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REVIEWS

From Pixels to Phenotypes: Quest of Machine Vision for Drought Tolerance Traits in Plants

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Abstract—Drought stress poses a significant threat to global agricultural productivity and food security. Understanding how plants adapt to drought conditions is crucial for developing drought-resistant crop varieties. Plants have been gifted with adaptation capacity to cope with situations arising from water deficit. Their capacity to acclimate is featured by adaptive changes in plants. The capacity to capture changes in shoot architecture has now been enhanced by the advent of non-invasive phenotyping techniques involving various imaging systems in plant phenomics platforms. These platforms thrive on the assumption that the plant responses reflected in terms of changes in the structure of the plant that can offer ample scope to employ machine vision for differentiating the responses of plants to soil-moisture deficit. Further, it is assumed that the detectable genetic variation in morphological traits responding to soil moisture deficit can provide hints about a plant's tolerance to stress and can be exploited to improve crop productivity in drought-prone areas. Genomic interventions utilizing high throughput phenotyping, make the selection of drought-tolerant genotypes easier. In recent years, machine vision has emerged as a powerful tool to study and quantify plant responses to drought stress. This article reviews the current state of knowledge on drought-adaptive responses in plants and explores the potential of genomic-assisted breeding tools coupled with high-throughput phenotyping platforms and machine vision to accelerate the elucidation of genotypic differences in adaptive traits. We also highlighted its role in deciphering the complex interplay of genotypic variations in drought-adaptive traits and harnessing artificial intelligence (AI) for machine vision data processing for the transformative potential in enhancing our understanding of plant responses to drought and expediting the development of climate-resilient crop varieties.

Keywords: drought, adaptive trait, machine vision, plant phenomics, artificial intelligence

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INTRODUCTION

Like many terrestrial organisms, plants rely on water for various cellular-level physiological processes, as water within plant cells drives growth and development [1]. Most plants, including those cultivated for food and fiber, absorb water from the soil through their root systems. Consequently, soil water deficits resulting from drought can significantly hinder plant growth by negatively impacting tissue water content impairing essential cellular activities [2]. Plants ability to tolerate such soil moisture deficits is crucial for sustaining crop productivity in drought-prone regions in the era of climate change. Nevertheless, translating these scientific findings into observable traits for distinguishing breeding lines remains elusive, primarily due to the complexity, time and labor-intensive nature of measuring cellular-level changes [3].

The fundamental alterations occurring at the cellular level, which ultimately manifest as changes in crop growth, development, and grain yield, hold immense potential for exploitation by plant breeders. However, some traits that can enhance grain yield stability across diverse environmental conditions may escape from the plant breeder's eye. Therefore, recent advancements in imaging systems offer promising avenues for harnessing the capabilities of machine vision to detect signals emitted by plants across various ranges of the electromagnetic spectrum, including the visible range, which can be captured using cameras [4]. These imaging systems have found extensive applications in various plant phenomics platforms designed to screen large populations of crop genotypes for variations in their responses to environmental cues [5].

Climate resilience traits are complex and are known to be influenced by component traits. However, phenotyping of component traits is difficult, and under such circumstances, high-throughput phenotyping platforms make the job of breeders easier. It is essential to understand that not every observable change in a plant's response to soil moisture stress represents an adaptive trait; many are mere consequences of stress. Therefore, the success of identifying relevant plant traits depends on the precision with which machine-detected observations can be linked to stress adaptation [6]. This review delves around the recent advances in imaging technologies in capturing crop response to moisture deficit and how these tools made breeder's task more convenient.

Physiological Manifestation of Shoot System Architecture during Soil Moisture Deficit

Escape, avoidance, and tolerance represent crucial adaptive strategies plants employ in response to drought stress [7]. Water stress tolerance traits are integral in maintaining tissue hydrostatic pressure, primarily achieved through osmotic adjustments [2]. These adjustments arise from synthesizing and accumulating compatible organic solutes in the cytoplasm and the influx of mineral solutes into vacuoles [8]. The ability of plants to employ these mechanisms plays a pivotal role, independently or cooperatively, in minimizing the detrimental effects of water limitations. Adequate maintenance of cell turgor ultimately influences leaf shape and overall shoot architecture [1].

Furthermore, it is worth noting that alterations in leaf temperature may play a pivotal role in regulating leaf water status under drought stress [9]. Deficit soil moisture stress induces an elevation of abscisic acid (ABA) levels within plant leaves, which could potentially compromise the plant's ability to regulate its temperature [10]. Structural dynamics and growth patterns, alterations in transpiration loss via stomatal conductance adjustments and distribution, leaf rolling, shifts in root-to-shoot ratios, the accumulation of compatible solutes, improved transpiration efficiency, osmotic and hormonal regulation, and delayed senescence are among the manifestations adopted by plants under conditions of soil moisture deficit [11].

Surrogate Traits to Explain Stress Responses in Plant Shoot

The preceding section has elucidated the scientific insights into adaptive mechanisms that unfold in response to stress, enabling plants to endure the challenges posed by soil moisture deficits. Global crop improvement programs are actively engaged in translating these scientific findings into genetically enhanced cultivars. However, many of these adaptive traits present significant challenges when integrating them into crop breeding programs to distinguish responses among diverse genotypes on a large scale, a prerequisite for accurately quantifying genetic variability [12]. Consequently, there is a compelling need for alternative traits, herein referred to as surrogate traits, that can facilitate the phenotyping of plant responses to environmental stressors, such as soil moisture deficits.

Machine vision, a subset of artificial intelligence (AI) and computer vision, involves the use of cameras and image analysis algorithms to extract quantitative data from images [13]. In the context of plant research, machine vision has proven to be a powerful tool for high-throughput phenotyping, enabling researchers to analyze various plant traits quickly and non-destructively (Fig. 1). This technology can be applied to study a wide range of traits related to drought adaptation [14].

In the context of plant phenotyping, particularly in the assessment of plant responses to stresses, including those induced by soil moisture stress, machine vision holds great potential. Within the machine vision domain, a diverse array of imaging systems is harnessed to capture plant responses automatically, typically within a framework often referred to as high throughput plant phenomics [15]. These systems can sense various wavelengths within the electromagnetic spectrum, encompassing the visible, infrared, and near-infrared ranges. Specifically, hyperspectral imaging systems are engineered to capture the reflectance characteristics of objects across different wavelengths, providing valuable spectral signatures of the observed subjects [16]. Numerous pieces of evidence substantiate the utility of these advanced imaging systems in unraveling plant responses to water deficit conditions and, subsequently, leveraging the phenotype data to identify pertinent genes.

The imaging systems referred to above provide the true or the false images, which are to be processed with relevant algorithms to extract the features that can be used to derive relevant parameters for assessing the plant responses [17]. When these features consistently align with stress responses and adaptation, they can serve as surrogate traits for the efficient screening of a large number of genotypes [12]. For instance, the area of plant images captured from various angles using high-resolution cameras within the visible electromagnetic spectrum can unveil biomass, a prevalent shoot parameter employed for assessing plant stress responses [18]. Demonstrably, surrogate traits such as digital volume, representing plant biomass, have been employed to distinguish plant responses across genotypes [19]. Alterations in shoot morphology, such as reductions in leaf size, may be attributed to ceased cell division, cell elongation, or desiccation-induced rolling or folding, and these changes can also be captured by imaging systems combined with appropriate algorithms for image analysis [20]. Parameters extracted from images, such as caliper length, compactness, eccentricity, and boundary point ratio, can serve as surrogate indicators elucidating stress-induced morphological changes in plants [21].

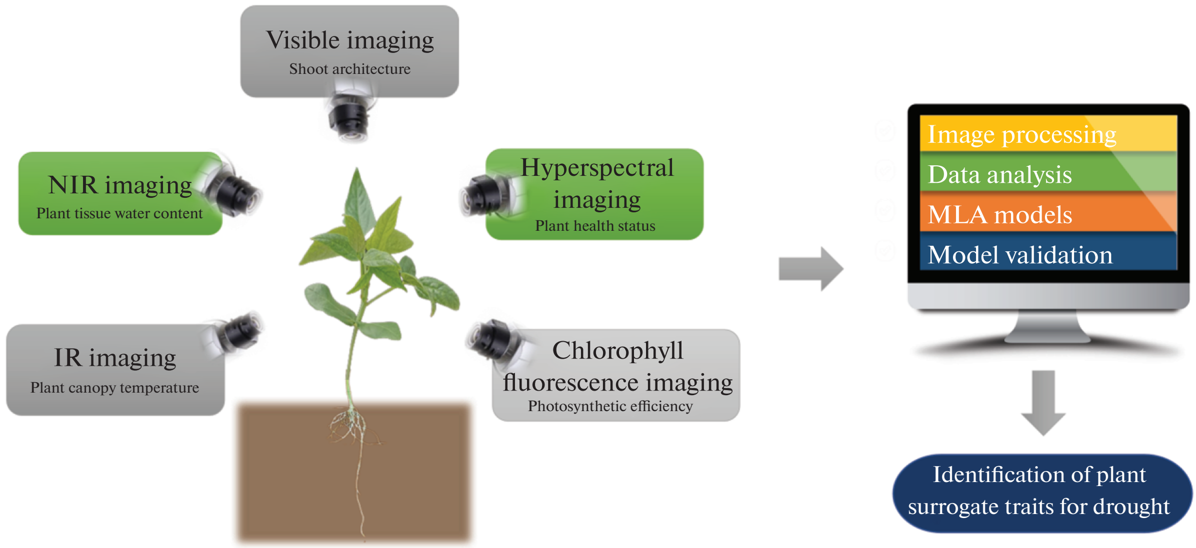

Fig. 1. Image-based phenotyping to determine plant surrogate traits for drought tolerance.

Similarly, indices derived from near-infrared (NIR) images can facilitate genotype differentiation based on leaf tissue water content, utilizing surrogate parameters to reveal relative water content [22]. Further, thermal imaging systems are commonly used to evaluate a plant's ability to regulate canopy temperature [23]. Stress-related indices, extracted from thermal images, can serve as surrogate traits for distinguishing genotypic responses to stress. Similarly, the chlorophyll fluorescence imaging system is a powerful tool for gaining insights into vital processes such as photosynthesis [18]. Chlorophyll fluorescence image features hold the potential to unveil a range of indices elucidating the performance of each key component of the electron transport chain under stress conditions. These indices can function as surrogate traits for dissecting underlying stress tolerance mechanisms and identifying critical components conducive to crop improvement [24].

Furthermore, hyperspectral signatures enable genotype differentiation based on metabolic changes occurring within plants in response to stress. Indices derived from hyperspectral reflectance have been proven effective in elucidating tissue desiccation [22]. Efforts are underway to employ imaging systems to elucidate variations in reproductive structures, such as inflorescence and grain morphology, through parameters extracted from images [25]. All these advancements in imaging science promise to translate plant stress's physiology into practical tools for identifying traits relevant to plant adaptation in agroecologies characterized by soil moisture deficits.

Harnessing AI for Machine Vision Data Processing

AI (Artificial Intelligence) and Machine Learning Algorithms (MLA) play pivotal roles in enhancing our understanding of drought-adaptive responses in plants using machine vision. AI and machine learning algorithms are instrumental in researching and developing drought-resistant crops by facilitating the rapid and precise analysis of plant responses to drought stress [26]. These technologies accelerate the elucidation of genotypic differences in adaptive traits and potentially revolutionize crop breeding strategies for improved food security in a changing climate [27].

AI, through its ability to process and analyze vast datasets generated by machine vision systems, enables the extraction of valuable insights into plant responses to drought stress. MLAs, particularly deep learning algorithms, provide the means to discern intricate patterns and relationships within these datasets, thereby aiding in identifying genotypic differences in adaptive traits more efficiently, as indicated in Table 1. Such advances are exemplified in studies like those by [36] and [37], where AI-driven analysis of plant phenotypic data has enhanced our understanding of plant responses to environmental stressors, including drought conditions (Table 2).

Machine vision emerges as an invaluable ally, bridging the gap between the intricate visual data captured and the meaningful biological insights derived. Through the lens of machine vision, the seemingly ordinary pixels in plant images are transformed into a treasure trove of information, offering profound insights into plant responses to drought stress [38]. Through the fusion of imaging technologies, data analytics, and AI-driven algorithms, machine vision unlocks the secrets hidden within plant pixels, revealing phenotypes that serve as key indicators of a plant's resilience to drought [39]. This powerful synergy between pixels and phenotypes exemplifies the transformative potential of machine vision in shaping the

Table 1. Significance of AI and MLA across various plant investigations

AI/MLA Application	Significance	Crops	References
Image Segmentation	Segmentation of plant images obtained through machine vision and isolation of different plant parts (e.g., leaves, stems, roots) for further analysis.	Wheat	[26]
Feature Extraction	AI/MLA can automatically extract quantitative features from plant images, such as leaf area, color, texture, and shape, aiding in trait quantification.	Rice, sorghum, barley	[28]
Phenotype Classification	Classification of plant phenotypes based on drought-related traits, helping to identify genotypic differences in adaptive responses.	Cotton, tomato, sunflower	[29, 30]
Trait Quantification	Quantification of specific drought-related traits, such as stomatal conductance, chlorophyll content, or root length, from plant images.	Potato, canola, lentil	[31, 32]
Genotype-Phenotype Association	Identifying genetic markers associated with adaptive traits facilitates marker-assisted breeding for drought resistance.	Maize, chickpea, sugarcane	[33, 34]
Predictive Modeling	Development of predictive models for plant responses to drought, aiding in selecting promising genotypes for breeding programs.	Sorghum,	[35]

Table 2. Application of AI models for trait estimation in different crops

AI Model	Analysis Method	Parameters Estimated	Significance	Crops	References
Convolutional Neural Networks (CNN)	Image segmentation and feature extraction	Leaf area, stomatal density	Efficiently assesses drought-induced leaf changes	Wheat	[41]
Recurrent Neural Networks (RNN)	Time series analysis	Soil moisture levels	Predicts soil water content patterns for irrigation	Maize	[42]
Random Forest	Hyperspectral imaging analysis	Chlorophyll content	Accurate estimation of plant health and stress levels	Cotton, Potato	[43, 44]
Long Short-Term Memory Networks (LSTM)	Time series prediction	Canopy temperature	Predicts plant stress responses based on temperature data	Tomato	[45]

future of crop improvement, ensuring food security, and mitigating the impacts of climate change [40].

Amalgamation of High Throughput Phenotyping (HTP) and Genomic Assisted Breeding (GAB) for Climate Resilience

The rapid development of phenomics has simplified the phenotyping of traits [46]. High-throughput phenotyping can effectively bridge the gap between genomics and phenomics (Fig. 2). In this regard, studies conducted using high-throughput phenotyping platforms in mapping the *QTLs* linked to the shoot architecture traits are mentioned here.

High throughput screening technique called "Rice Automatic Phenotyping (RAP)" platform was employed in maize. A set of 167 RILs was phenotyped employing the RAP platform from seedling stage to the tasseling stage at 16 different time intervals. A total of 106 phenotypic traits, including 10 plant morphological traits, 22 leaf architecture traits, one plant color trait, three biomass-related traits, and 64 growth-related traits, were emphasized. QTL mapping identified a total of 938 QTLs for 42 phenotypic traits recorded at 16 different intervals. The phenotypic variance explained for each QTL was ranged from 5.5 to 26.6% [47]. This study emphasizes the importance of HTP platforms in GAB era. To identify the drought-tolerant barley accessions a set of 47 accessions was screened and a

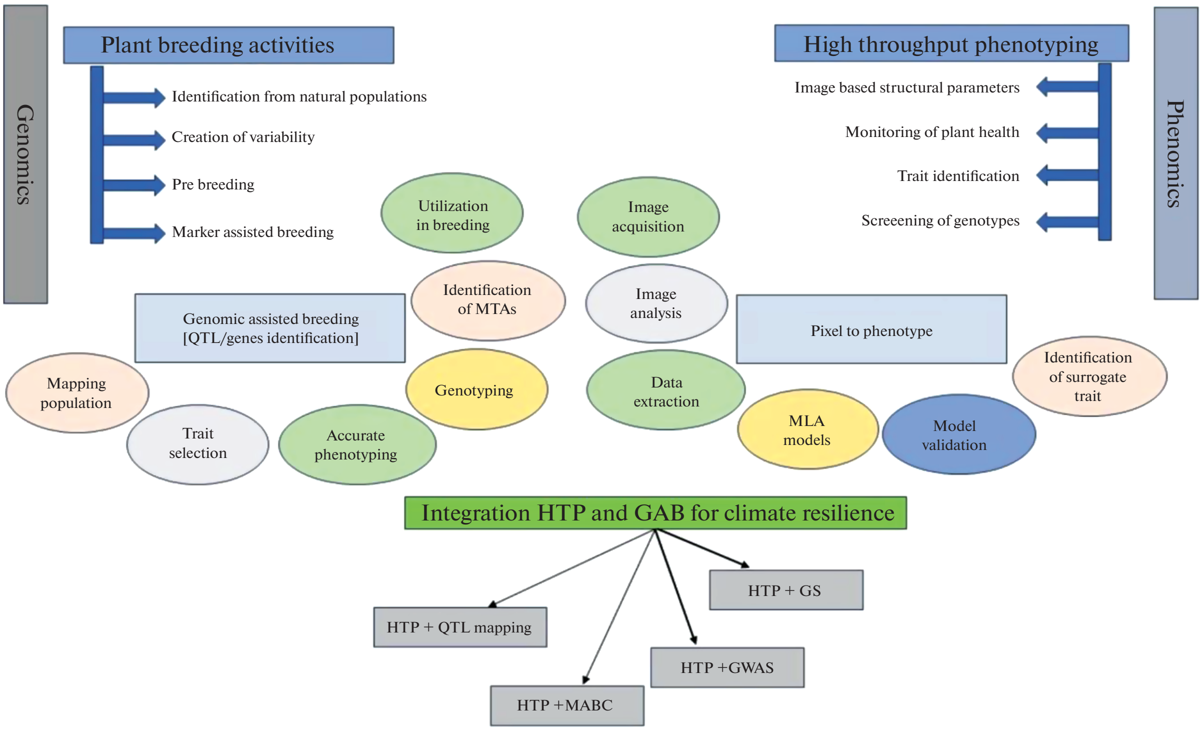

Fig. 2. Combining high throughput phenotyping (HTP) with genomic-assisted breeding (GAB) to enhance climate resilience for drought.

phenotyping platform "The Plant Accelerator" was employed. The biomass accumulation from the image-based estimation was highly correlated with the actual phenotype-based biomass accumulation (r = 0.98), indicating the usefulness of HTP platforms. Furthermore, a total of 44 QTLs were detected for 11 drought-tolerance imparting traits. Phenotyping of young plants using HTP platforms coupled with DNA markers assists in predicting adult plant performance during stress [32]. Another study demonstrated by Ajayi [48] aimed to map the *QTLs* imparting drought tolerance in barley in a set of 192 RILs derived by crossing parents contrasting for drought tolerance (Otis (R) × Golden Promise (S)). Biotron facility was employed for rapid generation advancement and short-term progressive drought was imposed during the heading period. A total of 23 *QTLs*, of which eight were specific to shoot dry weight were identified across barley chromosomes that could be used as an indirect selection criterion for identifying drought-tolerant lines.

QTL mapping fails significantly in improving polygenic traits. An extension of MAS, called Genome Wide Association Studies (GWAS), which considers of genome-wide markers that are significantly linked to the trait of interest [49], is found to be more effective. A combination of HTP and GWAS can bring about more success in improving the crops for climate resilience. Studies conducted using HTP and GWAS are presented in Table 3.

To further leverage the potential of machine vision in elucidating genotypic differences in drought adaptive traits, a strategic way forward involves integrating multi-disciplinary expertise [56]. Collaborative efforts among plant biologists, computer scientists, engineers, and data scientists are essential to refine machine vision algorithms explicitly tailored to capture plant responses to drought. The development of standardized protocols and image analysis pipelines will enable the reproducibility of results across studies and institutions. The genomic-assisted breeding has become robust as phenotyping platforms are highly effective in accurately measuring climate resilience traits. Additionally, investments in creating comprehensive image databases with diverse genotypes and controlled drought conditions can serve as valuable resources for training machine learning models and improving the accuracy of trait quantification. Furthermore, to ensure the practical applicability of machine vision in plant breeding programs, efforts should be made to bridge the gap between research laboratories and agricultural fields. On-farm validation of machine vision-based phenotyping tools, coupled with farmer engagement, can facilitate the integration of this technology into real-world agricultural practices. The dissemination of user-friendly, cost-effective, and portable machine vision systems to breeders and farmers will democratize access to advanced phenotyping capabilities and empower them to make informed decisions for selecting drought-

Table 3. GWAS integrated with HTP for improving the plant performance

Crops	Population used	Phenotyping platforms	Traits considered	Models used	QTNs or the candidate genes identified	References
Rice	533 accessions	RGB imaging	29 leaf traits (6 size—related traits, 7color—related traits, 16 shape—related traits)	Mixed linear model (MLM)	73 loci for size-related traits, 123 for color related traits, 177 for shape related traits	[50]
	360 accessions	Visible light/RGB imaging	Projected shoot area	Random regression model	7 QTLs	[51]
	357 accessions	RGB imaging	Projected shoot area	EMMA	442 SNPs	[51]
	553 accessions	visible light/RGB imaging	Relative growth rate, transpiration rate, transpiration use efficiency (TUE)	MLM	QTL specific TUE	[52]
	378 accessions	visible light/RGB imaging	Projected shoot area	Bayesian LASSO regression model	2 QTNs (Quantitative trait nucleotide)	[51]
Maize	252 inbreds	near-infrared, visible light/RGB and fluorescence imaging	Plant fresh weight, plant dry weight, biovolume estimation at 11 different developmental stages	MLM	12 MTAs (Marker Trait Association)	[53]
Bread wheat	335–352 genotypes	light detection and ranging (LIDAR)	Canopy height, average daily stem elongation rates	MLM	10 MTAs for final height, 3 MTAs for temperature response,	[54]
Barley	1420 NAM lines	RGB imaging	14 growth traits related to drought tolerance	MLM	3 candidate genes	[55]

resistant crop varieties. In this way, machine vision along with genomic-assisted breeding, has the potential to accelerate our understanding of genotypic differences in drought-adaptive traits and drive tangible improvements in crop resilience and food security in the face of escalating climate challenges.

CONCLUSIONS

The integration of machine vision technology into the exploration of drought-adaptive responses in plants represents a significant stride toward expediting our comprehension of genotypic distinctions in adaptive traits. This interdisciplinary approach, merging biology, computer science, and engineering, has already demonstrated its prowess in delivering rapid, precise, and high-throughput phenotyping capabilities. Future endeavors to harness the benefits of imaging systems for trait identification hinge largely on the optimization of protocols, encompassing image acquisition, processing, and analysis for each imaging system. The application of Artificial Intelligence (AI) and machine learning assumes a pivotal role in managing and analyzing the substantial volumes of data generated within the high-throughput plant phenomics platform. These technologies are instrumental in facilitating trait and gene identification for crop improvement. The amalgamation of advanced imaging techniques with machine learning and data integration strategies empowers researchers to unearth novel insights into plant responses to drought stress. Ultimately, this knowledge can be harnessed to develop more resilient and productive crop varieties, contributing to global food security in the face of changing climate and increasing water scarcity.

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AUTHOR CONTRIBUTION

VH and JR: conceptualization; writing of the original draft. SM, MS, HD, and BP: resources; editing.

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ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This work does not contain any studies involving human and animal objects.

CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

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