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Accelerating Crop Breeding in the 21st Century: A Comprehensive Review of Next Generation Phenotyping Techniques and Strategies

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ABSTRACT
Biotic and abiotic stress factors significantly impede crop productivity and lead to substantial economic losses. Given the projected human population of 9 billion by 2050 and the necessity to double current food production to meet the demands of this growing populace, enhancing crop productivity has become a pressing concern. In recent years, substantial progress has been made in the field of high-throughput phenotyping technologies, enabling precise measurements of desired traits and efficient screening of large plant populations under diverse environmental conditions. These advancements involve the integration of advanced robotics, high-tech sensors, imaging systems, and computing power to unravel the genetic basis of complex traits associated with plant growth and development. Furthermore, advanced bioinformatics tools have emerged to analyze the vast amounts of multi-dimensional, high-resolution data collected through phenotyping at both the genetic and whole-plant levels, considering specific environmental conditions and management practices. The integration of genotyping and phenotyping approaches facilitates a comprehensive understanding of gene functions and their responses to various environmental stimuli. This integrated approach holds significant promise for identifying solutions to the major constraints limiting crop production. This review focuses on the recent breakthroughs in plant phenomics and various imaging techniques, emphasizing the applications of different high-throughput technologies in both controlled and natural field conditions. These advancements are crucial steps towards addressing the challenges posed by stress factors and ultimately achieving sustainable and increased crop yields to meet the demands of the growing global population.

Keywords: Genotyping, high throughput, imaging, phenotyping, sensors, stress

Introduction

In changing global climatic conditions, crop plants face various biotic and abiotic stresses throughout their life span, leading to significant losses in growth, development, and yield. As the global population continues to grow, ensuring environmental sustainability while enhancing agricultural production has become a critical goal for agricultural research. To meet the increasing food demand by 2050, the rate of yield gain must be doubled (Anonymous, 2017). The challenge of developing high-yielding, climate-resilient crop varieties has been exacerbated by deteriorating climatic conditions, such as higher CO_2 concentrations, temperature fluctuations, heat stress, and irregular rainfall (Rosenzweig et al., 2014). These stressors emphasize the need to develop new crop varieties with improved resistance against biotic and abiotic stresses. Phenotyping, which involves characterizing and quantifying plant traits, has emerged as a crucial technique for improving crop productivity based on better morpho-physiological characteristics (Furbank et al., 2011). In recent years, high-throughput phenotyping platforms have been developed, allowing for the analysis of phenotypic responses of multiple genotypes under reproducible environmental conditions. In the pursuit of meeting the growing global demand for food, agriculture has experienced rapid transformation, particularly in crop breeding techniques. The 21st century has presented unprecedented challenges, necessitating a transformative shift in crop breeding strategies to address the needs of a rapidly expanding global population. The urgency to enhance crop productivity, resilience, and sustainability has driven researchers and breeders to explore novel approaches, leading to the emergence of next-generation phenotyping techniques as a powerful tool to revolutionize crop breeding.

To tackle the challenges posed by climate change and global population growth, crop breeding must focus on efficient resource utilization and environmental adaptability. Phenotyping, which has been an essential aspect of crop improvement since the domestication of crops, plays a crucial role in establishing the genotype-phenotype relationship. However, conventional phenotyping methods have been limited by low throughput, labor-intensiveness, and destructiveness, leading to a genotype-phenotype gap (Walter et al., 2009). To bridge this gap and accelerate crop improvement, researchers have developed next-generation phenotyping techniques, integrating advanced genomic technologies like Next Generation Sequencing (NGS) and Single Nucleotide Polymorphism (SNP) arrays (Golzarian et al., 2011). These technologies have enabled the acquisition of genotypic information at a faster and more cost-effective rate. However, the development of phenotyping methods has not kept pace with genomics, highlighting the need for improved phenotyping approaches. Next-generation phenotyping techniques are revolutionizing crop breeding by offering comprehensive and high-throughput assessments of diverse plant traits, such as growth dynamics, stress responses, nutrient uptake, and disease resistance (Kumar et al., 2015). Advancements in technology, data analytics, and genomics have played a pivotal role in reshaping the phenotyping landscape, allowing breeders to extract valuable insights from data-rich phenotyping datasets. The pressing challenges faced by agriculture demand faster and more effective crop breeding strategies. Next-generation phenotyping techniques are crucial for identifying and selecting desirable traits at an early stage of plant development which expediting the breeding process. By leveraging automation, remote sensing, imaging, and genomics, researchers can obtain vast amounts of data on crop traits with unparalleled precision and efficiency. This review aims to provide a comprehensive analysis of the next-generation phenotyping techniques, different imaging techniques, remote sensing with UAVs and their potential applications in addressing global food challenges.

Phenomics: A novel tool for next generation phenotyping

Phenomics is a multidisciplinary science that emerged from the Human Phenome Project initiated in 1997 (Freimer and Sabatti 2003). It focuses on the expression of an organism's genome as observable traits within a specific environment (Houle et al., 2010). Utilizing sensor-aided, non-destructive, and high-throughput automated methods, phenomics enables the comprehensive acquisition and analysis of high-dimensional phenotypic data on an organism-wide scale (Kumar et al., 2015). Referred to as the Next Generation Phenotyping (NGP), phenomics represents a promising solution to bridge the gap between phenotypes and genotypes (Ahmed et al., 2023). By employing non-invasive sensors, automated data processing for trait extraction, robotized delivery of plants to sensors, and vice versa, as well as robotized plant culturing, phenomics offers an automated data management pipeline for seamless and efficient analysis of processed data (Cobb et al., 2013; Arend et al., 2016). This advanced approach allows researchers to delve into the inner workings of living plants, gaining valuable insights into the relationship between genotypes and phenotypes. As such, phenomics holds great potential for advancing our understanding of plant biology and facilitating the development of improved agricultural practices.

Traditional Phenotyping

Until the last decade, plant phenotyping primarily relied on traditional agro-morphological traits, categorized into qualitative and quantitative data (Liu et al., 2010). Qualitative data served for diagnosing highly heritable traits unaffected by environmental fluctuations, regulated by major genes, while quantitative data represented traits influenced by gene interactions and affected by genotype and environment interactions (G x E) (Bogard et al., 2014). Both types of data were scaled using nominal, ordinal, continuous, or binary scales to express the degree of trait expression. Plant breeding predominantly focused on major traits related to agronomic performance, tolerance or resistance to biotic and abiotic stresses, and quality attributes such as nutritional and flavor traits. The International Plant Genetic Resources Institute (IPGRI) and other international plant research organizations established a standardized "descriptor" scheme to catalog plant traits, providing a common language for understanding plant characteristics and facilitating successful characterization of plant genetic resources (Kumar et al., 2015). In traditional phenotyping technique, destructive sampling, manual visual/ instrument aided measurements are used. This technique is very time consuming and labor intensive [Figure 1(A)].

Modern Phenotyping

Plant phenotyping involves studying the complex interplay between genotype and environment, where genotype encompasses all genes, phenotype is the result of gene-environment interaction, and phenome refers to gene expression under existing conditions (Furbank and Tester, 2011). This rapidly evolving concept aims to connect genetic information, plant functionality, and agricultural characteristics through the measurement of phenomes, known as phenomics (Bilder et al., 2009). Crucial for the scientific accuracy of molecular breeding, phenotyping bridges the gap between genes and phenotypes, particularly in crop-environment studies. By facilitating the association among genotype, phenotype, and environment, phenotyping plays a crucial role in achieving sustainable and efficient crop production, considering changing agricultural conditions and climate change. Moreover, it allows functional studies of specific genes, forward and reverse genetic analysis, and the development of crops with desirable traits (Xiong et al., 2007).

High-throughput phenotyping platforms have gained popularity, enabling precise assessments of numerous traits in controlled environments, while recent advancements in technology have also enabled field phenotyping platforms, allowing large-scale measurements and analysis in diverse growing conditions using imaging techniques with sensors on field vehicles or flying platforms which is nondestructive in nature (Tardieu and Schurr 2009). Overall, phenotyping is indispensable in understanding gene networks, predicting global climate changes, and devising strategies for effective crop adaptation and production. In the modern phenotyping, non-destructive sampling [Figure 1(B)] and automatic machines were used. There is a visualization of multi parameter data at one time. One example of modern phenotyping given by Benamar et al., (2013). Plants grown in greenhouses are then conveyed by robotics via conveyer belt to the inspection unit for inspection. There are many kinds of imaging platforms, including visual, thermal, florescence, and others. Data will then be evaluated and interpreted after image processing whereas when plants are in the field, information is collected by using stationary or mobile sensors such as aerostats, phenocopters, etc., finally data were analyzed and interpretant it.

Exploring the Significance: Why Detailed Phenomics and Multi-Trait Analysis for Transforming Crop Breeding?

Obtaining accurate phenotypes has long been a challenge in crop breeding due to the time and cost-intensive nature of direct field measurements. However, recent developments in field phenomics have revolutionized the study of plant phenotypes across diverse environmental conditions. Modern phenomics methods, utilizing hyperspectral/multispectral cameras, now enable the acquisition of extensive reflectance data at various stages of crop development under different environments (Atkinson et al., 2018). This progress in phenotyping technology has facilitated swift and precise data collection for essential agronomic traits for the concept of high-throughput phenotyping (HTP). HTP aims to reduce data costs per plot and enhance early-season prediction accuracy by incorporating highly heritable secondary phenotypes that are closely correlated to selection phenotypes. Open-source software solutions like FieldImageR have further minimized processing expenses, making HTP data more cost-effective and accessible for agricultural research and crop improvement (Matias et al., 2020).

Furthermore, empirical evidence underscores the significance of multi-trait analysis in significantly improving prediction accuracies, especially when considering genetic and residual correlations within the modeling process. The emergence of new genomic models that incorporate multiple traits and environments has unlocked immense potential for harnessing correlations between different variables and disentangling diverse effects. These models can account for complex interactions such as trait × environment, trait × genotype, and trait × genotype × environment, leading to a more comprehensive understanding of the underlying genetic architecture (Montesinos-López et al., 2016).

By integrating contemporary Genomic best linear unbiased prediction (GBLUP) multi-trait models with those incorporating environmental information and two & three-way interaction terms, researchers can develop a potent, unified and whole genome prediction model. This holistic approach empowers them to make more precise and comprehensive predictions, offering promising avenues for advancing agricultural research and crop breeding endeavors. With the ability to consider a wide range of genetic and environmental factors, such advanced prediction models pave the way for more efficient and effective crop breeding strategies, ultimately contributing to the development of resilient and high-yielding crop varieties to meet the challenges of an ever-changing world (Crossa et al., 2021).

Advance tools for plant phenotyping in 21st Century

Image acquisition for plant phenotyping: Manual vs. Automated

Researchers can choose either a manual or automated approach for image acquisition in their image processing pipeline. The manual method involves using a standard camera on a tripod, positioned optimally to reduce distortion, with preprocessing steps to further minimize any distortion (Basak et al., 2019). The setup includes a uniformly colored wall (preferably light blue) and strategically placed light sources for appropriate illumination, enabling precise image capture of various plants.

On the other hand, transitioning to an automated image acquisition process offers significant advantages. This includes high-throughput data collection, reduced human error, and standardized imaging protocols (Li et al., 2016). The automated system employs sensors, cameras, and robotic systems to capture images of plants at different growth stages, facilitating efficient study of plant development and responses to environmental factors on a large-scale and standardized level (Hartmann et al., 2011).

Enhanced Image Processing Pipeline for High-Throughput Plant Phenotyping

The image processing pipeline for high-throughput plant phenotyping is designed to efficiently process large volumes of plant images and extract precise information for further analysis (Atkinson et al., 2018) (Figure 2). This pipeline involves several key steps, which are detailed below:

i. Region of Interest (ROI) Definition: The pipeline begins by precisely defining the regions of interest within the captured images. This step involves identifying specific areas or regions where plant analysis will take place, ensuring that only relevant parts of the images are considered for further processing.

ii. Object Segmentation: Next, it performs advanced object segmentation techniques to accurately separate the plants from the background or any unwanted elements in the image. This ensures that only the plant objects are isolated for subsequent analysis, minimizing any potential interference.

iii. Object Extraction Display and Verification: Once the objects are successfully segmented, the pipeline presents the extracted plant objects for meticulous visual inspection and verification. This feature allows users to assess the accuracy of the segmentation and make any necessary adjustments, ensuring the quality of subsequent analysis.

iv. Morphological Refinement: The pipeline applies precise morphological operations, such as dilation or erosion, to the extracted plant objects. These operations serve to refine the object boundaries, remove noise, and enhance the accuracy of the subsequent analysis, producing more reliable results.

v. Compilation of Comprehensive Analysis Results: The pipeline compiles the analysis results for all the plants into a structured and easily interpretable table format. This table consolidates quantitative measurements and derived traits for each plant, facilitating efficient data analysis and comparison.

vi. Visual Representation of Processing Steps: To aid in understanding and quality control, the processing steps performed on each plant are visually represented as an image stack. This stack presents a series of images depicting the different stages of the analysis, providing a comprehensive overview of the processing workflow and enabling better insights into the data processing steps.

By following this enhanced image processing pipeline, high-throughput plant phenotyping platforms can effectively handle large volumes of plant images, extract precise and relevant information, and present the results in a structured manner for further analysis and interpretation. The pipeline's advanced techniques ensure improved accuracy and efficiency, making it an indispensable tool for high-throughput plant phenotyping research.

Imaging technology for plant phenotyping

Plant phenotyping relies on imaging technologies that enable non-destructive and high-throughput analysis of plant traits (Omari et al., 2020) (Figure 3).

Some commonly used imaging techniques are summarized below:

i. RGB Imaging: Captures images using standard color cameras, providing visual information about plant appearance and traits related to color, size, shape, and canopy coverage. The process involves detecting reflectance from the leaf or canopy in the visible spectrum (400 to 780 nm) and generating RGB images (Basak et al., 2019). This method is low-cost, user-friendly, and visually more interpretable. However, it is susceptible to variations in lighting conditions, which can impact the accuracy of the results.

ii. Multispectral Imaging: Captures images in multiple discrete wavelength bands beyond the visible spectrum, enabling analysis of specific traits such as chlorophyll content, leaf nitrogen levels, water stress, and disease detection.

iii. Hyperspectral Imaging: Captures images across a wide range of narrow and contiguous wavelength bands, providing detailed spectral information for each pixel (Huang et al., 2012). It allows analysis of biochemical and physiological traits at a fine level of detail, used for applications like crop disease detection and nutrient status assessment. This method provides highly precise information in narrow spectral bands, allowing for detailed analysis of specific phenomena (Perez-Sanz et al., 2017). However, the extensive image processing required for handling the large volume of data can lead to high costs associated with this approach.

iv. Thermal Imaging: Involves capturing infrared radiation emitted by plants, correlating with their temperature. Useful for detecting temperature variations, identifying stress conditions, and assessing water use efficiency. The technique entails detecting the emission of heat radiation from objects in the thermal infrared wavelength region (8-14 micrometers) (Tardieu et al., 2010) . This method provides a straightforward correlation between the acquired information and canopy temperature, making it useful for thermal analysis. However, it may be challenging to detect small changes in temperature due to its coarse resolution, which can limit its precision in some applications.

v. 3D Imaging: Utilizes techniques like stereo vision, structured light, or time-of-flight cameras to capture depth information of plant structures. This technology enables the measurement of plant height, biomass, branching patterns, and canopy architecture.

vi. Fluorescence Imaging: Captures emitted light by plants in response to excitation with specific wavelengths. Provides insights into photosynthetic activity, stress responses, and nutrient status.

vii. X-ray Imaging: X-ray imaging provides non-invasive and high-resolution visualization of internal plant structures, particularly roots (Flavel et al., 2012). This technology facilitates the study of root architecture, nutrient uptake patterns, and interactions with the soil environment. When combined with advanced image analysis algorithms, these imaging technologies enable comprehensive and quantitative assessment of diverse plant traits. As a result, researchers gain a deeper understanding of plant growth, development, stress responses, and productivity.

Remote Sensing with Unmanned Aerial Vehicles (UAVs): Expanding Horizons for Enhanced Insights

Aerial imaging, including plant, field, farm, and country scales using different systems from drones to satellites (Figure 4), has revolutionized agricultural research. Drones, also known as UAVs, offer a versatile platform capable of rapidly gathering data over expansive regions and potentially providing high spatial resolution images, with pixel sizes as small as 1 mm (Zhou et al., 2017). Leveraging advanced IT techniques like deep learning, millions of remote sensing images can be processed with remarkable accuracy and speed (Yao et al., 2017). As a result, remote sensing has found widespread application in monitoring drought stress response, evaluating nutrient status and growth, detecting weeds and pathogens, predicting crop yields, and identifying QTLs. The high-resolution imagery obtained by UAVs, capturing canopy color and texture features at remarkable spatial and temporal resolutions, has become instrumental in various phenotyping tasks (Shi et al., 2019). This wealth of detailed information enables efficient feature mining and analysis, facilitating tasks such as leaf area index estimation, wheat ear identification, weed detection, and seed performance evaluation in crop i.e. rapeseed (Nguyen and Lee 2006). Furthermore, researchers are actively investigating optimal resolution determination, highlighting the continuous efforts to harness the full potential of UAV-based remote sensing in agricultural applications.

Drone Mission Planning and Data Acquisition Steps for DJI Phantom Pro V2 in Agricultural Monitoring:

i. Mission Planning: Set various parameters to prepare the drone for data capturing. Develop a detailed flight plan for the drone to follow and collect images. Specify camera angle, scan line overlap, Ground sampling distance, and other parameters to obtain images with desired properties.

ii. Image Acquisition: Acquire image data, considering challenges such as illumination conditions, temperature, and in-scene parameters like background obscuring. Implement safety measures to ensure a successful flight and data capture.

iii. Image Transfer: After data acquisition, transfer the image data along with metadata (e.g., geo-locations, number of samples, flight speed, exposure, dark and white references) to a laptop or secondary storage. Regularly empty the onboard storage to avoid overlapping data from previous missions.

iv. Pre-processing: Mosaic the individual field images into a single image for further processing. Attach geo-locations to the images and ortho-rectify them to prepare for analysis.

v. Data Analytics: Utilize tools like Pix4D to calculate vegetation indices for the crop using the index calculator. Define the index formula and apply it to calculate index images from the ortho-mosaic data.

vi. Visualizing Digital Surface Model (DSM): Generate a DSM using Pix4D to calculate crop height from the soil surface. The DSM data aids in visualizing the crop's three-dimensional structure.

The Loop of Crop Phenotype-to-Genotype: Leveraging Multiomics for Crop Improvement

The integration of crop phenotyping with functional genomics studies represents a pivotal advancement in crop improvement (Close et al., 2011). Through a high-throughput and multiscale phenotyping platform, dynamic phenotypic traits of extensive crop genetic populations can be efficiently obtained. This platform enables the merging of phenotypic data with other omics data, such as genomics, transcriptomics, proteomics, and metabolomics, facilitating comprehensive multiomics analysis (Li et al., 2018). By employing QTL mapping and GWAS, researchers can effectively mine QTL/genes and identify key genetic elements associated with desirable traits (Wing et al., 2018). Moreover, when combined with genetic transformation techniques, these findings can be harnessed to drive significant improvements in crop genetics, thereby enhancing crop yield, resilience, and quality (Figure 5). The synergistic approach of multiomics-driven phenotyping with functional genomics holds immense promise in accelerating crop breeding and ensuring food security in the face of evolving environmental challenges (Zhang et al., 2019).

High-Precision Phenotyping in Field Conditions

High-precision phenotyping in the field under natural conditions is of utmost importance as pot experiments in controlled environments may not accurately represent plant behavior in real field settings due to limited soil volume and slower moisture extraction patterns (Morisse et al., 2022). To effectively phenotype genotypes for various traits, stable and less environmentally influenced traits are preferred (Halperin et al., 2017). Key physiological traits, such as water-use efficiency, can be measured through carbon isotope discrimination using leaf sampling. Other essential parameters, including photosynthesis, chlorophyll content, thermal imaging of the canopy, transpiration, stomatal conductance, root depth, and mass, directly or indirectly reflect plant water status and functional ability under stress conditions (Figure 6) (White et al., 2012). For traits that involve a combination of multiple factors, like canopy cooling, can be influenced by high root density, stomatal conductance, and hormonal regulation, field-based evaluation becomes more pertinent. Screening for drought tolerance entails comparing yield performance and flowering under irrigated and rainfed conditions, determining the drought susceptibility index (DSI) for each genotype (Poorter et al., 2016). High-precision phenotyping for drought tolerance can be achieved through approaches such as dug-out plots with moisture gradients or rainout shelters, which prevent raindrops from reaching the plot to assess genotypes performance under extreme drought conditions (Gosa et al., 2019). Such meticulous phenotyping has led to the identification of drought-tolerant genotypes in various crops, demonstrating traits such as lower DSI and improved productivity, along with morphophysiological characteristics conferring drought resistance.

High-Precision Phenotyping in Controlled Conditions

High-precision phenotyping in controlled conditions is a crucial aspect of developing improved genotypes through breeding (Weber et al., 2012). While secondary morphological traits can be easily assessed in the field, traits associated with stresses require controlled environments for better understanding (Figure 6). Managed facilities play a vital role in increasing the accuracy of trait measurements, controlling major environmental parameters like temperature, light, and humidity (Rebetzke et al., 2013; Vadez et al., 2014). Certain traits, such as photosynthetic efficiency, can be rapidly and accurately measured using specialized imaging systems (Tardieu et al., 2017). For root-based traits and stress tolerance, controlled environments like greenhouses and growth chambers are essential, as field conditions may not adequately capture their variability (Kwon et al., 2015). Although various methods have been developed for estimating complex traits in controlled environments having some pose challenges in large-scale phenotyping. Precise phenotyping in controlled conditions is pivotal for comprehending stress response and enhancing breeding efforts to develop stress-tolerant genotypes and improve crop productivity (Deery et al., 2016).

Future Prospects and Challenges

Phenomics is poised to enter the era of 'Big Data,' presenting the crop science community with the imperative to synergize artificial intelligence technology and foster international collaborative research. This strategic fusion is fundamental to establish a novel theoretical framework for analyzing crop phenotypic information. The ultimate goal is to construct a robust technical system capable of high-throughput, multi-dimensional, and intelligent phenotyping of crops while efficiently handling vast amounts of big data. This system should seamlessly integrate data from diverse sources, encompassing multi-modality, multiscale, and phenotypic, environmental, and genotypic conditions.

Undoubtedly, the road ahead for crop phenomics entails a spectrum of challenges in the forthcoming 5-10 years, notably in the realm of phenomics, a momentous transition into the big-data era is unfolding, characterized by its high-throughput capacity, multi-dimensionality, and multi-scale nature. Our focus lies in exploring diverse phenotyping approaches encompassing crop morphology, structure, and physiological data, which exhibit three distinct multi-characteristics: multi-domain (including phenomics, genomics, and other relevant domains), multi-level (spanning from traditional small to medium-scale data up to large-scale omics data), and multi-scale (encompassing crop morphology, structure, and physiological data at various levels, from cellular to whole-plant levels). Recognizing the limitations of single and individual phenotypic information in meeting the demands of association analysis within the emerging 'omics' era, we acknowledge that comprehensive and systematic phenomics information will form the bedrock of future research endeavors. In light of the extensive multi-domain, multi-level, and multi-scale phenotypic information available, there is an urgent imperative to harness the latest advancements in artificial intelligence, particularly in depth learning, data fusion, hybrid intelligence, and swarm intelligence. These cutting-edge approaches hold significant promise in developing robust big-data management processes, essential for supporting critical aspects such as data integration, interoperability, ontologies, shareability, and global accessibility. By strategically adopting these technologies, we can unlock the full potential of the diverse phenotypic data and pave the way for transformative advancements in agricultural research and crop science on a global scale.

The comprehensive analysis and utilization of crop genotype (G) - phenotype (P) - environment (E) information is a pivotal objective. As highlighted by Coppens et al., (2017), the future of plant phenotyping relies on collaborative synergism at national and international levels. Addressing the challenges posed by multi-omics data necessitates novel solutions, notably intelligent data-mining analytics, which can effectively unravel the intricate biological processes governing plant growth and development. Thus, in turn, advances plant breeding efforts, enabling the development of climate-resilient and high-yielding crops that are urgently required to meet evolving environmental demands.

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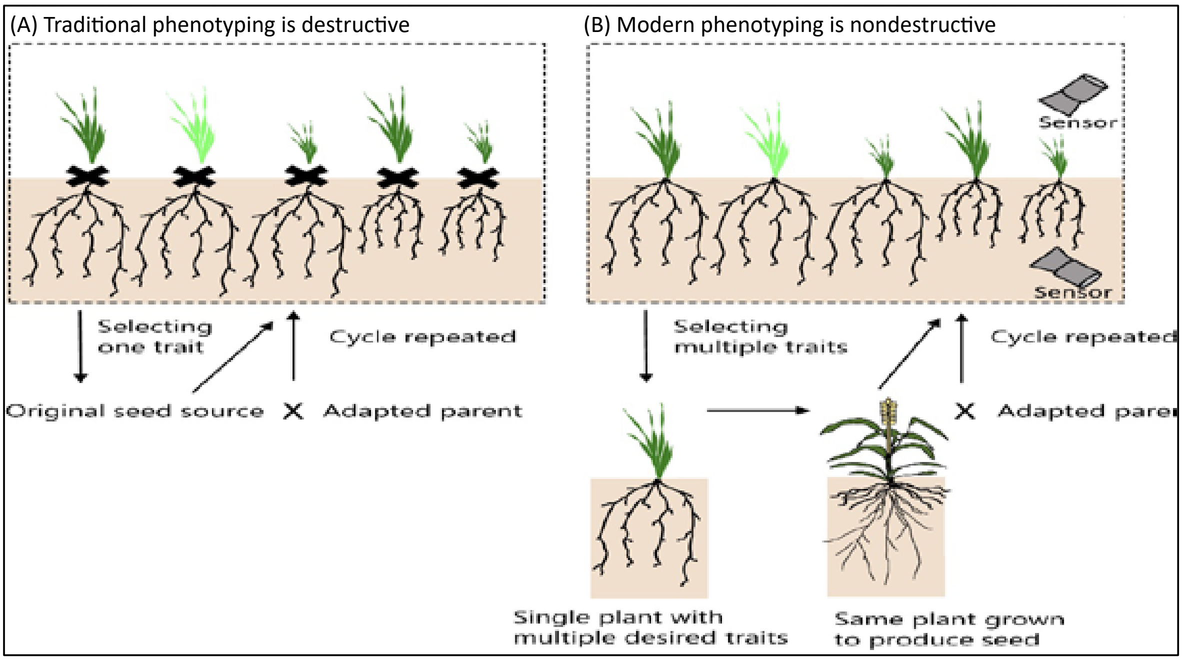

Figure 1. Traditional phenotyping vs Modern phenotyping (Saoirse et al., 2011)

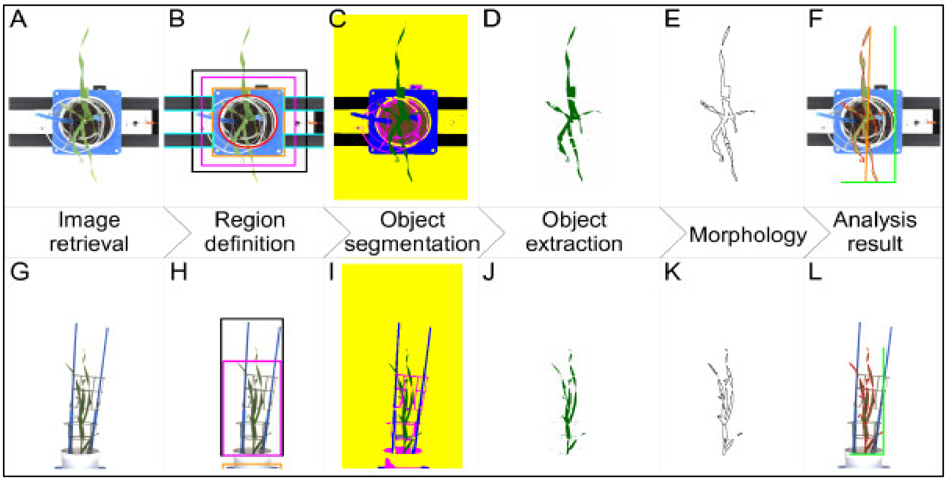

Figure 2. High-throughput image analysis pipeline for top view (A-F) and side view (G-L) images. (Hartmann et al., 2011)

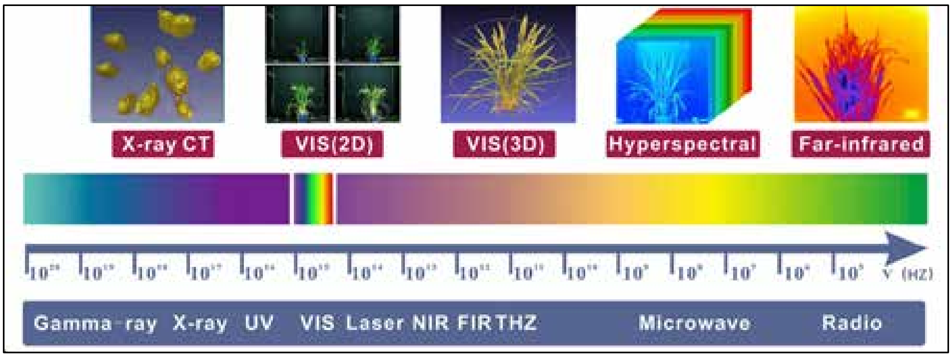

Figure 3. Crop Phenotyping and the Diversity of Spectra Utilized for Exemplification. (Yang et al., 2020)

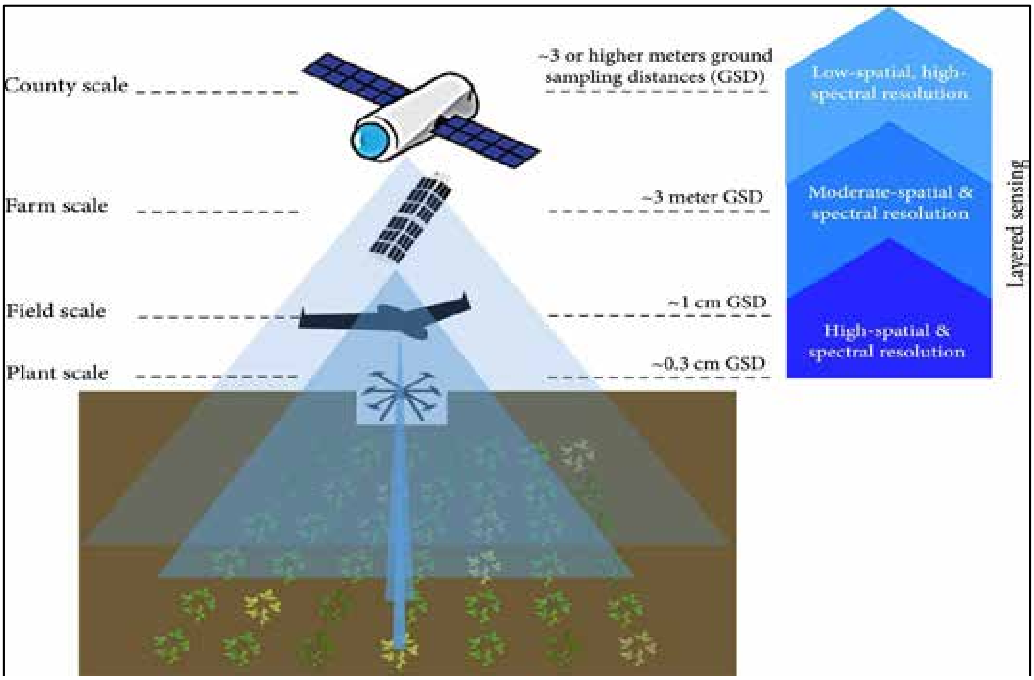

Figure 4. Using Drones for Versatile Crop Phenotyping: Different Scales and Sensing Levels. (Guo et al., 2021)

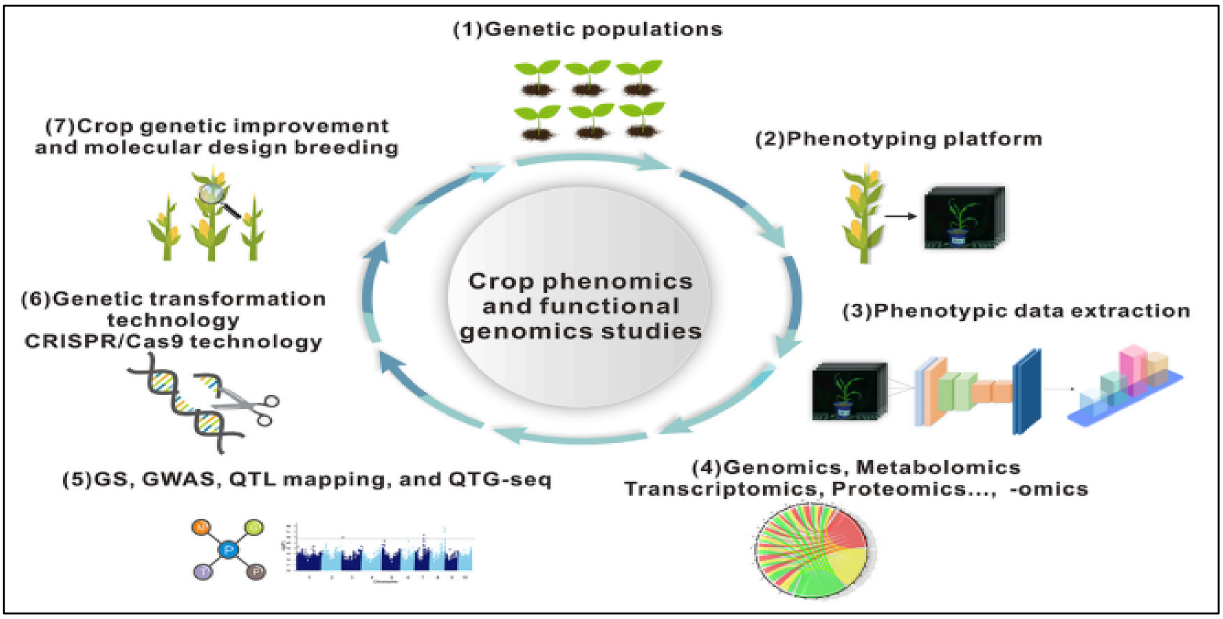

Figure 5. Crop Phenotype-to-Genotype Loop. (Yang et al., 2020)

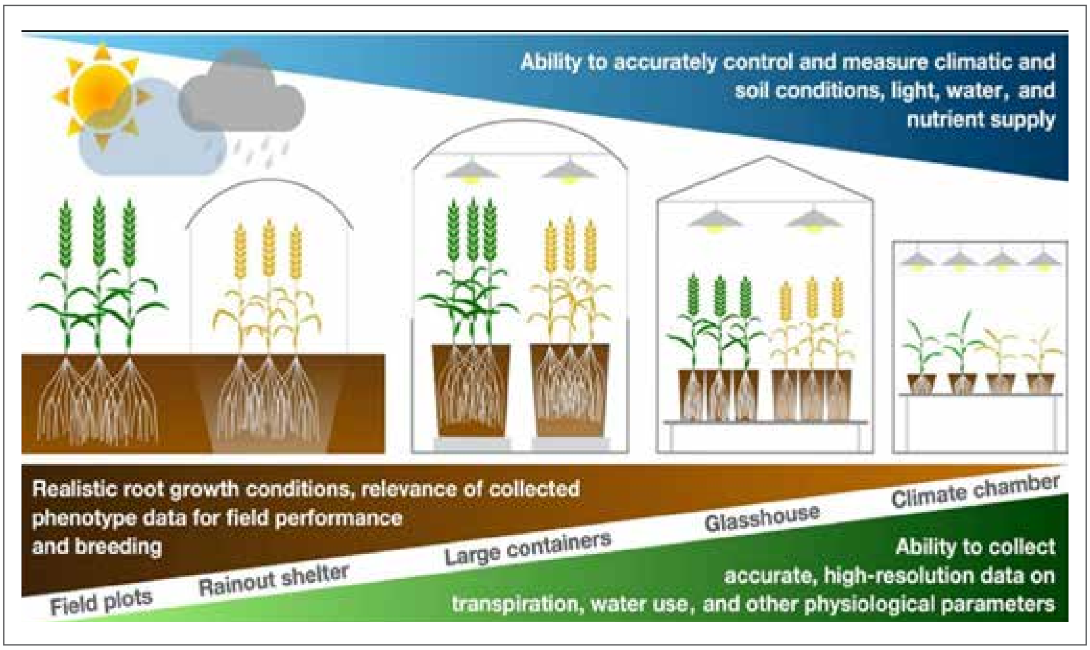

Figure 6. Field vs Controlled environment phenotyping. (Stahl et al., 2020)

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