Review

Integration of High-Throughput Water-Sensitive Phenotyping for Crop Water Demand Diagnosis: Technical Pathways, Research Progress, and Challenges

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Integration of High-Throughput Water-Sensitive Phenotyping for Crop Water Demand Diagnosis: Technical Pathways, Research Progress, and Challenges

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Abstract

Accurate diagnosis of crop water demand is a core challenge in alleviating agricultural water scarcity. Traditional diagnostic methods, which rely mainly on soil moisture sensor monitoring or empirical models based on meteorological data, suffer from limitations such as insufficient spatiotemporal representativeness and an inability to reflect crop physiological status in real time, leading to an annual water waste of 10–30%. Therefore, developing technologies that enable real-time, non-destructive, and precise monitoring of crop water status is crucial. In recent years, the rapid advancement of high-throughput phenotyping technology has provided revolutionary tools to address this challenge. By integrating multi-source sensors (e.g., thermal infrared and hyperspectral imaging), multi-dimensional response characteristics of crops under water stress can be rapidly acquired. This paper systematically reviews research progress in using high-throughput phenotyping to obtain water-sensitive phenotypic traits and construct crop water demand diagnosis models. It focuses on: (1) the connotation and acquisition techniques of key water-sensitive phenotypic indicators, such as canopy temperature, spectral indices, and chlorophyll fluorescence; (2) the advantages, limitations, and fusion strategies of multi-platform data acquisition systems, including unmanned aerial vehicles (UAVs), ground mobile platforms, and satellite remote sensing; and (3) the construction methods, performance evaluation, and practical application cases of diagnostic models based on machine learning (e.g., Random Forest, XGBoost), deep learning (e.g., CNN, LSTM), and mechanism-coupled models. The innovation of this review lies in its systematic integration of the entire technological chain—"phenotyping acquisition → model construction → decision-making"—while identifying current research challenges, including field environmental complexity, model generalization capability, data barriers, and interpretability. Future development pathways are proposed, focusing on low-cost sensing, explainable AI, multi-source data fusion, and cloud-edge collaborative decision systems. This review aims to provide a systematic theoretical and practical reference for water management in precision irrigation and smart agriculture.

Keywords: machine learning; multi-sensor fusion; precision irrigation; smart agriculture; water-sensitive phenotyping

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1. Introduction

Global agricultural water use accounts for over 70% of total freshwater consumption, while climate change exacerbates the spatiotemporal unevenness of water resources, leading to inefficient irrigation. Therefore, developing precise and efficient crop water demand diagnosis technologies is crucial for smart agriculture. Traditional crop water demand diagnosis methods include soil physical parameter diagnosis based on the Soil-Plant-Atmosphere Continuum (SPAC) theory and empirical

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model estimation based on meteorological data, such as the Penman-Monteith equation [1]. However, in obtaining soil physical parameters with sensors, the representativeness of soil monitoring points is limited, while sensors cause certain damage to the soil but are still difficult to reflect the real water absorption status of the root system [2]. In addition, empirical models for estimations are highly dependent on local parameters, rely on experience, and often lag behind the actual physiological needs of crops. These methods cannot capture real-time physiological changes, leading to biased irrigation decisions. As a result, annual water waste reaches 10-30%[3]. According to relevant agricultural economic research estimates, the annual global direct economic losses caused by yield reduction and inefficient water utilization due to irrigation decision-making deviations in wheat, rice, corn, and other top three staple crops alone have exceeded 10 billion US dollars. Therefore, there is an urgent need to develop direct diagnostic technologies based on crop water response signals, for which high-throughput phenotyping offers a groundbreaking solution. The high-throughput phenotyping technology, leveraging advanced sensors and automated platforms, can quickly obtain multi-dimensional physiological and morphological response characteristics of crops under water stress, namely water-sensitive phenotypes, and then construct crop water demand diagnosis models, enabling rapid, non-destructive, and automated acquisition of multi-dimensional crop traits[4].

In recent years, several reviews have explored crop water monitoring technologies. For instance, Jones systematically summarized plant physiological response mechanisms but did not address high-throughput phenotyping technologies[5]. Paoletti et al. reviewed hyperspectral imaging and deep learning without linking them to practical demands for water stress diagnosis[6]. Klompenburg et al. (2020) examined machine learning for yield prediction but neglected water-specific modeling[7]. Previous studies have limitations. For example, they did not fully explore the potential of multi-sensor data fusion, overlooked the challenges of generalizing machine learning models in complex field conditions, and lacked discussion on cost-effective solutions. Since 2020, sensor costs have decreased significantly while their performance has improved[8]. With the advancement of AI, real-time processing of complex phenotyping data has now become feasible. Additionally, field validation studies have accumulated sufficient evidence to evaluate technology readiness levels. Nevertheless, none of the existing review articles have addressed these parallel advancements. Therefore, there is an urgent need for a comprehensive review systematically covering phenotype acquisition, model construction, and practical implementation.

This review is motivated by three critical imperatives: the growing urgency to reduce agricultural water waste amid escalating water scarcity, recent technological breakthroughs in phenotyping that enable plant-based water diagnostics, and the absence of a comprehensive framework integrating these advances into practical irrigation solutions. With particular emphasis on the transformative role of high-throughput phenotyping in water management, we establish direct linkages between quantifiable plant responses and irrigation decision-making, thereby facilitating a paradigm shift from soil-based to plant-based diagnostic approaches. In this study, we make several unique contributions to diagnosing crop water demand using high-throughput phenotyping technology, addressing existing research gaps. We systematically integrate multi-sensor technologies and data fusion strategies to establish a comprehensive water-sensitive phenotyping acquisition system, bridging the gap between laboratory research and field application. Innovatively, we construct a multidimensional "phenotype–physiology–environment" correlation framework to elucidate the response mechanisms of key water-sensitive phenotypic indicators to water stress, enhancing the physiological interpretability of phenotypic data. We thoroughly compare and evaluate various modeling approaches, with a focus on tackling the generalization challenges of data-driven models in complex field environments and proposing pathways for improving model robustness. Finally, within the context of large-scale technology application, we specifically analyze cost-effective implementation scenarios and provide practical roadmaps, which are expected to facilitate the transition of high-throughput phenotyping technology from theoretical research to precision irrigation practices. Together, these contributions fill the research gap in the integrated analysis of the complete “phenotypin–modeling–decision-making” chain and offer a new paradigm for water resource management in smart agriculture.

2. Connotation and Scope of Water-Sensitive Phenotypes

2.1. Physiological and Biochemical Responses of Crops Under Water Stress

When crops are subjected to water stress, they will give a series of adaptive responses from the molecular level to the plant level. Water deficit first causes partial stomatal closure to reduce crop transpiration and water loss, while leading to limited CO_2 supply, thus inhibiting crop photosynthesis and reducing the photosynthetic rate [9]. Crops will accumulate osmoregulatory substances such as proline and soluble sugars to maintain their cell osmotic potential [10]. The abscisic acid signaling pathway is activated, and the root system will synthesize and transport ABA to the leaves through the xylem to induce stomatal closure [11]. Cell membrane stability may decrease, while membrane lipid peroxidation leads to increased electrolyte leakage [12-13]. These internal physiological and biochemical response processes need to be captured through external phenotypic indicators [14].

2.2. Key Water-Sensitive Phenotypic Indicators

Water-sensitive phenotypes are "visualized" indicators of crop responses to water stress, which are ultimately reflected in observable or measurable phenotypic changes. Identifying and quantifying water-sensitive phenotypic indicators that are highly sensitive to water changes and easy to obtain with high throughput is the basis for constructing diagnostic models.

In terms of the morphological structure, leaves are one of the most sensitive organs of crops. Water stress often leads to increased leaf angle or curling, which tends to be vertical to reduce light absorption and heat load, loss of cell turgor, leaf wilting, inhibition of leaf area expansion, limited cell division and expansion, and smaller new leaves, decrease in leaf area index (LAI) and canopy coverage [15]. Root architecture is an important underground response, including root length, density, and depth. Magnetic resonance imaging (MRI) can obtain root architecture phenotypic indicators through non-invasive three-dimensional imaging, which can simultaneously obtain the root structure and water transport dynamics. It can realize in vivo continuous monitoring with a time resolution of about 1 hour, and has outstanding visualization ability for deep roots (>50 cm), but its cost is high, which hinders its field application [16].

In terms of crop physiological functions, crop canopy temperature is currently the most widely used water-sensitive phenotype. When transpiration is weakened due to stomatal closure, leaves cannot effectively cool through transpiration, resulting in a significant rise in canopy temperature and an increase in the Crop Water Stress Index (CWSI). CWSI is used to quantitatively characterize water stress [17]. The thermal infrared imaging technology can quickly, dynamically, and multi-scale observe and obtain this key information, and calculate CWSI accordingly [18]. The spectral reflection characteristics of leaves and canopies are extremely sensitive to water status. Water stress will lead to changes in leaf internal structure and a decrease in water content, significantly affecting the reflection and absorption in the near-infrared and short-wave infrared bands. Vegetation indices such as the Normalized Difference Water Index (NDWI), Water Index (WI), and Photochemical Reflectance Index (PRI) [19-21] are widely used to indicate water status. The hyperspectral imaging technology can more timely and non-destructively capture the finer water absorption characteristics of leaf water in different bands, to invert quantitative indicators such as leaf equivalent water thickness [22]. Finally, the photosynthetic apparatus is very sensitive to water stress, and chlorophyll fluorescence parameters are key indicators reflecting the physiological state of plant photosynthesis. Water stress will reduce the maximum photochemical efficiency (Fv/Fm) and actual quantum efficiency of PSII in the photosynthetic system, which can be indirectly evaluated by measuring the fluorescence signal emitted by chlorophyll molecules under light excitation [23]. Notably, recent research has demonstrated that the strength of the relationship between this fluorescence signal

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(particularly Sun-Induced Chlorophyll Fluorescence, SIF) and photosynthesis is significantly influenced by sensor viewing geometry, whereby hemispherical measurements can more reliably reflect the photosynthetic physiological status compared to nadir observations[24]. The chlorophyll fluorescence imaging technology can realize early diagnosis, spatial resolution, and multi-parameter synchronous measurement.

An ideal water-sensitive phenotypic indicator should not only exhibit high sensitivity and rapid response to water deficit but also be suitable for high-throughput field deployment. This includes having a short lag time between the onset of stress and phenotypic expression, a wide dynamic range for clear signal detection, high measurement repeatability, and strong correlation with underlying physiological processes as well as final yield or quality metrics[25-26]. However, a significant challenge lies in the inherent difficulty of simultaneously satisfying all these desirable traits. For instance, physiological indicators such as canopy temperature and spectral indices respond quickly but are susceptible to interference from environmental factors such as wind speed, solar radiation, and cloud cover[27-28]. Morphological traits like leaf wilting are visually intuitive but often emerge later than physiological changes, reducing their utility for early stress detection. Furthermore, although root architecture is a fundamental response to water stress, obtaining high-throughput, non-destructive phenotypic data from the root zone remains one of the most persistent and prominent challenges in the field[29-30].

3. High-Throughput Water-Sensitive Phenotype Acquisition Platforms and Technologies

Phenotype-based water demand diagnosis depends on technical means for efficient, accurate, and large-scale acquisition of water-sensitive phenotypic indicators.

3.1. Platform Types

In recent years, unmanned aerial vehicles (UAVs) has developed rapidly, so UAV platforms have become the main force for field high-throughput phenotype acquisition. They play a vital role in crop phenotype research thanks to their high flexibility, ability to quickly cover large fields, and ability to carry different types of sensors. UAV platforms equipped with RGB imaging sensors have a lower cost and can detect growth status, but can only process visible phenotypes. Whereas, those equipped with infrared imaging sensors can be used for thermal imaging monitoring of physiological status but have a higher cost and complex integration. In contrast, those equipped with hyperspectral sensors can provide fine spectral information, but have a large data volume and difficult processing [31-32].

Ground mobile platforms are widely used in phenomics facilities and small to medium-sized fields. For example, the cart-mounted Phenocart and tractor-towed BreedVision can dynamically monitor crop water status with self-contained sensors and are less affected by environmental factors such as wind. They are able to provide stable measurements closer to the canopy [33], yet less efficient than UAV platforms. At the higher end of technological sophistication, fully automated gantry systems like the Field Scanalyzer provide unparalleled data quality and throughput for precise phenotyping in field plots, albeit at a significant cost[34].

Satellite remote sensing has become an important tool for agricultural monitoring leveraging its large-scale coverage and periodic observation characteristics. It can provide crop growth status at different spatial scales, and obtain key parameters such as canopy reflectance, temperature, and soil moisture by carrying sensors in different bands to invert crop growth status and water stress. Satellites such as Sentinel-2 [35] have incorporated spatial, temporal, and spectral capabilities unprecedentedly, and play a more important role in regional water monitoring [36]. However, they are affected by cloud interference and acquire instantaneous data, but are difficult to capture the diurnal dynamic changes of water status.

Fixed field monitoring networks are important means to obtain accurate data in agricultural production and ecological research. Combining flux towers, automatic weather stations, and deploying spectral or thermal imaging sensors, they can realize continuous monitoring of specific points and provide valuable time-series data [37].

3.2. Sensor Technologies

In the following, core sensor technologies will be introduced., The thermal infrared imaging technology is mainly based on the infrared radiation characteristics of objects to obtain canopy surface temperatures for calculating CWSI. The hyperspectral imaging technology can capture fine spectral reflection characteristics and becomes a key technology for inverting leaf water content, and chlorophyll content[38]. Multispectral cameras can obtain limited spectral bands and calculate vegetation indices, while RGB cameras are low-cost sensors that can be used with data processing software are becoming more and more miniaturized, weighing only 100g with red, green, and near-infrared spectral bands, for instance [39-40]. Light Detection and Ranging (LiDAR) technology has high resolution and can quickly and non-destructively record a large amount of three-dimensional data [41], to analyze plant height, canopy structure parameters, and biomass to indirectly reflect crop growth status and potential water stress effects. In addition, the chlorophyll fluorescence imaging technology is mainly found in facility environments or ground platforms to provide spatial distribution information of photosynthetic functions. Besides, the MRI magnetic resonance imaging technology has been described in 2.2 above. The comparison of sensor performance is summarized in Table 1.

Table 1. Sensor Technical Performance Comparison Chart.

Sensor Technology	Primary Function	Advantages	Limitations	Application Scenarios
Thermal infrared imaging	Measures canopy temperature and calculates CWSI	Real-time transpiration monitoring, highly sensitive to water stress	Susceptible to environmental conditions, relatively high cost	Field-based water stress diagnosis, precision irrigation decisions
Hyperspectral imaging	Captures detailed spectral reflectance features; estimates leaf water content and chlorophyll levels	Provides multi-band data for quantitative biochemical analysis, non-destructive	Large data volume, complex processing, expensive equipment	Laboratory research and controlled environments
Multispectral camera	Acquires limited spectral bands for vegetation index calculation	Cost-effective, user-friendly, suitable for large-scale monitoring	Lower spectral resolution than hyperspectral imaging, limited information depth	Field crop growth monitoring
RGB camera	Captures visible spectrum images for morphological analysis	Low-cost, lightweight, easily deployable on automated platforms	Limited to visible spectrums, cannot directly reflect physiological status	Crop growth monitoring, early disease detection
LiDAR	3D modeling for measuring height, canopy structure, and biomass	High resolution, unaffected by lighting, penetrates into canopy for substructure analysis	Complex data processing, limited deep root monitoring capability	Crop height dynamics, canopy architecture analysis

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Chlorophyll fluorescence imaging	Detects photosynthetic efficiency for early water stress diagnosis	High sensitivity for early stress detection, excellent spatial resolution	Requires dark adaptation, complex field operation, expensive equipment	Controlled environments and ground-based platforms
MRI	Non-invasive 3D imaging of root architecture and water transport dynamics	Enables continuous in vivo monitoring, visualizes deep roots (>50cm)	Extremely high cost, limited field applicability, temporal resolution of approximately 1 hour	Root phenotyping research

At present, multi-sensor fusion is a development trend, including RGB and LiDAR sensor fusion, hyperspectral and LiDAR fusion, and fluorescence-thermal imaging combined technology.[42-44]. In this way, data from different sensors will be combined, complemented and verified, significantly improving the comprehensiveness and accuracy of diagnosis.

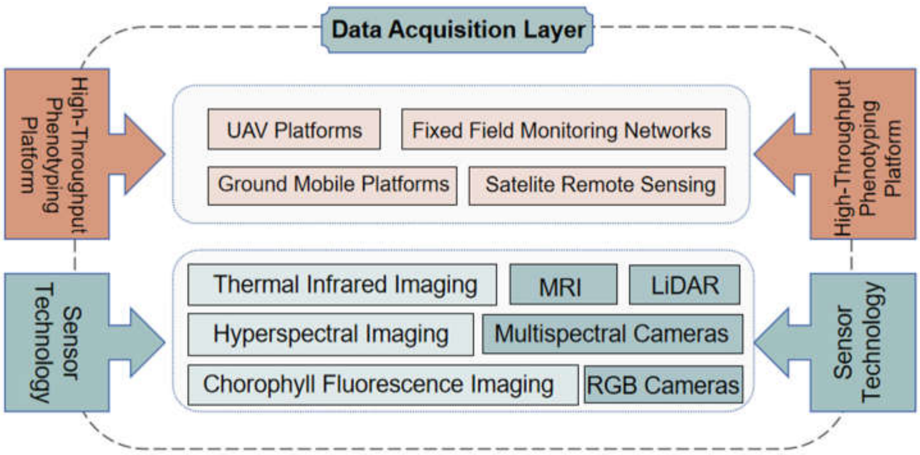

Figure 1. Architecture of High-Throughput Water-Sensitive Phenotyping Acquisition System.

3.3. Data Processing and Feature Extraction

Following data acquisition via multi-source sensors, a high-throughput water-sensitive phenotyping platform requires a sophisticated and systematic data processing workflow to transform raw data into analyzable features[45]. First, image preprocessing is essential to ensure data quality and consistency. This includes radiometric calibration (converting digital values to physical units such as radiance or reflectance) to correct for sensor-specific errors and variations in illumination conditions; geometric correction to eliminate distortions caused by optical systems and platform motion; panoramic stitching, particularly for platforms like UAVs, to create composite images covering large field areas; and denoising algorithms to improve the signal-to-noise ratio (SNR), a step especially critical for hyperspectral and thermal infrared data[46-48].

Subsequent feature engineering involves extracting meaningful information related to water stress. This includes calculating established vegetation indices, which serve as effective proxies for water content and photosynthetic efficiency[49]. For high-dimensional data like hyperspectral imagery, spectral feature selection and dimensionality reduction are crucial to avoid the "curse of dimensionality" and highlight informative wavelengths[50]. Techniques such as Principal Component Analysis (PCA) transform correlated spectral bands into uncorrelated principal components, while Partial Least Squares (PLS) regression directly models the relationship between spectral data and target variables. Additionally, texture features and morphological features provide complementary information on stress-induced structural changes[51]. Analysis of canopy

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temperature distribution from thermal infrared data goes beyond average temperature by utilizing statistics from temperature histograms to capture spatial heterogeneity of stress within the canopy[52].

For 3D phenotypic data acquired via LiDAR or stereo imaging, point cloud data undergo registration and surface reconstruction to generate 3D mesh models of plants. This enables the quantification of key canopy stereostructural parameters—such as plant height, canopy volume, leaf angle distribution, and gap fraction—which are indirectly related to water status and transpiration rates[53-54]. Similarly, for root systems, the MRI data processing workflow involves segmenting the root system from the soil background to quantify root architecture parameters, including total root length, root volume, and depth distribution. This multi-tiered processing pipeline allows for the standardized and automated extraction of water stress-related features from heterogeneous raw data, providing reliable multi-dimensional data support for building accurate diagnostic models[55-56].

4. Construction of Crop Water Demand Diagnosis Models

4.1. Crop Water Demand Diagnosis Models Based on Water-Sensitive Phenotypes

After obtaining high-quality water-sensitive phenotype data, it is necessary to construct appropriate models to convert them into diagnostic information that can guide irrigation. Such models should be able to determine whether crops are under water stress and evaluate the severity of stress if any, combine historical phenotype data and environmental forecasts to predict crop water demand in the short term, and estimate key variables difficult to measure, such as leaf water potential.

There are various modeling methods. First, the empirical statistical models, whose core is to establish a statistical relationship between water-sensitive phenotypic indicators and measured crop water status to diagnose crop water demand, mainly including regression analysis and threshold methods based on vegetation indices or canopy temperature[57]; they are simple and intuitive with a low calculation cost, yet with limited nonlinear fitting ability , and poor universality among different environments or crop varieties[58].

Second, the machine learning (ML) models have become a core tool in modern water demand diagnosis due to their strong nonlinear fitting capabilities and advantages in processing high-dimensional, multi-source data[59]. Their applications can be categorized based on task type as follows: For qualitative diagnosis, classification algorithms are primarily used. Support Vector Machines (SVM) perform well in high-dimensional spaces and are particularly suitable when the number of features exceeds the number of samples. Random Forest (RF), as an ensemble method, reduces overfitting by averaging the results of multiple decision trees, while also enabling effective evaluation of feature importance, which is crucial for identifying the most responsive phenotypic indicators[60]. Although the K-Nearest Neighbors (KNN) algorithm is simple in principle, it incurs high computational costs when processing large datasets. The Naive Bayes classifier offers a probabilistic approach that is efficient for preliminary analysis. In quantitative prediction, regression algorithms dominate. Ensemble methods such as Gradient Boosting (e.g., XGBoost, LightGBM) often achieve state-of-the-art results by sequentially correcting errors from previous models, demonstrating high accuracy and efficiency[61]. Artificial Neural Networks (ANNs), with their multi-layer structure, are capable of learning complex relationships between inputs and outputs[62]. Rotation Forest [63], as another ensemble technique, enhances model diversity and performance. A notable advantage of many machine learning models is their inherent ability to rank input features by importance. This functionality is widely used to identify the most informative water-sensitive phenotypic indicators from a large set of potential variables, thereby optimizing data collection strategies and improving model interpretability[64]..

Third, deep learning models show great potential in feature learning and complex spatiotemporal data processing, especially suitable for processing complex multi-source heterogeneous data. To be precise, convolutional Neural Networks (CNN) are perfect for processing image data, as they can automatically extract spatial-spectral features from RGB, thermal infrared, multispectral, or hyperspectral images to achieve accurate classification of water stress [65-66]. Recurrent Neural Networks/Long Short-Term Memory Networks (RNN/LSTM) are good at processing time-series data. Continuous multi-day phenotype monitoring data can be input into RNN/LSTM to capture the dynamic evolution law of crop water status and realize predictive diagnosis [67]. Fusion models such as CNN-RNN/LSTM architecture can further integrate spatial and temporal information to provide more comprehensive diagnosis.While deep learning models demonstrate powerful performance, they require substantial labeled data for training. However, field-collected phenotypic data often suffer from insufficient effective samples due to the high costs of annotation, leading to degraded model performance. Additionally, the interpretability challenges of these models hinder their acceptance in agricultural practice[68].

Fourth, physiological mechanism-coupled models are to use high-throughput obtained water-sensitive phenotype data as input or assimilation variables. Through combining with mechanism models based on physical processes of crop growth and development and water transport, such as the Soil-Plant-Atmosphere Continuum (SPAC) model, they could improve the simulation accuracy and prediction ability for water stress with the data assimilation or parameter optimization methods. They not only retain the physical interpretability and extrapolation ability of the mechanism model but also make up for the defect that traditional models are insufficient in depicting real-time environmental responses through phenotype data. However, they are more complex, and their parameter sensitivity varies greatly.

The input of the models usually includes one or more water-sensitive phenotypic indicators, environmental factors such as air temperature, humidity, photosynthetically active radiation (PAR), wind speed, crop parameters such as crop variety and growth period, and sometimes information on initial soil conditions. Their output should consider the model objectives, including crop stress status labels, crop stress grade labels, water demand index, recommended irrigation amount, and estimated leaf water potential, and actual evapotranspiration [69].

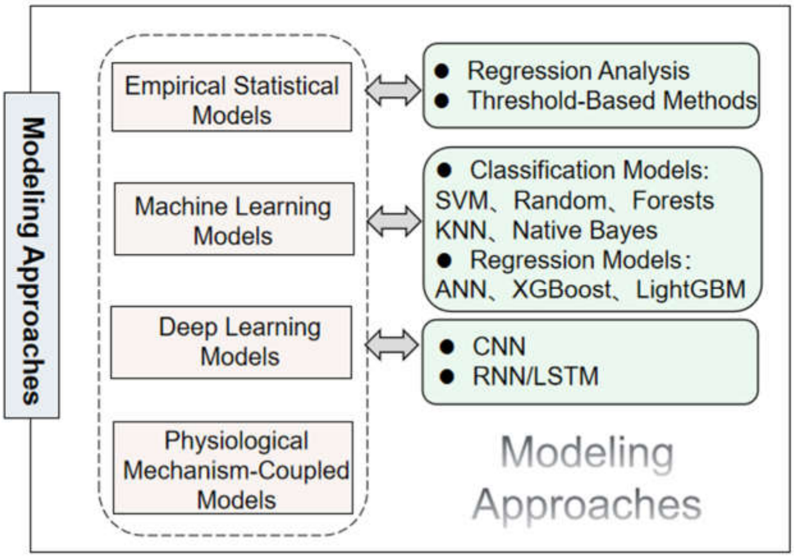

Figure 2. Taxonomy and Modeling Approaches for Crop Water Demand Diagnosis.

In recent years, high-throughput water-sensitive phenotyping technology has proven its effectiveness across multiple practical applications. For instance, Tang et al. employed UAV-mounted hyperspectral sensors to monitor water stress in tomato fields, achieving precise leaf water potential prediction (R^2=0.89) by combining the Photochemical Reflectance Index (PRI) with XGBoost regression models, a 23% accuracy improvement over traditional canopy temperature-based CWSI methods.This technology has been piloted in California, where cloud-based models deliver real-time irrigation recommendations to farmers via smartphones, reducing diagnostic delays, demonstrating

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the technical maturity for transitioning from research to practice. For producers seeking immediate implementation, cost-effective solutions include smartphone-based thermal imaging (capturing canopy temperatures at dawn/dusk with automated CWSI calculation triggering irrigation alerts when >0.6, achieving >80% accuracy for small farms), drone-mounted multispectral cameras for monthly NDWI mapping with cloud-generated stress maps, or cooperatively owned field monitoring stations that share data costs while delivering group alerts via mobile platforms[34,40,70].

4.2. Model Validation and Evaluation

Model validation and evaluation should emphasize the reliability of validation data, the comprehensiveness of evaluation indicators, and the systematicness of validation strategies. The performance of the constructed model needs to be strictly validated using independent, high-quality ground-measured data to ensure its accuracy. Commonly used validation data include leaf water potential, transpiration, actual evapotranspiration, representative soil moisture sensor data, and final yield and quality data. For classification-related problems, indicators such as accuracy, F1 score, and AUC value can be used to evaluate the ability to distinguish stress status. For regression-related problems, the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) are employed to quantify prediction accuracy[69,71]. In addition, the Nash-Sutcliffe efficiency coefficient (NSE) is introduced to evaluate model robustness. In terms of validation strategies, in-situ field validation, as the most direct validation method, can truly reflect the performance of the model in actual agricultural production. Considering the impact of differences in water responses between C3 and C4 crops, in addition to independent test sets and cross-validation, it is also necessary to test the robustness and universality of the model in different locations, years, and crop varieties, and finally combine real-time field performance to provide a scientific basis for precision irrigation decisions[72]. See Table 2 for details.

Table 2. Key Performance Evaluation Metrics for Water-Sensitive Phenotype-Based Crop Water Demand Models.

Category	Metrics	Definition	Target Range
Classification	Accuracy	Proportion of correctly classified instances	⩾0.7 (acceptable), ⩾0.9 (excellent)
	F1-score	Harmonic mean of precision and recall	⩾0.7 (balanced), ⩾0.9 (excellent)
	AUC-ROC	Area under the receiver operating characteristic curve	0.7-0.8 (fair), 0.8-0.9 (good), ⩾0.9 (excellent)
Regression	R^2	Coefficient of determination	⩾0.6 (acceptable), <0 indicates invalid
	RMSE	Root mean square error	Closer to 0 preferred (units dependent)
	MAE	Mean absolute error	Robust to outliers; direct error interpretation
	NSE	Nash-Sutcliffe efficiency coefficient	⩾0.6 (acceptable), ⩾0.8 (good), ⩽0 invalid
Robustness	CV(NSE)	Coefficient of variation of NSE across cross-validation folds	<15% indicates stability

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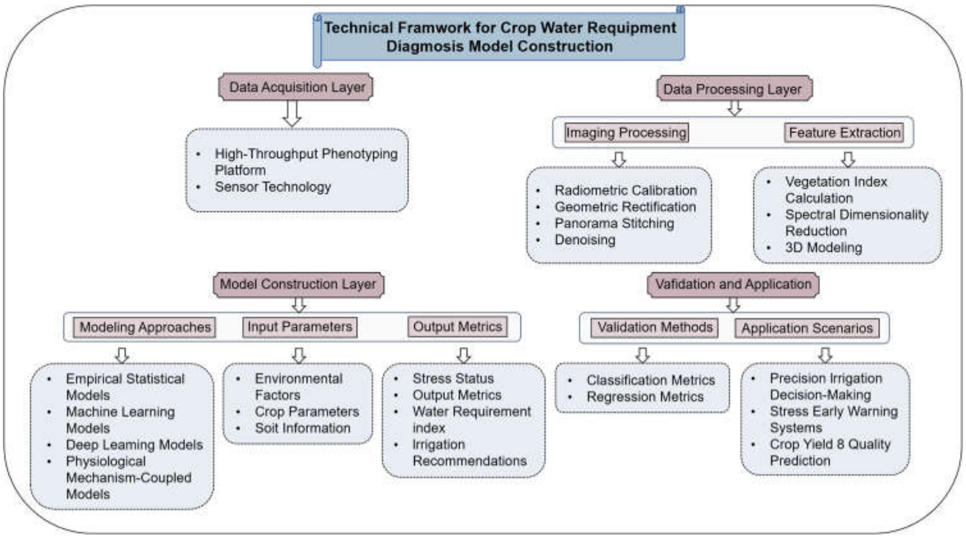

Figure 3. Technical Framework for Constructing Crop Water Demand Diagnosis Model.

5. Challenges and Future Directions

Although this technology is superior in being real-time and non-destructive, it still faces many challenges. Specifically, the complexity of the field environment places high demands on sensor accuracy and data processing algorithms, while high-precision sensors and platforms are still costly. Besides, sensor operation and data analysis require professional knowledge, thus limiting large-scale promotion of this technology. For example, a single MRI root imaging system costs over 2 million yuan and requires specialized sample pretreatment, limiting its application to laboratory research only[73]. Non-destructive acquisition methods for high-throughput water-sensitive phenotypes of underground roots are still a key challenge. In addition, massive data storage, transmission, processing, and analysis also require strong computing infrastructure and efficient algorithms. The high-dimensional nature of hyperspectral data demands substantial computational resources for analysis, particularly for GPU-accelerated deep learning models (e.g., convolutional neural networks, CNNs). Meanwhile, the prohibitive costs and maintenance requirements of GPU hardware compel small-scale farmers to rely on third-party cloud computing services, significantly increasing production costs [74]. Biologically, crop water stress responses are strongly affected by genotypes, environmental conditions, and management measures, resulting in decreased model performance when applied to different crops in different regions. Crops have different sensitivities to water and response phenotypes at different growth stages, so that the model is restricted by the complexity of such growth periods[75]. It is also important to distinguish phenotypic changes caused by water stress from signals of other stresses such as nutrient deficiency, pests and diseases, high temperature, or normal physiological changes. Understanding how phenotypic responses ultimately translate into yield and quality losses still requires in-depth research[76]. Constructing models with strong generalization ability and high robustness requires large-scale, high-quality, and well-annotated public datasets covering a wide range of conditions, which are still unavailable. Models for real-time field applications need to optimize computing efficiency and consider the possibility of deployment on edge devices. How to effectively integrate the strong learning ability of data-driven models with the physical interpretability and extrapolation ability of mechanism models is a fusion paradigm we need to explore[77].

Future research should focus on advancements in several key areas. First, hardware innovation and cost reduction are essential. Efforts should prioritize developing more robust, low-cost, and intelligent phenotyping sensors and autonomous platforms. This includes miniaturizing sensors and enhancing their weather resistance to withstand harsh field conditions, as well as leveraging smartphone-based imaging and Internet of Things (IoT) technologies to significantly lower the

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barrier to entry for individual farmers[78]. Second, it is crucial to strengthen fundamental research on the linkage between phenotypes, physiology, and yield. A deeper investigation into the mechanisms connecting multi-scale water-sensitive phenotypes with underlying physiological processes—and ultimately with yield and quality formation—will enhance the biological relevance and predictive power of diagnostic models[79]. Third, comprehensive and in-depth integration of high-throughput phenotyping data with other big data sources should be promoted. Such integration will facilitate the construction of "digital twin" farmlands—virtual replicas capable of simulating and predicting crop responses through computational models, thereby supporting scenario testing and optimized decision-making[80]. Fourth, a new generation of artificial intelligence models that combine high accuracy with interpretability should be developed. Related research should focus on explainable AI (XAI) techniques, transfer learning (to enable model adaptation in new environments with limited data), and lightweight model architectures optimized for deployment on edge computing devices in the field[81]. Fifth, establishing a real-time, closed-loop diagnostic and decision-support system based on a cloud-edge collaborative architecture represents a critical end goal. This involves processing massive datasets in the cloud while executing time-sensitive tasks on edge devices, enabling a seamless "perception–diagnosis–decision–execution" feedback cycle[82]. Finally, it is imperative to conduct large-scale, long-term validation trials across diverse crops, geographical regions, and climatic conditions. This effort must extend beyond technical validation to include socio-economic research, the development of viable business models, and the formulation of supportive policies to facilitate technology adoption and ensure sustainability and equity[83].

6. Conclusions

The integration of high-throughput water-sensitive phenotyping for diagnosing crop water demand represents a paradigm shift from traditional soil- and atmosphere-centric methods to a direct, plant-based approach. This review demonstrates that by non-destructively and rapidly capturing the physiological and morphological response signals of crops to water stress, this technology effectively solves the critical limitations of traditional diagnostic methods, such as poor timeliness, insufficient accuracy, and lag, thereby providing a novel and robust technical pathway for precision crop water management. Significant progress has been made in screening key water-sensitive phenotypic indicators, developing automated phenotyping platforms, and applying advanced machine learning and deep learning models, collectively providing empirical support for the implementation of a complete 'phenotyping-modeling-decision-making' technological chain. However, in practical applications, it still faces many challenges such as field environment complexity, biological complexity, model generalization ability, data barriers, and interpretability. In the future, through in-depth interdisciplinary integration, continuous breakthroughs should be made in technological innovation, mechanism exploration, data fusion, model upgrading, and system integration to achieve more intelligent, universal, and practical crop water demand diagnosis and provide irrigation decision support. Accordingly, a government-research-enterprise collaborative promotion mechanism will be established, so that the technology could expand from research to large-scale application, and provide core technical support for raising water use efficiency. ultimately, this will ensure global food security, and advance the smart water-saving agriculture under the dual-carbon goal.

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Abbreviations

The following abbreviations are used in this manuscript:

CWSI	Crop Water Stress Index
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
MRI	Magnetic Resonance Imaging
NDWI	Normalized Difference Water Index
PRI	Photochemical Reflectance Index
SPAC	Soil-Plant-Atmosphere Continuum
UAV	Unmanned Aerial Vehicle
WI	Water Index

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