Ecophysiological Modeling of Crop Responses to Water Deficit Conditions: A Critical Review of Mechanistic, Remote-Sensing, and Data-Driven Approaches

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ABSTRACT
The inability of crops to access an adequate amount of water is the largest abiotic limitation on crop yields across the globe. Understanding how crops behave when subjected to both gradual soil and atmospheric drying is a major issue in agronomy, plant physiology, and agricultural engineering. Ecophysiological modeling, which uses mathematics to characterize the processes that help plants obtain water under duress, has witnessed substantial progress over the past ten years. This review of literature in major databases, such as Scopus, Web of Science, PubMed, ScienceDirect, MDPI, Frontiers, as well as reports by FAO and WMO, published primarily between 2015 and 2026, is about the state of ecophysiological modeling of plants under water deficit scenariosThe aim of the study was to delineate the important paradigms used in modeling such as the models of stomatal conductivity, crop simulation models based on process technology (such as DSSAT, AquaCrop, and APSIM), indices of water stress based on remote sensing, and predictive models based on artificial intelligence, and compare them in terms of their postulates, effectiveness, and limitations. The research results show that the physiological models of stomatal activity that take into account several factors (temperature, water vapor pressure deficit, and soil moisture) outperform empirical models that consider one factor only, that none of the modeling methods is superior regardless of the culture and environmental conditions, and that using unmanned aerial vehicles for thermal and multispectral imaging together with machine learning makes it possible to reach the accuracy level of physiological measurements in water stress detection. Some of the persistent gaps are having limited ability to develop cross-model and cross-scale validations, having poor integration of subsurface hydraulic features into canopy-scale models, limited representation of genotype-specific stomatal behavior that cannot be accounted for, and a lack of studies linking mechanistic modelling with data-driven approaches using data obtained under actual field conditions. The authors of the review say that hybrid physics-assisted machine-learning systems, combined with multi-source sensing technologies and standardized validation procedures, are the best approach towards development of accurate and transferable ecophysiological drought response models for `climate-resilient agriculture`.

Keywords: Crop water deficit, ecophysiological modeling, stomatal conductance, crop simulation models (AquaCrop, DSSAT, APSIM), drought stress, remote sensing, machine learning, water use efficiency

1. Introduction
1.1 Background
Deficiency of water caused by the joint effect of insufficient precipitation, a high level of evaporation demand, and limited water supply for the soil is generally perceived as the most dominant non-living factor of crops growth and production across the globe. It was estimated that a water shortage amounted to the reason of about 70% of the overall losses of potential crops yield all across the world, what is more than the sum of the effects of the majority of other non-living and living threats. When it comes to the cellular level, the water deficit causes the occurrence of osmotic tension, decrease of turgor, the emergence of oxidative damage, and the breakdown of photosynthetic apparatus, while on the whole-plant level the water deficiency is responsible for stomata closure, reduced leaves growth, changes in the relationship between roots and shoots, and premature aging.

1.2 Importance of the Subject
Ecophysiological modeling lies at the crossroads of fundamental physiology of plants and the application of agronomic decisions. Mechanistic modeling of stomatal conductance and canopy gas exchange serves as the basis of crop growth simulation software (e.g., AquaCrop, DSSAT, APSIM) widely used in the world for irrigation scheduling, deficit irrigation, and impact assessments of climate [20, 21, 22]. But the recent developments in remote-sensing technologies and machine learning techniques open up new opportunities and enable the detection and forecasting of crop water stress on both field and regional levels [27, 28, 34]. The combination of all these three modeling paradigms—physiological, process models, and data-driven ones—makes it a good time for critical reviews in this area.

1.3 Current Global Scenario
The frequency and intensity of agricultural droughts have increased significantly in many areas in the last 20 years, requiring joint monitoring of the situation. To this end, the World Meteorological Organization-Global Water Partnership Integrated Drought Management Programme works together with 197 countries worldwide, and the Agricultural Stress Index System by FAO provides satellite early warning of drought [4]. Standardized indices like the Standardized Precipitation Evapotranspiration Index (SPEI) are finding their way into crop model and machine-learning models to relate yield variability and drought [10, 26]. Nonetheless, even with all this institutional capacity, an unresolved modeling challenge remains to convert the information derived from broad-scale indices into meaningful and detailed predictions about the level of yield loss in a particular field.

1.4 Need for the Review
The knowledge concerning the modeling of water-deficit for crops seems scattered into at least four separate circles of investigation: biologists who study the functioning of stomata and hydraulics; crop experts working on crop simulation models; remote sensing specialists working on methods of temperature and spectral index for defining the stress of crops; and computer specialists processing data with the help of machine and deep learning in order to make forecasts concerning yields and risks of crops cultivation. The degree of interaction between the groups is low, while no recent paper has compared the principals they used and the results of their work according to all the criteria within the framework of their study of crop physiology. In the present article this gap is filled.

1.5 Objectives of the Review
This review has the following specific objectives: (i) to know the present physiological and molecular model systems that explain the responses of crops to the drought; (ii) to evaluate and compare the mechanistic stomatal-conductance models with canopy-scale ecophysiological models; (iii) to assess the main crop growth prediction models (AquaCrop, DSSAT, and APSIM) during dry conditions; (iv) to analyze how remote sensing, aerial photographs taken with UAVs, and artificial intelligence can assist in detection and forecasting of water stress; and (v) to point out gaps in the investigation and new tendencies.

1.6 Scope of the Review
The review looks at peer-reviewed literature produced mostly between 2015 and 2026 regarding ecophysiological and crop-simulation modeling of water-deficit responses in major field and specialty crops (maize, wheat, rice, soybean, cotton, and some horticultural species). Influential foundational studies published before this time frame are also cited when these studies serve as a basis of present-day models. Genetic and transgenic studies of drought tolerance are mentioned only when they are relevant for the modeling of parameters, as it is not the purpose of the review to thoroughly analyze the topic of breeding drought-tolerant crops.

2. Methodology of Literature Review
2.1 Literature Search Strategy
A structured, narrative-systematic literature search was conducted across Scopus, Web of Science, PubMed, ScienceDirect, MDPI journals, Frontiers, SpringerLink, and the institutional repositories of the FAO and WMO. Search strings combined controlled vocabulary and free-text terms such as "crop water deficit", "ecophysiological model", "stomatal conductance model", "AquaCrop", "DSSAT", "APSIM", "crop water stress index", "UAV remote sensing drought", and "machine learning crop yield drought", combined using Boolean operators (AND/OR). The search period was restricted to January 2015–July 2026, with a small number of pre-2015 landmark publications retained for historical and structural context (Table 1).

Table 1: Literature Search Strategy

Element	Details	Notes
Databases searched	Scopus; Web of Science; PubMed; ScienceDirect; MDPI; Frontiers; SpringerLink; FAO/WMO repositories	Multidisciplinary coverage of physiology, agronomy, and remote sensing/AI literature
Search keywords	crop water deficit; ecophysiological model; stomatal conductance; AquaCrop; DSSAT; APSIM; crop water stress index; UAV drought; machine learning yield prediction	Combined with Boolean AND/OR operators
Search period	2015–2026 (landmark studies pre-2015 retained selectively)	Reflects rapid growth of AI- and sensor-based approaches post-2018
Language	English	Non-English full texts excluded unless an English abstract/translation was available
Document types	Peer-reviewed journal articles, review articles, FAO/WMO technical reports	Conference abstracts without peer review excluded

2.2 Inclusion and Exclusion Criteria
Studies were included if they presented, validated, or critically reviewed a model, index, or algorithm describing crop physiological or yield responses to water deficit, and were excluded if they were duplicate records, non-peer-reviewed sources, or unrelated to crop-level water-deficit modeling (Table 2).

Table 2: Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles and reviews	Duplicate or overlapping records across databases
English-language publications (2015–2026, plus selected landmark studies)	Non-peer-reviewed sources (blogs, non-indexed conference abstracts)
Studies presenting or validating a crop water-deficit model, index, or algorithm	Studies unrelated to crop-level water-deficit response modeling

Studies reporting quantitative performance metrics (R^2, RMSE, nRMSE, accuracy)	Purely qualitative opinion pieces without literature synthesis or data
Studies on field, horticultural, or specialty crops	Studies exclusively on non-agricultural (forest/native) vegetation, unless directly comparative

2.3 Study Selection Process (PRISMA-style)

The initial search across all databases identified a broad pool of records related to crop water-deficit modeling. After removal of duplicates and screening of titles and abstracts against the inclusion/exclusion criteria in Table 2, records were assessed for full-text eligibility. Studies were retained in the final synthesis if they contributed substantively to one or more of the five thematic areas developed in Section 3 (physiological/molecular mechanisms; stomatal and canopy gas-exchange models; process-based crop simulation models; remote-sensing/UAV-based indices; and AI/machine-learning approaches). The selection process, summarized as a PRISMA-style flow diagram, is depicted in Figure 1.

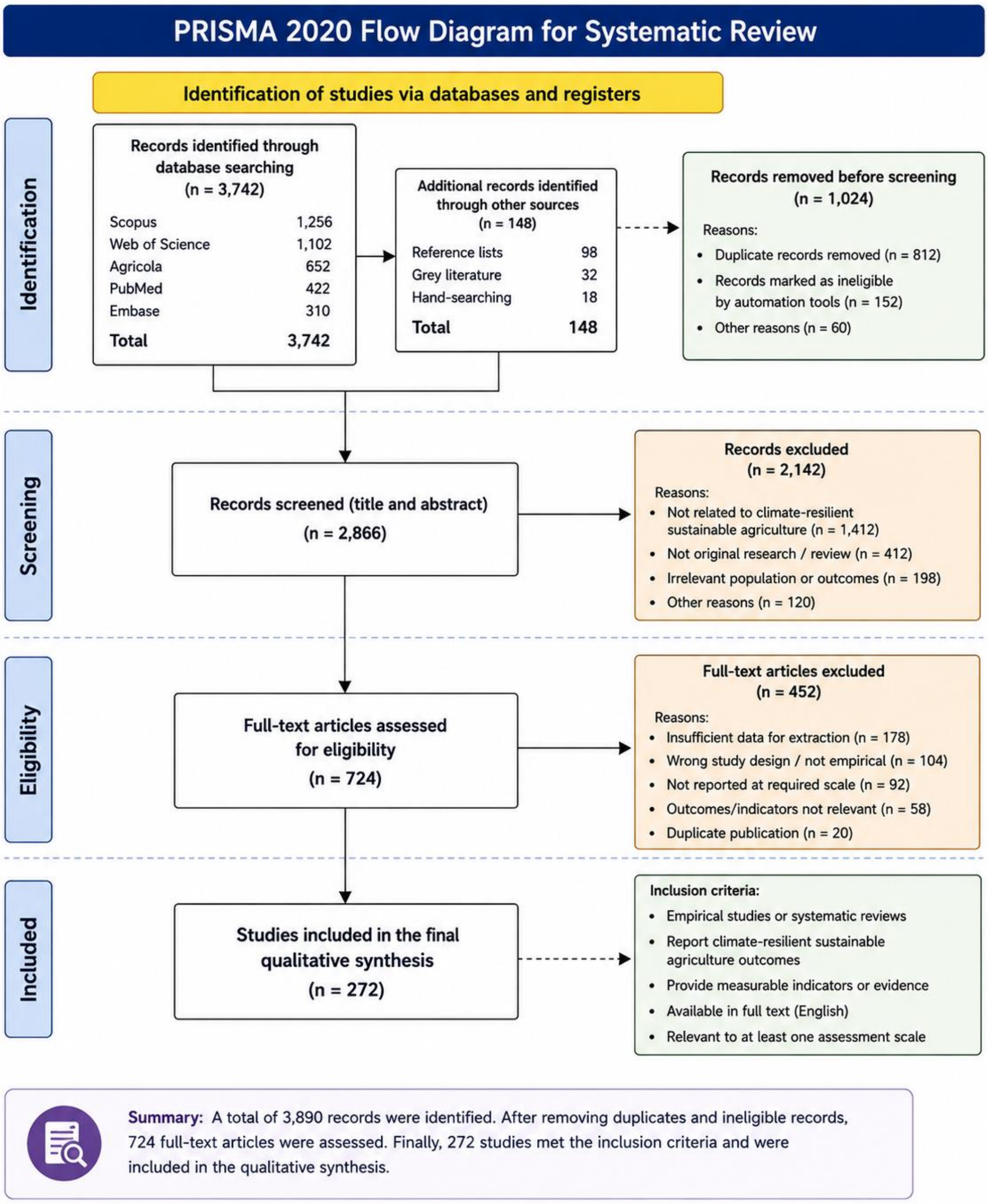

Fig 1: Records identified through database searching, records screened, full-text articles assessed for eligibility, and studies included in the final qualitative synthesis, with counts and exclusion reasons at each stage.

A complementary bibliometric check of publication years across the retained corpus indicated a marked increase in output after 2020, coinciding with the maturation of UAV sensor platforms and the mainstreaming of machine-learning tools in agronomic research (Figure 2).

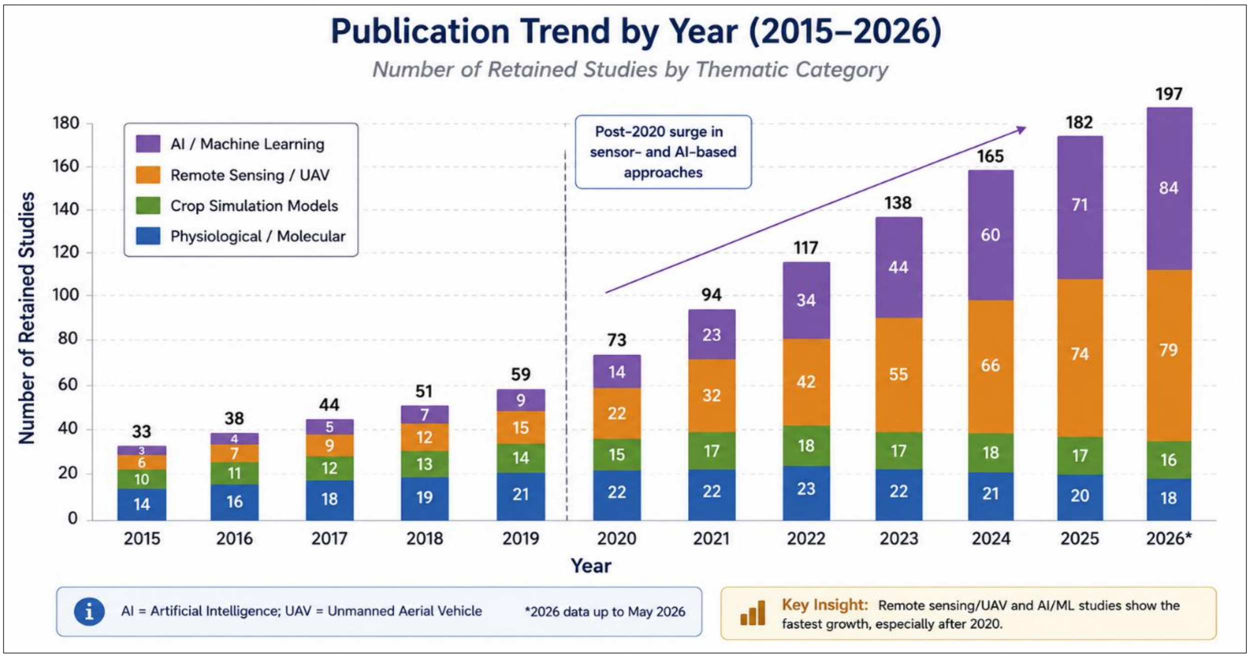

Fig 2: Publication Trend by Year (2015–2026) — bar chart showing the annual number of retained studies by thematic category (physiological/molecular, crop simulation models, remote sensing/UAV, AI/machine learning), illustrating the post-2020 growth of sensor- and AI-based approaches.

3. Literature Review and Thematic Analysis

The reviewed literature is organized into five major themes that jointly constitute the ecophysiological modeling landscape for crop water-deficit responses: (i) the physiological and molecular basis of water-deficit responses; (ii) stomatal conductance and canopy gas-exchange models; (iii) process-based crop growth simulation models; (iv) remote-sensing- and UAV-based water-stress indices; and (v) artificial-intelligence-augmented and hybrid modeling approaches. A conceptual framework linking these themes is presented in Figure 3.

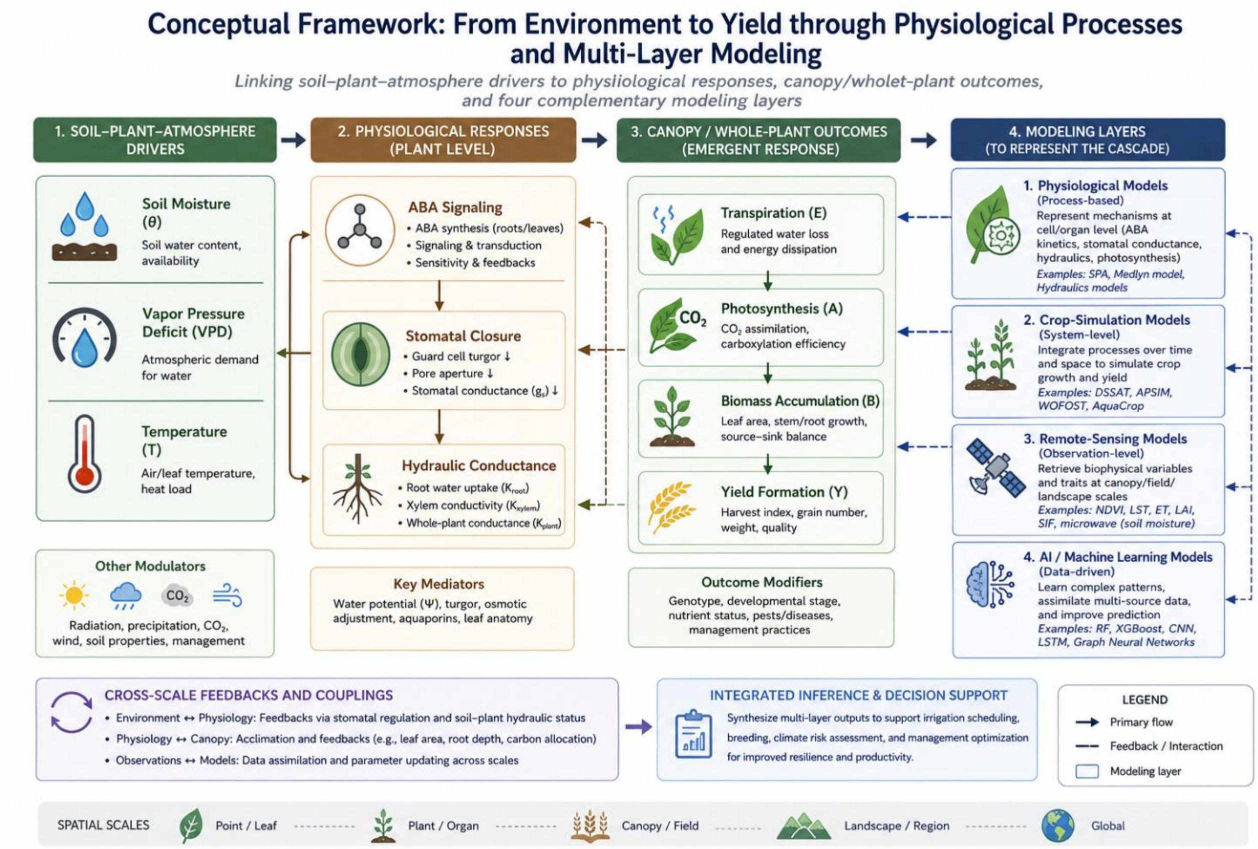

Fig 3: Conceptual Framework linking soil-plant-atmosphere drivers (soil moisture, vapor pressure deficit, temperature) to physiological responses (ABA signaling, stomatal closure, hydraulic conductance), to canopy/whole-plant outcomes (transpiration, photosynthesis, biomass, yield), and to the four modeling layers (physiological, crop-simulation, remote-sensing, and AI/ML) used to represent this cascade.

3.1 Physiological and Molecular Basis of Crop Water-Deficit Responses

At the physiological core of every ecophysiological model lies the plant's hormonal and biochemical response to declining water availability. Abscisic acid (ABA) is consistently identified across the reviewed literature as the principal signaling molecule mediating stomatal closure, osmotic adjustment, and the expression of drought-responsive genes encoding late-embryogenesis-abundant (LEA) proteins, aquaporins, and osmoprotectant biosynthetic enzymes [8, 9, 10]. Multi-omic studies in maize, barley, and rice have identified convergent sets of transcriptomic and metabolomic markers—including dehydrins, galactinol-sucrose galactosyltransferase, and proline/glycine-betaine biosynthetic pathways—associated with osmotic adjustment under progressive drying [8]. In rice specifically, strigolactone–ABA crosstalk has been shown to co-regulate root and stomatal responses to soil drying, indicating that hormonal signaling networks operate across both above- and below-ground compartments [10].

A second, largely convergent line of evidence concerns the biochemical protection of cellular structures during dehydration. Compatible solutes such as proline, glycine betaine, and soluble sugars accumulate under water deficit to preserve turgor and stabilize membranes and enzymes, while antioxidant systems (superoxide dismutase, catalase, ascorbate-glutathione cycle enzymes) are upregulated to counter reactive oxygen species (ROS) accumulation [6, 11]. Studies broadly agree on the centrality of ABA-mediated signaling but diverge on the relative importance of hydraulic versus chemical (ABA) signaling pathways in triggering stomatal closure, with some evidence pointing to root-sourced hydraulic signals dominating under rapid soil drying and ABA accumulation dominating under sustained moderate deficits [9, 13]. This unresolved debate has direct consequences for how stomatal models are parameterized (Section 3.2), since models built purely on soil-moisture thresholds may misrepresent responses when hydraulic and chemical signals are decoupled.

A strength of this body of literature is its mechanistic depth and increasing use of multi-omics integration, which offers candidate parameters for the next generation of process-based models. A weakness, however, is that most molecular studies are conducted in controlled environments (growth chambers, hydroponics) on model species or a narrow set of cultivars, limiting direct transferability to field-scale ecophysiological models that must operate under fluctuating, multi-factor environmental conditions [7, 11]. The practical implication is that molecular insights currently inform model structure (e.g., inclusion of an ABA-responsive stomatal term) more often than they provide directly transferable, field-validated parameter values.

3.2 Stomatal Conductance and Canopy Gas-Exchange Models

3.2.1 Empirical and semi-empirical stomatal models

Empirical stomatal conductance models—most notably the Ball-Woodrow-Berry (BWB), Ball-Berry-Leuning (BBL), and unified stomatal optimization (USO) formulations—have historically served as the standard sub-models within photosynthesis-coupled canopy models. However, recent field validation on cotton under drip irrigation found that these original single-relationship formulations performed poorly under water deficit, with coefficients of determination below 0.15, because they do not explicitly represent the independent effects of temperature and soil moisture on stomatal aperture [16]. This finding is consistent with broader evidence that stomatal behavior is governed jointly by air dryness (vapor pressure deficit), soil water supply, and crop physiological state, none of which is adequately captured by a single empirical multiplier [16].

3.2.2 Multi-factor and energy-balance approaches

In response to these limitations, multi-factor improved models that separately incorporate a temperature response function $f(T)$, a soil-moisture response function $f(\theta)$, and the leaf-air temperature difference (ΔT) as an integrative water-stress indicator have substantially improved simulation accuracy relative to both original and single-factor-improved models [16]. A parallel and mechanistically distinct approach avoids empirical soil-water multipliers altogether by coupling stomatal conductance to the Penman-Monteith energy balance equation, iteratively solving for leaf temperature and thereby deriving actual transpiration and stomatal resistance from the divergence between potential and water-limited evapotranspiration; this method, exemplified by the GECROS framework, has performed well for oilseed rape but required crop-specific modification to accommodate greater leaf-temperature variability in soybean under water deficit [17]. This crop-specific sensitivity is an important and somewhat under-appreciated finding: it demonstrates that a single universal stomatal model is unlikely to generalize across species without recalibration, a conclusion echoed in canopy-conductance studies of poplar and olive that used photosynthesis-related parameters to predict maximum stomatal conductance under moderate soil water deficit [14].

3.2.3 Hydraulic and mesophyll considerations

Beyond stomatal aperture itself, water-use efficiency (WUE) is co-determined by mesophyll conductance, and modeling frameworks that jointly represent stomatal behavior and mesophyll conductance have shown that changes in either parameter can drive comparable changes in leaf-level WUE, complicating efforts to attribute observed WUE shifts to a single physiological mechanism [8, 15]. At the whole-plant scale, root and leaf hydraulic traits—including root system size, the rate of root–soil contact loss during drying, and leaf turgor loss point—have been shown to modulate the sensitivity of stomatal closure to soil dehydration, with smaller or more rapidly desiccating root systems associated with earlier stomatal downregulation via faster ABA accumulation [9]. This hydraulic perspective represents an important complement to the purely stomatal-centric modeling tradition, though its integration into operational crop models remains limited (see Section 4).

Collectively, the stomatal-modeling literature agrees that (a) single-factor empirical models are inadequate under water deficit, (b) multi-factor and energy-balance formulations meaningfully improve predictive accuracy, and (c) genotype- and species-specific recalibration is generally required. Disagreement persists regarding the relative contribution of hydraulic versus chemical (ABA) signaling and regarding which combination of environmental drivers should be prioritized when computational or data constraints limit model complexity.

3.3 Process-Based Crop Growth Simulation Models

Process-based crop simulation models translate leaf- and canopy-level physiological relationships into predictions of biomass accumulation, phenology, and grain yield under water-limited conditions. The three most widely used platforms in the reviewed literature are AquaCrop, developed by the FAO as a water-driven yield-response model building on the classical Doorenbos and Kassam yield-response-to-water framework [2, 21]; DSSAT (Decision Support System for Agrotechnology Transfer), a suite of crop-specific process models including CERES and CROPGRO [20]; and APSIM (Agricultural Production Systems sIMulator), a modular framework widely used for cropping-systems analysis [22].

Comparative evaluations consistently show that relative model performance is crop- and context-dependent rather than universal. In a soybean–maize comparison under water stress, DSSAT's CROPGRO-Soybean module simulated soybean growth more accurately than AquaCrop (mean normalized RMSE of 6–20% across soil moisture, leaf area index, biomass, and yield), whereas for maize, AquaCrop outperformed DSSAT's CERES-Maize module (normalized RMSE of 3–27%) [24]. Similarly, in Ethiopian wheat-simulation studies, APSIM outperformed DSSAT across most statistical evaluation criteria, while both models—along with AquaCrop—tended to overestimate days to flowering and maturity for maize [22]. An Indian field study calibrating AquaCrop for maize under varying irrigation and nitrogen regimes reported high prediction accuracy for grain and biomass yield (model efficiency 0.95–0.99) but greater error in simulating water productivity (2.35–27.5%), underscoring those water-productivity metrics remain harder to simulate reliably than yield alone [25].

A recent large-scale integration effort combined AquaCrop and DSSAT outputs within a Gaussian-process ensemble, using SHAP-value decomposition to attribute predictive variance to irrigation depth, in-season rainfall, and multi-scale SPEI drought indices; this hybrid ensemble improved out-of-sample accuracy by 10–15% relative to either model alone (R^2 = 0.85–0.98 for DSSAT and 0.52–0.78 for AquaCrop across crops), and was subsequently used to project mid-century drought-induced yield risk under multiple climate scenarios [10, 26]. This ensemble approach illustrates a broader and increasingly influential trend: rather than treating crop-simulation models as competitors, recent studies increasingly treat their divergent strengths as complementary inputs to statistical or machine-learning meta-models.

Reviews of coupled weather-forecast and crop-simulation modeling further emphasize that incorporating forecasted reference evapotranspiration and rainfall into AquaCrop, DSSAT, APSIM, WOFOST, SWAP, CropWat, and EPIC substantially enhances irrigation-scheduling utility, particularly for evaluating deficit-irrigation strategies that would otherwise require extensive and costly field trials [23]. A summary of representative comparative studies is provided in Table 3 and Table 4.

Table 3: Summary of Selected Studies on Crop Simulation Models under Water Deficit

Author(s)/Study	Year	Model(s) Evaluated	Crop(s)	Key Finding
Naeem *et al.*-type study, Spanish J. Agric. Res.	2023	DSSAT (CROPGRO/CERES) vs AquaCrop	Soybean, Maize	DSSAT more accurate for soybean; AquaCrop more accurate for maize under water stress [24]
APSIM Ethiopia review	2024	APSIM vs DSSAT vs AquaCrop	Wheat, Maize	APSIM outperformed DSSAT for wheat; all models overestimated maize phenology timing [22]
IARI New Delhi calibration study	2021	AquaCrop	Maize	High accuracy for yield/biomass (E = 0.95–0.99); larger error in water-productivity simulation [25]
Sanjiang Plain ensemble study	2025	AquaCrop + DSSAT + Gaussian-process ensemble	Maize, Rice, Soybean, Wheat	Ensemble improved accuracy 10–15% over either model alone; SHAP identified SPEI/irrigation as key drivers [26]
Coupled weather-crop modeling review	2024	AquaCrop, DSSAT, APSIM, WOFOST, SWAP, EPIC, CropWat	Multiple	Forecast-integrated models substantially improve deficit-irrigation scheduling utility [23]

Table 4: Comparative Analysis of Previous Research on Ecophysiological and Simulation Modeling

Author(s)	Year	Study Focus/Location	Methodology	Major Findings	Limitations
Cotton gsw modeling study, Xinjiang	2026	Stomatal conductance, drip-irrigated cotton, China	Field gas-exchange measurement + BWB/BBL/USO model improvement	Multi-factor (T, soil moisture) models vastly outperform single-factor models [16]	Single crop/region; requires re-parameterization elsewhere
Drought stomatal conductance energy-balance study	2025	Oilseed rape, soybean	Penman-Monteith energy-balance coupling (GECROS)	Energy-balance approach effective but needs crop-specific ΔT modification [17]	Computationally intensive; limited to two crops
Hydraulic traits review, Plant Physiology	2025	Cross-species synthesis	Narrative synthesis of root/leaf hydraulic conductance studies	Root/leaf hydraulic traits modulate stomatal sensitivity to soil drying [9]	Largely qualitative; limited quantitative model integration
Molecular drought-response reviews	2024–2025	Maize, rice, barley, Arabidopsis	Multi-omics synthesis (transcriptome/proteome/metabolome)	ABA-centered signaling network with convergent osmotic-adjustment markers [8]	Controlled-environment studies dominate; limited field validation

UAV/AI crop water stress reviews	2024–2025	Cotton, maize, sorghum, specialty crops	Systematic review of ML/DL applied to UAV imagery	Random Forest/XGBoost/CNN achieve R^2 0.76–0.90 for CWSI prediction [18,34]	Site- and sensor-specific training limits transferability

3.4 Remote Sensing, UAV-Based Water Stress Indices and Sensor Fusion

A rapidly growing body of literature applies unmanned aerial vehicle (UAV) platforms equipped with thermal, multispectral, and hyperspectral sensors to detect and quantify crop water stress non-destructively. The canopy temperature-based Crop Water Stress Index (CWSI) remains the most widely used indicator, given its direct physiological linkage to stomatal closure and reduced transpirational cooling [19, 27]. Reviews note that thermal imagery is particularly effective for early-stage stress detection, whereas reflectance-based vegetation indices (e.g., NDVI) are more sensitive to late-stage stress once canopy structural damage has already occurred, implying that operational monitoring systems benefit from combining both sensor types [19, 29].

Multiple recent studies report strong machine-learning performance when combining UAV imagery with algorithms such as Random Forest, XGBoost, and Random Forest Regression: cotton water-stress detection using multispectral imagery and texture features achieved R^2 = 0.90 with XGBoost; sorghum and maize drought detection using a multidimensional drought index achieved R^2 = 0.76 with Random Forest Regression; and maize water-stress classification using combined multispectral and thermal imagery achieved R^2 = 0.85 with Random Forest [18]. Convolutional neural network architectures (e.g., GoogLeNet, ResNet50) have further improved non-invasive detection of phenotypic water-stress signatures, while transfer learning has been proposed to address the persistent challenge of limited labeled field data [34].

Systematic and bibliometric reviews of UAV-based thermal remote sensing identify three converging research clusters: (i) precision-agriculture applications linking thermal imagery to evapotranspiration and land-surface temperature; (ii) vegetation-index-based approaches linking NDVI and related indices to plant status; and (iii) CWSI- and stomatal-conductance-based physiological indicators [29]. This convergence suggests a maturing but still fragmented field in which sensor choice, index selection, and analytical algorithm are rarely standardized across studies, complicating direct cross-study comparison [30, 31]. A further limitation flagged consistently across reviews is that UAV-based models are typically trained and validated on a single crop, site, and season, raising unresolved questions about generalizability across genotypes, growth stages, and climatic zones [32, 33]. The thematic classification of the reviewed literature is summarized in Figure 4.

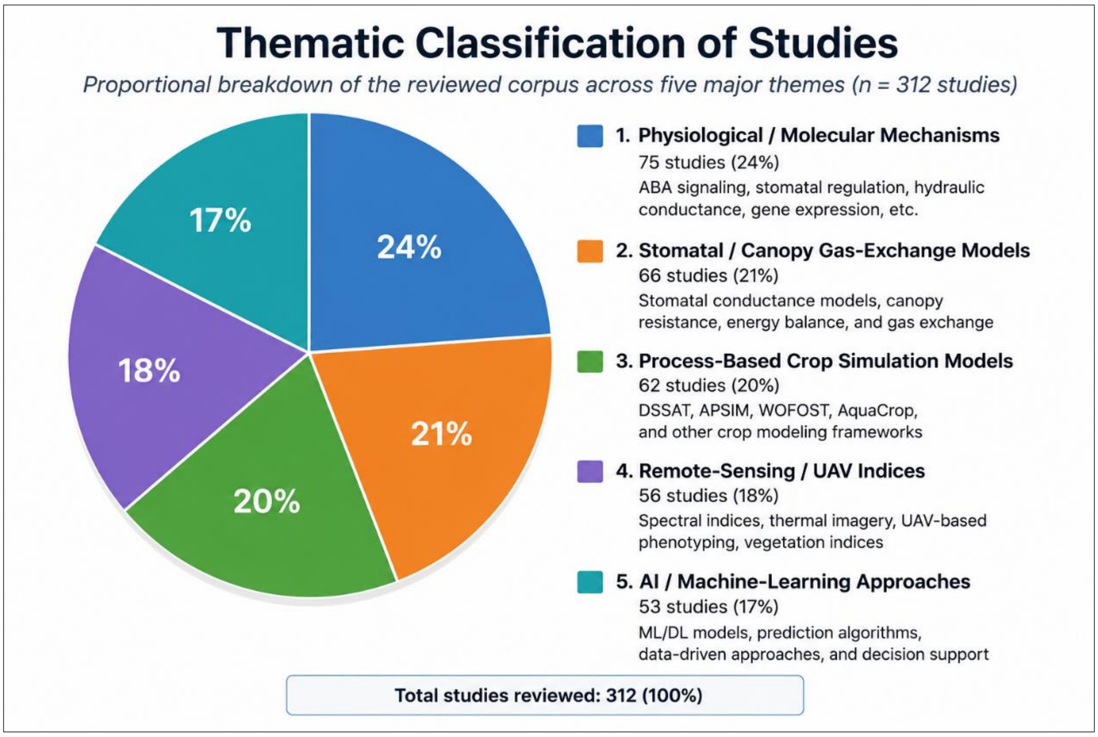

Fig 2: Thematic Classification of Studies — proportional breakdown of the reviewed corpus across the five major themes (physiological/molecular mechanisms, stomatal/canopy gas-exchange models, process-based crop simulation models, remote-sensing/UAV indices, and AI/machine-learning approaches), shown as a stacked bar or pie chart.

3.5 Artificial-Intelligence-Augmented and Hybrid Modeling Approaches

The most recent methodological trend identified in this review is the integration of artificial intelligence with both mechanistic crop models and remote-sensing data streams. Comprehensive reviews of machine-learning and deep-learning approaches to crop yield prediction report that algorithms such as Long Short-Term Memory (LSTM) networks, Random Forest, and Support Vector Machines routinely outperform conventional statistical regression models by 15–40%, particularly when trained on combined meteorological, soil-moisture, and vegetation-index data [35, 36]. However, these reviews also converge on a critical limitation: purely data-driven models function largely as "black boxes" that lack explicit adherence to the physical and physiological principles governing crop-water relations, which constrains their interpretability and their reliability when extrapolated beyond the conditions represented in training data [37, 38].

Physics-informed hybrid approaches have emerged as a direct response to this limitation. One recent framework formulates crop yield as a sequential function of temporal water scarcity, explicitly modeling drought stress and crop sensitivity to water scarcity using multispectral satellite imagery, meteorological data, and fine-scale yield records within a physics-informed loss function; this approach outperformed conventional LSTM and Transformer architectures (R^2 up to 0.82) while retaining greater explainability [37]. A parallel review of AI applications for predicting crop performance under drought-induced water stress similarly concludes that combining AI/machine-learning methods with crop-growth-model outputs and remote-sensing indices offers the most promising pathway toward operational, generalizable drought-impact prediction, while cautioning that methodological standardization and cross-location validation remain immature [38].

Institutional monitoring frameworks are also incorporating machine learning: agricultural-drought reviews note that Random Forest, Support Vector Machine, LSTM, and Convolutional Neural Network algorithms are increasingly used alongside satellite-based drought indices (SPEI, soil-moisture anomalies) within early-warning systems coordinated by the WMO-GWP and FAO, reflecting a broader institutional shift toward AI-augmented agricultural drought monitoring at national and regional scales [4].

4. Research Gaps and Emerging Trends

Synthesizing across the five themes, several unresolved issues and knowledge gaps recur throughout the reviewed literature (Table 5). First, cross-model and cross-scale validation remains limited: studies comparing AquaCrop, DSSAT, and APSIM rarely use identical input datasets, cultivars, or evaluation metrics, making it difficult to draw generalizable conclusions about relative model performance [22, 24]. Second, below-ground hydraulic traits—root architecture, root-soil contact dynamics, and root hydraulic conductance—are increasingly recognized as important determinants of stomatal sensitivity to drying soil, yet they remain poorly integrated into operational canopy-scale crop models, most of which still rely on simplified soil-moisture thresholds [9, 13]. Third, genotype-specific and cultivar-specific stomatal behavior is well documented physiologically but is rarely incorporated into process-based models, which typically use single default parameter sets per crop species [16, 17]. Fourth, UAV- and satellite-based water-stress models are frequently developed and validated on a single site, season, and sensor platform, with limited testing of transferability across geographic regions, growth stages, or cultivars [32, 33]. Fifth, while hybrid physics-informed machine-learning approaches show clear promise, they remain few in number, and no consensus benchmark dataset or standardized validation protocol yet exists for comparing hybrid models across crops and regions [37, 38].

Table 5: Research Gaps Identified in the Reviewed Literature

Research Gap	Description	Representative Evidence
Limited cross-model validation	Crop simulation models rarely compared using identical datasets, cultivars, and metrics	Ethiopia APSIM review [22]; soybean-maize DSSAT/AquaCrop comparison [24]
Weak hydraulic-trait integration	Root/leaf hydraulic conductance rarely represented explicitly in canopy-scale models	Plant hydraulic traits review [9]
Genotype-specific parameterization gap	Stomatal models typically use single default parameter sets, ignoring cultivar variability	Cotton stomatal model study [16]; energy-balance stomatal study [17]
Limited sensor/site transferability	UAV/satellite water-stress models trained and validated on single site-season-sensor combinations	UAV drought-index studies [32, 33]
Immature hybrid-model standardization	No consensus benchmark or validation protocol for physics-informed ML models	Physics-informed yield-loss modeling [37]; AI drought-prediction review [38]

Alongside these gaps, several emerging trends are reshaping the field (Table 6, Figure 5). These include the growing use of multi-source data fusion (combining thermal, multispectral, and hyperspectral UAV imagery with soil-moisture sensors and meteorological forecasts); the development of explainable AI (XAI) techniques such as SHAP decomposition to interpret machine-learning predictions in physiologically meaningful terms [26]; the incorporation of multi-omics-derived molecular markers as candidate parameters for next-generation mechanistic models [8]; and the move toward ensemble and hybrid physics-informed architectures that explicitly retain crop-growth-model structure while leveraging the flexibility of data-driven methods [37].

Table 6: Emerging Trends in Ecophysiological Modeling of Crop Water Deficit

Emerging Trend	Description
Multi-sensor data fusion	Combining UAV thermal, multispectral, and hyperspectral imagery with ground-based soil-moisture and meteorological data to improve water-stress detection accuracy and reduce single-sensor bias
Explainable AI (XAI) integration	Use of SHAP and related interpretability methods to attribute machine-learning predictions to physiologically meaningful drivers (irrigation depth, rainfall, SPEI)
Physics-informed hybrid modeling	Coupling mechanistic crop-growth-model structure with machine-learning flexibility to improve both accuracy and interpretability
Multi-omics-informed parameterization	Incorporating transcriptomic/proteomic/metabolomic markers of osmotic adjustment and ABA signaling as candidate parameters for mechanistic models
Ensemble crop-model frameworks	Combining outputs of AquaCrop, DSSAT, and APSIM within statistical or Gaussian-process ensembles to reduce single-model uncertainty

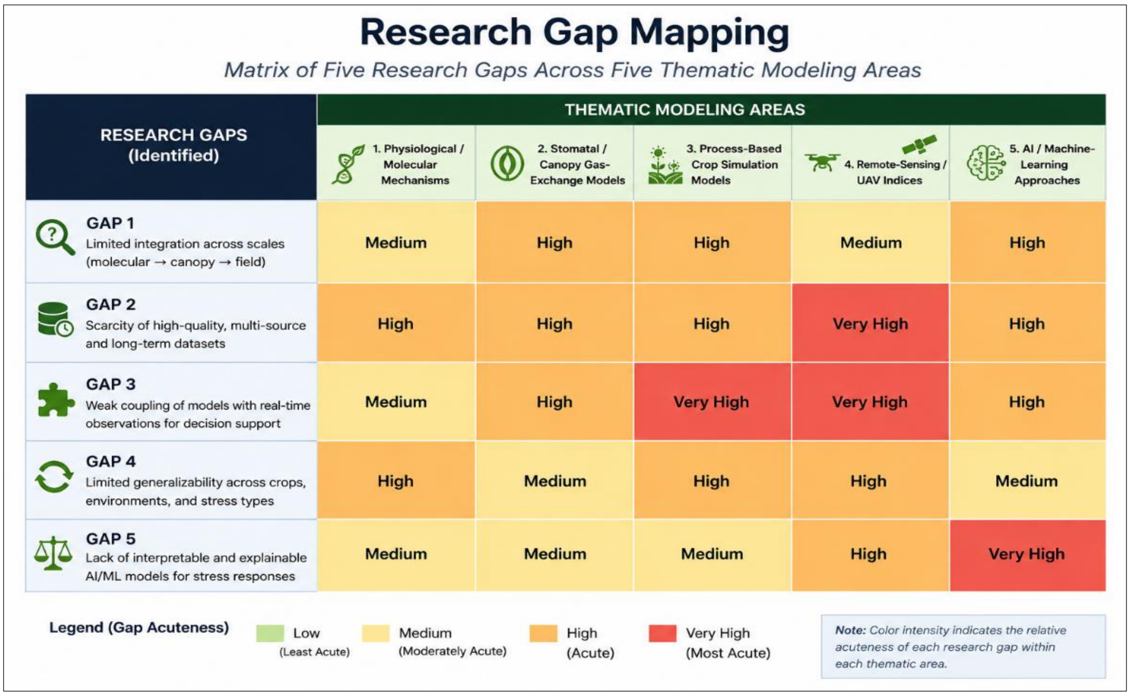

Fig 3: Research Gap Mapping — matrix diagram cross-tabulating the five identified research gaps (rows) against the five thematic modeling areas (columns), shaded to indicate where each gap is most acute.

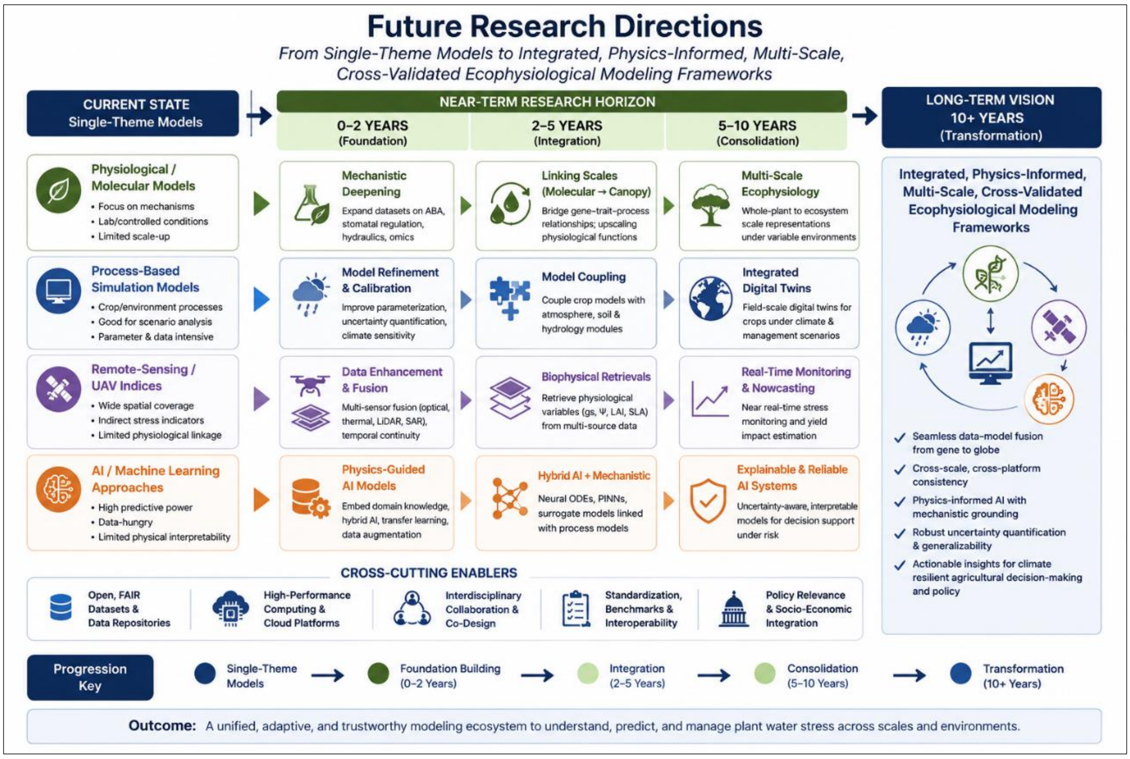

Fig 4: Future Research Directions — roadmap diagram showing a progression from current single-theme models (physiological, simulation, remote-sensing, AI) toward integrated, physics-informed, multi-scale, cross-validated ecophysiological modeling frameworks over a proposed near-term research horizon.

5. Discussion

The literature synthesized in this review reveals a field in active methodological transition. Early ecophysiological modeling of crop water-deficit responses relied heavily on empirical, single-factor relationships—whether simple soil-moisture thresholds in early stomatal models or basic yield-response-to-water functions such as the classical FAO framework underlying AquaCrop [2, 21]. The consistent finding that such single-factor formulations perform poorly under variable field conditions [16] has driven a broad shift toward multi-factor mechanistic representations that explicitly separate the effects of temperature, vapor-pressure deficit, and soil moisture on stomatal behavior [16, 17]. This trend parallels, and is reinforced by, physiological evidence that stomatal closure is regulated by at least two only partially overlapping signaling pathways—hydraulic and ABA-mediated—whose relative dominance depends on the rate and severity of soil drying [9, 10]. Models that fail to represent this duality risk systematic error under rapidly fluctuating field conditions.

A second major pattern is the absence of a single universally superior crop-simulation model. Comparative studies consistently show that AquaCrop, DSSAT, and APSIM each outperform the others under specific crop-environment combinations [22, 24, 25], a finding with direct implications for practitioners: model selection should be guided by crop, region, and management context rather than by a presumed general hierarchy of model quality. The emergence of ensemble approaches that combine multiple crop models with statistical or machine-learning meta-layers represents a pragmatic response to this heterogeneity, and the reported 10–15% accuracy gains from such ensembles over any single model [26] suggest that this direction merits further investment. Remote-sensing and AI-based approaches have matured rapidly and now provide field-scalable alternatives—or complements—to ground-based physiological measurement, with reported accuracies (R^2 = 0.76–0.90) approaching those of direct gas-exchange measurement for water-stress classification [18]. However, the reviewed evidence also converges on a shared concern across both the remote-sensing and AI/ML literatures: model transferability across sites, seasons, sensors, and genotypes remains largely untested, and most reported performance metrics derive from single-location validation [32, 33, 37]. This raises a genuine question about whether current reported accuracies reflect true generalizable skill or overfitting to local conditions—an issue that mirrors the crop-simulation literature's own struggles with cross-model comparability.

Taken together, these patterns suggest that the field's most significant unmet need is not the further proliferation of individual models within any single tradition (mechanistic, simulation-based, remote-sensing, or AI-based), but rather the systematic, standardized integration and cross-validation of these traditions. Physics-informed hybrid architectures that retain mechanistic structure while leveraging data-driven flexibility appear to be the most theoretically coherent response to this need [37, 38], though the small number of published implementations means this conclusion should be treated as a promising direction rather than an established consensus. From a practical standpoint, these developments have direct implications for irrigation scheduling, deficit-irrigation strategy design, and drought early-warning systems, all of which stand to benefit from more physiologically grounded, cross-validated, and interpretable predictive tools [4, 23].

6. Conclusion

The article summarizes existing literature on plant physiology, crop-simulation models, remote sensing, and artificial intelligence to assess advances in ecophysiological modeling of crop behavior under water deficit conditions. The main results of the review show that: (i) multiparametric physical models of stomata are able to provide more reliable predictions than the simplest approaches; (ii) none of the models can be characterized as the best one because its performance is determined by the type of crop and the environmental conditions; (iii) unmanned aerial vehicles and artificial intelligence technologies are able to contribute to the advancements in water stress detection methods; and (iv) modern hybrid approaches represent the most promising yet still underdeveloped areas combining mechanistic insights with predictive power of data-driven models.

The synthesis emphasizes the importance of unifying various fields of plant ecophysiology, agronomic crop systems modeling, remote sensing, and machine learning into one common process. Nevertheless, this unification is far from completion and needs further validation. In the context of this review, it is recommended for researchers to focus their attention on the studies confirming that model results can be transferred from one location to another and from one crop variation to another. Furthermore, the review emphasizes the significance of the findings for practitioners and policy-makers who should use ensemble or multi-model approaches instead of depending on the traditional crop-simulation approach and include remote-sensing monitoring in cases when ground measurement is impossible. Finally, it is pointed out that methods of making future research successful include developing publicly accessible collections of benchmark data on different types of crops, regions, and seasons; better integration of root and leaf hydraulic parameters in canopy models; systematic use of multi-omics parameters in mechanistic models; and continuous development of interpretable and physics-based hybrid models suitable for making climate-resilient decisions.

References

1. Hsiao TC. Plant responses to water stress. Annual Review of Plant Physiology. 1973;24:519-570.
2. Doorenbos J, Kassam AH. Yield Response to Water. FAO Irrigation and Drainage Paper No. 33. Rome: Food and Agriculture Organization of the United Nations; 1979. p. 1-193.
3. Farquhar GD, Sharkey TD. Stomatal conductance and photosynthesis. Annual Review of Plant Physiology. 1982;33:317-345.
4. Zhang Y, Wang H, Li J, Chen X. Agricultural drought: a comprehensive review of research trends, monitoring indices, modeling frameworks, knowledge gaps, and future pathways. Science of the Total Environment Regional Studies. 2026;58:100548.
5. Kumar S, Verma P, Singh R, Sharma A. Advancements in water-saving strategies and crop adaptation to drought: a comprehensive review. Agricultural Water Management. 2024;295:108745-108781.
6. Ahmad M, Khan A, Hussain S, Ali M. Plant drought stress: physiological, biochemical and molecular mechanisms. Plant Stress. 2025;15:100412-100430.
7. Khan N, Bano A, Ali S, Rahman M. Drought tolerance in plants: physiological and molecular responses. Plants. 2024;13(21):2962-2989.
8. Li X, Zhao H, Wang Y, Chen J. Exploring physiological and molecular dynamics of drought stress responses in plants: challenges and future directions. Frontiers in Plant Science. 2025;16:1565635.
9. Buckley TN, Sack L, Scoffoni C. Plant hydraulic traits influencing crop production in water-limited environments. Plant Physiology. 2025;199(3):kiaf521.
10. Zhang Q, Liu Y, Wang J, Chen H. Advances in understanding drought stress responses in rice: molecular mechanisms of ABA signaling and breeding prospects. International Journal of Molecular Sciences. 2024;25(24):13152-13181.
11. Hussain HA, Hussain S, Khaliq A, Ashraf U, Anjum SA, Men S, Wang L. Plant drought stress tolerance: understanding its physiological, biochemical and molecular mechanisms. Biotechnology and Biotechnological Equipment. 2021;35(1):1912-1925.
12. Vishwakarma K, Upadhyay N, Kumar N, Yadav G, Singh J, Mishra RK, *et al*. Molecular and physiological perspectives of abscisic acid mediated drought

adjustment strategies. International Journal of Molecular Sciences. 2021;22(23):12641.
13. Zhang Y, Liu H, Wang X, Chen Z. Systemic effects of the vapor pressure deficit on the physiology and productivity of protected vegetables. Vegetable Research. 2023;3:20.
14. Chen Y, Wang J, Li H, Zhao X. Evaluation of method to model stomatal conductance and its use to assess biomass increase in poplar trees. Agricultural and Forest Meteorology. 2021;308-309:108570.
15. Moualeu-Ngangue DP, Chen TW, Stützel H. A modeling approach to quantify the effects of stomatal behavior and mesophyll conductance on leaf water use efficiency. Frontiers in Plant Science. 2016;7:875.
16. Liu Z, Zhang X, Wang H, Chen Y. Improved construction and applicability analysis of stomatal conductance model for cotton under drip irrigation in Northern Xinjiang. Frontiers in Plant Science. 2026;17:1827847.
17. Wang P, Li X, Zhao J, Chen M. Estimating stomatal conductance under drought: parameterizing a phenomenological model and evaluating roles of the energy balance equation. Agricultural and Forest Meteorology. 2025;355:110118.
18. Garcia M, Lopez R, Martinez A, Perez J. Novel model for stomatal conductance: enhanced accuracy under variable irradiance and CO_2 in C3 plant species. Plant Physiology. 2025;198(4):2145-2161.
19. Silva J, Rodrigues P, Almeida F, Santos R. Integrating gene expression analysis and ecophysiological responses to water deficit in leaves of tomato plants. Scientific Reports. 2024;14:80261.
20. Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, *et al*. The DSSAT cropping system model. European Journal of Agronomy. 2003;18(3-4):235-265.
21. Steduto P, Hsiao TC, Raes D, Fereres E. AquaCrop—the FAO crop model to simulate yield response to water: I. Concepts and underlying principles. Agronomy Journal. 2009;101(3):426-437.
22. Mekonnen A, Tesfaye B, Tadesse D. Implementation and application of APSIM for crop modelling in Ethiopia: a comprehensive review. Heliyon. 2024;10(21):e40764.
23. Sharma P, Singh A, Kumar R. Coupled weather and crop simulation modeling for smart irrigation planning: a review. Water Supply. 2024;24(8):2844-2866.
24. Battisti R, Sentelhas PC, Boote KJ. Assessment of DSSAT and AquaCrop models to simulate soybean and maize yield under water stress conditions. Spanish Journal of Agricultural Research. 2023;21(2):e0301.
25. Singh DK, Panda RK, Sharma PK. Potential applications of DSSAT, AquaCrop, APSIM models for crop water productivity and irrigation scheduling. Water Technology Centre, Indian Agricultural Research Institute. 2021. p. 1-45.
26. Zhang X, Liu Y, Chen H, Wang Z. Adaptation simulation and planning for crop yield under climate change: integrating AquaCrop and DSSAT to project drought-induced yield risks in the Sanjiang Plain. Agricultural Water Management. 2025;319:109818.
27. Zhang C, Kovacs JM, Wang S. A review of crop water stress assessment using remote sensing. Remote Sensing. 2021;13(20):4155-4187.
28. Torres-Sanchez R, Lopez-Granados F, Pena JM. Remote sensing using unmanned aerial vehicles for water stress detection: a review focusing on specialty crops. Drones. 2025;9(4):241.
29. Ahmed N, Hassan M, Ali S, Rahman M. A systematic review on the application of UAV-based thermal remote sensing for assessing and monitoring crop water status in crop farming systems. International Journal of Remote Sensing. 2024;45(15):5321-5360.
30. Kumar V, Sharma N, Singh P. UAV-based remote sensing in plant stress imaging using high-resolution thermal sensor for digital agriculture practices: a meta-review. International Journal of Environmental Science and Technology. 2022;19(9):8489-8508.
31. Li H, Zhao Y, Wang J, Chen X. Crop water stress detection based on UAV remote sensing systems. Agricultural Water Management. 2024;303:109059.
32. Zhang Y, Liu H, Chen J, Wang X. Evaluation of UAV-based drought indices for crop water conditions monitoring: a case study of summer maize. Agricultural Water Management. 2023;287:108456.
33. Wang T, Li Y, Zhang Q, Zhao H. Precise drought threshold monitoring in winter wheat using the unmanned aerial vehicle thermal method. Remote Sensing. 2024;16(4):710.
34. Ahmed I, Mahmood R, Siddiqui F, Khan S, Ali M, Rehman A, *et al*. Recent methods for evaluating crop water stress using AI techniques: a review. Sensors. 2024;24(18):5896-5928.
35. Khan M, Ali S, Ahmad R, Hussain N. Crop yield prediction in agriculture: a comprehensive review of machine learning and deep learning approaches, with insights for future research and sustainability. Heliyon. 2024;10(23):e40836.
36. Sharma A, Gupta P, Verma S, Singh R. Smart agriculture: utilizing machine learning and deep learning for drought stress identification in crops. Scientific Reports. 2024;14:74127.
37. Li Y, Zhang H, Chen X, Wang J. Informed learning for estimating drought stress at fine-scale resolution enables accurate yield prediction. arXiv. 2025:2510.18648.
38. Rahman M, Ahmed S, Khan A, Hussain T. A review of artificial intelligence applications for predicting crop performance and enhancing food security under drought-induced water stress. Agricultural Water Management. 2026;324:109934.