



Dynamic thermal imaging for crop water stress detection across phenological stages: Enhancing irrigation scheduling precision

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Abstract

Thermal remote sensing and derived indices such as the crop water stress index (CWSI) can assess crop water status and support precision irrigation. However, most operational and artificial intelligence (AI)-based approaches rely on fixed, season-long thresholds to interpret canopy–air temperature differences and often overlook the influence of crop phenology. This review synthesises evidence from grapevine, wheat, maize, potato and several other crops on how developmental stage affects the non-water-stressed baseline (NWSB), CWSI thresholds and irrigation-scheduling algorithms. It covers CWSI theory and estimation practices; crop-specific, phenology-dependent behaviour of baselines and thresholds; a comparison of threshold-based, machine learning, Internet of Things (IoT), digital twin and Food and Agriculture Organization (FAO)-56 approaches with respect to crop phenology; and a conceptual framework for phenology-aware scheduling. Across the reviewed crops, baseline behaviour generally varied systematically across the growing season, the relationship between CWSI and crop water status generally strengthened after canopy closure and CWSI measured during reproductive stages was generally most closely related to yield. A quantitative audit of 56 AI-, thermal-imaging-, or CWSI-based studies found that 78.6 % either did not explicitly incorporate crop phenology or relied on day of year as a temporal proxy, whereas only 5.4 % explicitly encoded phenological stage. The proposed framework considers phenology explicitly in baseline estimation, threshold setting and data fusion or machine learning for irrigation scheduling; the framework will require multi-year, multi-site field validation before operational use. Future research should prioritise standardised phenology definitions and long-term, multi-location studies to establish and validate stage-specific parameters.

Keywords: canopy temperature; crop water stress index; machine learning; non-water-stressed baseline; phenological stage; precision irrigation

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1. Introduction

Water scarcity and climate change are placing increasing pressure on agricultural production, particularly in rain-fed systems, creating a need for precision irrigation based on crop physiological status rather than on conventional calendar- or soil-water-based approaches (1, 2). Thermal imagery and derived indices such as the crop water stress index (CWSI) are increasingly used to assess and predict crop water stress from handheld sensors, unmanned aerial vehicles (UAVs) and satellite platforms (3–5). The CWSI relates the canopy–air temperature difference (canopy temperature (T_c)– air temperature (T_a)) to the atmospheric vapor pressure deficit (VPD) and is used to characterise variation in crop water status associated with stomatal regulation. The lower baseline, or non-water-stressed baseline (NWSB), is derived from well-watered references, whereas the upper baseline represents a non-transpiring canopy; both can be

obtained through empirical regression or through theoretical modelling of the (T_c – T_a)–VPD relationship. Comparing empirical and theoretical CWSI formulations for maize across two growing seasons, found that neither growth stage nor growing season significantly shifted the empirical baseline, whereas the theoretical baseline varied significantly between seasons; the two approaches tracked sap-flow-measured water stress with R^2 values of 0.55 and 0.49, respectively (6). In common bean (*Phaseolus vulgaris* L.), compared empirical and combined baseline-estimation methods and reported root mean square error (RMSE) values of 1.0 °C for the lower baseline and 1.8 °C for the upper baseline (7). These findings show that baseline selection itself introduces substantial uncertainty and that errors in baseline parameterisation can propagate into CWSI estimates and the interpretation of crop water status (8).

Recent reviews on phenotyping and remote sensing have emphasised the importance of spatiotemporal scale in capturing the spatial variability of water stress and have discussed the roles of artificial intelligence (AI) and the Internet of Things (IoT) in capturing its temporal variability (9, 10). Other reviews cover UAV-based thermal sensing for plant stress detection in specialty crops (4) and the use of multispectral and thermal UAV sensors in viticulture and other crops (11–13). Few of these studies, however, treat crop phenological stage as a critical, deterministic factor in interpreting thermal data or setting irrigation thresholds.

This review addresses that gap. Dynamic thermal imaging is defined here as the phenology-based interpretation of thermal observations, in which the canopy–air temperature signal is interpreted against the crop's developmental stage rather than against a single, season-long non-water-stressed baseline and a single, season-long CWSI threshold. Shifts in baselines and stress thresholds across developmental stages therefore need to be built into advanced precision-irrigation models. The objectives of this review are to:

1. Revisit the theory of CWSI and recent advances in CWSI estimation, focusing on baseline-estimation procedures.
2. Summarise published information on crop-specific, often phenology-dependent, response patterns, focusing on baseline shifts and CWSI–water potential relationships across plant development.
3. Evaluate published approaches to modelling irrigation schedules from remote-sensing data with respect to crop phenology, or its absence.
4. Outline a conceptual model for phenology-aware irrigation scheduling and identify research gaps and future directions.

To complement the narrative synthesis, a quantitative audit was conducted of recent AI-, thermal-imaging- and CWSI-based irrigation studies published between 2020 and 2026. The audit classified studies according to whether crop phenology was explicitly incorporated into modelling and decision-making. Fig. 1 summarises the sensing platforms, stage-identification and parameterisation steps, modelling approaches and irrigation decision outputs examined in this review.

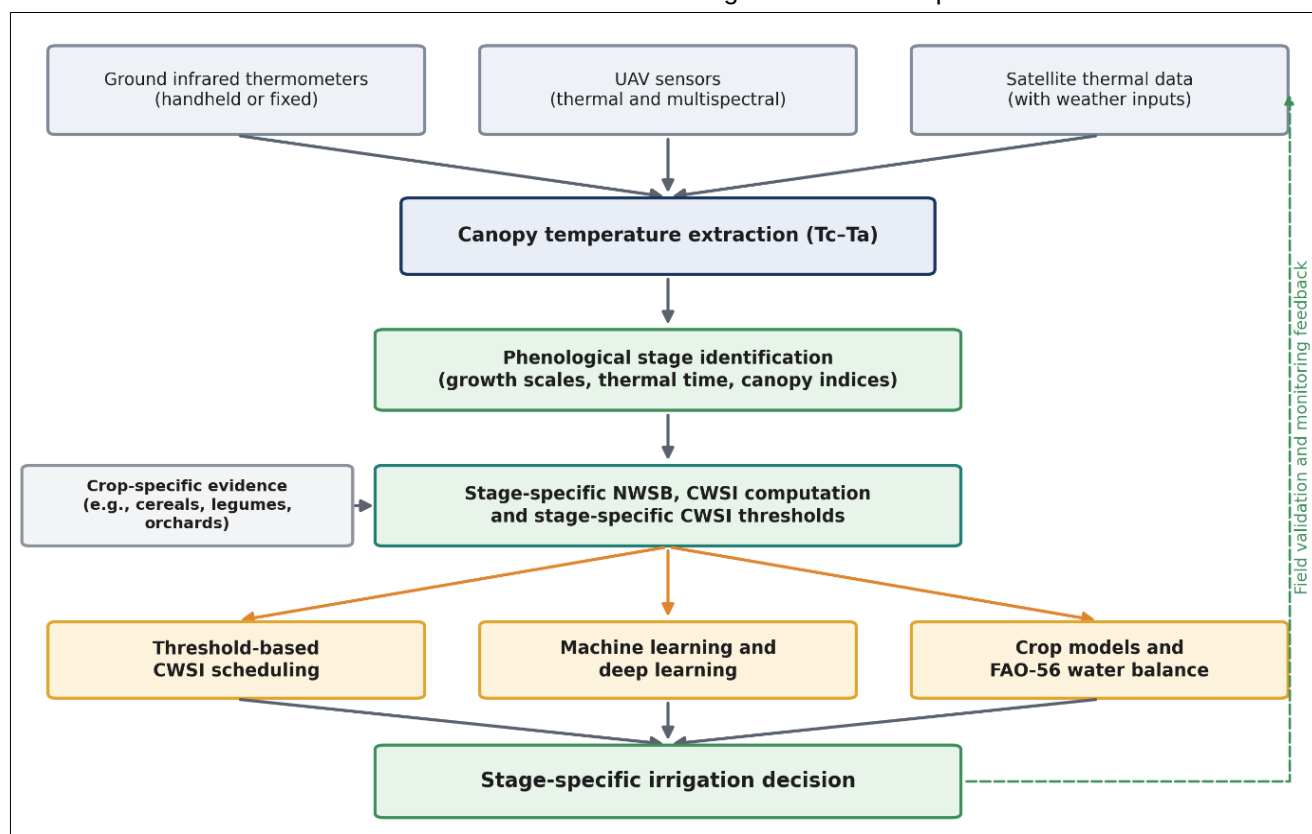


Fig. 1. Review workflow linking ground, unmanned aerial vehicles (UAV) and satellite thermal observations to canopy temperature extraction ($T_c - T_a$), crop-stage identification and stage-specific non-water-stressed baseline (NWSB), crop water stress index (CWSI) computation and threshold setting.

CWSI: crop water stress index; FAO: Food and Agricultural Organization; NWSB: non-water-stressed baseline; T_c : canopy temperature; T_a : air temperature; UAV: unmanned aerial vehicles.

Crop-specific evidence informs calibration, while threshold-based scheduling, machine-learning methods and crop-model or FAO-56 water-balance approaches support irrigation decisions. Field validation and monitoring feed new observations back into the workflow. FAO-56, FAO Irrigation and Drainage Paper 56.

Review methodology

To support the quantitative literature audit reported in Fig. 2, a non-systematic, narrative literature search was conducted in Scopus, Web of Science and Google Scholar (2020–26) using combinations of the terms "crop water stress index", "thermal imaging", "machine learning" OR "deep learning" OR "IoT" and "irrigation scheduling". Studies were eligible if they applied AI, machine learning or an algorithmic decision model to integrate thermal- or CWSI-derived data for irrigation-relevant water-stress assessment. An algorithmic decision model was defined as an explicit, reproducible procedure that converts thermal or CWSI inputs into an irrigation-relevant output, such as a statistical or machine-learning regression or classification model, a threshold-based decision rule, an evapotranspiration or water-balance model driven by thermal data, or an optimisation or reinforcement-learning algorithm. Studies that only described a sensing or imaging method or only reported correlations between thermal indices and physiological variables without a predictive or decision-support model, were excluded. Because the review is descriptive rather than systematic, a flow chart of records that were identified, screened and excluded was not prepared; the audit is intended to describe general patterns in the literature rather than to provide an exhaustive, reproducible inventory. The 56 retained studies were classified according to their explicit use of phenology: (i) no explicit phenology logic; (ii) day of year used as a continuous time proxy; (iii) a fixed phenological phase structure (e.g., the initial, development, mid-season and late-season periods of Food and Agriculture Organization (FAO) Irrigation and Drainage Paper No. 56, FAO-56); and (iv) explicit encoding of discrete phenological stages. One author coded all 56 studies. A second author then checked each classification against the full text of the study, rather than coding the dataset independently and disagreements were resolved by discussion. Because the second author verified rather than independently coded the dataset, a formal inter-rater agreement statistic such as Cohen's kappa could not be computed; this is acknowledged as a limitation of the audit.

Thermal indices and sensing platforms for crop water stress

Crop water stress index fundamentals: Empirical and theoretical formulations

Two families of CWSI formulations are in use and they differ in how the reference limits are obtained. The empirical formulation normalises the measured canopy–air temperature difference between two baselines established in the field: $CWSI = [(T_c - T_a) - (T_c - T_a)_{LL}] / [(T_c - T_a)_{UL} - (T_c - T_a)_{LL}]$, where the lower limit (LL) is the NWSB, a linear regression of $T_c - T_a$ against VPD for well-watered vegetation and the upper limit (UL) is the $T_c - T_a$ of a non-transpiring canopy (14). The empirical approach needs only canopy temperature, air temperature and humidity, but its baselines are specific to crop, climate and growth stage and they must be re-derived from well-watered and non-transpiring reference

measurements. The theoretical formulation derives both limits from the canopy energy balance, so that CWSI approximates $1 - E/E_p$, the fractional reduction of actual relative to potential transpiration (15). It requires net radiation, wind speed and estimates of the aerodynamic and canopy resistances in addition to the variables of the empirical method. The theoretical approach is therefore less dependent on local reference plots but more demanding in instrumentation and its accuracy depends on how well the resistances are parameterised. Field comparisons reflect this trade-off. In maize, growth stage and season did not significantly affect the empirical baseline, whereas the theoretical baseline varied significantly between seasons (6); The empirical, reference-surface and theoretical CWSI variants differed sharply in their sensitivity to soil-water depletion (16); and validated an energy-balance formulation against sap-flow-derived transpiration without an empirical baseline (17). For phenology-adaptive use, the practical consequence is that empirical baselines must be re-established for each stage, whereas theoretical formulations shift the calibration burden to stage-dependent canopy properties, such as canopy height and canopy resistance, that enter the resistance terms.

Whichever formulation is used, errors in the input measurements propagate into CWSI values. Previous researcher analysed this for six species (almond, mandarin, orange, turfgrass, maize and squash) monitored with mast-mounted infrared radiometers at midday on cloudless days in Spain and the USA, considering typical errors in air temperature (0.2–1 °C), canopy temperature (0.25–2 °C) and relative humidity (5–10 %). Because the baseline slopes differed among these species (from -0.5 to -3 °C per kilopascal (kPa⁻¹)), the resulting bias in CWSI is species-specific and may not transfer directly to other crops or sensing systems. Baselines also move with crop development. In a maize–wheat sequence, established separate upper and lower $T_c - T_a$ baselines under irrigation treatments ranging from 60–100 % of crop evapotranspiration (ET_c), found that the baselines varied with growth stage and irrigation treatment, with the largest canopy–air temperature differences at anthesis (wheat) and silking (maize) and derived CWSI thresholds of 0.29 for wheat and 0.31 for maize from quadratic relationships between CWSI and grain yield and water productivity (18). Baseline methodology and crop stage therefore jointly influence how reliable CWSI is as a stress indicator, a distinction seldom acknowledged in irrigation studies that adopt a single generic baseline throughout the growth cycle. Because the sensitivity of CWSI to soil-water depletion also differs among computation approaches, with the theoretical and empirically derived baselines most sensitive only under severe stress (soil-water depletion above 80 % of the total available water in the root zone, in a maize field in Nebraska, USA) (16), each approach requires its own, separately calibrated irrigation-triggering threshold, which compounds the phenology-calibration burden documented for individual crops below.



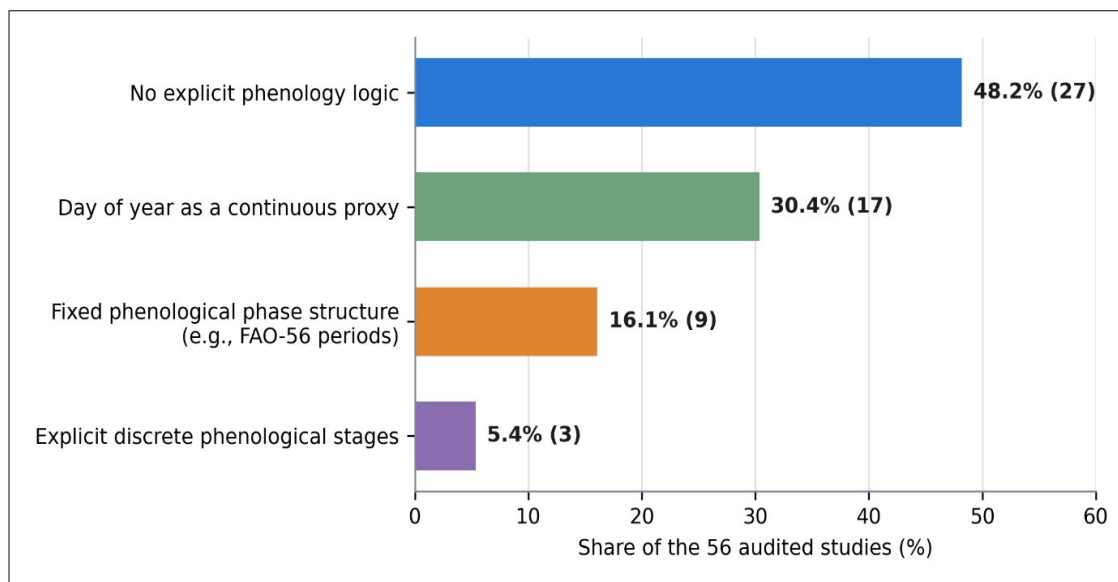


Fig. 2. Distribution of phenology-integration approaches among 56 artificial intelligence (AI)-, thermal-imaging- and crop water stress index (CWSI)-based irrigation studies (published from 2020–26).

No explicit phenology logic (27 studies; 48.2 %), day of year used as a continuous proxy (17; 30.4 %), a fixed phenological phase structure such as the FAO-56 periods (9; 16.1 %) and explicit encoding of discrete phenological stages (3; 5.4 %). FAO: Food and Agricultural Organization.

Alternative thermal indices and simplified approaches

When a complete NWSB cannot be established, or when the reference measurements it requires are impractical, simpler or complementary thermal indices can be used (Table 1). They differ in the reference information they need and, consequently, in how strongly their interpretation depends on crop stage. The simplest are the raw canopy–air temperature difference ($T_c - T_a$) and canopy temperature depression, which require no baseline but combine the effects of water status with those of VPD, radiation and wind; their threshold values are therefore not transferable across days, sites, or stages without normalisation, which was the original motivation for the CWSI (14). The stomatal-conductance indices (IG and I3) that normalise canopy temperature against wet and dry reference surfaces measured at the same time, so that the references experience the same weather as the canopy; the reference surfaces must, however, mimic the optical and aerodynamic properties of the crop, which change as the canopy develops (19). At the other end of the complexity range, the water deficit index (WDI) combines the surface–air temperature difference with a spectral vegetation index in a trapezoid whose vertices are computed from the energy balance, extending CWSI-type interpretation to partially vegetated surfaces in which soil and canopy temperatures are mixed (20). Because the vegetation-index axis of the trapezoid tracks canopy cover, the WDI implicitly accounts for one aspect of phenology, the change in fractional cover, but not for stage-dependent changes in stomatal behaviour. The optical trapezoid used in optical trapezoid model-based evapotranspiration (OPTRAM-ET) follows the same logic without a thermal band (21).

Several studies reviewed here use simplified, T_c -only indicators. Previous study derived four such

indicators from UAV-based red–green–blue (RGB) and thermal imagery of maize at a single vegetative stage (22); a simplified CWSI for cotton (*Gossypium hirsutum* L.) that correlated more closely with stomatal conductance than the standard empirical CWSI at flowering and boll development (23); and the canopy-to-air temperature ratio to be among the most influential predictors of stomatal conductance in almond (*Prunus dulcis* (Mill.) D.A. Webb) (24). Integrating thermal-infrared observations with chlorophyll fluorescence and reflectance-based indices may further improve the discrimination of water stress from other sources of plant stress (3). None of these alternatives remove the phenology problem: indices without explicit baselines trade calibration effort for weaker normalisation and their thresholds are as stage-dependent as those of the CWSI, so the stage-specific calibration argued for in this review applies to them as well.

Sensing platforms and operational considerations

Canopy temperature measurements for CWSI estimation come from handheld infrared thermometers (IRTs), fixed-position IRT networks, ground- and UAV-based thermal sensors and space-borne thermal imagers. In maize, UAV-mounted optical and thermal sensors used to estimate foliar temperature and stomatal conductance and reported that UAV-derived indicators tracked ground-based measurements of physiological water status across the season (25). The UAV-based thermal and multispectral sensors combined to estimate land-surface energy fluxes and irrigation requirements, achieving greater accuracy than single-sensor approaches and demonstrating the potential value of sensor fusion for operational water management (26). The UAV studies fusing thermal with RGB or multispectral imagery have shown the value of multi-sensor data for separating the plant canopy from

the background soil (22) and related approaches range from edge-computing sensing systems for monitoring the physiology of apple (*Malus domestica* Borkh.). The automated calibration of stomatal conductance models from thermal imagery using synthetic images generated by a 3D biophysical model (27, 28); however, few of these studies incorporate an explicit stage-specific element into the analysis. Two influential reviews frame the operational maturity of these platforms. Previous research reviewing infrared thermal CWSI applications broadly, identified canopy-segmentation strategy as the main technical bottleneck limiting accurate T_c extraction and pointed to deep-learning-based segmentation as the most promising near-term direction (29). The importance of radiometric calibration and reference-panel measurements for reliable comparison among UAV thermal studies, a requirement frequently unmet in the phenology-agnostic studies audited in this review (30). Extending this synthesis to specialty and perennial crops, 104 UAV water-stress studies published between 2012 and 2024, found vineyards to be by far the most extensively studied system and identified sensor calibration, computational cost and limited multi-sensor fusion as recurring constraints (4).

Each platform imposes specific limitations on phenology-adaptive monitoring (Table 2). Handheld and fixed infrared thermometers sample a small footprint; before canopy closure, that footprint mixes soil and leaves unless the sensor is carefully aimed and fixed sensors must be repositioned as the canopy grows, so the measurement geometry itself changes with

phenology. Their near-continuous record, however, makes fixed sensors well suited to detecting the timing of stage transitions and to building stage-specific baselines at reference plots. The UAV thermal cameras resolve individual rows or tree crowns, allowing soil pixels to be excluded at every stage, but flights are limited by wind, rain, battery endurance and aviation rules and they depend on radiometric calibration with reference panels (30). A mission cadence of days to weeks can miss short, sensitive windows such as anthesis in cereals and uncalibrated drift between flights makes data from different stages difficult to compare. Satellite thermal sensors provide free, repeatable, wide-area data, but native thermal pixels (tens of metres to about 1 km) mix soil and canopy until full cover; overpass times are set by the orbit rather than chosen for the midday window commonly used for CWSI (31), although computing CWSI for each acquisition time can widen that window (32); clouds interrupt the time series and the revisit interval of a single high-resolution thermal sensor is longer than many phenological stages. Data fusion reduces but does not remove these limits (33–35). In practice, fixed infrared sensors are most useful for stage-specific calibration, UAVs for within-field mapping at scheduled key stages and fused satellite products for regional monitoring and for flagging stage transitions that trigger targeted UAV or ground measurements. The UAV missions currently appear to offer the most practical compromise between resolution and revisit frequency for phenology-adaptive scheduling at the field scale.

Table 1. Thermal indices used for crop water-stress assessment and the dependence of their interpretation on crop phenology

Index	Inputs and reference data	Dependence on phenology	Main limitations	Key references
Canopy–air temperature difference ($T_c - T_a$) and canopy temperature depression	T_c and T_a only; no baseline VPD	Threshold values change with canopy cover and stage	Confounded by radiation and wind; thresholds not transferable across days, sites, or stages	(14, 22)
Empirical CWSI	T_c , T_a and VPD; NWSB regression from well-watered references and an upper limit from non-transpiring references	NWSB and upper limit shift with growth stage; stage-specific baselines needed	Reference plots required for each crop, climate and stage; valid mainly under clear-sky midday conditions	(6, 14, 18)
Theoretical (energy-balance) CWSI	T_c , T_a , VPD, net radiation, wind speed and aerodynamic resistance and canopy resistances	Canopy height and resistance change with stage and must be reparameterised as the crop develops	Demanding instrumentation; sensitive to resistance estimates	(6, 15–17)
Stomatal-conductance indices (IG, I3)	T_c and simultaneous wet and dry reference surfaces	Reference surfaces must match canopy properties as they change	Reference surfaces difficult to maintain in the field; point or small-area scale	(19)
Water deficit index (WDI)	Surface–air temperature, a vegetation index and meteorological data for the trapezoid vertices	Accounts for changing fractional cover but not for stage-dependent stomatal behaviour	Energy-balance computation of vertices; mixed soil and canopy pixels	(20, 21)
Simplified and ratio indices (e.g., simplified CWSI, T_c/T_a ratio)	T_c from segmented canopy imagery and T_a	Evaluated mostly at single stages	Transferability across stages rarely tested	(22–24)

VPD: vapour pressure deficit; NWSB: non-water-stressed baseline; T_c : canopy temperature; T_a : air temperature; CWSI: crop water stress index.



Table 2. Sensing platforms for canopy temperature and their limitations for phenology-adaptive monitoring

Platform	Spatial and temporal characteristics	Strengths for phenology-adaptive use	Limitations for phenology-adaptive use	Examples
Handheld infrared thermometers	Point measurements; manual, on demand	Low cost; simple; ground truth for reference baselines	Labor-intensive; footprint mixes soil and leaves before canopy closure; view-angle and operator effects	–
Fixed infrared sensor networks	Point to small area; continuous (minutes)	Capture diurnal cycles and stage transitions; suited to building stage-specific baselines at reference plots	Limited spatial representativeness; sensors must be re-aimed or raised as the canopy grows; maintenance	(37)
Low-cost thermal cameras	Plant to plot scale; on demand	Imaging at low cost; allows canopy segmentation	Lower radiometric accuracy; calibration required	(13)
UAV thermal sensors (often with multispectral or RGB sensors)	Centimeter to decimeter resolution; per mission (days to weeks)	Resolve rows and crowns and exclude soil at all stages; flights can be scheduled for key stages	Weather, endurance and aviation rules; radiometric calibration and drift; processing expertise; cadence can miss short stages	(22, 25, 26, 30, 51)
Satellite thermal sensors and thermal–optical fusion	About 30 m (sharpened) to 1 km; daily to about 16 days; cloud gaps	Wide area; free data; long archives for multi-season baselines	Mixed pixels before canopy closure; overpass time set by orbit; cloud gaps; small fields smaller than native thermal pixels	(33–35, 55)

UAV: unmanned aerial vehicles; RGB: red, green and blue.

Phenology-dependent thermal dynamics: Evidence across crops

The general form of the stage-dependent responses is illustrated conceptually in Fig. 3. The figure shows stage-specific NWSB regressions, an example of stage-specific CWSI threshold logic, physiological responses to increasing water stress and associated canopy reflectance patterns. The crop-specific evidence is reviewed below using a common structure: evidence on baselines, evidence on thresholds, other relevant findings and the main evidence gaps. Crops for which only one to three studies were found are grouped together and the strength of the evidence for each crop is summarised in Table 3.

A) Grapevine (*Vitis vinifera* L.)

Baselines: Among the studies reviewed, none reported separate NWSBs for defined grapevine phenological stages. The evidence is indirect: in a Merlot vineyard under semi-arid conditions, the relationship between CWSI and stem water potential was stronger when seasonal, phenology-linked variation was accounted for than when observations were pooled across the season (36) and modelling the grapevine crop coefficient from UAV spectral and structural data acquired at several phenological stages over two seasons, found that spectral indices became less sensitive after véraison, whereas canopy structure remained closely related to the crop coefficient throughout the season (11).

Thresholds: Grapevine thresholds are usually expressed through stem water potential rather than as stage-specific CWSI values. In a drip-irrigated Cabernet Sauvignon vineyard, a non-linear correlation between CWSI and midday stem water potential ($R^2 = 0.72$) from a low-cost wireless infrared sensor network, sufficient to map intra-vineyard variability (37) and in greenhouse-

grown grapevine identified 14:00 local time as the best observation time for CWSI, with stomatal conductance showing the strongest correlation with CWSI (31).

Other findings: The mapping vine water status with multispectral UAV imagery and machine learning observed that the correlation between spectral or thermal indicators and plant water potential changed over the growing season (12). A spatial machine-learning model developed that included topography, elevation and the normalised difference vegetation index (NDVI) as explanatory variables and found that the spatial component substantially improved CWSI prediction. The UAV-based thermal mapping has been used to assess seasonal water-stress dynamics (36, 39); combining nadir and oblique flights produced the most geometrically accurate 3D CWSI representation ($R^2 = 0.72$ against LiDAR) (39). Beyond thermal data, multisource remote-sensing and soil data have improved yield prediction and irrigation decision-making in Mediterranean vineyards (40).

Evidence gaps: Grapevine is the most extensively studied system in UAV water-stress research, yet stage-resolved NWSBs and CWSI thresholds for key stages such as flowering, fruit set and véraison have not been established (4).

B) Wheat (*Triticum aestivum* L.)

Baselines: In a maize–wheat cropping sequence in Punjab, the wheat canopy–air temperature difference was largest at anthesis and that the baselines varied with growth stage and irrigation treatment (18). In Mediterranean breeding trials, the canopy–air temperature responses differed with both time of day and developmental stage (41).



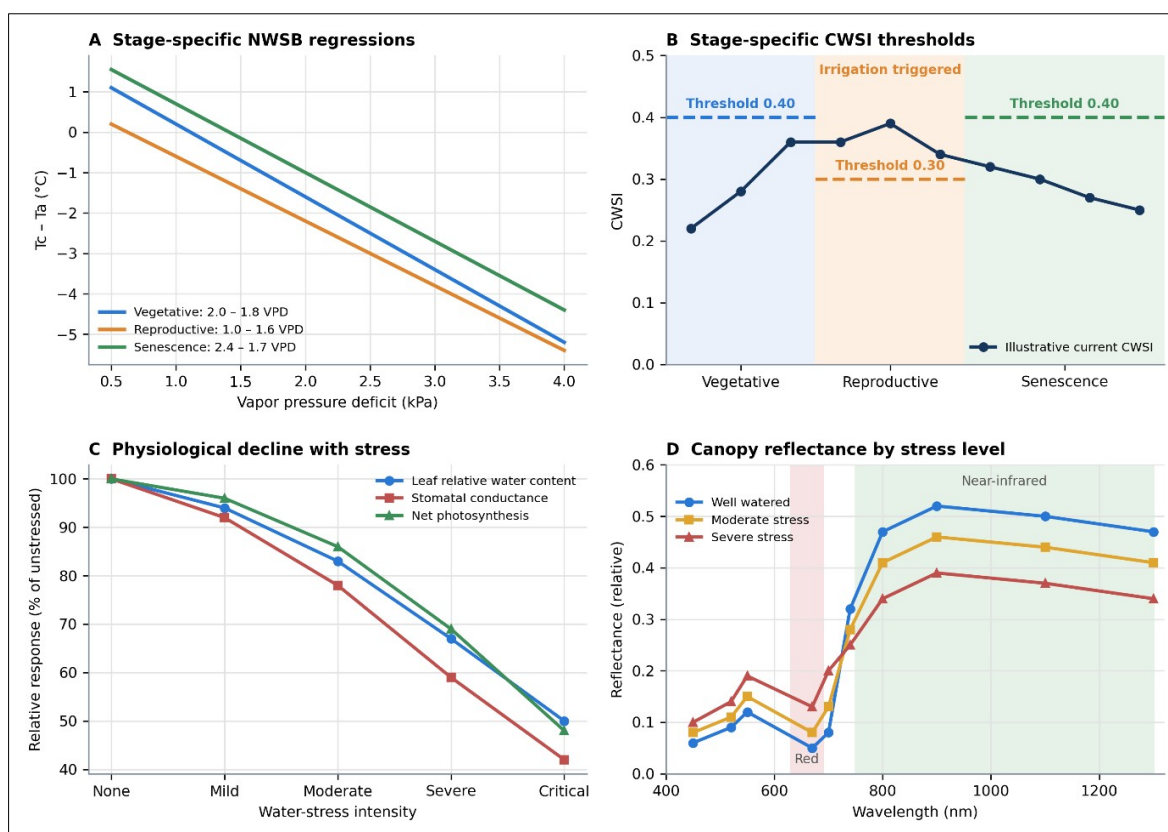


Fig. 3. Conceptual illustration of thermal and physiological responses across crop development. (A) Illustrative stage-specific NWSB regressions of canopy–air temperature difference ($T_c - T_a$) against vapor pressure deficit (VPD); the vegetative and reproductive baselines are those of the worked example in the text, (B) Example of stage-specific CWSI thresholds (0.40 for vegetative, 0.30 for reproductive and 0.40 for senescence stages); the illustrative current-CWSI trajectory exceeds the threshold only during the reproductive stage, (C) Normalised declines in leaf relative water content, stomatal conductance and net photosynthesis with increasing water-stress intensity, (D) Conceptual canopy-reflectance responses in the visible and near-infrared regions under well-watered, moderate-stress and severe-stress conditions.

Values and relationships are illustrative, not measured data; the thresholds are not universal recommendations. CWSI: crop water stress index; NWSB: non-water-stressed baseline; VPD: vapor pressure deficit.

Table 3. Phenology-dependent dynamics of crop water stress index (CWSI) baselines and thresholds across major crops, with the main evidence gaps

Crop	Key phenology-dependent findings	Reported threshold(s)	Main evidence gap	References
Grapevine (<i>Vitis vinifera</i> L.)	CWSI–stem water potential relationship is stronger when seasonal or phenology-linked variation is accounted for than when data are pooled; spectral indices less sensitive to the crop coefficient after véraison; 14:00 best observation time in greenhouse grapevine	Not reported as a stage-specific CWSI threshold; relationships expressed through stem water potential	No stage-resolved NWSB or thresholds for flowering, fruit set, or véraison	(11, 12, 31, 36–39)
Wheat (<i>Triticum aestivum</i> L.)	Largest canopy–air temperature difference at anthesis; CWSI during anthesis and post-heading predicts grain yield better than pre-heading or season-mean CWSI; drought thresholds increase from jointing to maturation	Season-level CWSI 0.29; normal-to-mild drought transition at 0.30, 0.33 and 0.41 across three phases	Few sites; vegetative-stage baselines and transferability across climates untested	(18, 41–43)
Maize (<i>Zea mays</i> L.)	Stage-specific NWSBs outperform a season-pooled baseline for physiological traits; baseline without stage variation better for yield prediction; largest canopy–air temperature difference at silking	Season-level CWSI 0.31; CWSI 0.35 associated with 64 % yield loss; stage-wise CWSI estimation $R^2 = 0.82$ (R1) to 0.86 (V5)	Stage-specific thresholds rarely validated in scheduling trials; single-stage segmentation methods	(18, 48–51)

Crop	Key phenology-dependent findings	Reported threshold(s)	Main evidence gap	References
Potato (<i>Solanum tuberosum</i> L.)	Suitable CWSI thresholds depend on the irrigation system; under furrow irrigation a stricter threshold saved water without a significant yield reduction	CWSI of about 0.4 under furrow irrigation (system-specific)	Evidence largely from one research group; no separate baselines for tuber initiation or bulking	(53, 54)
Rice (<i>Oryza sativa</i> L.)	CWSI detected early water stress; standing water compresses the canopy–air temperature differential	Not reported; adjusted $R^2 = 0.86$ for the CWSI–water status regression	Single study; relationship not resolved by stage; conclusions provisional	(56)
Cotton, legumes and safflower	CWSI detected cotton cultivar differences only in the mid-to-late season; thermal and spectral proxies detect soybean stress before visible wilting	Not reported as a cross-study threshold	One to three studies per crop; stage at which CWSI becomes informative must be established first	(5, 7, 23, 57–61)
Orchard and perennial crops (almond, olive, citrus, nectarine)	Leaf water potential the most responsive indicator in almond; CWSI computed for each acquisition time usable from mid-morning to mid-afternoon (nectarine); CWSI- and ET-based management zones agree closely	Almond CWSI 0.12–0.15 (maximum water savings with minimal yield effect); midday CWSI–stem water potential $R^2 = 0.83$ (nectarine)	Phenological stages rarely resolved; alternate bearing requires multi-year data	(13, 24, 32, 62–66)
Cross-crop synthesis	Baselines or CWSI relationships shift through the season in most stage-resolved studies; CWSI–water status relationships appear weaker before canopy closure; reproductive-stage CWSI relates most closely to yield	Wheat 0.29 and maize 0.31 (season-level)	Stage-labeled, multi-site calibration data	–

NWSB: non-water-stressed baseline; CWSI: crop water stress index.

Thresholds: A season-level CWSI threshold of 0.29 was derived for wheat from quadratic relationships between CWSI and grain yield ($R^2 = 0.93$) and water productivity ($R^2 = 0.89$) (18). The UAV-based drought thresholds was calculated for the jointing–heading, heading–filling and filling–maturation phases and found that the CWSI value marking the transition from normal to mild drought increased from 0.30 in the first phase to 0.33 in the second and 0.41 in the last, indicating that a single fixed threshold would misclassify drought severity in some phases (42). Across two years under drip and flood irrigation, the CWSI during anthesis and post-heading was more strongly associated with grain yield than CWSI measured before heading or expressed as a whole season mean (43).

Other findings: High classification accuracy for water-stress detection in winter wheat from thermal–RGB imagery and AI classifiers, although model performance differed with sampling date across growth stages (44). The CWSI has also been applied directly to schedule wheat irrigation (45) and thermal and RGB imaging combined with artificial neural networks has been used to assess salt tolerance among wheat genotypes (46). Three spectral drought indices performed as well as or better than CWSI, the temperature–vegetation drought index and the vegetation health index against soil-moisture measurements, indicating that non-thermal alternatives can, under certain conditions, match the diagnostic capability of CWSI (47).

Evidence gaps: Wheat has the clearest evidence for stage-specific thresholds, but it comes from a small number of sites; baselines for the vegetative stages and their transferability across climates and cultivars have not been tested.

C) Maize (*Zea mays* L.)

Baselines: Growth stage is increasingly treated as a first-order variable in maize thermal-dynamics research. The growth-stage-specific NWSBs for the vegetative, reproductive and maturity stages under combined water and salt stress in two genotypes and found that CWSI computed from the stage-specific baselines indicated stomatal conductance and photosynthesis well, whereas CWSI computed from a baseline without stage variation better indicated yield and crop water productivity (48). The largest canopy–air temperature difference at silking (18), whereas no significant effect of growth stage on the empirical baseline in Colorado, USA (6).

Thresholds: A season-level CWSI threshold of 0.31 for maize ($R^2 = 0.85$ for the CWSI–grain yield relationship) (18). Under five deficit-irrigation treatments, CWSI directly to yield loss, with a CWSI of 0.35 corresponding to a 64 % yield loss and found that CWSI measured at tasseling (55 days after sowing) under greenhouse conditions best predicted final yield (49). The results imply that the optimal baseline strategy depends on whether CWSI is used for physiological monitoring or for yield prediction (48).



Other findings: On smallholder farms, machine-learning algorithms for estimating CWSI from UAV multispectral data; the best model, random forest with combined bands and vegetation indices, predicted CWSI with $R^2 = 0.85$, RMSE = 0.05 and mean absolute error (MAE) = 0.04, with the field data split 70 : 30 into training and test sets (50). In a later study, the same group estimated CWSI separately at the V5, V10, V14 and R1 stages and obtained R^2 values of 0.86, 0.85, 0.85 and 0.82, with the lowest errors at V10 (RMSE = 0.03), indicating that estimation accuracy differs among stages (51). The plastic film mulching and irrigation deficit level both shaped the Tc–VPD relationship (52). A red–green vegetation-index-based Otsu segmentation closely matched ground-truth canopy temperature ($R^2 = 0.94$; RMSE = 0.7 °C) at the late vegetative stage (V7–VT) (22) and CWSI with an energy-balance approach and validated it against sap-flow-derived transpiration (RMSE of 0.06), independently of an empirical baseline (17).

Evidence gaps: Maize has the strongest stage-resolved baseline evidence, but segmentation methods and indicators developed at one stage have rarely been tested on reproductive-stage canopies and stage-specific thresholds have seldom been validated in scheduling trials (22).

D) Potato (*Solanum tuberosum* L.)

Baselines: Stage-specific potato baselines were not reported in the studies reviewed.

Thresholds: The thermal-imagery-based CWSI thresholds for timing irrigation, applied from 30 days after planting, under drip and furrow systems and found that suitable thresholds depended on the irrigation system: under furrow irrigation, a stricter threshold (CWSI of about 0.4) saved water without significantly reducing fresh tuber yield, whereas under drip irrigation stricter thresholds reduced yield (53).

Other findings: An open-source thermal-image-processing software was developed to support potato irrigation management and demonstrated its effectiveness in canopy-temperature-based field tests (54) and UAV-derived evapotranspiration in an irrigated potato field was within 3 % of eddy-covariance measurements (55).

Evidence gaps: The threshold evidence comes largely from one research group and environment and the stages most sensitive to water deficit, such as tuber initiation and tuber bulking, have not been assigned separate thermal baselines (53, 54).

Other field crops with limited evidence: Rice, cotton and legumes

For rice, cotton, soybean, common bean and safflower, the thermal evidence reviewed here is limited to one to three studies per crop, mostly from single sites and seasons. These crops are therefore grouped and their findings should be read as indicative rather than conclusive.

A) Rice (*Oryza sativa* L.): Paddy and aerobic rice systems present a distinct thermal-sensing problem because standing water and high humidity compress the canopy–air temperature differential relative to upland crops. The rice evidence rests on a single study: CWSI detected water stress early, when plant water status had declined to about 90 % of that under conventional management and a regression of CWSI against plant water status (assessed from SPAD readings, chlorophyll content, ion leakage and relative water content) gave an adjusted R^2 of 0.86 (56). Water treatments began at mid-tillering and the relationship was not resolved by stage, so whether it holds across the reproductive stages of rice, or whether tighter reproductive-stage thresholds are needed as in maize and wheat, is unknown. Conclusions for rice are therefore provisional and are flagged as a limitation of this review.

B) Cotton: Across eight cultivars and four irrigation treatments (0–90 % of evapotranspiration replacement), CWSI detected differences among cultivars only in the mid-to-late growing season, whereas the enhanced vegetation index was the most reliable index for screening drought-tolerant cultivars (57). The simplified CWSI, measured at flowering and boll development, correlated more closely with stomatal conductance ($R^2 = 0.66$) and transpiration ($R^2 = 0.59$) than the empirical CWSI ($R^2 = 0.47$ and 0.53) (23) and used UAV thermal imagery to map within-field variability in cotton water status (58).

C) Legumes and safflower: In soybean [*Glycine max* (L.) Merr.], UAV multispectral and thermal time series distinguished drought-tolerant from susceptible accessions before visible wilting could be scored (59), hyperspectral and thermal sensing combined to monitor stomatal conductance, transpiration and photosynthesis in soybean and maize under drought (5) and thermal infrared imagery distinguished water status and growth differences between arbuscular mycorrhizal and non-inoculated soybean (60). In common bean, empirical and combined baseline-estimation methods have been compared (7) and in safflower (*Carthamus tinctorius* L.) reported a consistent CWSI–water stress relationship across cultivars under four irrigation regimes (61).

Evidence gaps: Stage-specific baselines and thresholds have not been reported for any of these crops. The cotton results indicate that the stage at which CWSI becomes informative must itself be established before stage-specific thresholds can be set.

Orchard and perennial tree crops

Baselines: The water-stress baselines for three almond cultivars with a handheld thermal camera and found leaf water potential to be the most responsive indicator of almond water status (62). A low-cost thermal camera for estimating the water status of citrus (*Citrus* spp.) and also reported site- and cultivar-specific relationships (13).



Thresholds: Almond CWSI thresholds of 0.12–0.15 that would maximise water savings while minimising effects on yield (62). Observation time also affects thermal thresholds in tree crops. In a nectarine [*Prunus persica* (L.) Batsch var. *nucipersica*] orchard, early results related CWSI to stem water potential (SWP) at midday ($R^2 = 0.83$) and to stomatal conductance at 09:00, 12:00 and 15:00 ($R^2 = 0.92, 0.77$ and 0.86), concluding that CWSI computed for each acquisition time can map water stress consistently between mid-morning and mid-afternoon (32), 14:00 as the best observation time in greenhouse grapevine (31). Stage-specific thresholds for tree crops therefore need to be paired either with a fixed acquisition window or with baselines specific to the acquisition time.

Other findings: In olive (*Olea europaea* L.), UAV thermal and multispectral indices across regulated deficit-irrigation treatments in a super-high-density orchard and found CWSI sensitivity to be modulated by ambient conditions and sensor limitations (63), whereas NDVI more reliably tracked vegetative growth and yield. In almond, CWSI- and evapotranspiration (ET)-based management zones captured more spatial variability (up to 73.6 %) than NDVI-based zones (up to 68 %), with strong agreement between CWSI- and ET-derived zones ($\kappa = 0.84$ – 1.00) (64); CWSI was related to SWP and intrinsic water-use efficiency ($R^2 > 0.85$) and that yield was predicted most accurately when CWSI was combined with pigment-sensitive vegetation indices (65); and adding thermal canopy-to-air temperature ratios to multispectral indices improved the prediction of stomatal conductance by up to 11 % (24). For *Citrus*, NDVI, green NDVI and the structure-insensitive pigment index most effective for distinguishing irrigation-deficit zones in Sicilian orchards (66).

Evidence gaps: Tree-crop studies seldom resolve phenological stages such as flowering, fruit set, pit hardening, or kernel filling and alternate bearing means that multi-year data are needed before stage-specific thresholds can be generalised.

Controlled environment and protected cultivation

Greenhouse and controlled-environment agriculture (CEA) settings remove some field-level sources of noise but introduce their own phenology and calibration issues. The CWSI for tomato (*Solanum lycopersicum* L.) across four growth stages in two soil types and found the closest agreement between calculated and camera-based CWSI at fruit expansion ($R^2 = 0.84$ in sandy loam and 0.76 in silt loam), together with a strong negative CWSI–yield relationship ($R^2 > 0.95$), indicating that the reliability of thermal estimation differs among stages (67, 68). The CWSI for high-tunnel tomato across four deficit-irrigation levels and reported a linear yield–CWSI relationship suitable for in-season yield forecasting. A dual-branch visual geometry group (VGG)-based deep network on 6000 paired thermal–optical UAV images spanning the full tomato life cycle to classify water stress directly from imagery, bypassing explicit CWSI computation; because the network was trained across

the full life cycle without stage-stratified evaluation, its reported accuracy cannot be decomposed into stage-specific performance (69). A complementary sensor-fusion approach, combining near-infrared reflectance-based water-index measurements with CWSI on a rail-mounted multi-sensor platform in a greenhouse tomato system and found that merging the two indices improved irrigation-timing accuracy over either index alone (70). Previous researches extended UAV-based thermal imaging to CEA under arid conditions and found that UAV-derived canopy temperature closely matched sensor-based measurements ($R^2 = 0.96$) and that CWSI was significantly associated with soil moisture content, supporting UAV-based CWSI as a viable evapotranspiration-estimation tool even in semi-enclosed CEA systems (71). Evidence from controlled and protected cultivation indicates that the reliability of thermal CWSI estimation can differ among developmental stages, while multi-sensor fusion and life-cycle-wide machine learning provide complementary approaches to improving water-status assessment. However, deep-learning models trained across multiple developmental stages should be evaluated using stage-stratified performance metrics to determine whether their accuracy is robust throughout the crop life cycle.

Satellite and multi-sensor data fusion for field-scale water status

Beyond UAV- and ground-based platforms, satellite thermal–optical fusion has become a practical route to field-scale, near-daily monitoring of crop water status, addressing the revisit-frequency limitation of UAV platforms. The feasibility of fusing Landsat, Sentinel-2, ecosystem spaceborne thermal radiometer experiment on space station (ECOSTRESS) and visible infrared imaging radiometer suite (VIIRS) data to map evapotranspiration time series at sub-field scales (33). In a related approach, Sentinel-2, Sentinel-3 and Landsat data combined to sharpen land-surface-temperature retrievals at field scale, meeting the requirements of UN Sustainable Development Goal indicator 6.4.1 and reduced RMSE by up to 1.5 K compared with previous approaches (34). This fusion framework was extended by sharpening VIIRS thermal observations using Sentinel-2 reflectance, achieving a potential combined revisit of two to three days (including Landsat) for 30-m evapotranspiration retrieval with a mean absolute error of 0.49 mm day^{-1} , comparable to the 0.45 mm day^{-1} reported for Landsat-only estimates (35). None of these fusion products has been evaluated against explicit phenological-stage boundaries, so their value for operational, sub-weekly irrigation advisories has not yet been assessed at stage-transition windows, where thermal signals change fastest; this is a direct opportunity to extend phenology-adaptive baseline logic from UAV to satellite platforms. Previous studies compared UAV, Landsat and fused Sentinel-2–MODIS ET estimates against eddy-covariance flux-tower measurements in an irrigated potato field and found that UAV-derived ET carried the smallest bias relative to ground truth (3 % lower), whereas the satellite-based

products underestimated ET by larger margins; this single-site comparison suggests that the trade-off between UAV resolution and satellite coverage will need to be managed within phenology-adaptive frameworks rather than resolved through platform choice alone (55). The upscaling field-level CWSI and agrometeorological observations toward regional irrigation management, although regional upscaling may introduce additional uncertainty because spatial differences in crop development and canopy condition complicate the transfer of phenology-specific thresholds (72). Complementary approaches seek to relax the dependence on thermal sensors altogether. The OPTRAM-ET, which derives actual evapotranspiration from an optical trapezoid soil-moisture model combined with a vegetation index and validated it against sixteen flux towers in the USA and Germany with performance comparable to conventional land-surface-temperature–vegetation-index models, offering a route to evapotranspiration estimation from optical-only satellites that lack a thermal band (21). Evapotranspiration was similarly derived from Sentinel-2 surface parameters using combination-equation models, achieving daily errors below 1 mm per day against flux-tower data when local meteorological data were used in a Californian vineyard, comparable to thermal-based energy-balance estimates from Landsat (73). Given the strong dependence of these optical-only or fused evapotranspiration estimates on canopy structure, six satellite-based leaf area index (LAI) retrieval methods in Californian vineyards and found that errors in LAI propagated asymmetrically into evapotranspiration and its partitioning, affecting modelled transpiration more than total ET. This asymmetry cautions tested against using optical-only or fused evapotranspiration products as drop-in replacements for thermal CWSI without independent validation at the level of ET components. None of these studies incorporated an explicit phenological-stage covariate, a gap that the framework proposed below addresses for both satellite-fusion products and UAV-based CWSI. Satellite and multi-sensor fusion can extend crop water-status monitoring from plot and UAV scales to field and regional scales, but current products have rarely been evaluated explicitly across phenological transitions. Incorporating crop developmental stage into satellite-derived thermal and ET products therefore represents an important next step toward operational, phenology-aware irrigation advisories.

Cross-crop patterns and conceptual synthesis

Across the crop species reviewed above, several general patterns emerge (Fig. 4). First, baselines or CWSI relationships changed through the growing season in most studies that resolved stages, including those in grapevine (36), maize (18, 48) and wheat (18, 42), although the empirical maize baseline (6) did not vary significantly with stage. Second, CWSI–plant water status relationships appear weaker or less consistent at early vegetative stages, when soil background contributes disproportionately to the thermal signal and

stronger once canopy closure is reached (57). Third, CWSI measured during the developmental window most critical for yield, typically flowering, anthesis, or grain filling, was more closely related to yield than CWSI measured earlier, which makes this window the priority for stage-specific thresholds (43, 49). Fourth, the appropriate baseline strategy depends on the objective: stage-specific baselines better describe physiological status, whereas season-integrated baselines can remain preferable for yield or water-productivity prediction (48). These patterns support a growth-stage-dependent approach to both baseline construction and threshold setting. The strength of this evidence differs markedly among crops: stage-resolved baselines exist for maize and, to a lesser extent, wheat; the evidence for grapevine, potato and tree crops is mostly indirect; and the rice evidence rests on a single study. Table 3 summarises the main phenological findings, reported thresholds and evidence gaps by crop.

From thermal dynamics to irrigation scheduling models

The scheduling approaches reviewed below differ less in the sensors they use than in how and whether, crop phenology enters the irrigation decision (Table 4). In threshold-based scheduling, phenology can enter only through the choice of baseline and threshold and most studies use a single season-long value. In data-driven models, phenology enters as an input feature, either explicitly as a stage variable or implicitly through day of year or cumulative time, or not at all; the audit summarised in Fig. 2 shows that explicit stage encoding is rare. The IoT and digital-twin systems provide the infrastructure to update decisions continuously but, in the systems reviewed, rely on soil and weather rules rather than on stage-specific crop signals. The FAO-56 water-balance scheduling encodes phenology explicitly through the crop-coefficient curve but does not use thermal information unless coupled with it. The approaches also differ in data requirements, interpretability and field validation. Threshold rules are transparent and inexpensive but not transferable across stages or sites; machine-learning (ML) and deep reinforcement learning models capture nonlinear interactions but need large, stage-balanced training data and have mostly been evaluated in simulation or at single sites (75); and FAO-56 scheduling is widely used but responds to crop stress only through a modelled soil-water balance. These complementary strengths and weaknesses motivate the hybrid approaches discussed at the end of this section.

Threshold-based crop water stress index scheduling

The simplest and most common approach is to trigger irrigation at CWSI thresholds obtained by correlating CWSI with yield or water potential across the entire growing season, often disregarding crop phenology. The CWSI thresholds (0.29 for wheat and 0.31 for maize) from the relationships of CWSI with grain yield and irrigation water productivity in a maize–wheat sequence (18), while a real-time CWSI assessment system developed for mandarin (*Citrus reticulata* Blanco) that



could, in principle, be extended to apply different thresholds as the crop develops (76). Because CWSI measured during reproductive stages is more closely related to yield than CWSI measured earlier in wheat and maize, a single season-long threshold may underestimate crop water requirements during reproductive stages and overestimate them during vegetative stages; this inference has not yet been tested directly in scheduling trials (43, 49).

Data-driven and machine learning-based irrigation models

Machine learning methods, including random forest, support vector machines and deep-learning architectures, have been combined with thermal and multispectral UAV data to estimate CWSI and water stress (10, 50, 51, 77). Deep learning to thermal images applied to identify water stress in film-mulched, drip-irrigated cotton (78), while developed an IoT-enabled intelligent irrigation system that used a deep-learning neural network to translate sensor data into irrigation decisions (79). Spatial ML models relating vine CWSI to topographic variables and NDVI have been used to prescribe site-specific irrigation schedules in vineyards (38). As Table 4 and Fig. 2 show, however, explicit consideration of crop phenological stage remains largely absent from current AI models, which more often use day of year as a continuous temporal proxy than encoding discrete physiological stages.

A parallel and increasingly prominent strand uses deep reinforcement learning (DRL) to prescribe irrigation actions sequentially rather than predicting CWSI as an intermediate variable. Early researchers framed wheat irrigation as a Markov decision process, trained a DRL agent in the agricultural production systems simulator (APSIM) crop-simulation environment with crop phenological stage, LAI and layered soil-water content among its state variables and found that the learned policy outperformed a conventional regional decision rule by up to 17 % across the testing years, illustrating how crop phenology can be encoded explicitly in irrigation scheduling, although the contribution of the phenology variable to this gain was not isolated (80). Deep reinforcement learning to set the daily irrigation amount as a function of evapotranspiration, soil moisture, future precipitation probability and the current growth stage, improving economic returns by 5.7 % and 17.3 % in a wet and a dry season, respectively (81). A calibrated DSSAT cotton-growth model coupled with a soft actor-critic DRL agent enhanced by a bidirectional long short-term memory (BiLSTM) temporal-attention module and a growth-stage-weighted reward function, improving water-use efficiency by 39.0 % (an 8.4 % yield gain alongside a 22.1 % reduction in water use) relative to fixed-schedule irrigation; the growth-stage-weighted reward is among the more explicit phenology encodings identified in this review, although the study is simulation-based and has not been field-validated. Against these gains, reviewing sixteen ML-based irrigation-scheduling studies, identified limited data availability, absent uncertainty quantification and a lack of physics-informed constraints as the principal barriers

to field deployment, cautioning that the reported gains from DRL and other ML approaches have mostly been demonstrated in simulation rather than in commercial field settings (75). A partial, field-oriented counterexample, coupling UAV-derived vegetation indices with an FAO-56 soil-water-balance term in a gradient-boosting model for pineapple (*Ananas comosus* (L.) Merr.) and reporting 91.1 % decision accuracy in a traffic-light irrigation decision-support system (83); because the FAO-56 term implicitly encodes crop-development stage through the crop-coefficient curve, this hybrid, physics-informed approach illustrates one practical route toward phenology-aware, field-deployable models. On the question of timing, BiLSTM networks trained on past climate, irrigation and soil-moisture data predicted end-of-season yields of tomato and potato ($R^2 = 0.97\text{--}0.99$) more accurately than standard long short-term memory and gated recurrent unit networks, indicating that irrigation-history and phenology-linked inputs carry predictive value beyond the irrigation decision itself (84). In an image-based rather than sensor-index approach, three deep convolutional architectures was compared (AlexNet, GoogLeNet and Inception V3) for classifying water stress directly from RGB imagery of maize, okra [*Abelmoschus esculentus* (L.) Moench] and soybean without an intermediate CWSI computation, with GoogLeNet reaching the highest accuracy (94.1–98.3 %, depending on crop) (85). Because the images were not partitioned by phenological stage, whether classification accuracy remains stable across the growing season, which the stage-dependent UAV-thermal evidence reviewed above suggests it may not, remains an open question for this image-classification approach.

Dynamic and Internet of Things-based irrigation systems

Internet of Things-enabled irrigation systems provide continuous acquisition of soil, weather and crop-related observations and can connect sensing systems with automated irrigation control (9, 86, 87). An irrigation strategy was proposed based on the IoT and a digital-twin model of the cultivated field and demonstrated that real-time water sensing combined with the digital-twin model improved water-use efficiency compared with a threshold approach. A digital twin for smart farming was built that integrated irrigation control for water saving, showing how a virtual representation of the crop and field, based on sensor data, can support real-time decisions in the field (89). Reviewing the current state of digital-twin applications in agriculture, most digital twins simulate soil moisture and weather conditions rather than plant-based metrics such as CWSI, which is not yet considered in current digital-twin frameworks (90). In broader reviews of smart sensing and IoT solutions in agriculture, that the phenology-aware decision logic remains a minority approach compared with threshold- or rule-based irrigation control, further supporting the need for data-fusion approaches that encode phenology explicitly (86, 87).



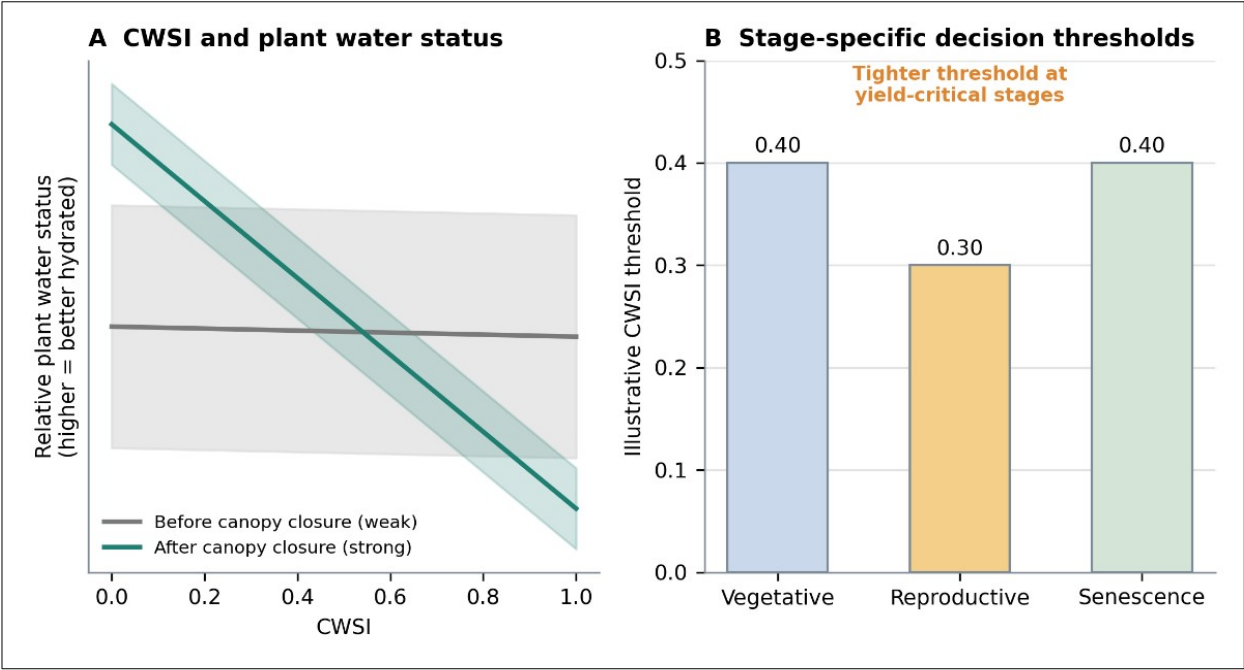


Fig. 4. Conceptual synthesis of phenology-dependent thermal interpretation and decision needs. (A) Schematic crop water stress index (CWSI)–plant water status relationships: a weak, variable association before canopy closure and a stronger negative association after closure; higher relative water-status values indicate better hydration, (B) Illustrative stage-specific CWSI thresholds, tightest at yield-critical reproductive stages, which may require crop-specific threshold calibration. The plotted relationships and thresholds are conceptual and are not measured data or universal values. CWSI: crop water stress index.

Table 4. Comparison of irrigation-scheduling approaches that use thermal or crop water stress index (CWSI) information and the way each incorporates crop phenology

Approach	Representative references	How phenology enters	Strengths	Limitations for phenology-adaptive use	Validation status
Threshold-based CWSI scheduling	(18, 42, 76)	Through the choice of baseline and threshold; usually a single season-long value	Transparent; inexpensive; easy to automate	Thresholds not transferable across stages, sites, or cultivars	Field-tested at individual sites
Machine-learning models (random forest, support vector machine, deep learning)	(50, 51, 77, 78)	As an input feature (explicit stage, day of year, or cumulative time) or not at all	Capture nonlinear interactions; fuse multiple sensors	Need large, stage-balanced training data; stage encoding rare; limited transferability	Mostly single-site evaluations
Deep reinforcement learning	(80–82)	As a state variable or stage-weighted reward	Sequential decisions; explicit optimisation of water and yield	Trained in crop-model simulations; field validation lacking	Mostly simulation
IoT and digital-twin systems	(79, 88–90)	Rarely; decisions mostly based on soil and weather rules	Continuous data streams; real-time automation	Canopy temperature and CWSI not yet assimilated; phenology logic rarely explicit	Prototypes and pilot systems
FAO-56 water-balance scheduling	(26, 91)	Explicitly, through the stage-dependent crop-coefficient curve	Widely used; computes irrigation amounts	Stress inferred only from modeled soil water; tabulated calendars may not match the observed crop	Widely used in practice
Hybrid thermal and water-balance approaches	(11, 73, 83)	Through the crop-coefficient curve, corrected with remote-sensing or thermal observations	Combine a direct stress signal with irrigation amounts	Few implementations; not evaluated at the stage level	Early field studies

CWSI: crop water stress index; FAO: Food and Agricultural Organization.



Within the phenology-adaptive framework proposed in this review, a digital twin would have a specific and testable role. Its virtual crop state would include the current phenological stage, estimated from thermal time and updated with vegetation-index observations; its parameter library would store the NWSB, upper baseline and CWSI threshold for each stage; and each new thermal acquisition would update the estimated crop water status against the parameters of the current stage before the decision engine proposes an irrigation amount. Crop simulation models already provide the phenology component of such a twin, as in the APSIM-based agent (80) and the DSSAT-based agent (82), both of which include growth stage in their state variables or reward function. What remains untested is the thermal component: none of the digital-twin systems reviewed here assimilated canopy temperature or CWSI, so the link between a stage-aware digital twin and thermal observations is, at present, a design proposal rather than a demonstrated system (88–90).

Crop-model-driven and Food and Agriculture Organization -56-based scheduling

Traditional irrigation scheduling relies on the crop coefficients (K_c) recommended in FAO-56 and the associated water-balance procedures (91). The UAV-based thermal and multispectral sensing coupled with energy-balance modelling gave better estimates of crop water requirements than the traditional K_c -based method, particularly where canopy cover is variable (26). The FAO-56 defines initial, development, mid-season and late-season periods that provide a broad developmental framework for irrigation scheduling; however, few of the studies reviewed here have explicitly incorporated dynamic, stage-specific CWSI thresholds into K_c -based adjustments.

Hybrid thermal and water-balance approaches

Thermal indices and FAO-56 water-balance scheduling have complementary weaknesses: the water balance estimates how much water to apply but infers stress only indirectly from modelled soil water, whereas CWSI detects stress directly but does not by itself indicate an irrigation amount. The two can be linked because both describe the reduction of actual relative to potential transpiration. In the dual crop coefficient procedure of FAO-56, adjusted crop evapotranspiration is computed as,

$$ET_c \text{ adj} = (K_s K_{cb} + K_e) ET_0,$$

where K_{cb} is the basal crop coefficient, K_e the soil-evaporation coefficient and K_s a water-stress coefficient that reduces transpiration as soil water is depleted (91). Because the theoretical CWSI is defined as $1 - E/E_p$ (15), the quantity $1 - \text{CWSI}$ provides an observation-based estimate of the transpiration reduction that K_s represents in the model, particularly after canopy closure, when soil evaporation is small. Three forms of hybrid follow from this relationship. First, thermal observations can be used to check or correct the modelled K_s , resetting the water balance when observed stress departs from simulated stress. Second,

the stage-dependent K_{cb} curve can be estimated from remote sensing (11) did for grapevine with UAV multispectral imagery did with Sentinel-2-based combination-equation models, so that the phenology encoded in the water balance reflects the observed crop rather than a tabulated crop calendar (73). Third, water-balance terms can be supplied as predictors to machine-learning models, in which an FAO-56 term implicitly carried crop-development stage into a gradient-boosting decision model (83). Energy-balance approaches that estimate crop water requirements from UAV thermal and multispectral data provide a further bridge between thermal sensing and quantitative irrigation amounts (26). Hybrids of the first kind remain rare in the studies reviewed and have not been evaluated at the stage level, but they combine the stage structure of FAO-56 with the direct stress signal of the CWSI and are therefore the basis of the operational framework proposed below.

A phenology-adaptive irrigation framework

Building on the evidence synthesised above, this review proposes a phenology-adaptive irrigation framework that makes growth stage a central, explicit component of thermal-based scheduling (Fig. 5). The framework has three components: (i) phenology-aware baseline calibration, in which the NWSB and upper baseline are defined for specific phenological windows, following the stage-resolved approach demonstrated for maize (18, 48); (ii) stage-specific threshold and decision logic, in which CWSI thresholds are assigned according to the crop's developmental stage, building on stage-specific drought thresholds for wheat (42) and on the closer relationship of reproductive-stage CWSI with yield (43, 49); and (iii) dynamic data-fusion and ML models, in which the crop's phenological stage is explicitly incorporated as an input parameter, building on the digital-twin concepts (90).

The proposed framework is a conceptual synthesis of the evidence reviewed above and has not yet been empirically implemented or validated as an integrated irrigation-management system. Each of its three components has separate empirical support in the cited literature, but the framework as a whole remains to be tested. Establishing its operational readiness will require multi-year, multi-site field trials to establish and cross-validate stage-specific baselines and thresholds across seasons and locations; benchmarking of the phenology-adaptive scheduling logic against conventional fixed-threshold and FAO-56 K_c -based scheduling on outcomes such as water use, yield and stress-onset detection lag; and evaluation of the robustness of automated phenology detection under field conditions before the framework can be recommended for operational irrigation control.

Operationally, the framework can be implemented as a seasonal cycle of seven steps (Table 5). Before the season, (1) stage definitions and a thermal-time model are selected for the crop and cultivar and (2) well-watered and non-transpiring reference measurements are planned for each stage window, so

that stage-specific NWSBs and upper baselines can be fitted locally or taken from a regional library. During the season, the current stage is estimated from thermal time and updated with vegetation-index observations and field scouting (3); thermal data are acquired within a fixed daily window (4), typically around solar noon under clear skies (31), or baselines specific to the acquisition time are used (32); CWSI is computed with the baseline of the current stage and compared with the stage-specific threshold (5); and if the threshold is exceeded, the irrigation amount is computed from the FAO-56 water balance, with the thermal observation used to correct the modelled stress coefficient (6). After the season, yield and water use are used to update the baseline and threshold library (7). At stage transitions, where the choice of parameters is least certain, the more conservative (lower) of the two adjacent stage thresholds can be applied until the transition is confirmed. The framework therefore requires three datasets that current studies rarely provide together: stage-labeled reference measurements, stage-labeled thermal observations and stage-specific yield-response data.

Phenology detection and stage definitions

A major practical challenge lies in accurate phenology identification and the available methods differ in accuracy, timeliness, cost and spatial scale (Table 6). Ground observation with standardised scales, such as the decimal code for cereals (92), the Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie (BBCH) scale for mono- and dicotyledonous crops (93) and the vegetative (V) and reproductive (R) stages used for maize (51), remains the reference method. It is accurate at the plot scale and resolves the reproductive stages that matter most for thresholds, but it is labour-intensive and cannot be applied continuously over large areas. Thermal-time models predict stage dates from growing degree days accumulated above a base temperature (94); they are inexpensive, can forecast upcoming transitions and run on standard weather data, but they must be calibrated for each cultivar and can drift when water or heat stress alters development, which are the conditions an irrigation system is meant to manage. Satellite vegetation-index time series, processed with curve-fitting tools such as time-series analysis (TIMESAT) (95) or with newer spectral approaches (96), detect green-up, peak canopy and senescence over large areas at low cost, but they resolve canopy-development phases better than short reproductive stages and cloud gaps and mixed pixels delay detection. The UAV-based phenotyping provides plot-level detail: multi-image UAV thermal phenotyping of canopy temperature aligned with discrete developmental windows rather than a uniform chronological division (97) and documented diurnal and phenological modulation of wheat canopy temperature,

but repeated flights are costly (41). Crop simulation models such as APSIM and DSSAT simulate phenology as part of the crop state and can be updated with observations, although their phenology modules also require calibration (80, 82). Because no single method is both timely and accurate at the reproductive stages, a combined approach is the most practical: a calibrated thermal-time model provides the default stage calendar, remote-sensing time series correct it at the field scale and targeted field scouting confirms the transitions to yield-sensitive stages, when thresholds change.

Stage-specific baseline construction

Reference plots for the empirical NWSB need to be well watered and representative of each phenological window. Previous researcher illustrated this directly by establishing separate upper and lower $T_c - T_a$ baselines for wheat and maize under a gradient of irrigation treatments and finding that the canopy–air temperature difference was largest at anthesis and silking, respectively (18). Early researcher offer a practical example of how growth-stage-specific NWSBs can be constructed and validated: baselines were built separately for three maize growth stages under water and salt stress and shown to track physiological traits better than a baseline without stage variation, which was nevertheless the better choice for yield-oriented applications (48).

A worked example illustrates how the choice of baseline and threshold changes the irrigation decision; the coefficients are hypothetical and were chosen only for illustration and the vegetative and reproductive baselines are those plotted in Fig. 3A. Suppose that reference measurements in a maize field give an NWSB of $(T_c - T_a)$ LL = 2.0 – 1.8 VPD during the vegetative stages and $(T_c - T_a)$ LL = 1.0 – 1.6 VPD during the reproductive stages, a season-pooled NWSB of $(T_c - T_a)$ LL = 1.5 – 1.7 VPD and an upper limit of $(T_c - T_a)$ UL = 4.0 °C, taken as constant here for simplicity. At a midday observation with VPD = 2.5 kPa and a measured $T_c - T_a$ of -0.5 °C, the lower limits are -2.5, -3.0 and -2.75 °C for the vegetative, reproductive and pooled baselines and the corresponding CWSI values are $(-0.5 + 2.5) / (4.0 + 2.5) = 0.31$, $(-0.5 + 3.0) / (4.0 + 3.0) = 0.36$ and $(-0.5 + 2.75) / (4.0 + 2.75) = 0.33$. If the stage-specific thresholds are 0.40 for the vegetative stages and 0.30 for the reproductive stages, the same canopy temperature does not trigger irrigation during vegetative growth but does trigger it during flowering. With the pooled baseline and a single season-long threshold of 0.35, the reproductive-stage observation gives a CWSI of 0.33 and no irrigation, that is, a missed irrigation at the most yield-sensitive stage. The example shows two separate effects of stage-specific calibration: the baseline changes the computed CWSI and the threshold changes the decision and either alone can reverse the outcome.

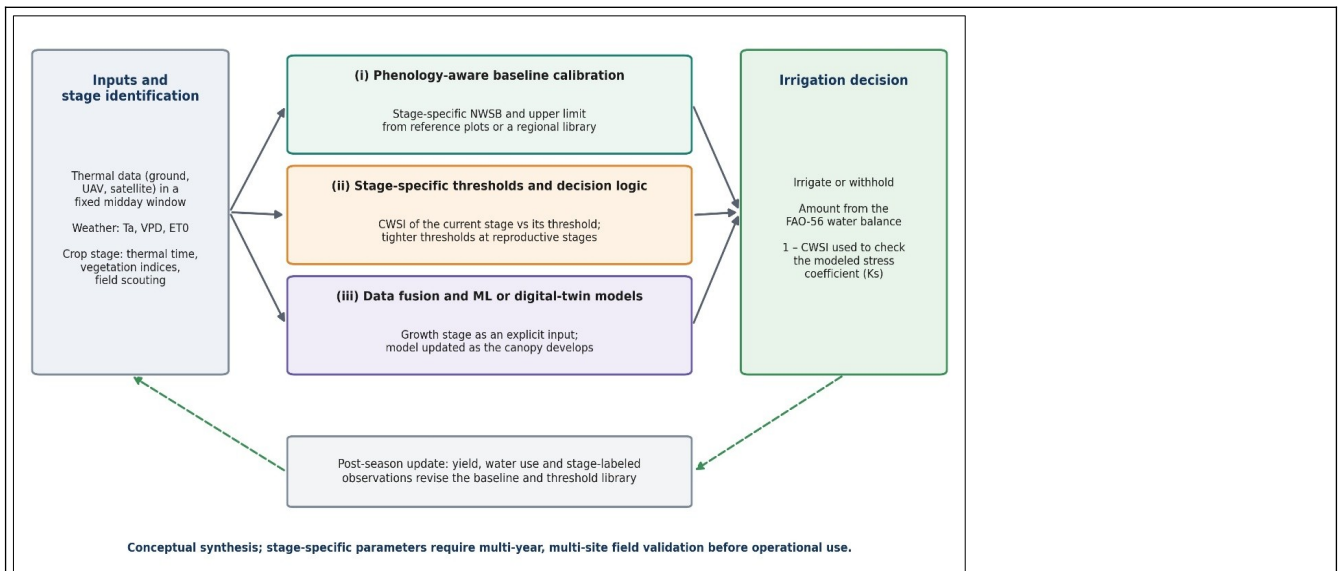


Fig. 5. Conceptual framework for phenology-adaptive irrigation scheduling. Thermal, weather and crop-stage inputs feed three components: (i) phenology-aware baseline calibration, (ii) stage-specific thresholds and decision logic and (iii) data fusion and machine learning (ML) or digital-twin models with growth stage as an explicit input.

The irrigation decision uses the FAO-56 water balance to set the amount, with $1 - \text{CWSI}$ used to check the modeled stress coefficient (K_s) and a post-season update revises the baseline and threshold library; the operational steps are listed in Table 5. This framework is a conceptual synthesis and has not been validated as an integrated irrigation-management system.

CWSI: crop water stress index; NWSB: non-water-stressed baseline; ML: machine learning; FAO: Food and Agricultural Organization; FAO-56: FAO Irrigation and Drainage Paper 56.

Table 5. Operational workflow of the proposed phenology-adaptive irrigation framework

Step	Timing	Inputs	Outputs	Supporting evidence
1. Define stages and thermal-time model	Before the season	Cultivar; standardised stage scale; base temperature	Stage calendar	(92–94)
2. Establish reference baselines	Before and during the season	Well-watered and non-transpiring references for each stage; T_c , T_a and VPD	Stage-specific NWSB and upper limits	(18, 48)
3. Detect the current stage	During the season (weekly or when triggered)	Thermal time; vegetation-index time series; field scouting	Current stage and transition dates	(95–97)
4. Acquire thermal data	Fixed midday window under clear skies	Infrared sensor, UAV, or satellite data; calibration panels	Canopy temperature and $T_c - T_a$	(30–32)
5. Compute CWSI and compare with threshold	Each acquisition	$T_c - T_a$, VPD and the baseline and threshold of the current stage	CWSI; irrigate or do not irrigate	(18, 42, 43)
6. Compute irrigation amount	When the threshold is exceeded	FAO-56 water balance; $1 - \text{CWSI}$ as a check on K_s	Irrigation depth and timing	(26, 83, 91)
7. Update the parameter library	After the season	Yield, water use and stage-labeled observations	Revised baselines and thresholds	Proposed in this review

CWSI: crop water stress index; FAO: Food and Agricultural Organization; VPD: vapour pressure deficit; NWSB: non-water-stressed baseline; T_c : canopy temperature; T_a : air temperature; UAV: unmanned aerial vehicles.

Stage-aware thresholds and decision rules

Thresholds can be defined from yield-response data by calibrating CWSI against yield penalties at different developmental stages, from physiological thresholds linked to water potential, or from a combination of both. Flowering- and post-heading-stage CWSI values predicted wheat grain yield more reliably than pre-heading or seasonal mean values, providing a direct, quantitative basis for stage-differentiated threshold setting (43). The CWSI-based irrigation scheduling has been demonstrated for wheat (45) and artificial neural networks have been trained on combined thermal and RGB imagery of wheat (46); including growth stage as an input variable in such models would allow stage-dependent thresholds to be learned implicitly rather than fixed in advance.

Data fusion and phenology-aware machine learning models

Multi-modal data fusion, combining thermal, multispectral and structural data streams, has emerged as a recent advance in UAV-based crop water monitoring (24, 26). Making these models phenology-aware requires explicitly encoding growth stage, for example as a categorical variable in random forest or neural-network models, following the stage-stratified approach used for maize, with the model updated as canopies transition between stages (51). Such frameworks lend themselves to extension with explicit phenology windows, moving towards digital twins for irrigation management that integrate stage-resolved thermal thresholds with real-time sensor fusion (88, 89).

Challenges, gaps and research priorities

The gaps identified in this review are not equally limiting. They are presented below in order of priority, judged by how directly each one prevents phenology-adaptive scheduling from being implemented.

Table 6. Methods for detecting crop phenological stage and their relative merits for phenology-adaptive irrigation

Method	Spatial scale	Timeliness	Strengths	Limitations	References
Field scouting with standardised scales (Zadoks, BBCH, V/R stages)	Plant to plot	Direct but periodic	Reference accuracy; resolves reproductive stages	Labor-intensive; not continuous; observer variation	(51, 92, 93)
Thermal-time (growing degree day) models	Field to region	Predictive; daily	Inexpensive; forecasts transitions; needs only weather data	Cultivar-specific calibration; errors under water or heat stress	(94)
Satellite vegetation-index time series	Field to region	Limited by revisit interval and clouds	Large areas at low cost; long archives	Weak for short reproductive stages; mixed pixels; detection delay	(95, 96)
UAV multispectral and thermal phenotyping	Plot to field	Per flight	High spatial detail; can be combined with thermal acquisition	Cost and flight frequency	(97)
Crop simulation models updated with observations	Field	Predictive; daily	Integrate weather, soil and management; basis for digital twins	Calibration and input-data demands	(80, 82)

UAV: unmanned aerial vehicles; BBCH: Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie.

Priority 1: stage-resolved calibration data

The most critical gap is the lack of multi-site, multi-season datasets that pair stage-labeled thermal observations with reference baselines and yield responses. Stage-specific baselines exist for only a few crops and sites (18, 48), the rice evidence rests on a single study (56) and none of the satellite fusion products reviewed has been evaluated at stage transitions. Without such data, neither thresholds nor ML models can be generalised. Evidence from the broader AI and precision-agriculture literature further highlights the challenge of operational scalability: translation of AI-based irrigation research into practice lags behind methodological development and data quality, diversity and availability are major constraints (98, 99). Open, stage-resolved repositories of thermal observations and baseline information should therefore be the first priority.

Priority 2: standardised phenology definitions and operational stage detection

Most thermal CWSI studies use ad hoc or study-specific definitions of phenology, which makes results from different studies difficult to compare and stage detection remains the least developed component of the proposed framework. Reporting the stage, on a standard scale, alongside every thermal observation would allow results to be pooled across studies. Even when a common approach is used within a crop, baseline selection may need to differ according to the intended application, such as physiological-status assessment versus yield or water-productivity prediction (48).

Priority 3: field validation of stage-aware decision systems

The vast majority of AI-based irrigation controllers focus on soil and weather relationships and do not explicitly consider thermal variables, much less phenological stage (9, 86); the most explicit phenology encodings are found in simulation-based deep reinforcement learning studies (80, 82) and ML gains have mostly been



demonstrated in simulation (75). Controlled field comparisons of stage-aware and fixed-threshold scheduling, reporting water use, yield and stress-detection lag, are needed. The integration of phenology-aware CWSI modules into IoT and digital-twin irrigation controllers, together with adaptive management-zone delineation that accounts for canopy developmental stage, is the natural test bed (64, 88, 89).

Priority 4: acquisition constraints

Repeated UAV thermal missions and the dependence of CWSI estimate on weather conditions at the time of image acquisition are practical limitations of continuous, stage-aware monitoring (72) and satellite thermal products remain too coarse or too infrequent for many fields, as discussed below for smallholder systems.

Cost and accessibility

The cost of phenology-adaptive monitoring has three main components: thermal data acquisition, stage detection and the expertise needed to process and interpret the data. Each scales differently with farm size. Satellite thermal data are free, but spatial resolution is the binding constraint for small farms. Around 84 % of the world's farms are smaller than 2 ha (100). A 1 ha field corresponds to about one native 100-m thermal pixel of the Landsat thermal sensor and to about two 70-m ECOSTRESS pixels, so neither can separate the crop from field margins or resolve within-field variation on most smallholdings; thermal sharpening to 30 m (35) raises this to about eleven pixels per hectare, which is sufficient for field-level but not within-field assessment. Thermal sharpening and fusion are therefore more important for smallholder systems than for large farms (33–35). The UAV surveys provide adequate resolution at any field size, but each flight carries fixed costs (equipment, a trained pilot, travel and processing) that are largely independent of field area, so the cost per hectare is highest on the smallest farms. The UAV-based CWSI estimation on smallholder maize demonstrated, but the repeated flights needed for stage-resolved monitoring multiply these costs (50). Low-cost thermal cameras (13) and wireless infrared sensor networks (37) reduce hardware costs and can provide the continuous records needed to build stage-specific baselines at a small number of reference sites. Stage detection is least expensive when based on thermal-time models run from weather data with occasional field scouting. Processing and interpretation, finally, require expertise that individual smallholders are unlikely to have, which points to service-based rather than farm-based delivery.

Equity and access for smallholders

Phenology-adaptive irrigation will reduce, rather than widen, differences in water productivity only if it is designed for the farms least able to invest in sensing. Four design principles follow from the evidence reviewed. First, sensing can be shared rather than owned: cooperatives, water-user associations, extension services, or private service providers can operate UAVs and reference infrared sensor sites for many farms,

spreading the fixed costs that make UAV monitoring most expensive per hectare on small fields. Second, regional libraries of stage-specific baselines and thresholds, built from reference sites and open data, would remove the need for each farm to calibrate its own baselines. Third, decisions can be delivered in simple forms, such as stage-specific irrigate or do-not-irrigate advisories sent by mobile phone, rather than as maps that require interpretation; the traffic-light decision-support system illustrates such a format (83). Fourth, the framework can be tiered: where thermal data are unavailable, a thermal-time stage calendar combined with the FAO-56 water balance still provides stage-aware scheduling and thermal observations can be added as they become affordable. These principles are proposals; none has yet been evaluated for phenology-adaptive thermal scheduling and participatory trials with smallholder farmers are needed to test which delivery models are adopted and whether they improve water productivity and income.

4. Conclusion

Thermal imaging and crop water stress index (CWSI) are well established for detecting crop water stress, yet their full potential remains unrealised as long as phenology is treated as a complicating variable rather than an integral component of the modelling framework. Evidence synthesised from maize, wheat, grapevine, potato and perennial fruit crops indicates that thermal responses, CWSI baselines and irrigation thresholds can vary with phenological stage, although the strength of this evidence differs widely among crops. Consequently, applying season-long thermal relationships without accounting for developmental stage may result in under- or overestimation of crop water stress, particularly during yield-sensitive developmental periods. A phenology-adaptive approach to irrigation scheduling can be built by designing flexible baselines that track crop development, defining stage-specific thresholds calibrated to the intended use of the index and coupling the thermal signal with the FAO-56 water balance to determine irrigation amounts.

The potential benefits for water conservation and food security are substantial but still to be demonstrated on a scale. The studies reviewed indicate that timing irrigation according to crop stress can save water without reducing yield: thermal-threshold scheduling of potato under furrow irrigation saved water without a significant reduction in tuber yield and a growth-stage-weighted deep reinforcement learning scheduler reduced simulated water use by 22.1 % while increasing cotton yield by 8.4 % (82). Directing water to the reproductive stages at which CWSI is most closely related to yield and withholding it when crops can tolerate mild stress, is the mechanism by which phenology-adaptive scheduling could raise water productivity, protecting yields in water-scarce seasons and releasing water for other uses. Delivered through shared services and simple stage-



specific advisories, these gains could extend to smallholder farms that are too small to justify their own sensing systems.

Over the coming decade, four developments would move the approach from concept to practice: open, stage-labeled calibration datasets spanning multiple sites and seasons; standardised phenology reporting in thermal studies; field trials that compare stage-aware with conventional scheduling on water use, yield and farm income; and delivery models, including digital twins and advisory services, designed for farms of all sizes. The next advance in thermal irrigation management lies not simply in improved detection of crop water stress, but in stage-aware systems that interpret thermal signals within the biological context of crop development and translate them into validated, timely and transferable irrigation decisions.

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Authors' contributions

JRM contributed to the conceptualisation, methodology, literature search, data curation, bibliometric analysis, visualisation; and writing and preparation of the original draft. PPC contributed to the conceptualisation, methodology, supervision, validation, writing, review and editing; and project administration. RKP contributed to the methodology, validation, technical guidance and writing, review and editing. KP contributed to data interpretation, validation, visualisation and writing, review and editing. SPM contributed to the investigation, validation, critical review and editing of the manuscript and final approval of 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 review article, the authors used Paperpal and Grammarly to improve language clarity, grammar, fluency and coherence. BioRender was used to create illustrations. The authors take full responsibility for the manuscript's content. Literature selection, critical evaluation, synthesis of evidence, interpretation and conclusions were undertaken entirely by the authors without AI assistance.

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