for detecting CWS; however, performance varied among designs and crops. GoogLeNet consistently outperformed AlexNet and Inception V3, achieving classification accuracies of 98.30, 97.50 and 94.16 % for maize, okra and soybean, respectively, due to its deeper architecture and multi-scale feature extraction capability. The models often converged within 5–10 epochs, showing computational efficiency ideal for near real-time applications (114).

Integration of unmanned aerial vehicle-based remote sensing and crop models for water stress detection

The integration of remote sensing data with crop models has emerged as a promising approach for monitoring CWS and optimising irrigation scheduling. The combination of multi-sensor data, with various spectral regions, into crop simulations offers a powerful tool for early detection and prediction of crop stress (144). While single optical sensors can provide useful data for crop monitoring, multi-sensor systems mounted on airborne platforms or UAVs are increasingly used to capture data from both HSP and TIR sensors, offering broader spectral coverage to detect crop stress at an early stage (9). The ability to measure leaf or Tc enables real-time monitoring of plant traits, such as stomatal conductance, offering a rapid response to stress that can be detected in min to hr.

Crop models, which simulate the complex interactions between soil, plant, water and atmosphere, are a key tool for assessing CWS (145). These models can be classified into deterministic or process-based models, which simulate the biophysical functions of the crop ecosystem (146). Dynamic crop simulation models such as agricultural production systems simulator (APSIM) (147), AQUACROP (FAO-66) paper (148), have become invaluable for predicting crop water requirements (CWR) and assessing the timing and amount of water stress. These models can also simulate the effects of water stress on various plant processes, such as biomass accumulation and yield and are useful for irrigation planning.

A recent study has shown the importance of integrating remote sensing data with crop models to optimise irrigation. For instance, remote sensing-based decision support systems (DSS) have become a valuable tool for irrigation scheduling, providing continuous data on crop water requirements and allowing for more precise irrigation interventions. These systems use data to estimate ET, soil moisture and plant water status, reducing the need for

costly fieldwork and enabling the provision of spatially distributed data. Advances in machine learning have further enhanced DSS, allowing for predictive irrigation scheduling based on data-driven patterns (149).

There are several crop models available that vary in terms of complexity, spatial resolution and the processes they simulate. AquaCrop, for instance, is a water-driven model developed by the FAO that links crop biomass accumulation to crop transpiration and ET. It is particularly useful for understanding water productivity and estimating crop water needs (150). Agricultural production systems simulator and DSSAT are more complex models that simulate a broader range of processes, including soil-plant interactions and nitrogen balance, making them more suitable for understanding the interactions between water stress and other factors like nutrient availability (147). These models can also use LAI or canopy cover as key variables, which can be obtained from remote sensing data, to simulate canopy development and predict crop performance (151). The integration of UAV based MSP and thermal sensors are illustrated in Fig. 3.

The digital accessible information system (DAISY) was integrated with APSIM to perform a simulation of crop growth under deficit irrigation and found that DAISY underestimated yield reductions under severe water stress and failed to simulate irreversible damage even after full irrigation was applied (152). In contrast, APSIM provided more accurate simulations. Similarly, the performance of CROPSYST and AQUACROP for sunflower growth under limited irrigation was examined and found that while AQUACROP required fewer inputs, CROPSYST performed better in simulating water use efficiency (WUE) under severe stress, due to its more detailed physiological representation (153).

Image processing and calibration

Immediately after the pre-flight preparations for UAV data acquisition, which involve selecting the UAV, sensor and planning the take-off (including location, timing and equipment), the UAV flight produces a significant amount of unprocessed data. Since UAV platforms typically lack real-time data processing capabilities, this data cannot be directly used to derive insights or conclusions. Consequently, post-flight processing steps like radiometric, atmospheric and geometric corrections are necessary to enhance the data and make it suitable for analysis.

The red-edge MSP camera (MicaSense, Inc., WA, USA) and FLIR Vue Pro R 640 camera was used to capture the UAV thermal images were used to obtain spectral and Tc images (17). After UAV images are acquired, they are subjected to radiometric calibration to eliminate distortions caused by environmental factors, sensor limitations and emissivity variations by collecting ground truth data. Mosaic processing is performed using Pix4Dmapper software (Pix4D, Inc., Lausanne, Switzerland) to get ortho-mosaic images (154). Further geo-referencing is done to rectify any spatial distortions by using ground control points (GCP). The geometrically corrected images are then segmented to identify and delineate areas of interest. Following these steps, the processed data undergoes feature extraction, focusing on parameters such as Tc, NDVI and NDRE with software like ArcGIS (version 10.4.1) (116) or QGIS (ver.3.12.3, Developers, Gruet, Switzerland) (155). Finally, statistical analysis is performed on the extracted features to calculate metrics such as mean, R^2 and RMSE values. The workflow for UAV image processing and analysis is represented in Fig. 4.

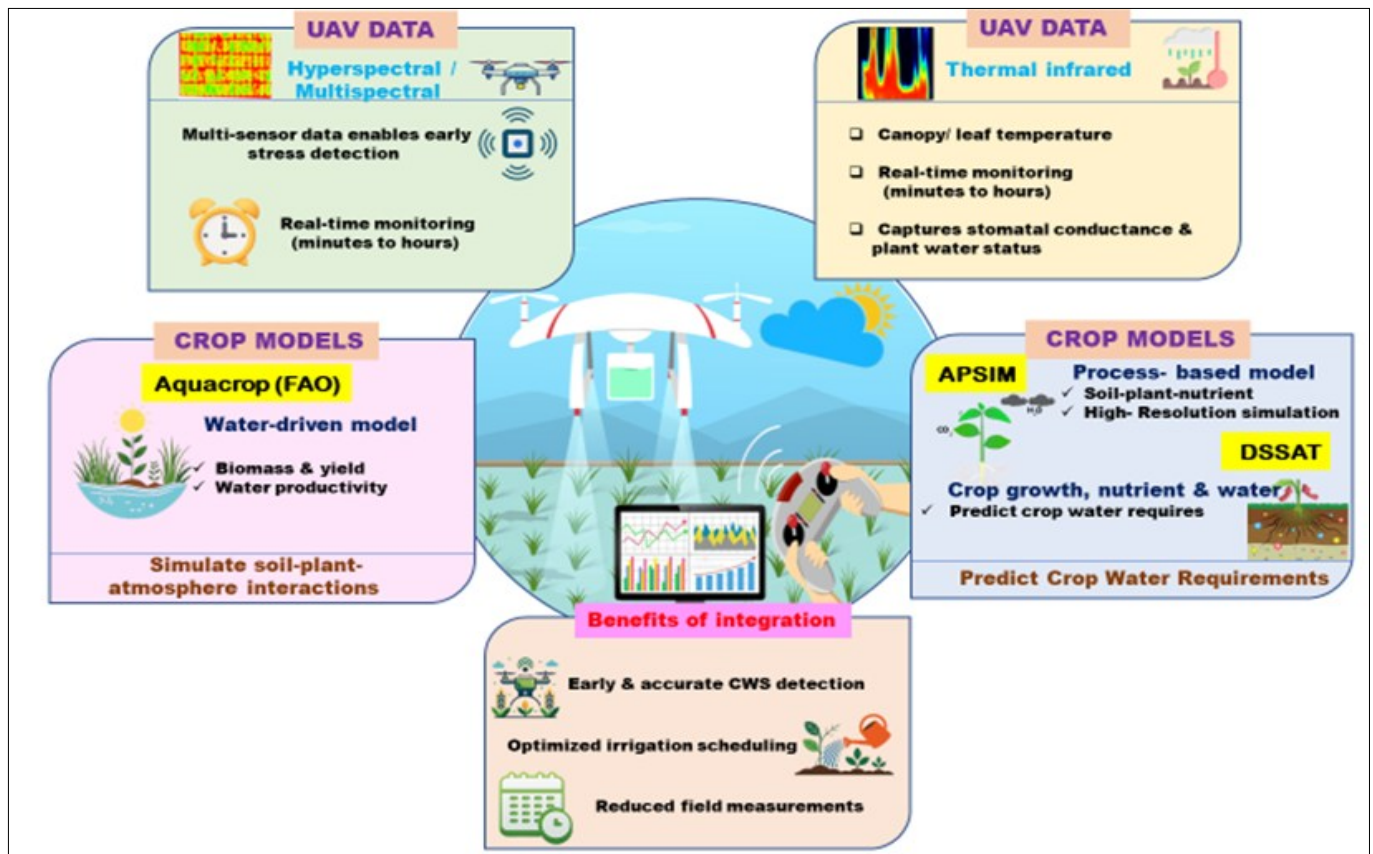


Fig. 3. Integration of unmanned aerial vehicle-based multispectral and thermal sensors with crop models.

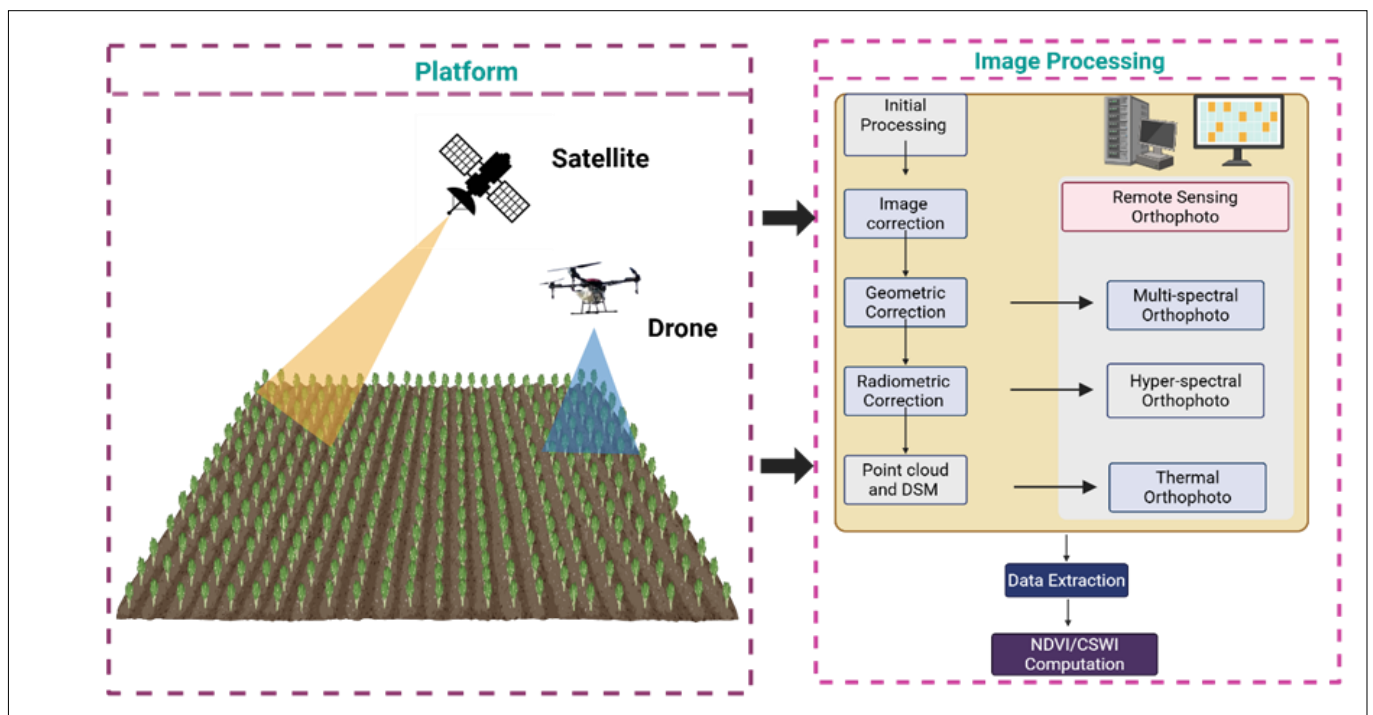


Fig. 4. Workflow of satellite and unmanned aerial vehicle-based crop monitoring and subsequent image processing used for data extraction and crop water stress index computation.

Advantages of unmanned aerial vehicle-based remote sensing

Unmanned aerial vehicle platforms have emerged as powerful tools in remote sensing, offering numerous advantages such as affordability, flexibility and independence from climatic factors. These platforms provide high temporal and spatial resolutions, making them ideal for agricultural applications (17). Among their various uses, UAVs are particularly effective in detecting CWS through the integration of low-cost data sources, primarily thermal

and MSP images. For instance, thermal imaging is commonly used to measure T_c , which is strongly related to transpiration rate, leaf water potential and stomatal conductance (127).

The advantages of UAV-based remote sensing extend beyond cost-efficiency. Unmanned aerial vehicles offer wide coverage, short measurement cycles and the capability for simultaneous data acquisition using multiple sensors (156). These features enable the rapid collection of high-resolution data, allowing

for real-time data acquisition. Additionally, UAVs can operate under conditions less impacted by cloud cover, which enhances their reliability for crop monitoring (157). In precision agriculture, UAV imaging technologies play a critical role in applications such as land use classification, crop stress detection and water and fertiliser management (158). Their capability for mapping in real time and quick image analysis facilitates the initial identification of CWS. This early detection is crucial for timely irrigation scheduling, as UAVs can effectively measure information from leaf to canopy level and field conditions (40).

Disadvantages of unmanned aerial vehicle-based remote sensing

While UAVs offer numerous advantages in remote sensing, their widespread adoption in agricultural applications is hindered by several challenges. One significant obstacle is the reduced flight time of UAVs and the varying regulatory frameworks across countries that complicate the integration of UAV technology (159). A critical challenge in the processing of UAV data involves the need for extensive pre-processing tasks to ensure data accuracy. For example, radiometric calibration of HSP or MSP images is essential due to the inherent variations in imaging conditions that can affect the quality of the data (160). Owing to the reduced load capacity of

UAV platforms, the thermal infrared cameras paired with UAVs are lightweight, uncooled categories which may lead to unstable T_c measurements and low mosaic precision. Issues such as inadequate tie-point numbers, geolocation errors and the need for critical pre-processing such as radiometric calibration, geometric correction and extraction of T_c result in complicating the use of thermal sensor for precise crop monitoring (75). The advantages and disadvantages of UAV in CWS assessment is depicted in Fig. 5. For e.g., DCNNs effectively detected stress-related features and showed a potential for application in real-time, image-based DSS, their practical applicability is limited by the need for high-quality annotated databases, robust calibration processes across different field conditions and simplified implementation strategies for farmer adoption (114). Comparative analysis of cost, scalability and accessibility of different sensors are given in Table 6. The high initial capital requirements for UAV platforms and sensors, as well as the requirement for trained professionals to operate and maintain these systems, sometimes limit their accessibility to smallholder farmers. Moreover, legal constraints such as flight permissions, operational safety standards and data privacy concerns pose organisational difficulties, particularly in regions with emerging UAV guidelines. Such problems limit the scalability and frequent usage

Table 6. Comparative evaluation of the cost, scalability and accessibility of different sensors

Sensor type	Typical sensors	Cost estimation	Scalability	Farmer accessibility	Key water stress indicators	Reference
RGB	Sony ILCE-5100, Canon S95, DJI Phantom 4 Pro	Low	High	Very high (image processing is easier, easy adopted)	GCC, ExG, MGDEXG	(161)
Hyperspectral	Resonon Pika-L, Cubert ULTRIS 5	High	Low-moderate	Low (complex image processing)	PRI, Red Edge Indices, Water Band Indices	(162)
Multispectral	MicaSense RedEdge, Tetracam Mini MCA6	Low	Moderate-high	Moderate (Requires data processing)	NDVI, PRI, NDWI, CWSI	(161)
Thermal	FLIR Vue Pro R, Workswell WIRIS 640	High	Moderate-high	Moderate (Needs Calibration)	CWSI, Canopy Temperature (T_c)	(163)

CWSI: crop water stress index; ExG: excess green index; GCC: green chromatic coordinate; MGDEXG: modified excess green vegetation index; NDVI: normalised difference vegetation index; NDWI: normalised difference water index; PRI: photochemical reflectance index.

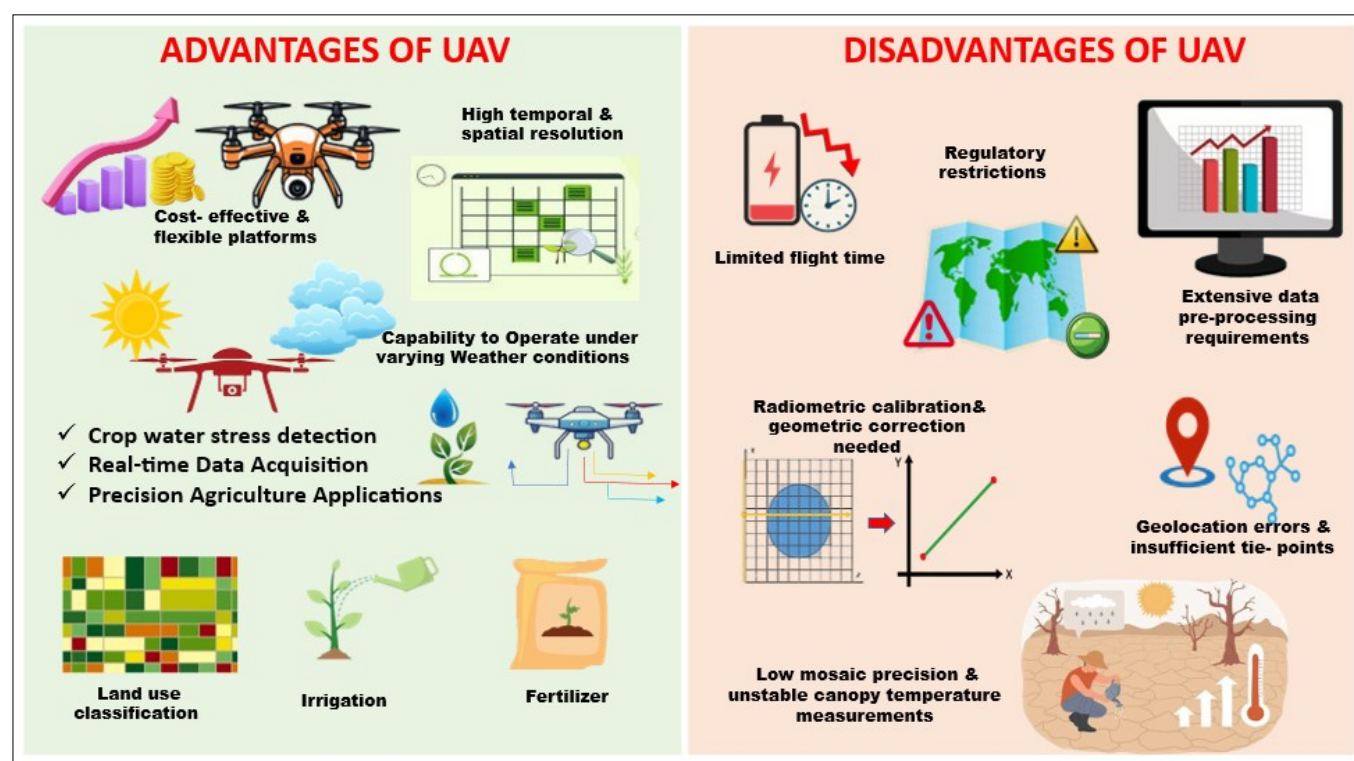


Fig. 5. Advantages and disadvantages of unmanned aerial vehicles in crop water stress assessment.

of UAV-based diagnostics, highlighting the need for low-cost solutions, simplified user interfaces and policy assistance systems to promote adoption (164).

Future perspectives

Future work might rely upon integrating thermal and narrow-band HSP imagery to advance the precise CWS monitoring. Additionally, the use of advanced data analysis techniques for real-time monitoring could help provide cost-effective solutions for farmers. The integration of meteorological parameters, such as extreme illumination, is another promising area of future research. However, challenges related to flight altitude, such as thermal infrared radiation reduction by the atmosphere, need to be addressed with appropriate corrections. Expecting that the integration of UAVs with remote sensing satellites could improve the accuracy of agricultural drought monitoring by providing valuable ground truth data at the field scale. To address some of the technical limitations of UAVs, such as flight duration and load capacity, companies like Harris Aerial are already working on integrating power generators (solar) into UAV platforms, enabling longer flight times and reducing the number of flights required. Increasing the load capacity of UAVs could also allow for larger sensor setups, enabling larger coverage areas and improving the productivity of UAV-based measurements for large farms.

Future research should prioritise improving image processing algorithms to account for soil background interference and shaded canopy areas. Integrating LiDAR or ML-based image processing with MSP and thermal sensors could offer more precise temporal and spatial information on plant water stress. Integration of UAVs with crop models primarily focuses on crop phenotyping, such as yield forecasting, but there is a possibility for using UAV-based data for assessing CWS in conjunction with crop models. These advancements will continue to enhance the effectiveness of UAVs in CWS assessment, leading to more sustainable and productive farming practices.

Conclusion

The advancements in unmanned aerial vehicle (UAV) based remote sensing for crop water stress (CWS) assessment have substantially provided precise, real-time and non-destructive monitoring solutions. Unmanned aerial vehicles mounted with thermal, multispectral (MSP) and hyperspectral (HSP) sensors, enable the generation of key vegetation indices such as the normalised difference vegetation index (NDVI) and crop water stress index (CWSI), which have exhibited high accuracy in detecting water stress across various crops. The study indicated that in spring maize, random forest (RF) models integrating UAV derived MSP and thermal indices with leaf area index (LAI) produced the best results ($R^2 > 0.575$, $RMSE < 0.073$) with plant water status was determined more precisely at the 9th leaf and milking stages and normalised stomatal conductance at tasseling and silking stages. Moreover UAV MSP vegetation indices (VIs), texture features (TFs) and texture indices (TIs) were employed to assess the efficacy of support vector machine (SVM), back-propagation neural network (BPNN) and extreme gradient boosting (XGBoost) in estimating canopy equivalent water thickness (CEWT) and CWSI in cotton indicating that the integration of spectral and textural data enhanced accuracy specifically, XGBoost VIs + TFs model obtained the highest value for CEWT ($R^2 = 0.75$), whereas XGBoost VIs + TFs + TIs model attained

more accuracy for CWSI prediction ($R^2 = 0.90$). The integration of UAV images with crop models has been revolutionising CWS assessment by enhancing precision and scalability. Leveraging machine learning (ML) and deep learning (DL) algorithms can further enhance this integration by enabling real-time updates, improving prediction accuracy and early stress detection. These advancements hold the potential to improve water use efficiency (WUE) and make this technology a keystone of sustainable crop production under climate induced water stress condition.

Acknowledgements

We are grateful to the University library, Tamil Nadu Agricultural University, Coimbatore for providing the e-library source to write this article.

Authors' contributions

SG conceived the idea and wrote the manuscript. VM and RJ revised and reviewed the manuscript. KT, PB, RR, GP, MA and KS reviewed and finalised the manuscript. All authors have read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and Quillbot in order to improve language and for grammar correction. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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