Journal of
Current Opinion in Crop Science

Journal homepage: www.jcocs.com; ISSN(O):2583-0392

REVIEW ARTICLE

Crop phenomics: Emerging tools for next-generation field crop improvement

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Article history:

Received: November 30, 2025
Accepted: December 27, 2025
Published: December 30, 2025

Citation:

Ashokkumar, K., Gogulavasan, M., & Prabhu, V. S. (2025). Crop phenomics: Emerging tools for next-generation field crop improvement. *Journal of Current Opinion in Crop Science, 6*(4), 298- 316. https://doi.org/10.62773/jcocs.v6i4.369

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ABSTRACT

Crop phenomics has emerged as a transformative discipline that bridges genomics and agronomy by enabling precise, high-throughput, and non-destructive measurement of plant traits. Over the past decade, more than 50 advanced phenotyping platforms have been established globally, ranging from controlled-environment facilities to field-based systems, underscoring the momentum of this technological revolution. With increasing demands for sustainable food production under climate change, phenomics offers unprecedented opportunities to accelerate genetic gains and optimize crop management. Recent advances in imaging technologies, sensor integration, and computational tools have expanded the scope of trait dissection in field crops. Ground-based systems, unmanned aerial vehicles (UAVs), and satellite-based remote sensing now provide scalable and high-resolution field phenotyping, while controlled-environment platforms deliver mechanistic insights into plant physiology and stress responses. The integration of hyperspectral, thermal, and 3D imaging with machine learning algorithms has enhanced trait extraction and predictive accuracy. Applications span diverse domains, including identification of stress-resilient genotypes, improvement of nutrient and water use efficiency, early disease detection, and precision breeding strategies. Despite these advances, challenges persist in data standardization, cost-effectiveness, and translating controlled-environment findings to field conditions. Adherence to FAIR (Findable, Accessible, Interoperable, and Reusable) data principles remains critical to ensure harmonized and comparable datasets across platforms. In future, the convergence of phenomics with genomics, enviromics, and artificial intelligence is poised to redefine crop improvement pipelines, enabling the development of resilient, high-yielding, and resource-efficient cultivars. This review synthesizes current tools and applications, highlighting the pivotal role of crop phenomics in advancing global food and nutritional security.

Keywords: phenomics, high-throughput phenotyping, imaging technologies, stress resilience, genomic prediction, precision agriculture.

1.INTRODUCTION

Crop phenomics is the systematic study of plant traits at multiple organizational scales, ranging from cellular and organ-level features to whole-plant and canopy architecture, using advanced sensing technologies, imaging platforms, and computational tools (Arunachalam & Andreasson, 2021; Jiang & Zhu, 2024; Kumari et al., 2025; Sun et al., 2025). Unlike traditional phenotyping, which is often labor-intensive and limited in scope, phenomics enables high-throughput, precise, and non-destructive measurement of complex traits under both controlled and field conditions (Furbank & Tester, 2011; Yang et al., 2020). By capturing dynamic plant responses to environmental stimuli, crop phenomics provides a comprehensive understanding of growth, development, and stress adaptation (Kaya, 2025).

A central role of phenomics is to bridge the long-standing genotype–phenotype gap, which has constrained the translation of genomic discoveries into practical crop improvement (Mir et al., 2019). While advances in next-generation sequencing have accelerated the identification of candidate genes and alleles, the lack of equally powerful phenotyping tools has slowed progress in linking genetic variation to agronomic performance (Cobb et al., 2013; Araus & Cairns, 2014). Phenomics platforms, when integrated with genomic selection, quantitative trait locus (QTL) mapping, and genome-wide association studies (GWAS), provide the resolution needed to dissect complex traits such as drought tolerance, nutrient-use efficiency, and yield stability (Mazis et al., 2020; Xiao et al., 2022; Kumari et al., 2025).

The urgency of advancing crop phenomics is underscored by the challenges of climate change, global food insecurity, and the need for sustainable intensification of agriculture (Maheswari et al., 2024; Nguyen et al., 2025; Denning et al., 2025). In this context, global initiatives such as the CGIAR phenotyping networks and other international collaborations play a pivotal role in harmonizing methodologies, sharing resources, and accelerating innovation to address these pressing challenges. Rising temperatures, erratic rainfall, and increasing biotic and abiotic stresses threaten crop productivity worldwide (Reynolds et al., 2020). In this context, phenomics provides tools to accelerate the identification of resilient genotypes, optimise resource-use efficiency, and support precision agriculture practices that minimise environmental footprints (Araus et al., 2018; Xu et al., 2022). By enabling rapid, scalable trait assessment, phenomics directly contributes to the development of cultivars capable of sustaining productivity under variable and resource-limited conditions (Chowdhuri & Pal, 2025).

This review discusses recent advances in crop phenomics, with a focus on tools, technologies, and applications in field crop improvement. This study highlights imaging modalities, field-based and controlled-environment platforms, and computational approaches that are reshaping phenotyping pipelines. Furthermore, this review study discusses the applications of phenomics in accelerating genetic gains, improving stress resilience, and supporting sustainable agriculture. Finally, the present study examines the challenges of scalability, data integration, and accessibility, and proposes future directions for integrating phenomics with genomics, enviromics, and artificial intelligence to drive next-generation crop improvement. The overview of phenomics was diagrammatically represented in Figure 1.

2. TOOLS AND TECHNOLOGIES IN CROP PHENOMICS

2.1. Imaging and Sensor-Based Platforms

Imaging and sensor-based platforms form the backbone of modern crop phenomics, enabling the non-invasive capture of plant traits across spatial and temporal scales. Traditional visual scoring methods are increasingly being replaced by high-throughput imaging systems that provide quantitative, reproducible, and scalable data (Elangovan et al., 2023; Abebe et al., 2023). Visible and multispectral imaging, for instance, are widely used to assess canopy architecture, growth dynamics, and biomass accumulation, providing insights into plant vigour and development under diverse environmental conditions (Furbank & Tester, 2011; Yang et al., 2020). These imaging modalities enable breeders to monitor growth trajectories and identify genotypes with superior performance in real-time.

Hyperspectral imaging has emerged as a powerful tool for capturing biochemical and physiological traits. By recording reflectance across hundreds of narrow spectral bands, hyperspectral sensors can detect subtle variations in pigment composition, nutrient status, and photosynthetic efficiency (Mahlein, 2016). This technology has been particularly valuable for early detection of abiotic stresses such as drought and salinity, as well as biotic stresses including fungal and viral infections, often before visible symptoms appear (Thomas et al., 2018). Such early detection capabilities make hyperspectral imaging a critical component of precision breeding and crop protection strategies. However, widespread adoption is constrained by the high cost of hyperspectral sensors and platforms, as well as the complexity of processing and analyzing large, multidimensional datasets. These limitations highlight the need for cost-effective sensor development, standardized data pipelines, and advanced machine learning approaches to fully realize the potential of hyperspectral imaging in crop improvement.

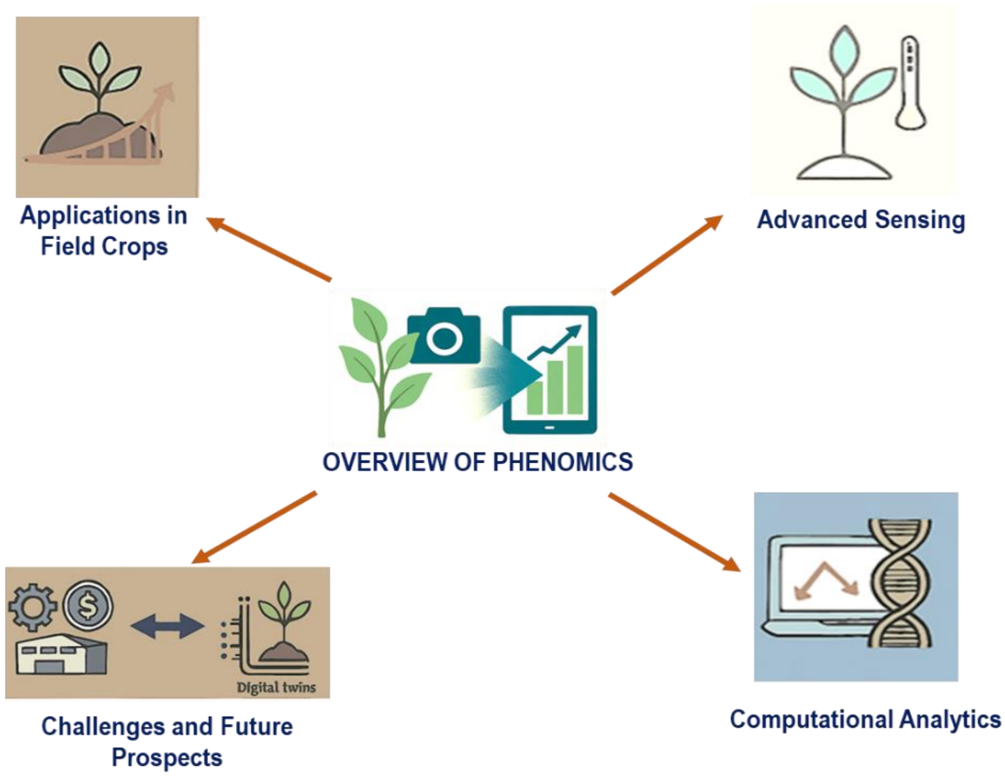

Figure 1. Overview of phenomics for next-generation field crop improvement

Thermal imaging provides complementary insights by quantifying canopy temperature, which serves as a proxy for transpiration and stomatal conductance (Dong et al., 2024). This approach has been widely applied to evaluate water-use efficiency and drought tolerance in cereals and legumes (Jones et al., 2009; Prashar & Jones, 2014). By integrating thermal data with genomic and physiological analyses, researchers can identify genotypes with superior adaptive responses to water-limited environments, thereby accelerating the development of climate-resilient cultivars (Srivastava et al., 2024).

Three-dimensional (3D) imaging and Light Detection and Ranging (LiDAR) technologies further expand the scope of phenomics by enabling structural phenotyping of plant architecture (Takhtkeshha et al., 2024; Liu et al., 2025; Li et al., 2025). These platforms capture detailed information on plant height, leaf angle distribution, and canopy volume, traits that are often correlated with light interception and yield potential (Madec et al., 2017; Khalifa & Albadawy, 2024). The integration of 3D imaging with machine learning algorithms has enhanced the accuracy of trait extraction, enabling efficient phenotyping of large populations in both controlled and field environments (Qian et al., 2022; Villa et al., 2024). Collectively, these imaging and sensor-based platforms represent a paradigm shift in crop phenotyping, providing the resolution and throughput necessary to bridge the genotype–phenotype gap.

2.2. Field-Based High-Throughput Platforms

Field-based high-throughput phenotyping (HTP) platforms have revolutionized the ability to evaluate large crop populations under realistic agronomic conditions (Li et al., 2021). Unlike controlled-environment facilities, these platforms capture plant performance directly in farmers' fields, thereby providing more accurate insights into genotype × environment interactions (Araus & Cairns, 2014; Sheikh et al., 2024). Ground-based systems, including tractor-mounted sensors and custom-built "phenomobiles," are among the earliest innovations in this domain. These platforms integrate multispectral, thermal, and LiDAR sensors to measure canopy architecture, biomass accumulation, and physiological responses with high precision (White et al., 2012; Sharma & Shivandu, 2024). Their proximity to the crop canopy ensures high-resolution data collection, although their scalability is often limited by field size and terrain.

Unmanned aerial vehicles (UAVs), or drones, have rapidly emerged as one of the most versatile tools for field phenotyping. Equipped with RGB, multispectral, hyperspectral, or thermal cameras, UAVs enable rapid, non-invasive, and scalable monitoring of crop traits across large experimental plots (Yang et al., 2017). UAV-based imaging has been successfully applied to assess canopy temperature, vegetation indices, and stress responses in cereals, legumes, and oilseeds, offering breeders a cost-effective and flexible alternative to ground-based systems (Zhang et al., 2019; Awais et al., 2021; Almawazreh et al., 2025). Their ability to capture temporal dynamics through repeated flights makes them particularly valuable for monitoring growth trajectories and stress adaptation.

At broader spatial scales, satellite-based remote sensing provides regional and even global perspectives on crop performance. Advances in spatial and temporal resolution of satellite imagery now allow monitoring of crop growth, yield forecasting, and stress detection at unprecedented scales (Lobell et al., 2015). While satellite data may lack the satisfactory resolution of UAV or ground-based systems, its integration with field-level phenotyping enables multi-scale analyses that link plot-level traits to regional crop productivity. Such integration is critical for scaling breeding outcomes to real-world agricultural systems and for informing policy decisions related to food security and climate resilience (Antonakakis & Zervakis, 2024; Bazrafkan et al., 2025). Together, ground-based, UAV, and satellite platforms represent complementary approaches in field-based phenomics. Ground systems provide high-resolution trait data, UAVs offer flexibility and scalability, and satellites extend phenotyping to regional and global levels (Alvarez-Vanhard et al., 2021). The convergence of these platforms, combined with advances in machine learning and data integration, is paving the way for holistic, multi-scale crop improvement strategies (Araus et al., 2018).

2.3. Controlled Environment Platforms

Controlled environment platforms, such as automated greenhouses and growth chambers, play a pivotal role in crop phenomics by enabling precise regulation of environmental variables, including light, temperature, humidity, and nutrient supply (Bouarroudj et al., 2025). These facilities allow researchers to minimize environmental noise and focus on genotype-driven trait variation, thereby improving the reproducibility of phenotypic measurements (Poorter et al., 2016). Automated systems equipped with conveyor belts, robotic imaging stations, and integrated sensor arrays facilitate high-throughput monitoring of plant growth, morphology, and physiology under standardized conditions (Fahlgren et al., 2015). Such platforms are particularly valuable for dissecting complex traits like photosynthetic efficiency, water-use dynamics, and nutrient uptake, which are difficult to isolate in field environments (Ozer et al., 2025).

Greenhouse-based phenotyping systems also provide opportunities to simulate specific stress scenarios, such as drought, salinity, or heat, under controlled conditions (Lee et al., 2025). By applying uniform stress treatments, researchers can evaluate genotype-specific responses with high precision and link these responses to underlying genetic and molecular mechanisms (Tardieu et al., 2017). This controlled approach accelerates the identification of stress-resilient genotypes and supports the development of predictive models for crop performance under variable field conditions.

In addition to aboveground traits, controlled environments have advanced root phenotyping, an area traditionally constrained by the hidden nature of root systems (Chandnani & Soolanayakanahally, 2025; Araujo et al., 2025). Rhizotrons, transparent growth containers that allow root visualization, enable continuous monitoring of root growth dynamics, architecture, and interactions with soil (Nagel et al., 2012). More advanced imaging techniques, such as X-ray computed tomography (CT) and magnetic resonance imaging (MRI), provide three-dimensional, non-invasive reconstructions of root systems in soil, offering unprecedented insights into root architecture and function (Mooney et al., 2012; Hussain et al., 2022). These tools are critical for identifying root traits associated with water and nutrient acquisition, which are central to breeding crops for resource-use efficiency (Langstroff et al., 2022). The tools and technologies used under various categories were summarized in Table 1.

Furthermore, the controlled environment platforms complement field-based phenotyping by providing mechanistic insights into plant responses under well-defined conditions. When integrated with genomic and computational approaches, these systems enable the discovery of trait–gene associations and the development of ideotypes optimized for both controlled and field environments. Their continued refinement and integration with high-throughput imaging and data analytics will be essential for advancing next-generation crop improvement strategies.

Table 1. Tools and Technologies in Crop Phenomics

Category	Tools / Technologies	Applications in Phenomics	References
Imaging Platforms	RGB imaging, multispectral imaging, hyperspectral imaging, thermal cameras, fluorescence imaging	Monitoring canopy architecture, pigment composition, photosynthetic efficiency, and stress detection	Mahlein, (2016): Kumari et al. (2024); Sun et al. (2025)
3D and Structural Phenotyping	LiDAR, 3D laser scanning, stereo vision, photogrammetry	Capturing plant height, leaf angle distribution, canopy volume, and architecture traits	Madec et al. (2017)
Root Phenotyping	Rhizotrons, minirhizotrons, X-ray computed tomography (CT), magnetic resonance imaging (MRI)	Non-invasive visualization of root system architecture, root growth dynamics, and soil interactions	Metzner et al. (2015)
Field-Based Platforms	Tractor-mounted sensors, phenomobiles, UAVs/drones, satellite remote sensing	High-throughput field phenotyping, stress monitoring, yield prediction, regional crop monitoring	Araus & Cairns, (2014); Yang et al. (2017)
Controlled Environment Systems	Automated greenhouses, growth chambers, conveyor-based imaging systems	Precise trait measurement under controlled conditions; stress simulation studies	Fahlgren et al. (2015); Tardieu et al. (2017)
Sensor Technologies	Soil moisture sensors, chlorophyll meters (SPAD), gas exchange systems, thermal probes	Physiological trait measurement (water-use efficiency, photosynthesis, nutrient status)	Jones et al. (2009); Prashar & Jones, (2014)
Computational & Data Analytics	Machine learning, deep learning, image analysis pipelines, crop growth models	Automated trait extraction, genomic prediction, digital twins, integration of multi-omics data	Singh et al. (2021); Zhao et al. (2019)

3. APPLICATIONS OF PHENOMICS IN FIELD CROP IMPROVEMENT

3.1. Accelerating Genetic Gains

One of the most significant contributions of crop phenomics lies in its ability to accelerate genetic gains by linking high-resolution phenotypic data with genomic information. Traditional breeding approaches often relied on low-throughput and subjective trait measurements, which limited the precision of genotype–phenotype associations (Reddy et al., 2025; Mansoor et al., 2025). With the advent of high-throughput phenotyping (HTP), breeders can now capture dynamic, quantitative traits at multiple developmental stages and environmental conditions, thereby improving the resolution of trait mapping and selection (Furbank & Tester, 2011; Araus & Cairns, 2014). A notable example is the successful identification of drought-responsive QTLs in maize through UAV-based canopy temperature imaging, which enabled the development of drought-tolerant hybrids now widely deployed in sub-Saharan Africa (Xu et al., 2022). This case illustrates how phenomics-driven trait discovery, when integrated with genomic prediction, can translate directly into breeding outcomes that enhance resilience and food security.

High-resolution phenotypic datasets have been particularly valuable in quantitative trait locus (QTL) mapping and genome-wide association studies (GWAS). By integrating phenomics data with genomic markers, researchers can dissect the genetic architecture of complex traits such as drought tolerance, photosynthetic efficiency, and yield stability (Cobb et al., 2013; Xiao et al., 2022; Visakh et al., 2024). For example, UAV-based imaging of canopy temperature and vegetation indices has been successfully used to identify QTLs associated with water-use efficiency in cereals (Pauli et al., 2016). Such approaches enhance the discovery of trait-linked loci and facilitate marker-assisted selection in breeding programs.

Beyond QTL mapping and GWAS, phenomics also strengthens genomic prediction (GP) models. GP relies on statistical algorithms to predict the breeding value of individuals based on genome-wide marker data (Alemu et al., 2024; Roy et al., 2025). The accuracy of these models depends heavily on the quality of the phenotypic data used for training. Incorporating high-throughput, multi-environment phenotypic datasets improves prediction accuracy, particularly for complex traits influenced by genotype × environment interactions (Xu et al., 2022; Crossa et al., 2017). Recent advances in artificial intelligence (AI) and machine learning have further enhanced GP by enabling the integration of nonlinear relationships, deep learning architectures, and multi-omic datasets. AI-driven GP approaches, such as convolutional neural networks and ensemble learning, can capture hidden patterns in large-scale phenotypic and genomic datasets, thereby improving prediction accuracy for traits with complex inheritance. Moreover, coupling AI-based GP with real-time phenomics data streams enables dynamic model updates, supporting adaptive breeding strategies across variable environments. This integration enables breeders to make more informed selection decisions earlier in the breeding cycle, thereby reducing time and cost while accelerating genetic gains.

Ultimately, the synergy between phenomics, genomics, and computational modeling is redefining the pace of crop improvement. By enabling precise trait dissection, enhancing prediction accuracy, and supporting data-driven selection, crop phenomics provides a robust framework for achieving sustained genetic gains in field crops (Cembrowska-Lech et al., 2023; Yang et al., 2025). This integration is especially critical in the face of climate change and global food security challenges, where the rapid development of resilient, high-yielding cultivars is essential (Reynolds et al., 2020). The application of phenomics tools in field crop improvement was summarized in Table 2.

Table 2. Applications of Crop Phenomics in Field Crop Improvement with Crop-Specific Examples

Application Area	Phenomics Approach / Tools	Key Outcomes	Crop-Specific Applications	References
Accelerating genetic gains	High-throughput imaging, UAV-based canopy monitoring, hyperspectral and thermal sensors	Improved QTL mapping and GWAS resolution; enhanced genomic prediction accuracy; faster selection cycles	*Maize:* UAV-based canopy temperature mapping for drought QTL discovery; *Wheat:* spectral indices linked to yield QTLs; *Soybean:* canopy imaging for drought QTLs	Xu et al. (2022); Burner et al. (2025)
Stress Physiology & Climate Resilience	Thermal imaging, hyperspectral reflectance, chlorophyll fluorescence, UAV-based time-series monitoring	Identification of drought-, heat-, and salinity-tolerant genotypes; real-time monitoring of dynamic stress responses	*Rice:* hyperspectral imaging for salinity tolerance; *Wheat:* thermal imaging for heat resilience; *Sorghum*: UAV-based drought stress monitoring; *Pigeonpea:* high-throughput	Araus & Cairns (2014); Reynolds et al. (2020); Prasad et al. (2026)

			phenomics for drought tolerance	
Nutrient Use Efficiency & Productivity	Hyperspectral imaging for nitrogen status, chlorophyll fluorescence, root phenotyping (rhizotrons, X-ray CT)	Screening for nitrogen-use efficient genotypes; identification of ideotypes with optimized root and canopy traits	*Maize:* hyperspectral reflectance for nitrogen-use efficiency; *Barley:* root CT imaging for phosphorus uptake traits	Yendrek et al., (2017); Lynch, (2019); Sun et al. (2025)
Disease & Pest Resistance	Hyperspectral and multispectral imaging, UAV-based disease mapping, machine learning classifiers	Early detection of biotic stress signatures; integration with precision crop protection strategies	*Wheat:* hyperspectral detection of Fusarium head blight; *Potato:* UAV-based mapping of late blight; *Soybean:* imaging for rust resistance; *Chickpea:* Image-based analysis for *Fusarium* wilt classification	Mahlein, (2016); Zhang et al. (2019); AlZubi (2025)
Breeding & Agronomic Applications	Phenomics-assisted selection, UAV and ground-based imaging for canopy traits, soil–plant sensor integration	Decision support for breeders; optimization of planting density, irrigation, and nutrient management	*Rice:* UAV-based canopy closure for planting density optimization; *Cotton:* multispectral imaging for irrigation scheduling; *Maize:* UAV-based canopy imaging for yield prediction; *Oilseed rape:* High-throughput phenotyping of individual plant height based on Mask-RCNN and UAV images	Yang et al. (2017); Araus et al., (2018); Shen et al. (2024); Fu et al. (2025)
Precision Agriculture & Sustainability	Integration of phenomics with digital agriculture platforms, AI-driven analytics, remote sensing	Site-specific management practices; reduced input use; improved resource-use efficiency and sustainability	*Sugarcane:* satellite-based monitoring for water-use efficiency; *Soybean:* AI-driven yield prediction models	Singh et al., (2021); Zhao et al. (2019); Wang et al. (2025)

3.2. Stress Physiology and Climate Resilience

Crop phenomics has become an indispensable tool for understanding plant responses to abiotic stresses such as drought, heat, and salinity, which are among the most pressing challenges to global food security (Angidi et al., 2025). Traditional stress screening methods often rely on destructive sampling or subjective scoring, limiting their scalability and reproducibility (Dogan et al., 2022). In contrast, high-throughput phenotyping (HTP) platforms enable the identification of stress-tolerant genotypes through precise, non-invasive, and dynamic measurements of physiological and morphological traits (Araus & Cairns, 2014; Reynolds et al., 2020). By capturing subtle variations in canopy temperature, chlorophyll fluorescence, and spectral reflectance, phenomics allows breeders to detect stress responses earlier and with greater accuracy than conventional methods (Pinto et al., 2020).

Drought tolerance, for example, has been extensively studied using thermal imaging and multispectral indices such as the normalized difference vegetation index (NDVI). While NDVI provides valuable insights into transpiration efficiency, stomatal conductance, and canopy water status, its utility is constrained by saturation at high biomass levels, which can mask genotypic differences in dense canopies. These tools nonetheless enable the selection of genotypes with superior water-use efficiency (Prashar & Jones, 2014; Guadarrama-Escobar et al., 2024; Mertens et al., 2023). Similarly, hyperspectral imaging has been applied to monitor photosynthetic performance and pigment composition under heat stress, facilitating the identification of heat-resilient cultivars (Cossani & Reynolds, 2012). In terms of salinity tolerance, root phenotyping platforms combined with imaging technologies such as X-ray CT and rhizotrons have revealed key architectural traits associated with ion exclusion and water uptake (Munns et al., 2020).

A significant advantage of phenomics lies in its ability to monitor dynamic stress responses in real time. Unlike static measurements, time-series imaging captures the progression of stress effects on plant growth and physiology, providing a more holistic understanding of genotype × environment interactions (Tardieu et al., 2017). For instance, UAV-based thermal and hyperspectral imaging has been used to track diurnal and seasonal stress responses in cereals, offering breeders valuable insights into resilience mechanisms under fluctuating field conditions (Yang et al., 2017). Such dynamic monitoring is critical for identifying genotypes that not only survive but also maintain productivity under stress.

By integrating stress physiology with genomics and predictive modeling, crop phenomics contributes directly to the development of climate-resilient cultivars (Amin et al., 2025). The ability to link stress-responsive traits with genetic markers accelerates marker-assisted and genomic selection, thereby shortening breeding cycles (Xu et al., 2022). As climate variability intensifies, phenomics-driven approaches will be central to designing ideotypes that combine yield potential with resilience, ensuring sustainable crop production in diverse agroecosystems.

3.3. Nutrient Use Efficiency and Productivity

Nutrient use efficiency (NUE) is a critical determinant of crop productivity and sustainability, particularly amid rising fertilizer costs and the environmental impacts of nutrient overuse. Traditional methods of assessing NUE rely on destructive sampling and chemical analyses, which are labor-intensive and limited in scalability. Crop phenomics provides a transformative alternative by enabling high-throughput, non-invasive monitoring of nutrient-related traits, thereby facilitating the identification of genotypes with superior nutrient acquisition and utilization (Fiorani & Schurr, 2013; Xu et al., 2020). Nitrogen-use efficiency, in particular, has been a significant focus of phenomics research, given nitrogen's central role in photosynthesis and biomass accumulation (Govindasamy et al., 2023). Hyperspectral imaging and chlorophyll fluorescence techniques allow precise quantification of leaf nitrogen content, photosynthetic efficiency, and pigment composition (Li et al., 2014). Beyond nitrogen, phenomics approaches are increasingly applied to phosphorus-use efficiency, where root imaging and 3D reconstruction technologies help characterize root system architecture traits that enhance phosphorus acquisition from low-availability soils. Similarly, potassium-use efficiency is being explored through ion-sensitive imaging and spectral analysis, enabling the detection of genotypes with improved stomatal regulation, osmotic adjustment, and stress resilience under limited potassium supply. Together, these tools enable breeders to screen large populations for genotypes that maintain high physiological performance under reduced nutrient inputs, thereby supporting the development of cultivars that combine productivity with environmental sustainability (Yendrek et al., 2017).

Phenomics also facilitates the screening of ideotypes, plants with optimized architectural and physiological traits for resource-use efficiency (Paez-Garcia et al., 2015). For example, canopy-level imaging can identify genotypes with improved light interception, while root phenotyping platforms such as rhizotrons and X-ray CT reveal root system architectures associated with enhanced nutrient and water uptake (Lynch, 2019). By integrating above- and below-ground phenotyping, researchers can design ideotypes that maximize resource capture and conversion efficiency, ultimately improving yield potential under both optimal and resource-limited conditions.

The integration of phenomics with genomic selection and crop modeling further enhances the capacity to predict and select for nutrient-efficient ideotypes (Morris & Nair, 2025). By linking high-resolution phenotypic data with genetic markers and simulation models, breeders can accelerate the development of cultivars tailored for sustainable intensification. This approach not only reduces reliance on external inputs but also contributes to climate-smart agriculture by lowering greenhouse gas emissions associated with fertilizer use (Xu et al., 2022).

3.4. Disease and Pest Resistance

Biotic stresses caused by pathogens and insect pests represent a major constraint to global crop productivity, often leading to significant yield losses and reduced food security. Traditional methods of disease and pest detection rely heavily on visual inspection, which is labor-intensive, subjective, and often limited to the appearance of visible symptoms (Abdullah et al., 2023; Xie et al., 2025). Crop phenomics provides a transformative alternative by enabling the early detection of biotic stress signatures through advanced imaging and sensor technologies. Hyperspectral imaging, for example, can detect subtle physiological and biochemical changes in plant tissues before visible symptoms appear, allowing for timely intervention (Mahlein, 2016). Similarly, thermal and chlorophyll fluorescence imaging have been used to identify early stress responses associated with pathogen infection or insect feeding (Pineda et al., 2018).

The integration of high-throughput phenotyping with precision crop protection strategies has opened new avenues for sustainable pest and disease management. By combining UAV-based imaging with machine learning algorithms, researchers can map disease incidence and severity across large fields, enabling site-specific application of fungicides, insecticides, or biological control agents (Sankaran et al., 2010; Zhang et al., 2019; Varadharajan et al., 2025). This targeted approach reduces chemical inputs, lowers production costs, and minimizes environmental impacts, aligning with the goals of sustainable intensification.

Phenomics also contributes to breeding for durable resistance by linking biotic-stress phenotypes to genomic data. High-resolution phenotyping of disease progression under controlled and field conditions facilitates the identification of quantitative trait loci (QTLs) and resistance genes associated with pathogen defense (Poland & Nelson, 2011). Such insights accelerate marker-assisted and genomic selection for resistant cultivars, reducing reliance on chemical control measures.

In the future, the convergence of phenomics, genomics, and digital agriculture is expected to transform disease and pest resistance strategies. Real-time monitoring of crop health, coupled with predictive modeling and decision-support systems, will enable proactive management of biotic stresses. This integration not only enhances crop resilience but also contributes to global food security by safeguarding yields against emerging pests and pathogens in a changing climate (Mahlein et al., 2019).

3.5. Breeding and Agronomic Applications

Crop phenomics is increasingly being integrated into breeding pipelines as a decision-support tool that enhances the efficiency and precision of selection. Traditional breeding often relies on yield-based evaluations, which are influenced by multiple confounding factors and may not fully capture the physiological basis of performance. Phenomics provides breeders with high-resolution, trait-specific data that can be linked to genomic information, thereby enabling phenomics-assisted selection (Cobb et al., 2013; Araus & Cairns, 2014). By quantifying traits such as canopy temperature, photosynthetic efficiency, and biomass accumulation, breeders can identify superior genotypes earlier in the breeding cycle, reducing time and cost while accelerating genetic gains (Song et al., 2021).

Beyond selection, phenomics also plays a critical role in optimizing agronomic practices. Imaging and sensor-based platforms allow real-time monitoring of crop responses to planting density, irrigation regimes, and nutrient management strategies (Srivastava et al., 2025). For instance, UAV-based multispectral imaging has been used to evaluate canopy closure and light interception at different planting densities, providing insights into optimal spatial arrangements to maximize yield (Yang et al., 2017). Similarly, thermal imaging and soil moisture sensors enable precise irrigation scheduling by detecting water stress before visible wilting occurs, thereby improving water-use efficiency (Prashar & Jones, 2014).

Nutrient management also benefits from phenomics-driven approaches. Hyperspectral imaging and chlorophyll fluorescence measurements can detect nutrient deficiencies, particularly nitrogen, at early stages, allowing for timely interventions (Yendrek et al., 2017). This capability supports site-specific nutrient management, reducing fertilizer waste and environmental impacts while maintaining crop productivity (Zhu et al., 2025). By integrating phenomics with precision agriculture tools, farmers and breeders can co-develop management strategies that are both resource-efficient and yield-enhancing.

The convergence of phenomics, genomics, and digital agriculture is redefining the interface between breeding and agronomy. By providing actionable insights into both genetic potential and management responses, phenomics enables the design of climate-smart ideotypes that are optimized not only for genetic resilience but also for agronomic efficiency (Reynolds et al., 2020). This holistic approach ensures that breeding outcomes are directly translatable to field conditions, thereby supporting sustainable intensification and global food security. The overview of phenomics applications in field crop improvement is shown in Figure 2.

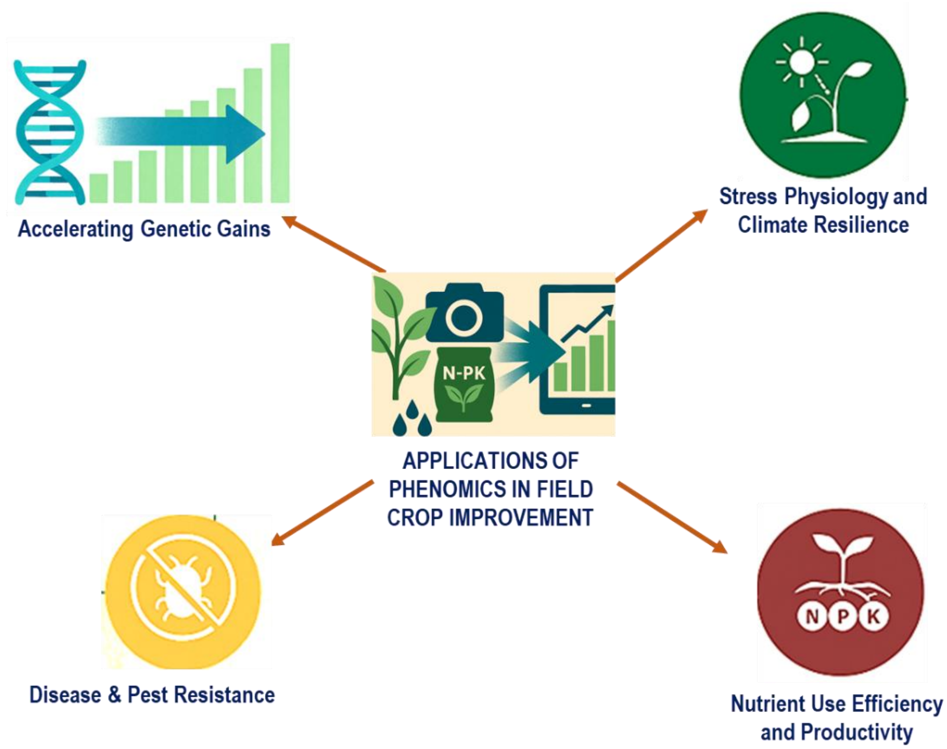

Figure 2. Overview of phenomics applications in field crop improvement

4. CHALLENGES AND LIMITATIONS

Despite the rapid advances in crop phenomics, several challenges continue to limit its widespread adoption and impact (Table 3). One of the most pressing issues is scalability, particularly the difficulty of translating results obtained under controlled-environment conditions to the field. While automated greenhouses and growth chambers provide valuable mechanistic insights, they often fail to capture the complexity of genotype × environment interactions that occur under natural conditions (Poorter et al., 2016; Achour et al., 2021). This discrepancy can lead to inconsistencies in trait expression and reduced predictive power when controlled-environment findings are applied to breeding programs targeting diverse agroecological zones (Tardieu et al., 2017; Kumar et al., 2022).

Another major limitation lies in data bottlenecks, including challenges in storage, standardization, and interoperability. High-throughput phenotyping platforms generate massive datasets from imaging, sensor arrays, and time-series monitoring, often exceeding the capacity of conventional data management systems

(Furbank & Tester, 2011; Kumar et al., 2022). The lack of standardized data formats and metadata descriptors further complicates data sharing and integration across platforms and research groups (Krajewski et al., 2015). Without harmonized standards, the reproducibility and comparability of phenomics studies remain constrained, limiting their utility for large-scale breeding initiatives.

Cost and accessibility also pose significant barriers, particularly for breeding programs in developing countries. Advanced imaging systems, UAVs, and computational infrastructure require substantial investment, making them less accessible to resource-limited institutions (Araus & Cairns, 2014; Kathambi et al., 2025). This disparity risks widening the technological gap between well-funded research centers and breeding programs in regions where food security challenges are most acute. Developing low-cost, scalable phenotyping solutions and open-source analytical tools will be essential for democratizing access to phenomics technologies (Yang et al., 2020).

Finally, issues of reproducibility and adherence to standard protocols remain critical concerns. Variability in experimental design, sensor calibration, and data processing pipelines can lead to inconsistencies across studies (Tardieu et al., 2017). Establishing community-wide standards for experimental protocols, data annotation, and quality control will be necessary to ensure that phenomics data are reliable, comparable, and reproducible across platforms and environments (Balakrishnan et al., 2024). Addressing these challenges will be key to realizing the full potential of crop phenomics to accelerate genetic gains and support sustainable agriculture.

Table 3. Summary of challenges and limitations in crop phenomics

Challenges	Description	Implications for Crop Improvement	References
Scalability & Translation	Controlled-environment results often fail to capture complex field variability	Limits the predictive accuracy of genotype performance across diverse agroecological zones	Poorter et al., (2016); Tardieu et al. (2017)
Data Bottlenecks	High-throughput platforms generate massive datasets; a lack of standardized formats and metadata	Hinders data sharing, integration, and reproducibility across platforms and research groups	Furbank & Tester (2011); Krajewski et al., (2015)
Cost & Accessibility	Advanced imaging systems, UAVs, and computational infrastructure are expensive	Restricts adoption in resource-limited breeding programs, widening the technology gap	Araus & Cairns, 2014; Yang et al., 2020
Reproducibility & Protocols	Variability in experimental design, sensor calibration, and data processing pipelines	Reduces comparability of results across studies; need for harmonized standards	Tardieu et al. (2017); Krajewski et al. (2015)
Integration with Genomics & Enviromics	Limited frameworks for linking phenomics with genomic and environmental datasets	Slows progress in dissecting G × E × M interactions and predictive breeding	Xu et al. (2022); Cooper et al. (2014)
Capacity & Training	Shortage of skilled personnel in imaging, data science, and computational biology	Limits the effective use of advanced phenotyping platforms and analytics	Yang et al. (2020); Singh et al. (2021)

5. FUTURE PERSPECTIVES

The future of crop improvement lies in integrating phenomics, genomics, and enviromics to create a holistic framework for understanding plant performance. While genomics provides insights into genetic potential, and enviromics characterizes environmental variability, phenomics bridges these domains by quantifying trait expression under diverse conditions (Xu et al., 2022). This multi-layered integration will enable breeders to dissect complex genotype × environment × management (G × E × M) interactions, thereby accelerating the development of cultivars tailored for specific agroecological zones and climate scenarios (Cooper et al., 2014). Recent advances in multi-omics approaches further highlight the importance of integrating transcriptomics, proteomics, and metabolomics with phenomics to unravel trait networks and enhance predictive breeding models (Zhang et al., 2022).

Advances in artificial intelligence (AI)-driven phenotyping pipelines are expected to transform the field further. Machine learning and deep learning algorithms are increasingly being applied to automate trait extraction, classify stress responses, and predict yield outcomes from high-dimensional datasets (Singh et al., 2021). These AI-enabled approaches not only enhance the accuracy and speed of phenotyping but also allow the discovery of novel trait associations that conventional analyses may overlook (Kundu et al., 2024; Thingujam et al., 2025). As computational power and algorithmic sophistication continue to grow, AI will play a central role in converting raw phenomics data into actionable knowledge for breeding and agronomy. Moreover, AI-powered genomic prediction frameworks are being developed to integrate phenotypic and molecular data, offering new pathways for sustainable crop improvement (Wójcik-Gront et al., 2024).

A critical priority for the coming decade is the democratization of phenomics tools, ensuring accessibility for smallholder farmers and resource-limited breeding programs (Singh et al., 2018). Low-cost imaging devices, smartphone-based sensing applications, and modular phenotyping platforms are emerging as scalable solutions that can extend the benefits of phenomics beyond well-funded research institutions (Araus et al., 2018). Coupled with open-source platforms and international collaborations, these innovations will foster data sharing, capacity building, and equitable access to cutting-edge technologies, thereby narrowing the technological divide between developed and developing regions (Krajewski et al., 2015).

Looking ahead, the concept of digital twins of crops, virtual models that simulate plant growth, development, and stress responses, represents a frontier in crop phenomics. By integrating real-time phenotypic, genomic, and environmental data, digital twins can provide predictive insights into crop performance under varying scenarios, guiding both breeding decisions and agronomic management (Zhao et al., 2019). Such innovations hold the potential to revolutionize crop improvement pipelines, enabling proactive responses to climate variability and ensuring global food and nutritional security (Biochem Journal, 2025).

6. CONCLUSION

Crop phenomics is transforming the landscape of modern agriculture by redefining how plant traits are measured, interpreted, and applied in breeding and agronomic practices. By integrating advanced sensing technologies, imaging platforms, and computational analytics, phenomics provides precise, high-throughput, and non-invasive insights into plant growth, physiology, and stress responses. These capabilities are bridging the long-standing gap between genomics and field performance, enabling breeders to accelerate genetic gains and design ideotypes tailored for diverse agroecological conditions. The applications of phenomics extend well beyond trait discovery. By linking phenotypic data with genomic prediction models, breeders can enhance selection accuracy and efficiency, while agronomists can optimize management practices such as planting density, irrigation scheduling, and nutrient application. Moreover, the ability to monitor dynamic plant responses in real time offers unprecedented opportunities to develop climate-resilient cultivars that can withstand drought, heat, salinity, and emerging biotic stresses. Despite these advances, several challenges remain. High costs, data bottlenecks, and the lack of standardized protocols continue to limit the scalability and accessibility of phenomics, particularly in resource-constrained breeding programs. Addressing these limitations through low-cost platforms, open-source data frameworks, and international collaborations will be essential to democratize phenomics and ensure its global impact. In the future, the merging of phenomics with genomics, enviromics, and artificial intelligence holds immense promise. By advancing toward digital twins of crops and predictive breeding pipelines, crop phenomics will play a pivotal role in securing sustainable productivity and global food and nutritional security amid climate change.

ACKNOWLEDGEMENT

Not Applicable

AUTHOR CONTRIBUTIONS

Kaliyaperumal Ashokkumar: Investigation, Conceptualization, Writing original draft, Review and editing. M. Gogulavasan and V. Sharvesh Prabhu: Formal analysis, Data curation and image preparation.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

FUNDING

There are no funders involved in this study.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not Applicable

CONSENT FOR PUBLICATION

Not Applicable

AVAILABILITY OF DATA AND MATERIALS

There is no data used for this review study.

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