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Review Article

AI / ML –Based Assessment of Plant Responses to Abiotic Stresses: A Physics-Driven Perspective

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ABSTRACT

Abiotic stresses such as drought, heat, salinity, flooding, and excessive radiation pose major constraints on plant growth and agricultural productivity, with their impacts intensifying under ongoing climate change. These stresses primarily disrupt fundamental physical processes governing energy balance, water transport, radiation interception, and soil–plant–atmosphere interactions. Conventional stress assessment approaches, often based on destructive sampling or static measurements, are limited in their ability to capture the dynamic and spatial complexity of stress responses under field conditions. This review adopts a physics-driven perspective to examine recent advances in Artificial Intelligence (AI) and Machine Learning (ML)–based approaches for assessing plant responses to abiotic stresses. Emphasis is placed on AI frameworks that integrate physically meaningful inputs, including thermal infrared signals, hyperspectral and multispectral reflectance, chlorophyll fluorescence, soil moisture dynamics, and micrometeorological variables. Representative case studies are discussed, demonstrating applications of physics-guided AI in drought and heat stress detection through energy balance relationships, salinity stress assessment using hyperspectral signatures, and flooding stress identification based on soil moisture and oxygen diffusion proxies. Hybrid approaches combining mechanistic crop and soil physics models with ML are also highlighted for their improved interpretability and robustness. The review concludes by outlining key challenges and future directions for physics-informed AI in precision agriculture and climate-resilient crop management.

Key words: AI, Abiotic stress, Plant stress physiology, Thermal imaging, Hyperspectral sensing, Physics-informed modeling, Precision agriculture

Introduction

Abiotic stresses such as drought, heat, salinity, flooding, and excessive radiation remain among the most significant constraints on plant growth and agricultural productivity worldwide. Their frequency, intensity, and spatial variability are increasing under ongoing climate change, posing serious challenges to global food security and ecosystem stability (Huang *et al*., 2013). Unlike biotic stresses, abiotic stresses primarily act through disruptions of fundamental physical processes, including energy exchange, water transport, radiation interception, and soil–plant–atmosphere interactions. Plant responses to abiotic stress involve coordinated physiological, biochemical, and molecular adjustments. However, stress perception and damage often begin at the physical level—manifesting as changes in canopy temperature, transpiration rate, spectral reflectance, or soil moisture dynamics—well before visible symptoms or irreversible yield losses occur (Jackson, 1986). Traditional stress assessment methods based

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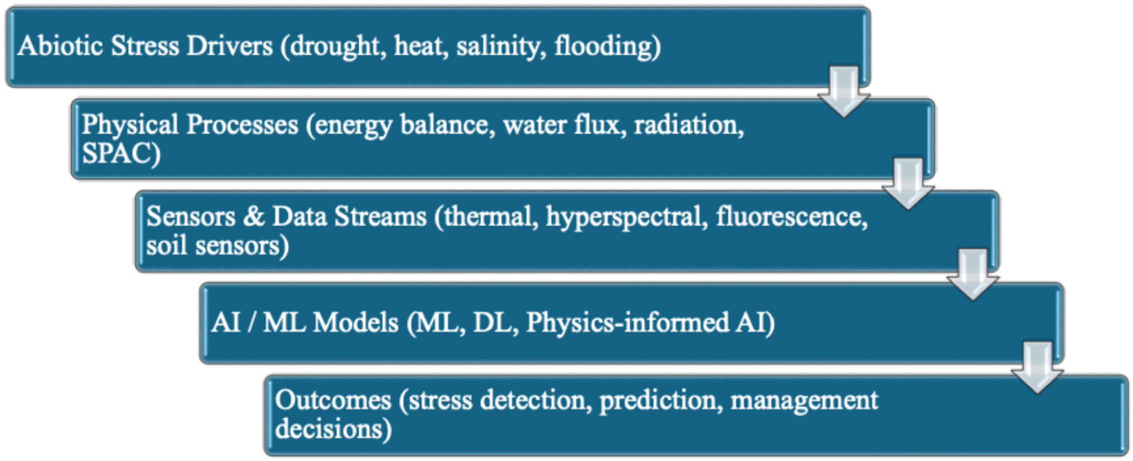

Fig. 1. Conceptual framework illustrating physics-driven AI for assessing plant responses to abiotic stress

on destructive sampling or snapshot physiological measurements are therefore limited in their ability to capture the dynamic, spatially heterogeneous nature of stress development under real field conditions.

Recent advances in AI and ML have transformed plant stress research by enabling the analysis of large, complex, and continuous datasets generated through remote sensing, imaging, and environmental monitoring. As highlighted by Koh *et al*. (2024), the rapid expansion of high-throughput phenotypic and environmental data has created both opportunities and challenges, necessitating computational approaches capable of extracting meaningful biological and physical insights from heterogeneous datasets. The emergence of high-throughput phenotyping platforms has further accelerated this transition by enabling large-scale, non-destructive measurement of stress-related physical traits, including canopy temperature, spectral reflectance, and growth dynamics, thereby generating datasets that are well suited for AI-based analysis (Gill *et al*., 2022).

This review adopts a physics-driven perspective, emphasizing AI and ML approaches that are grounded in physical principles governing plant–environment interactions. Rather than treating stress detection as a purely data-driven problem, we focus on models that integrate physically meaningful variables such as energy balance components, water potential gradients, spectral reflectance properties, and soil moisture dynamics. The objectives of this review are to

(i) outline the physical basis of plant responses to abiotic stress,

(ii) examine AI and ML methods applied to physically derived stress signals,

(iii) discuss representative case studies, and

(iv) identify challenges and future directions for physics-informed AI in agricultural systems.

Physical Basis of Plant Responses to Abiotic Stress

Energy Balance and Thermal Stress

The thermal status of a plant canopy is governed by the surface energy balance, which describes the partitioning of net radiation into sensible heat, latent heat, and ground heat fluxes. Under optimal conditions, latent heat loss through transpiration plays a dominant role in dissipating absorbed energy, maintaining canopy temperatures close to ambient air temperature. Heat stress arises when this balance is disrupted, often due to stomatal closure or reduced water availability, leading to elevated canopy temperatures. Thermal infrared sensing exploits this physical relationship by measuring emitted longwave radiation, which is directly related to surface temperature through the Stefan–Boltzmann law. Jackson (1986) demonstrated that increases in canopy temperature relative to air temperature serve

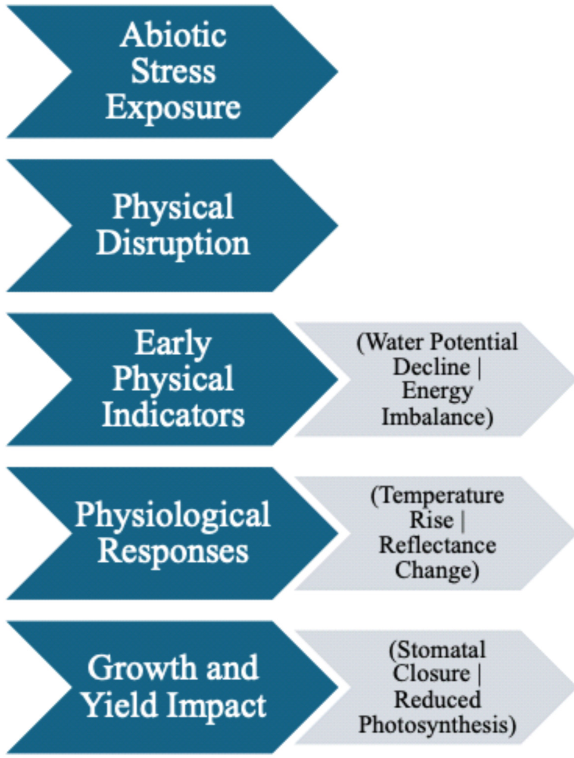

Fig. 2. Physical-to-physiological progression of plant responses to abiotic stress

as reliable indicators of plant water stress and impaired transpiration, providing a quantitative and non-destructive means of stress detection.

Water Transport and Drought Physics

Drought stress is fundamentally a hydraulic phenomenon governed by water potential gradients along the soil–plant–atmosphere continuum. Soil moisture depletion, increased atmospheric demand, and reduced hydraulic conductivity collectively constrain water flow from soil to leaves, resulting in reduced transpiration and altered canopy energy balance. These physical constraints precede downstream physiological and molecular responses (Huang *et al*., 2013).

From a physics-driven perspective, variables such as soil moisture content, vapor pressure deficit, canopy temperature, and evapotranspiration provide direct insight into drought stress intensity. AI and ML models that incorporate these physically meaningful inputs have greater potential for robustness and generalization than models relying solely on visual symptoms or single physiological traits.

Radiation Interaction and Spectral Properties

Plant canopies interact with incoming solar radiation through absorption, reflection, and transmission, processes governed by optical physics. Changes in pigment concentration, cellular structure, and water content under stress alter canopy reflectance across the visible, near-infrared, and shortwave infrared regions. Jackson (1986) provided a detailed physical explanation of how stress-induced changes in leaf hydration and canopy architecture influence spectral signatures, forming the basis for remote sensing of plant stress.

Hyperspectral and multispectral sensing techniques exploit these principles by capturing stress-related variations across hundreds of narrow wavelength bands, enabling detection of subtle stress signals before visible damage occurs. Advances in imaging-based phenomics have demonstrated that such spectral responses can be monitored continuously across spatial and temporal scales using ground-based, UAV, and satellite platforms, enabling early detection of abiotic stress before visible symptoms appear (Gill *et al*., 2022).

AI and ML for Physics-Based Stress Assessment

The integration of AI and ML with physically derived plant and environmental data has become increasingly important for handling the scale and complexity of modern stress phenotyping datasets. Koh *et al*. (2024) highlighted the rapid growth of genomic, phenomic, and environmental datasets related to plant stress and emphasized the role of advanced ML models in extracting predictive and mechanistic insights from such data. The increasing volume and dimensionality of phenotypic and environmental datasets have made conventional statistical approaches insufficient for comprehensive stress analysis. High-throughput phenotyping and remote sensing generate complex, multi-modal data streams that require advanced ML and deep learning techniques for effective interpretation. However, purely data-driven models often suffer from limited interpretability and poor generalization across environments, highlighting the need for AI frameworks that are guided by physical principles and domain knowledge (Gill *et al*., 2022; Koh *et al*., 2024).

ML techniques—including regression models, support vector machines, random forests, and deep learning architectures—have been widely applied to stress detection tasks using thermal, spectral, and environmental inputs. Importantly, when these models are trained on variables with clear physical meaning, their predictions are more interpretable and transferable across environments.

A notable example of physics-guided AI is provided by Kumar *et al*. (2023), who developed a stress sensing framework based on continuous electrical resistance measurements of plant growth media, explicitly linking physical changes in ion mobility and nutrient uptake to stress onset through mechanistic modeling combined with ML.

By applying Drude's physical model to relate electrical resistance with charge carrier concentration, changes in nutrient uptake—reflecting both physical and physiological processes—were associated with the onset of stress. ML approaches such as k-nearest neighbours and long short-term memory networks were subsequently used to identify anomalies and predict stress severity, highlighting the effectiveness of integrating physically grounded models with data-driven learning.

Machine learning (ML) has increasingly demonstrated its potential in agricultural diagnostics and stress assessment. Several studies have applied ML algorithms for early detection of plant diseases and for improving crop management strategies under stress conditions (Patel & Machal, 2021). In the context of water stress monitoring, UAV-based multispectral imagery has been successfully used to map maize water stress, leading to the development of empirical models for the Crop Water Stress Index (CWSI) (Zhang *et al*., 2019).

Beyond imaging-based approaches, ML has also been applied to molecular-level stress prediction. A k-mer-based feature encoding strategy coupled with support vector machines (SVM) was used to predict abiotic stress-responsive microRNAs, highlighting the utility of computational approaches in stress-resilient crop development (Pradhan *et al*., 2023). More recently, integrative frameworks combining molecular markers with phenotypic traits have gained attention. The GenPhenML approach demonstrated high predictive accuracy in classifying barley genotypes under drought and salinity stress using neural network models, underscoring the value of multi-scale data integration in ML-based stress assessment (Akbari *et al*., 2024).

Online resources and large-scale data infrastructures supporting AI-driven stress analysis

A wide range of online bioinformatic resources now support the analysis of large-scale biological datasets, including genomic, epigenomic, transcriptomic, proteomic, and other high-dimensional '-omic' data, which increasingly complement AI-driven approaches for plant stress analysis. In plant genomics, large-scale natural variation datasets such as the 1001 Genomes Project provide extensive resources for linking genetic diversity with phenotypic variation, enabling the exploration of hundreds of traits across diverse Arabidopsis thaliana accessions (Alonso-Blanco *et al*., 2016).

One of the most widely used platforms, The Arabidopsis Information Resource (TAIR), offers curated information on gene functions and integrates a wide range of analytical tools relevant to plant biology (Reiser *et al*., 2017). Similarly, databases such as Ensembl Plants (Kersey *et al*., 2018), PLAZA (Van Bel *et al*., 2018), and PANTHER (Mi *et al*., 2010) facilitate the exploration of gene families, evolutionary relationships, and functional annotations across plant species.

Beyond genomics, epigenomic resources provide additional layers of information relevant to stress adaptation. DNA methylation and other epigenetic modifications generated from large-scale sequencing experiments can be visualized using platforms such as the EPIC-CoGe browser (Nelson *et al*., 2018) and the 1001 Epigenomes project (Kawakatsu *et al*., 2016). Although these resources are primarily molecular in nature, they form an important data backbone that can be integrated with sensor-based and physically derived variables in AI frameworks, supporting multi-scale analyses of plant responses to abiotic stress.

Case Studies of Physics-Driven AI Applications

Drought Stress Detection

Drought stress detection represents one of the most mature applications of physics-based remote sensing and AI integration. Thermal infrared measurements of canopy temperature, interpreted through energy balance principles, have been widely used to quantify plant water status.

ML models trained on canopy temperature, soil moisture, and atmospheric variables have further improved drought stress prediction by capturing non-linear interactions among physical drivers. Such approaches enable early detection of stress and support irrigation scheduling before irreversible yield losses occur.

Heat Stress Assessment

Heat stress is closely linked to failures in energy dissipation mechanisms, particularly under conditions of high radiation and limited water availability. Thermal imaging provides a direct physical measure of canopy heating, while AI models enable discrimination between transient temperature fluctuations and sustained heat stress events. Physics-guided AI frameworks that integrate radiation, temperature, and humidity data offer improved prediction of heat stress tolerance across genotypes and environments.

Salinity Stress Monitoring

Salinity stress alters plant water relations and ion homeostasis, leading to changes in leaf optical properties and transpiration dynamics. Hyperspectral sensing has been used to capture stress-induced shifts in reflectance associated with osmotic and ionic stress. ML models trained on these spectral signatures have demonstrated potential for early salinity stress detection, particularly when grounded in the physical basis of light–matter interactions.

Flooding and Hypoxia Stress

Flooding stress imposes a distinct set of physical constraints on plants, primarily through reduced oxygen availability in the root zone and altered soil physical properties. Prolonged waterlogging limits gas diffusion, leading to hypoxic or anoxic conditions that disrupt root respiration and nutrient uptake. These changes rapidly propagate through the soil–plant–atmosphere continuum, affecting transpiration, canopy temperature, and spectral characteristics. Multi-sensor remote sensing approaches integrating thermal, microwave, and spectral data have been shown to improve discrimination between flooding-induced stress and other abiotic stresses by capturing soil moisture dynamics, canopy temperature changes, and altered radiation signatures.

Remote sensing approaches grounded in physical principles have demonstrated potential for detecting flooding-induced stress. ML models trained on soil moisture proxies, thermal signatures, and environmental variables can therefore distinguish flooding stress from drought or heat stress when physics-based constraints are incorporated.

Kumar *et al*. (2023) further illustrated how physical changes in nutrient uptake dynamics under stress can be captured using continuous electrical resistance measurements of the growth medium. Although their study focused on generalized stress detection, the approach is highly relevant for flooding conditions, where altered ion mobility and root function directly affect charge carrier concentration. The use of anomaly detection algorithms and time-series learning models enabled early stress forecasting before visible symptoms appeared.

Multi-Stress and Climate-Driven Stress Scenarios

In real agricultural systems, plants are rarely exposed to a single stress factor in isolation. Climate change has increased the likelihood of compound stress scenarios, such as simultaneous heat and drought or flooding followed by salinity stress. These complex interactions pose significant challenges for conventional stress assessment methods. High-throughput phenotyping and multi-sensor remote sensing platforms are particularly valuable for studying compound stress scenarios, as they enable simultaneous monitoring of multiple stress-responsive physical traits under dynamic environmental conditions. ML models trained on such datasets can disentangle overlapping stress signals when supported by physics-based constraints (Gill *et al*., 2022; Koh *et al*., 2024).

Koh *et al*. (2024) highlighted the growing availability of large-scale phenotypic, environmental, and omics datasets capturing multi-stress responses across species and environments. AI and ML models capable of integrating heterogeneous data streams offer a powerful means of disentangling overlapping stress signals. However, without a physics-driven framework, such models risk overfitting and poor transferability.

Physics-guided AI approaches that incorporate energy balance, hydrological variables, and radiation physics provide a mechanistic foundation for interpreting multi-stress responses. By anchoring predictions in physical constraints, these models improve robustness under novel climatic conditions, a critical requirement for climate-resilient agriculture.

Physics-Guided and Hybrid AI Modeling Approaches

Physics-Informed ML

Physics-informed ML represents a paradigm shift from purely data-driven modeling toward approaches that embed physical laws and constraints within AI frameworks. In plant stress assessment, this involves guiding model inputs, architectures, or loss functions using principles such as conservation of energy, mass transfer, and radiative transfer. Recent advances in scientific ML have demonstrated the effectiveness of hybrid frameworks that embed neural networks within mechanistic differential equations. Universal Differential Equation (UDE)–based approaches preserve known physical processes, such as transport and diffusion, while allowing data-driven learning of complex biological interactions. Such models have shown improved interpretability, robustness, and noise tolerance compared to purely empirical approaches, as demonstrated in soil organic carbon dynamics under varying uncertainty conditions (Raju *et al*., 2025). Physics-informed deep learning models that explicitly incorporate physical constraints, such as energy balance principles, have demonstrated improved robustness and transferability in large-scale evapotranspiration estimation, highlighting their potential for drought stress assessment in plants (Wang *et al*., 2026).

ML models that incorporate canopy temperature, net radiation, and vapor pressure deficit implicitly respect these physical limits, reducing the likelihood of biologically implausible outputs.

Coupling Mechanistic Models with AI

Hybrid approaches combining mechanistic crop or soil physics models with ML have gained increasing attention. Mechanistic models capture well-established physical processes but often struggle with parameterization and scalability. ML, on the other hand, excels at pattern recognition but lacks interpretability when used alone.

By coupling these approaches, hybrid models leverage the strengths of both. Koh *et al*. (2024) emphasized that integrating mechanistic understanding with AI-driven analysis enhances predictive performance while maintaining biological and physical interpretability. Such frameworks are particularly valuable for extrapolating stress predictions across environments and seasons.

In recent years, increasing attention has been directed toward resolving the trade-off between physics-driven approaches and purely data-driven models.

Table 1. Comparison between purely data-driven AI and physics-driven AI approaches for plant abiotic stress assessment

Aspect	Pure Data-driven AI	Physics-driven AI
Input features	Raw images/data	Physically meaningful variables
Interpretability	Low	High
Generalization	Poor	Better
Climate robustness	Weak	Strong
Agricultural relevance	Limited	High

Table 2. Comparison between purely data-driven and physics-driven artificial intelligence approaches for plant abiotic stress assessment

Aspect	Purely Data-Driven AI Approaches	Physics-Driven AI Approaches
Primary inputs	Raw images or sensor data	Physically meaningful variables (temperature, radiation, water flux, soil moisture)
Use of physical laws	Not explicitly considered	Explicitly incorporated or constrained
Interpretability	Low (black-box models)	High (physically explainable predictions)
Generalization across environments	Limited	Improved
Robustness under climate variability	Weak	Strong
Data requirement	Very large datasets required	Effective even with moderate datasets
Risk of overfitting	High	Reduced
Applicability to field conditions	Often limited	High
Relevance to precision agriculture	Moderate	High

Fig. 3. Conceptual comparison between data-driven and physics-driven artificial intelligence approaches

Physics-based methods offer high interpretability, whereas data-driven models often achieve superior predictive accuracy under complex environmental conditions. To bridge this gap, hybrid frameworks that combine physical understanding with data-driven learning have emerged as a major research focus, leading to a paradigm shift in evapotranspiration (ET) estimation from single-model approaches toward multi-paradigm strategies.

At the data level, physically interpretable features—such as outputs from process-based models—are increasingly used as additional inputs to machine learning models, thereby introducing physical consistency and rational constraints into data-driven predictions (Karpatne *et al*., 2017). At the model level, hybrid approaches that integrate physical and data-driven components have been proposed, enabling closer interaction between mechanistic understanding and learning-based inference (Reichstein *et al*., 2019). These hybrid models are commonly implemented using serial or parallel coupling strategies, depending on the degree of interaction between physical and data-driven components (Shang *et al*., 2023). To address the inherent "black-box" nature of many machine learning models, explainable AI techniques are increasingly adopted to improve transparency and interpretability (Huang *et al*., 2023).

Despite these advances, robust cross-domain estimation remains a key challenge, particularly when models trained in data-rich regions are applied to data-poor environments. One promising strategy involves learning transferable representations of ET processes from data-rich regions and leveraging this knowledge in regions with limited observations. Within this context, physics-constrained approaches impose strong restrictions by explicitly embedding governing equations—such as the surface energy balance—into the model loss function (Hao *et al*., 2022). In contrast, physics-informed approaches introduce softer constraints at the architectural level, allowing models to capture general physical relationships, such as variable correlations and response thresholds, without enforcing rigid equations (Jia *et al*., 2018). Given the mechanistic differences in ET processes across climatic and geographic regions, such architectural-level soft constraints have shown greater potential for improving generalization and prediction accuracy in data-poor regions. Consequently, effective hybrid modeling requires deep coupling between physical principles and data-driven learning, rather than simple model combination, to enable a transition from region-specific customization toward globally adaptive ET estimation frameworks.

Applications in Precision Agriculture and Climate-Resilient Farming

Physics-driven AI and ML frameworks have direct applications in precision agriculture, where timely and accurate stress detection is essential for optimizing management practices. Remote sensing–based stress indicators derived from thermal and spectral data enable spatial mapping of stress severity across fields, supporting targeted irrigation, fertilization, and drainage interventions. Recent sensor–AI integrated frameworks have demonstrated the feasibility of real-time plant stress detection by coupling physical sensing with ML, thereby enhancing the applicability of AI in precision agriculture (Garg *et al*., 2025).

Kumar *et al*. (2023) demonstrated the potential for low-cost, physics-based sensing systems combined with ML to support small and marginal farmers. By focusing on physically meaningful parameters such as nutrient uptake dynamics, these approaches offer scalable solutions that do not rely on expensive imaging infrastructure.

At broader scales, physics-informed AI can support climate-resilient crop management by integrating weather forecasts, soil data, and crop models to anticipate stress events. Such predictive capabilities are increasingly important under variable and extreme climatic conditions.

Challenges and Limitations

Despite significant progress, several challenges

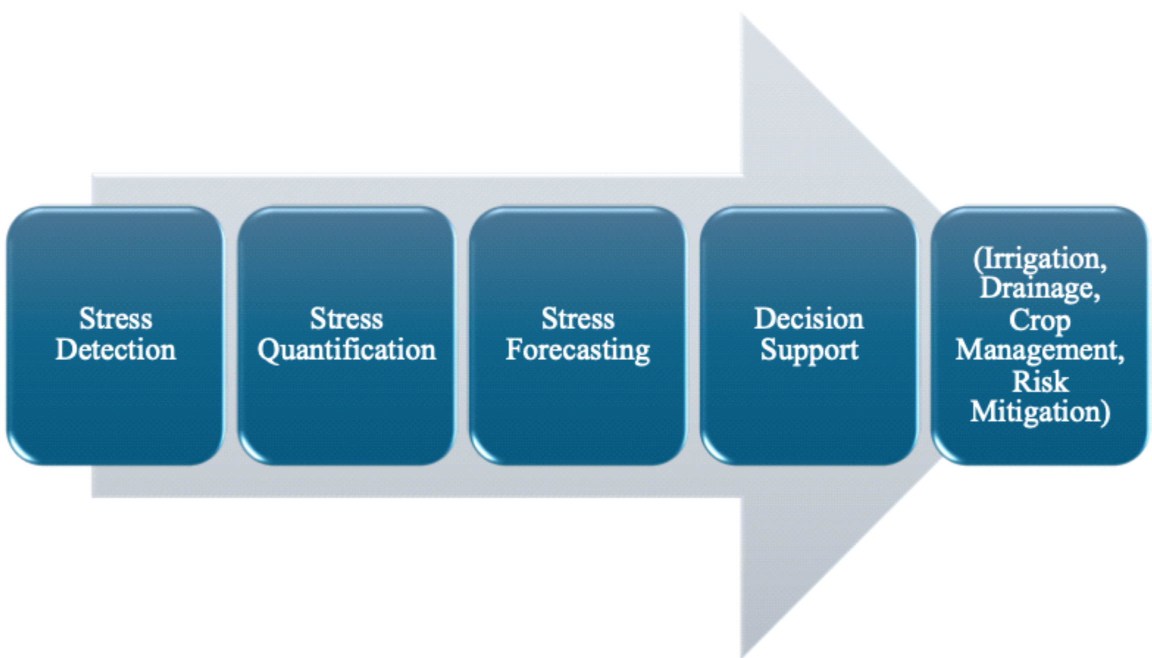

Fig. 4. AI-enabled pipeline from abiotic stress assessment to decision support in agriculture

limit the widespread adoption of physics-driven AI approaches in plant abiotic stress assessment. Data heterogeneity remains a major issue, as datasets vary widely in spatial resolution, temporal frequency, and measurement accuracy. Standardization of sensor data and metadata is essential for robust model development.

Model interpretability is another critical concern. While physics-guided frameworks improve transparency, complex deep learning models can still function as "black boxes." Koh *et al*. (2024) emphasized the need for explainable AI approaches that allow researchers and practitioners to understand how predictions are generated. Studies employing physics-informed AI frameworks have shown that embedding physical constraints can substantially reduce overfitting and improve robustness under noisy and incomplete datasets, although challenges remain in scaling such approaches to field and regional levels (Gill *et al*., 2022; Raju *et al*., 2025). Physics-guided scientific ML approaches that integrate mechanistic understanding with data-driven models offer improved interpretability and robustness, addressing key limitations of purely data-driven AI frameworks. Scalability also poses challenges, particularly when transitioning from controlled experiments to field or regional scales. Environmental variability, sensor noise, and management practices introduce additional complexity that must be accounted for in model design

Future Perspectives

Future research in physics-driven AI for plant stress assessment should focus on tighter integration between physical models, sensor technologies, and ML frameworks. Advances in sensor miniaturization, Internet of Things (IoT) platforms, and cloud-based analytics will further enable continuous, real-time stress monitoring. The convergence of phenomics, remote sensing, and physics-informed AI offers a promising pathway toward transferable, climate-aware stress prediction models. Future developments are expected to increasingly rely on hybrid approaches that combine physical modeling, high-throughput sensing, and explainable ML to address the complexity of plant stress responses under global climate change (Gill *et al*., 2022; Koh *et al*., 2024).

The growing availability of large-scale stress datasets highlighted by Koh *et al*. (2024) presents an opportunity to develop transferable and climate-aware AI models. Incorporating uncertainty quantification and explainability into these models will be critical for decision-making in agricultural systems.

Conclusions

Abiotic stresses exert their effects on plants primarily through disruptions of fundamental physical processes governing energy balance, water transport, radiation interaction, and soil–plant–atmosphere dynamics. This review has demonstrated that AI and ML approaches grounded in these physical principles provide a robust and interpretable framework for assessing plant responses to abiotic stress.

By integrating physically meaningful inputs such as canopy temperature, spectral reflectance, soil moisture, and nutrient uptake dynamics, physics-driven AI models enable early, non-destructive, and predictive stress assessment. Representative case studies from remote sensing and sensor-based monitoring highlight the advantages of hybrid physics–AI approaches over purely data-driven methods.

As climate variability continues to intensify abiotic stress impacts, physics-informed AI frameworks will play an increasingly important role in precision agriculture and climate-resilient crop management. Continued collaboration between plant scientists, physicists, and computational researchers will be essential to translate these advances into practical and scalable solutions.

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