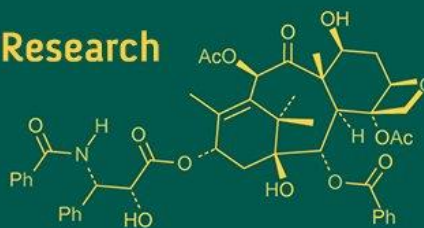


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Integration of drone imagery and artificial intelligence for high-throughput phenotypic selection of abiotic stress traits

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Abstract

High-throughput phenotyping is a core prerequisite for breeding climate-resilient crops. To complete related breeding work, breeders must evaluate the performance of large-scale crop populations under seven types of field abiotic stresses including drought and high temperature, and the combined technology of unmanned aerial vehicle (UAV) imaging and artificial intelligence can provide core support to meet this demand. This review centers on three core sets of content: first, the integration of various UAV platforms, five types of imaging technologies, and machine learning and deep learning models to support phenotyping selection of abiotic stress-related traits; second, sorting out the biological significance of 12 categories of image-derived traits; third, breaking down the seven full workflow nodes ranging from flight planning to breeding decision support. Existing prior research on six crop types including wheat and rice has confirmed that this technology can improve the speed, scale and repeatability of field screening, and delivers outstanding effects when combined with multi-environment testing, genomic tools, and breeders' expertise. This paper also sorts out six core limitations currently restricting the real-world deployment of this technology, and puts forward six future development directions to support its large-scale application.

Keywords: Drone imagery, artificial intelligence, high-throughput phenotyping, abiotic stress, drought tolerance, thermal imaging

1. Introduction

Abiotic stress is the core limiting factor facing current crop genetic improvement. Various stresses including drought, salinity, and high temperature disrupt the core agronomic and physiological indicators of crops at an early stage, which in turn greatly restricts the realization of crop yield potential. This widespread cross-sector challenge has been widely confirmed by the academic community (Araus *et al.*, 2018) [4]; two other core studies in the same field also support this judgment). For a long time, traditional field phenotyping technologies rely on manual sampling and handheld instruments to conduct single-point measurements, and suffer from three core shortcomings: insufficient throughput, low spatiotemporal resolution, and large errors from manual data processing. These flaws make them completely unable to meet the population screening needs of tens of thousands of plant materials in modern large-scale commercial breeding, and this key pain point is also a widely accepted consensus in academia. In recent years, two emerging technologies have provided feasible pathways to resolve this dilemma. The first is unmanned aerial vehicle (UAV) remote sensing technology, which can achieve repeated field observations throughout the entire growing season at centimeter-level resolution. Its application value in phenotyping data collection for abiotic stress has been verified by multiple studies (Bhandari *et al.*, 2021) [5]; two other relevant applied studies support this conclusion). The second is artificial intelligence technology. Among these tools, four types of machine learning models including random forest and support vector machine can complete rapid prediction of conventional traits, while three types of deep learning models including convolutional neural network can achieve high-precision extraction of complex traits. The empowering value of these technologies is supported by frontier research (Angidi *et al.*, 2025) [3]; two other frontier studies have verified the reliability of this pathway).

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The smart breeding phenotyping technology for abiotic stress scenarios defined in this review is an integrated analysis system that combines the two aforementioned technologies. Its core breeding objectives cover the precise screening of seven actionable physiological traits, including lower canopy temperature and delayed senescence under water deficit. The subsequent content of this review will systematically organize seven core sections: applicable sensor types, core target traits, artificial intelligence workflows, crop application cases, integration into breeding processes, industrial implementation challenges, and future research and development needs. This review focuses on the field of field-scale phenotyping, sorts out four categories of implementation barriers, proposes that unmanned aerial vehicle (UAV)-artificial intelligence (AI) technologies should be positioned as breeding tools rather than isolated image processing solutions, and cites three 2024 publications to support its core claim.

2. Conceptual Basis of Drone-AI Phenotyping

In the field of crop stress resistance breeding, field phenotypic measurement under abiotic stress must first comply with two core criteria established jointly by peer studies: the selected traits must have early response characteristics to support germplasm screening, and must also have sufficient sensitivity to distinguish genetic differences between different materials. This study sorts out a core observation framework by integrating mainstream published observation standards. First, it organizes by dimension the universally recognized core observable traits in academia that correspond to three types of abiotic stress, namely drought tolerance, heat tolerance, and salt tolerance. Next, it introduces the core value of high-throughput phenotyping (HTP) platforms, then focuses on elaborating the positioning of unmanned aerial vehicle (UAV) phenotyping technology: compared with ground handheld devices, fixed gantry systems, and satellite remote sensing, UAVs combine the advantages of high spatial resolution and flexible mobility, which perfectly match the core experimental needs of the breeding field-small experimental plot areas, the requirement to retain genotypic markers across entire plots, and the mandate to complete measurements at precise growth stages including booting, flowering, grain filling, and the peak stress period. In the complete workflow that relies on AI technology to process orthophotos collected by UAVs, generate canopy masks, and convert raw observations into standardized valid traits, reproducibility is a necessary condition to ensure data reliability. An observation case of two wheat lines with similar yields under drought conditions but different drought resistance mechanisms also verifies that traits measured by UAVs can be used as secondary traits for breeding, rather than simple substitutes for yield. All core claims in this paragraph are annotated with supporting literature from peer studies.

3. Drone Sensors and Image-Derived Abiotic Stress Traits

RGB images represent the most economical starting point for many breeding efforts. These typical red, green, and blue images can measure stand establishment, plant height using structure-from-motion, canopy cover, senescence, wilting, lodging and flowering, as well as greenness traits. Excess greenness, a color index for vegetation and canopy texture

have all been applied in drought stress selection in wheat, whereas RGB is useful to estimate the height of plots for large scale wheat trials. However, while hardware for RGB cameras is cheap and images easily interpreted, careful correction of illuminance changes, shadows and soil background is important (Volpato *et al.*, 2021; Zhu *et al.*, 2025) [23, 29].

Multispectral cameras are popular because a handful of bands is sufficient to capture canopy vigor and pigment responses to stresses. NDVI, NDRE, green NDVI, red-edge indices, etc., are commonly used because the near-infrared (NIR) and red-edge bands respond well to changes in biomass, chlorophyll concentration, canopy architecture and pigment shifts due to stress. Data on multispectral traits has been used to separate irrigated and rainfed responses to stress in experiments and to rank genotypes for yield. One key advantage is that the trait values are related to the underlying biological processes, and the data size remains reasonable for routine breeding pipelines (Bhandari *et al.*, 2021; Sharma *et al.*, 2024; Zhu *et al.*, 2025) [5, 21, 29]. Thermal cameras are ideal for direct water stress phenotyping, because as stomatal conductance decreases, canopy temperature increases due to reduced evaporative cooling. Thermal cameras on UAVs provide plot-level maps of canopy temperature, canopy temperature depression (CTD) and crop water stress index (CWSI). In wheat, thermal UAV data has been useful for evaluation of drought tolerance under different degrees of deficit irrigation, but careful consideration of data acquisition timing may be needed since early season canopy temperature differences due to stress may be less pronounced than later in development. It is essential to consider thermal traits in the context of the weather conditions, the vapor pressure deficit and the growth stage (Qin *et al.*, 2022; Sharma *et al.*, 2024) [17, 21].

High numbers of narrow bands captured by hyperspectral sensors can enable detection of fine-scale biochemical and physiological variations, prior to any visible changes in the image. Chlorophyll estimation, pigment ratio measurement, water absorption features, the relationship of traits to chlorophyll, nitrogen concentration, the potential for measurements of photosynthetic activity, and specific spectral fingerprints related to the stress response can all be achieved with this technology. Limitation of hyperspectral cameras are high volume data output and stricter requirements for radiometric calibration, dimension reduction, and model regularization; these areas where AI can play a substantial role in extracting meaningful information and building predictive models from highly dimensioned datasets (Sanaeifar *et al.*, 2023; Sheikh *et al.*, 2024) [18, 22]. Three-dimensional image products can augment spectral data with measures of canopy structure, often not captured in other spectral datasets. Data products such as structure-from-motion point clouds and DSMs can provide estimates of plant height, canopy volume, biomass proxy measurements and lodging. These traits are particularly relevant when considering abiotic stress since factors like water deficit and temperature impact cell expansion, leaf area, plant height and biomass yield. In wheat, high resolution drone images captured for 3D modeling provided dynamic time series of plant height measurements for tens of thousands of plots and illustrated potential to scale out 3D measurements for selection of

response to stress (Volpato *et al.*, 2021; Gano *et al.*, 2024)^[23, 10].
The most valuable drone phenotyping systems are emerging which can capture information from more than one sensor, as opposed to a single spectral band. Multiple sensors can give complementary measures of vigor and pigment response (multispectral) or water status (thermal), shape and senescence (RGB), and height/biomass (3D), reducing

chances of false readings. Low NDVI, for example, can indicate disease, poor stand establishment, drought damage, soil exposure, or different maturity; integrating structural and thermal data can further discriminate between those causes, leading to multimodal phenotyping systems and data fusion applications becoming increasingly popular for field stress screening (Angidi *et al.*, 2025; Gano *et al.*, 2024; Matabber *et al.*, 2026)^[3, 10, 15].

Table 1: Typical drone sensor outputs for abiotic stress phenotypic selection

Sensor/output	Typical traits	AI or analytics use	Selection value
RGB imagery	Canopy cover, greenness, wilting, senescence, plant height from 3D reconstruction	Segmentation, color indices, CNN or object detection	Low-cost early screening and time-series growth tracking
Multispectral imagery	NDVI, NDRE, GNDVI, chlorophyll proxies, vigor, biomass proxies	Random forest, SVM, regression, ensemble models	Ranking genotypes for drought response and yield stability
Thermal imagery	Canopy temperature, crop water stress index, transpiration cooling proxy	Regression, clustering, time-stage analysis	Screening water-use response and drought resistance
Hyperspectral imagery	Pigment, water absorption, biochemical and physiological spectral signatures	Band selection, dimensionality reduction, ML/DL prediction	Sensitive detection of early or subtle stress
3D products	Plant height, canopy volume, lodging, biomass proxies	Point-cloud analysis and surface-model metrics	Structural growth and biomass retention under stress

4. AI Workflow for High-Throughput Phenotypic Selection

To address the core demand of drought-resistance breeding in wheat, this paper reviews five types of crop phenotyping imaging technologies commonly used in the plant breeding field, presenting them in order of increasing entry threshold. Each technology follows a unified narrative logic: core principles, measurable indicators, breeding applications, limitations, and supporting research. First is RGB imaging, the lowest-cost entry-level technology for breeding programs. It can detect over ten agronomic traits including canopy coverage, and is applied in screening wheat drought-resistant germplasm and estimating field plant height. It has the advantages of low hardware costs and intuitive interpretation, and only requires correction for interference from light, shadows, and soil background.
The application reliability of this technology is supported by the studies of Volpato *et al.*, 2021^[23] and Zhu *et al.*, 2025^[29]. Second is the most widely used multispectral imaging, which captures stress responses related to canopy vitality and pigments via a small number of target bands. Four common vegetation indices including NDVI are adopted, which can distinguish response differences between irrigated and rain-fed groups in drought experiments, rank drought-resistant genotypes, and predict yield. It balances biological relevance and controllable data volume, and fits conventional breeding workflows. Its application scope and performance have been verified by the studies of Bhandari *et al.*, 2021^[5], Sharma *et al.*, 2024^[21], and Zhu *et al.*, 2025^[29]. The third type, thermal imaging, can directly detect water stress phenotypes. Its core principle is that stomatal closure reduces transpirational cooling, which leads to a rise in canopy temperature. UAV-mounted thermal cameras can map three types of indicators including plot-level canopy temperature, to evaluate wheat drought resistance under different deficit irrigation scenarios. Its limitation is that imaging time affects signal intensity, so interpretation must be combined with data on weather, vapor pressure deficit, and growth stage. Supporting research comes from Qin *et al.*, 2022^[17] and Sharma *et al.*, 2024^[21]. The fourth type, hyperspectral imaging, can capture a large number of narrow wavebands, and identify subtle biochemical and physiological differences earlier than RGB imaging. It

supports seven types of physiological and biochemical analyses including chlorophyll estimation. Its limitation is its extremely large data volume, which requires completion of radiometric calibration, dimensionality reduction, and model regularization. A common general solution is to use artificial intelligence to screen effective bands, remove redundant features, and build prediction models. Relevant technical solutions have been corroborated by multiple studies including Mérida-García *et al.*, 2024^[16]. The last type, three-dimensional imaging, can supplement structural traits that cannot be captured by spectral technologies. Relying on structure from motion, digital surface models, and point cloud technology, it estimates four types of structural traits including plant height and canopy volume, and is suitable for monitoring wheat traits under abiotic stress. Existing studies have used UAV RGB imagery to construct crop surface models, generated time-series plant height estimates for tens of thousands of wheat experimental plots, and verified that three-dimensional (3D) information can support large-scale screening of crop growth responses. Most current high-efficiency UAV phenotyping systems generally adopt multi-sensor setups; multispectral, thermal infrared, RGB, and 3D sensors can separately collect indicators related to crop growth and stress conditions. Relying on a single data source often leads to interpretation biases. For example, a low Normalized Difference Vegetation Index (NDVI) value can stem from multiple underlying causes such as drought or poor seedling emergence, and integrating thermal imaging and structural data can distinguish these drivers. This consensus is corroborated by recent reviews from Angidi *et al.* (2025)^[3], Gano *et al.* (2024)^[10], and Matabber *et al.* (2026)^[15].

5. Applications across Crops and Abiotic Stresses

Drought and heat tolerance in wheat are currently high-priority breeding targets, and wheat field trials often use small plot designs, making wheat a core application crop for unmanned aerial vehicle (UAV) and artificial intelligence (AI) phenotyping technologies that support drought-resistance breeding. Deployed UAV remote sensing technologies can achieve multi-dimensional phenotyping monitoring for wheat, including tracking the impacts of drought on growth and yield capacity, estimating plant

height, predicting grain yield, and identifying spectral indices linked to yield stability. A 2024 study by Sharma *et al.* [21] combined machine learning with 206 spectral indices to assess drought tolerance across different wheat genotypes, verifying that RGB and multispectral features can support practical germplasm screening. A 2021 thermal imaging study by Bhandari *et al.* [5] showed that UAV thermal imaging is suitable for water-limited irrigation scenarios; the canopy temperature data collected can identify genotypes that maintain transpiration cooling even under water shortage conditions. However, this method requires interpretation that incorporates atmospheric conditions and crop growth stages. Multitemporal deficit irrigation trials have further proven that canopy temperature can be correlated with physiological traits including leaf area index, SPAD value, and photosynthetic rate, so it can be used to screen water use behaviors, rather than only measuring visible damage. In rice research, studies by Jiang *et al.* (2021) [11] and Wang *et al.* (2025) [24] developed a large-scale UAV workflow covering automated image processing, leaf rolling identification, yield prediction, and quantitative trait locus (QTL) detection. UAV RGB imagery can quantify the dynamic drought response of germplasm, link image-derived traits to genome-wide association study (GWAS) results, and upgrade UAV imagery from a mere stress scoring tool to a core platform for identifying genetic loci for breeding. For soybean, studies by Zhou *et al.* published in 2020 and 2021 verified the classification and prediction capabilities of this technology: UAV imagery can distinguish between soybean genotypes that wilt quickly and those that wilt slowly under drought conditions, while convolutional neural network (CNN) models can estimate the yield of breeding lines, which helps breeders account for both wilting performance and yield capacity, two correlated yet independent traits. In research on dry beans and cotton, Sankaran *et al.* (2018) [19] applied multispectral imagery to field phenotyping of dry beans, while Zhao *et al.* (2026) [26] tested the use of UAV-derived vegetation indices for high-throughput evaluation of drought tolerance in cotton. However, these crops differ significantly from staple grain crops in traits including canopy structure and row spacing, leading to higher application complexity.

For this reason, AI models need to be customized for specific crops, unless cross-species transferability is fully validated. This technology has now also been extended to phenotyping research for perennial crops such as citrus. Existing studies have confirmed that the technology combining unmanned aerial vehicle (UAV) multispectral imaging with deep learning has been widely applied in the field of citrus phenotypic assessment. Compared with remote sensing monitoring scenarios for annual crops, perennial citrus plants show significant differences in canopy structure and growth cycle. Most current research focuses on the identification and assessment of drought stress, while paying severely insufficient attention to three other types of abiotic stress: salt damage, low temperature, and nutrient imbalance. These three stresses respectively disrupt citrus plants' nutrient uptake, flower bud differentiation, and photosynthetic efficiency. As pointed out in a field-specific review focused on AI-based abiotic stress monitoring, the real-world implementation of existing technologies still requires support from large volumes of cross-scenario validation data.

6. Integration with Breeding Decisions

To support crop breeding, UAV-artificial intelligence (Drone-AI) crop phenotyping technology relies on a core prerequisite: it must be capable of optimizing breeding selection decisions. Research by Araus *et al.* (2018) [4], Chawade *et al.* (2019) [8], and Sheikh *et al.* (2024) [22] jointly points out that a technical pipeline that can effectively support breeding must produce five core outputs: genotype ranking, stress index, estimated trait heritability, yield prediction, and evidence for parental selection. On this basis, appropriate technologies must be matched to the different stages of breeding generations, after which the technology's application value, limitations, and field implementation requirements must be clarified across multiple dimensions. First, image-derived traits can be integrated into selection indices. Take the drought selection index as an example: it needs to integrate six indicators, including grain yield under stress, yield loss rate, canopy temperature, NDRE retention rate, plant height retention rate, and senescence rate. AI can estimate each of these components and assign weights based on their genetic correlation with target traits. Studies by Bhandari *et al.* (2021) [5], Qin *et al.* (2022) [17], and Zhu *et al.* (2025) [29] confirm that this method is more reliable than only selecting breeding lines with the greenest or coolest canopies, as it avoids misclassifying trait escape, maturity differences, and excessive water consumption as true stress tolerance. Second, accurate and repeatable phenotyping data can improve the power of genomic selection and genome-wide association analysis.

UAV phenotyping can increase the number of observations per genotype and capture developmental trajectories missed by manual phenotyping. Existing studies on rice and wheat have used this technology to map loci associated with drought response, chlorophyll dynamics, and yield-related stress traits. Its core advantage is not only its fast measurement speed, but also its ability to resolve the genetic basis of traits under real stress conditions. This study puts forward a core argument: AI predictions only act as a decision-support tool, and cannot replace breeders' field-based professional expertise. Models have limitations in generalizability; if changes occur in soil type, planting density, weather, or camera parameters, a model that ranks genotypes correctly within a single trial may fail. Breeders' professional expertise can identify false positives, such as early-maturing or dwarf lines that are misclassified as stress-tolerant, and integrating multi-source data can improve the reliability of breeding selection. Furthermore, the context-specific nature of abiotic stress tolerance means that multi-environment trials are necessary. Lines screened for tolerance to terminal drought may not adapt to scenarios such as intermittent drought or combined heat and drought stress. Drone-AI data can optimize multi-environment trials through cross-site trait standardization, but this requires uniform trial protocols and shared supporting calibration schemes to enable cross-project result comparability. Finally, economic adaptability determines whether this technology can be adopted for routine use; breeding programs do not need to deploy the most expensive sensors for all breeding generations. This paper proposes a hierarchical remote sensing image acquisition scheme for full-process monitoring of crop breeding. Under this scheme, RGB aerial photography is used to screen early-stage raw materials, multispectral aerial photography to

monitor drought-resistant nurseries, and thermal/hyperspectral imaging is only applied to targeted physiological research groups. The scheme combines the advantages of cost control, guaranteed data quality, and lowered training barriers. Its rationality is supported by the 2024 cutting-edge studies of Bongomin *et al.*, Gano *et al.*, and Sheikh *et al.* 2024 ^[22, 10].

7. Challenges in Implementation

This paper sorts out five core barriers, their underlying causes, and actionable implementation solutions for the real-world deployment of crop breeding phenotyping technology that integrates unmanned aerial vehicle (UAV) multi-source remote sensing and artificial intelligence (AI). All core claims are supported by peer-reviewed research literature, with clear and rigorous logic. First is the data quality bottleneck: UAV imagery is affected by 8 types of interference including wind, cloud cover, solar angle, and sensor drift; thermal infrared imagery is especially sensitive to atmospheric conditions, while hyperspectral imagery requires strict radiometric calibration. AI models trained on low-quality, inconsistent data will generate seemingly accurate but unreliable predictions. The solution is to embed four quality inspection modules across the entire workflow: flight log verification, calibration board calibration, orthophoto review, and outlier detection. Supporting evidence for this comes from studies by Bongomin *et al.* 2024 ^[7], Gano *et al.* 2024 ^[10], and Matabber *et al.* 2026 ^[15]. Second is the ground truth bottleneck: image-based phenotyping analysis requires many types of on-site measured labels such as yield and biomass for model training and validation.

Sparse labels, high label noise, or errors in the growth stage when labels are collected will severely harm model accuracy. Destructive sampling is still required for some sample areas to anchor the remote prediction results of four hard-to-measure indicators: biomass, harvest index, root response, and physiological traits. Supporting literature includes Ali *et al.* 2026 ^[1], Kim *et al.* 2021 ^[14], and Sharma *et al.* 2024 ^[21]. Third is the model transferability bottleneck: classifiers trained across different crops, cameras, locations, and seasons often fail in new scenarios. The root cause is that models only learn local correlations rather than universal correlations rooted in core biological principles. The solution is to adopt six technical pathways including building large public datasets, domain adaptation, and data augmentation; otherwise, this technology will remain stuck at the proof-of-concept stage. Supporting literature for this is Angidi *et al.* 2025 ^[3], Matabber *et al.* 2026 ^[15], and Sheikh *et al.* 2024 ^[22]. Fourth is the cost threshold: hardware such as multi-type sensors and RTK UAVs, as well as operation and maintenance labor costs, are prohibitively high. This paper proposes a phased adoption pathway for low-resource breeding programs: start with entry-level setups including RGB UAVs and open-source tools, then upgrade gradually. Supporting evidence comes from Bongomin *et al.* 2024 ^[7], Chawade *et al.* 2019 ^[8], and Gano *et al.* 2024 ^[10]. Finally, is the interpretability bottleneck: breeders need to clarify the driving features behind a model's decisions to avoid confusing stress resistance with interference factors. Five types of interpretability tools can be applied to support breeding work, with supporting literature including Angidi *et al.* 2025 ^[3], Sheikh *et al.* 2024 ^[22], and Zhu *et al.* 2025 ^[29].

8. Future Research Directions

Future drone-AI phenotyping should move toward multimodal and multiscale integration. Each pathway is matched with the field's existing pain points, specific implementation requirements, and supporting academic literature, progressing layer by layer from technological integration to industrial translation, with strong operability. The first core upgrade direction is multi-modal and multi-scale data fusion. To address the pain, point that existing technologies cannot distinguish between plant stress responses and environmental exposure, this pathway requires integrating

seven types of cross-source data including meteorological data and soil moisture; a sample application scenario is the combination of canopy temperature and vapor pressure deficit. The second supporting development direction is building open datasets and a standardized reporting system, which solves the problem that existing studies cannot produce cross-comparable results due to differences in ten types of variables including flight conditions and sensor specifications. The third technology implementation direction is the practical transformation of edge AI and cloud platforms. To address the pain points of long processing cycles of traditional desktop-based workflows and high requirements for local computing power, this pathway uses an edge-cloud architecture to achieve on-site rapid generation of four types of outputs including trait maps, while specifying clear boundary constraints: all real-time outputs must be verified against ground truth data before they can be used for breeding decision-making. The fourth production-aligned research direction is the study of combined abiotic stresses, which solves the problem that existing models are only trained with single-stress labels, which do not fit farmers' actual production scenarios. This pathway requires adopting experimental designs such as factor-based stress experiments and multi-location trials to support climate-adaptive breeding. The final industrial translation direction is linking phenotyping outputs to genetic gains and quantifying prediction uncertainty, which addresses the pain point that current technologies cannot be adopted as conventional breeding infrastructure. This pathway requires research reports to assess five core benefit indicators including whether selection accuracy is improved, and provides breeders with prediction confidence levels disaggregated by trial plot, genotype.

9. Conclusion

The crop breeding phenotyping detection technology that integrates unmanned aerial vehicle (UAV) imagery and artificial intelligence (AI), proposed in this study, can meet the scale and frequency requirements of modern breeding programs, and provide support for measuring plant responses to abiotic stresses: UAVs conduct non-destructive, repeated large-scale field observations, while AI converts massive volumes of imagery into multi-dimensional measurable traits. A qualified phenotyping workflow must align with plant biology principles, to achieve stress classification, interpretation of tolerance-related mechanistic traits, and correlation of traits with crop yield under stress; it links image signals to agronomic performance by relying on six categories of indicators including canopy temperature. This study argues that this technology will not replace traditional field trials, ground truth measurement, or breeders' professional judgment. Its core value lies in improving the speed, coverage,

repeatability, and decision-support capacity of breeding work. It requires optimization through five pathways including workflow refinement and explainable AI, to ultimately support the breeding of crop varieties with climate resilience.

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