PHENOMICS IN ABIOTIC STRESS MANAGEMENT

Abstract

Several abiotic stresses resulting from increased population, global warming, and other possible climatic conditions have affected the development and production of several agriculturally essential crops. Drought, flood, salinity, high temperature, and other abiotic stressors affect plant physiology as well as its appearance which can occasionally result in a famine-like condition. In this context, plant breeders have a difficult problem in developing climate-resilient varieties: understanding the crops reaction to various stress situations and the underlying stress resistance processes. Over the last decade, advances in molecular tools and functional genomics have made the process of cloning and characterization of essential genes much easier that driving abiotic stress traits. To fully assess a genotype's potential under stress, however, phenotypic behaviour must be evaluated, as well as the components that coordinate such reactions. As a result, in this post-genomic age, sophisticated phenotyping technologies are required for optimal use of the huge amount of genetic data in climate-resilient breeding. Advanced phenomics devices measure shoot and root development, chlorophyll content, canopy temp, and other morphological features of plants in response to various abiotic stimuli with a high degree of precision and in a short amount of time. As a result, phenomics is an important tool for narrowing the gap between genotyping and phenotyping, and it is highly advisable for addressing climate change.

Keywords: Phenomics, Abitoic Stress, Imaging Techniques, Data Management.

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I. INTRODUCTION

The lack of identification and study of abiotic characteristics resulted in a poor exploitation of plant genetic resources. As a result, identifying a genotype that possesses abiotic stress resistance or tolerance is only achievable if we have accurate and reliable phenotyping data of the germplasm. Phenotyping of important abiotic stress traits is generally considered as the most laborious and technically challenging because of the repeatable experiments are required across many locations and seasons. Chilling stress, heat stress, waterlogging, and drought stress all needed a unique environment, and trial management was time-consuming. Over the last decade, researchers have shown interest in developing novel high throughput phenotyping techniques and methodologies for phenotyping abiotic stress, such as imaging, image processing, sensors, spectroscopy, robotics, machine learning and high-performance computing. These techniques may be used not only in the lab, but also in the field, allowing for high-throughput phenotyping study in both uncontrolled and controlled environments. Plant performance evaluation in the field is now much faster, enabling more flexible, entire life cycle measurement of plant that is less reliant on destructive tests. The sophisticated high throughput facilities like green house, glass chamber, hydroponics and aeroponics increases data recording precision and decreased the requirement for field replication. As a result of these advancements, the area of reliable and exact phenotyping for major features of abiotic stresses has changed, bringing in the age of ‘phenomics’. In the present chapter we provided an overview of these developments. We explain in details of phenomics, its types based on its utility, different imaging techniques used in phenomics, phenomics data management and lastly major achievements gain from phenomics.

II. PHENOMICS

The overall phenotype of organism is called as phenome [1], i.e., the expression of the genome for a characteristic in a specific environment, whereas phenomics refers to the big collection of high-dimensional data sets. In fact, phenomics is utilized as a paradigm for genetics. But, it is not the same as genomics. Total genome characterization is attainable in genomics, but whole phenome characterization is difficult in phenomics due to the variability in expression of phenotype across environmental contexts [2]. The term 'phenome' has been coined as a counterpoint to the phrase 'genome.' The genome is an entire combination of all genes available in an organism. As a result, the phenome would be the sum total of the traits express by an organism. The study of plant development, performance, and composition is known as plant phenomics. Forward and reverse phenomics are the two kinds of phenomics. Forward phenomics applies phenotyping techniques to choose useful genotypes with desirable features from a large pool of germplasm. As a result, the 'best of the best' germplasm can be identified. The plant breeding cycle have accelerated by screening a wide variety of plants at the seedling stage with the use of high-throughput, fully automated, and high-resolution phenomics approaches. When the 'best of the best' germplasm with desirable characters are already known, reverse phenomics is applied. As a result of reverse phenomics, we can learn about the mechanisms that make 'best' germplasm to the best.

III. TYPES OF PHENOMICS BASED ON UTILITY

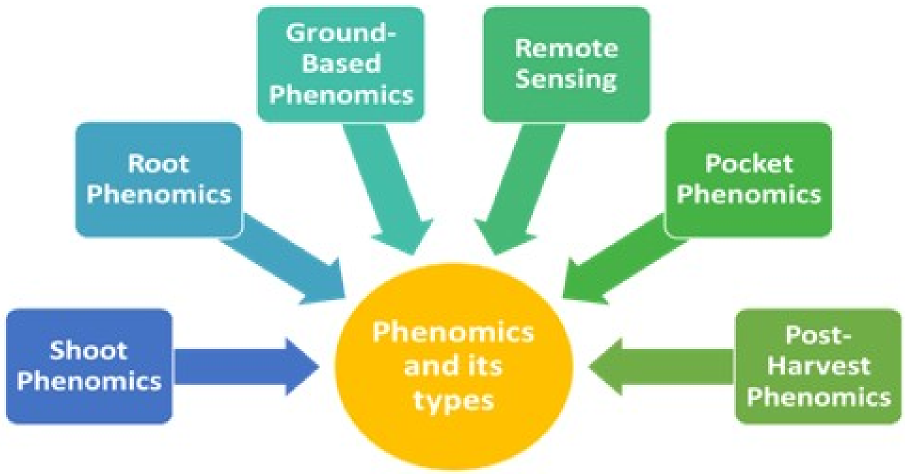

Figure 1: Different Types of Phenomics based on Utility

1. **Shoot Phenomics:** The shoot phenomics uses a high throughput platform to identify and record various yield contributing traits likes plant height, seed size, plant colour, chlorophyll content, aboveground biomass, plant architecture. The table 1 provided the different platforms for shoot phenotyping along with their advantages and disadvantages. The best imaging-transfer method (plant-to-sensor or sensor-to-plant) is determined by the retrieved characteristics, the volume size of the measured species, greenhouse capacity, and other factors. The various image sensors were employed to record the observations. With the help of sensor many physiological parameters have been recorded. Installation of sensor depend on the parameters such as traits that have been record, size of plant, greenhouse or field area etc. Sensors are directly attached to the plant or group of plants and other way is sensor fixed in one place which called imaging stations and with the help of conveyor belt, data of plant is recorded. This is called plant-to-sensor method. Plant-to-sensor mode is used by CropDesign, Scanalyzer3D and HRPF.

2. **Root Phenomics:** Roots are important parts of plant that determine water uptake and absorption of nutrients, impacting drought resistance as well as growth and yield. Compared to shoot phenotyping, root phenotyping is difficult and complex [3] because recording observation below the soil is time consuming and costly as well as laborious. Advancement of high throughput root phenomics provided variety of solutions for recording various roots characteristics some of which provided in table 1. The different root characteristics namely root length, root diameter, root weight, root area, angle, tip number and spatial distribution plays important role in breeding especially abiotic stress breeding.

   The study of these traits were very different in common filed conditions. Use of hydroponic, aeroponic, and green house somewhat help in recording of precise root phenotyping data. Root system architecture (RSA) phenotyping imaging platform, magnetic resonance imaging (MRI), positron emission tomography (PET), X-ray radiation and CT scanning further boost up root phenomics with higher level of accuracy.

3. **Ground-based Phenomics:** Ground based phenotyping is carried out using fixed or mobile platform fitted in filed. Tower equipped with different kinds of sensors are easy to build as well as they having less maintenance. These sensors were used to record different vegetative and reproductive growth stages of plants as well as monitor different biotic and abiotic stresses. Plant height, leaf colour, leaf area index, days to anthesis, nitrogen content, tiller density, number of flowers, number of pods, grain yield, moisture content, lodging, and dry biomass have all been measured using digital cameras, infrared cameras, time-of-flight depth sensors, kinect cameras, stereo cameras and four digital single-lens reflex cameras. Mostly the open-air imaging platforms are vulnerable to changing environmental conditions.

   Many of these issues are addressed by sensors mounted on manually operated carts or self-propelled tractors. A cart containing multiple sensors, including an ultrasonic sensor, a normalized difference index (NDVI) sensor, a thermal infrared radiometer, a portable spectrometer, an RGB camera, and a proximity sensor, was used to obtain plant height, NDVI, temperature, reflectance spectra, and RGB imagery for soybean and wheat canopy traits [4].

   The fixed phenotyping tower had the advantage of being simple to construct and maintain, but the problem was that it only provided restricted crop information in defined locations, and costs for large-scale experiments were high. One of the ground based platform were highlighted in table 1.

4. **Remote Sensing:** Drones or unmanned aerial vehicles (UAV's) provide a versatile framework for rapidly collecting data across wide regions and possibly producing high spatial resolution photos. Machine learning is a cutting-edge IT technology that can process millions of remote sensing photos with great accuracy and speed [5]. As a result, remote sensing is frequently utilised to track drought stress response, measure nutrient content and growth, spot weeds and diseases, and forecast yield [6]. Multiple imaging sensors fitted on UAVs can be utilised to acquire spectral information in visible or near-infrared bands for plant nutritional diagnostics and stress surveillance. High-resolution UAV photography has been used for a variety of phenotyping objectives, including estimating leaf area index [6], identifying wheat ears [7], detecting weeds [8], and evaluating seeding effectiveness in rapeseed [8]. Multispectral cameras can detect spectral information in the red edge and near-infrared regions and have been used for chlorophyll-based diagnostics [9] and water stress monitoring [10]. UAV remote sensing has showed significant promise for high-throughput phenotyping, which will benefit to abiotic stress breeding. Yet, there are certain limitations to the usage of UAVs that need be discussed: (1) the fly period and loading capacity are restricted; (2) local flight rules and regulations may be a restraint; and (3) rigorous standards for operating technicians should be enforced to assure flight safety.

5. **Pocket Phenomics:** The exponential advancement of mobile phones with high-resolution sensors and substantial computer power has resulted in the development of plant phenomics apps. Furthermore, components of smartphones technology have been

integrated into other customized handheld devices, expanding the range of optical and other sensors and improving the connection and mobility of classic phenotyping tools. Plant breeders have traditionally employed handheld portable devices to test a variety of characteristics such as chlorophyll content in leaf (SPAD) and soil moisture (Tensiometer). Many of these devices are inherently difficult, necessitating training, low accuracy and close attention. Advance "pocket" or "wearable" phenomics equipment will fundamentally alter and speed phenotyping. The opportunities and challenges associated with pocket phenotyping include:

- Combining different sensors into one portable device is difficult and challenging;
- Required a level of expertise and integral data quality control;
- Leveraging artificial intelligence techniques to build robust models to face complex field conditions.

6. **Post-Harvest Phenomics:** The harvested portion of the crop is the most commercially important, and mechanical techniques for processing and monitoring yield and quality, both during the harvesting process are already exist. During the harvesting process, global positioning system (GPS) and sensors might be included in the combine harvester to examine and record various data automatically. Seed quality evaluation employs imaging methods that are easily adaptable to research purposes. The comparatively straightforward integration of 2D picture capture, data export and feature extraction and has simplified seed phenotyping, allowing for a broad, cost-effective assessment of grain type and size variation. Open-source and user-friendly image analysis software, along with a low-cost scanner or 2D and 3D camera, enables greater accessibility. SmartGrain, PANorama, GrainScan, phenoSeeder, SeedCounter, and P-TRAP are recommended as versatile instruments for accurately quantifying post-harvest features (Table 1).

IV. IMAGING TECHNIQUES

Advanced phenotyping methods employ a variety of imaging techniques to capture the association among the crops and light that is transmitted, reflected, or absorbed. The intensity, colour and diffraction of light used to assess quantitative phenotypic features with the precision and accuracy. The visible-light imaging, infrared and thermal-based imaging, fluorescence imaging, spectroscopic imaging, and other integrated imaging techniques are now in use for precise phenotyping of crops in a variety of conditions.

1. **Visible Light Imaging:** Visible light imaging has long been used to assess various abiotic stress responsive attributes. The various vegetative as well as reproductive growth features such as biomass [11], shoot tip elongation, root architecture and leaf morphology, panicle and seed morphology, and so on are being studied using visible light imaging approaches which were based on two-dimensional (2D) digital images [12]. The visible spectrum is susceptible to visible imaging sensors like silicon sensors (CCD or CMOS arrays) [13]. This sensor commonly used in imaging. The more advancement in imaging techniques carry forward 2d imaging to 3 dimensional imaging technology resulted in increases in precision on complex phenotypes. Combination of both combined 2D and 3D imaging technologies, are used to many crops [14]. Image analyzer tools able to capture various abiotic stress tolerance characteristics in small and big populations, such as mapping populations or association mapping populations, making it easier to conduct genetic research to uncover mechanism driving tolerance-related trait variations.

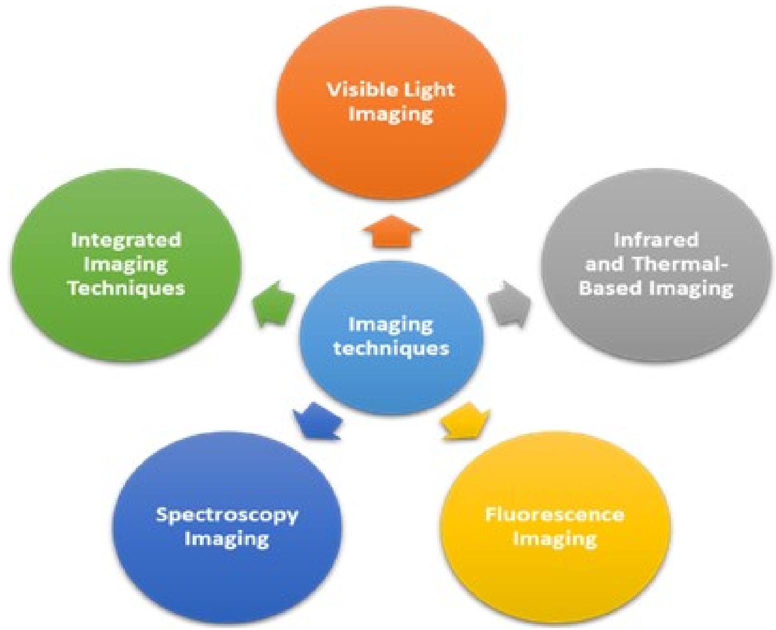

Figure 2: Advanced Imaging Techniques for Accurate Phenotyping

2. **Infrared and Thermal based Imaging:** Infrared and Thermal Based Imaging is based on Stefan–Boltzmann equation (R14T4) in which radiation is recorded and visualized by different sensors. It uses internal molecular movements to create infrared rays [15]. Two types of band, namely near-infrared and far-infrared bands having bandwidth of 0.9 to 1.55 m and 7.5 to 13.5 m, respectively are used in infrared imaging technology with high throughput sensitive thermal cameras (3–14 m) [16]. Additionally, the combination of infrared and visible imaging platform provides a more details imaging phenotyping of different abiotic tress attributes likes water content, colour pigments and physiological traits with well spectrum distinct spectrum of lights [17]. Infrared imaging technology also use to measured canopy temperatures to examining stromal activities in case of salinity and drought stresses [14]. At present, a number of intelligible thermal cameras having high thermal sensitivity are available to supervise plant canopy temperature. These thermal cameras able to produce high spatial resolution pictures with exact measurements in broad areas in real-time [16]. Thermal imaging technology is now using to record leaf water content and gas exchange. Thermal imaging widely uses in recording various abiotic traits. Thermal imaging check temperature variation in plant canopy and surrounding air used to measured drought tolerance ability of plants. It is also enables osmotic tolerance and Na + exclusion-based assessment of drought and salinity tolerance, as well as the measuring of relative chlorophyll content and leaf color [18; 19; 20].

Table 1: Different Platforms used to Study Phenomics with Merits and Demerits

Applications	Platforms	Merits	Demerits	References
Shoot phenomics	GROWSCREEN; Phenoscope; PlantScreen; Phenovator; PHENOPSIS (DB);	Relatively inexpensive, quick, and automated	Not recommended for larger crops	[21, 22, 23, 24, 25]
	TraitMill; Scanalyzer3D; PHENOARCH; HRPF	Dynamic and automated used to acquire shoot growth, biomass etc.	Costly to maintain and upgrade; needs diverse skills.	[26, 27, 28, 29]
	PhenoBox	Affordably priced and simple to maintain	Large-scale screening is labor-intensive.	[30]
Root phenomics	PlaRoM; RhizoTubes; GiARoots RootReader3D; Rhizoslides; Rhizoponics; RADIX	Obtain 2D root system designs at a low cost.	Required transparent medium for root scanning	[31, 32, 33, 34, 35, 36, 37]
	GROWSCREEN-Rhizo	High-throughput methods for acquiring shoot and root attributes	In 2D rhizotrons, root development is restricted	[38]
	PET–CT; MRI–PET; MRI–CT	Obtain 3D root system designs.	Expensive; time-consuming; no specialised prototype for agriculture research	[39, 40, 41]
Ground-based phenomics	CPRS	Installing and maintaining the system is simple.	Very little crop information was received.	[42]
	Field Scanalyzer	High picture resolution; integration of several optical sensors	Expensive; imaging area is restricted; ambient light is varied	[42]
	BreedVision	Integration of many optical	Wet soil and climatic conditions	[43]

		sensors; steady imaging circumstances; picture region that is not restricted	limit its ability to grow (rainy and strong breeze)	
Remote sensing	Drones or UAVs equipped with multiple sensors	Various sensors are integrated; the imaging region is not restricted; and the imaging process is quick. installation and usage flexibility	Information cannot be obtained below the canopy; stringent operational and local aviation rules must be observed to ensure flight safety.	[6]
Pocket phenomics	PocketPlant3D	Affordably priced, versatile to use, and simple to promote	Limited features and a single purpose; absence of strong models for dealing with complex field situations	[44]
Post-harvest phenomics	Seed Evaluation Accelerator (SEA)	automatically threshed and yield-related features that can be measured quickly	Grain and panicle qualities in 3D are not available.	[45]
	PANorama; P-TRAP	There is no requirement for threshing to quantify grain properties.	Manual separation of plants is required; 3D grain characteristics are not available.	[46, 47]
	PhenoSeeder	With excellent precision, extract 3D characteristics from individual seeds.	Low measurement speed; threshing required	[48]
	CT scan, X-ray	Without threshing, extract 3D grain features.	Expensive; time-consuming; new species require a custom image analysis methodology.	[49,50]
	Hyperspectral imaging	Determine the amount of protein in a sample and other physiological or biochemical data.	Difficult and expensive; physiological or biochemical markers necessitate bespoke image analysis and model updates.	[51]

3. **Fluorescence Imaging:** Fluorescence is generated after the emission of low-wavelength light that has been absorbed. Fluorescence imaging shines blue light (500 nm) on the plants, which causes fluorescence light to be produced in the red spectrum at 600–750 nm. In fluorescence imaging different fluorescent spectrum were recorded and converted into colour signals using computer algorithms [52]. In phenomics, chlorophyll fluorescence is commonly measured to reveal the impact of various stresses on plant's capacity to deal with photosynthesis efficiency [52]. Stomatal mobility, plant metabolite and phloem loading and unloading studied using fluorescence imaging [53; 54]. Fluorescence emission is captured by single excitation wavelengths in the red to a far-red area (360–740 nm) and the blue to a green region (360–740 nm) [14]. The chlorophyll fluorescence imaging (ChlF) were used in rice [26] and Arabidopsis [24] has been employed to determine plant growth and development, its morphology, colour of leaves and photosynthetic performance under salt stress.

4. **Spectroscopy Imaging:** Spectroscopy imaging uses the interaction of solar radiation with plants and it is captured with hyperspectral and multispectral cameras. Furthermore, Hyperspectral imaging separates pictures into bands, resulting in an electromagnetic spectrum [17]. NDVI (normalized difference vegetation index) analyses PRI (photochemical reflectance index), red and near-infrared reflectance, CRI (carotenoid reflectance index) defines three wavebands in the yellow area, and connects the functional state of no photochemical energy conservation [54]. In the near-infrared range, leaf and canopy architecture to be measured through radiation reflected from higher leaves to lower leaves. Furthermore, when the wavelength and absorption rise, the reflectance of the leaf falls, indicating its water content. This spectral reflectance data is used to generate vegetation indices and allows for NDVI detection. Penuelas and Filella [55] and Din *et al.* [56] found that vegetation indices are linked to pigment content, water status, and active biomass.

5. **Integrated Imaging Techniques:** Various technological advancements, such as functional imaging and optical 3D structural tomography, have switched toward live imaging of plants. Under the functional imaging category, positron emission tomography (PET) and ChlF imaging assess photosynthetic performance by concentrating on physiological changes under stress [57]. PET is a non-destructive imaging technique that employs positron-emitting radionuclide metabolite compounds tagged with C11, N13, or Fe52 [58]. Magnetic resonance imaging (MRI) is an improved technique that creates images by combining magnetic fields and radio waves and is used to capture root architecture in pots and internal physiological processes, as well as water diffusion and transportation via xylem and phloem in crop plants such as tomatoes, tobacco, poplars, and castor beans [59, 60]. The combination of MRI and PET creates a new picture that may be used to track real-time changes in plant function and structure. By combining PET and MRI with [C11]-labeled CO2, Jahnke *et al.* [40] investigated photo assimilation in sugar beet taproots and shoot-to-root carbon fluxes. Radiometric fluorescence sensors, Forster resonance energy transfer (FRET) is a more sophisticated and exceptional noninvasive or nondestructive method for molecular phenotyping [61]. A single FRET sensor can identify a variety of different routes and dynamic activities in plants. FRET has effectively identified calcium and zinc dynamics in real-time in roots during sugar transport, as well as subcellular spatial and temporal resolution [61]. FRET's strong

phenotyping capability allows it to answer all of the fundamental questions about plant growth and development.

Selecting the right imaging sensors and imaging-transfer methods are both important in developing phenotyping facilities that are dependent on the various experimental aims. RGB, fluorescent, thermal, hyperspectral, and 3D imaging all have advantages and disadvantages: (1) While RGB imaging (also known as visible light imaging) is the most cost-effective and extensively used method for measuring plant or organ morphological features, biomass, and plant development [28], it does not give physiological information. (2) Fluorescent imaging, when equipped with particular excitation light, may reflect physiological signals such as photosynthetic function and reactive oxygen species signal [62]. (3) Thermal imaging (also known as far-infrared thermal imaging) may be used to determine the temperature of a plant or leaf, which is also impacted by external variables [10]. Furthermore, neither fluorescence nor thermal imaging can offer enough spectrum information. (4) Hyperspectral imaging may give a wealth of spectral (visible and near-infrared) and spatial information at the same time, allowing it to be used to detect illness severity, hydration status, and other physiological features. However, the hyperspectral sensor is expensive, and processing hyperspectral data (gigabytes each sample) might be challenging [63]. (5) When compared to 2D imaging, 3D imaging approaches, primarily image-based [64] and laser scanning-based [65], can produce 3D models and gain more spatial and volumetric features. The current tendency is to mix numerous imaging techniques based on the strengths of the various imaging technologies. Several studies have compared the various imaging methods used in plant phenotyping [66, 67].

V. PLANT PHENOMICS DATA MANAGEMENT:

High-throughput plant phenotyping technology generates a vast quantity of data, which needs adequate collection, storage, backup, processing, and maintenance. In-plant phenomics, modeling, and analysis of phenotypic data are critical activities. Differences between the picture and actual measurement will be reduced using proper phenotypic data processing methods. For a better understanding of phenotypic data and its linked gene function, we require clever categorization and management tools. Big data should be integrated and managed for its intended application. The efficient administration of large plant phenotypic data may become one of the most difficult tasks in plant phenomics in the future. Data management processes primarily consist of data collection, storage, documentation, and data quality enhancement which were summarized below;

1. **Data Collection:** The raw data collection and storage procedure in phenotyping platforms is the first step in the data management process. Sensors are still insufficient for phenotypic data gathering, whether digital or manual phenotyping is used. To assist in successful data interpretation, data formats are required [68]. Imaging sensors can acquire a high number of pictures in a short amount of time. In picture collecting and storage, the frame size and frame rate of the data package are essential. High-throughput phenotyping platforms have been developed to collect phenotypic data of plants used for data collection presented in table 2.

Table 2: Image Analysis Programs and Phenotyping Platforms

Plant Tissue	Software	Purpose	References
Roots	WinRhizo Tron	Root area, volume, length	http://www.regent.qc.ca/products/rhizo/RHIZOTron.html
	Root reader 3D	Root system architecture	[35]
	EZ-Rhizo	Root system architecture	[69]
	RootTrace	Counting and measuring root morphology	[70, 71]
	DART	Root system architecture	[72]
	SmartRoot	Quantification of growth and architecture in root	[73]
	Gia-Roots	Root system architecture	[34]
Leaves	TraitMill	Measurement for various agronomic characteristics	[74]
	PHENOPSIS	Measurement of water deficit-related traits	[75]
	LeafAnalyser	Rapid analysis of leaf shape	[76]
	HTPheno	Measurement for various shoot characteristics	[77]
	LemnaTec 3D Scanalyzer	Leaf color, shape, size, and architecture	[78], http://www.lemnatec.com
Seeds	WinSEEDLE	Volume and surface area measurements of seeds	http://www.regent.qc.ca products/needle/WinSEEDLE.html
	SHAPE	Measurement of seed shape	[79,80]
	SmartGrain	Measurement of seed shape	[81]

2. **Data Storage:** The organization of files is an essential aspect of data storage. In datasets, keeping track of documents and their versions, such as directory structure names and file naming rules, is crucial. Raw data is uploaded and kept on the file server for multisite projects. The output files are saved on the file server after being processed by scripts, and copies may be downloaded by each participant [68]. To organize and gather plant phenotypic data, phenotype data is maintained in numerous public databases [82]. Following are the different databases that are in the public domain (Table 3).

Table 3: Publically Available Databases of Different Crops

Sr. No.	Databases	Purpose	Online Link	References
1	Soybase	It is a comprehensive database of soybean genetics, genomics, and associated data resources.	http://soybase.org	[83]
2	MaizeGDB	It provides data on maize sequencing, stock, phenotype, genotypic and karyotype variation, and chromosomal mapping.	http://www.maizegdb.org	[83]
3	PHENOPSIS DB	A public information system was created for the storing, browsing, and sharing of online data as well as offline data gathered by experimenters and experimental metadata.	http://bioweb. supagro.inra.fr/phenopsis	[22]
4	Gramene	Gramene offers publicly accessible data sources for cereals such as rice, sorghum, and maize. It also displays map domains, markers, genes, proteins, pathways, and phenotypes, as well as Quantitative Trait Loci (QTL) and genetic diversity/natural variation.	http://www.gramene.org/db/diversity/diversity_view	[84]
5	IonomicsHub	IonomicsHub is a collaborative worldwide network for many species such as Arabidopsis, rice, soybean, maize, and Brassica. Ionomics is the measurement of an organism's overall elements composition to solve biological challenges.	http://www.ionomicshub.org	[85]
6	Rice mutant database	It contains data on more than 129,000 rice T-DNA insertion lines and mutant phenotypes.	http://rmd.ncpgr.cn	[86]
7	Oryza tag line	The Oryza tag line provides information on 21,588 T-DNA lines and 13,000 rice phenotypes.	http://oryzatagline. cirad.fr	[87]
8	T3 Triticeae toolbox	It contains SNP, phenotypic, and pedigree data from Triticeae CAP wheat and barley germplasm.	http://triticeaetoolbox. org	[88]

9	Tomato mutant database	The Tomato mutant database is a large population of tomato mutants.	http:// zamir.sgn.cornell.edu/mutants	[89]

3. **Documentation and Metadata:** Data documentation, also known as metadata, will aid in the detailed understanding of data and will assist other researchers in finding, using, and correctly citing the data. Structured or tagged information, such as the Data Documentation Initiative (DDI) standard's XML format, is ideal since XML provides flexibility in presentation while still being preservation-ready and machine-actionable. The W3C (World Wide Web Consortium) created XML (eXtensible Markup Language), which is the governing organization for all Web standards. Because the format allows for machine action and metadata reuse, structured XML-based metadata is appropriate for recording research data.

4. **Data Quality:** Effective knowledge extraction from large-scale phenotypic data necessitates improved data quality. Data cleaning, data quality monitoring, and data integration (Herbert and Wang 2007) are the three strategies for managing data quality for biological data. Data cleaning is the process of finding and eliminating mistakes, anomalies, and inconsistencies from data to enhance its quality [89; 90]. One approach is to use data mining techniques to find outliers to clean up the data [91]. A dynamic filter has been designed to detect and eliminate anomalies in phenotypic data to reduce the number of biological discoveries that are lost [92]. There are three main steps in a dynamic filter: 1) find abnormal candidates, 2) fine-tune abnormality detection, and 3) recognize abnormalities iteratively. After going through all data management steps, the effective data should be shared and preserved for the research process as well as the researchers themselves. A well-designed data repository not only makes data more accessible to all project participants but also decreases the chance of data loss.

In recent years phenomics were widely used for screening the different abiotic stresses on crops. Recording of abiotic stress trait data is difficult and often misleading with other factors such as nutritional deficiency or excessively, environmental changes and biotic stress. Precise scoring of abiotic stress and its interpretation is necessity to developed and/or identify suitable genotypes resistances to abiotic stresses as well as future breeding strategies. The different phenomics instrument used for scoring morphological traits, physiological traits as well as abiotic resistance traits. Advancement of imagining technology, drone technology, machine learning and sensors boost up the phenomics in abiotic stresses breeding. Theses technology provided accurate result without any errors result in precise analysis of data and getting perfect outcome of experiments. Many researchers developed and used different instrument, sensors, platform, and algorithms for scoring and analysis of abiotic stress data. This information was surly helpful for many researchers for their future abiotic stress breeding experiments. Furthermore, lowering the cost of these revolutionary phenotyping technologies and enhancing their dependability and extendibility might aid future gain in abiotic stress breeding.

VI. CONCLUSION

This chapter discusses current advances in plant phenomics. Second, it emphasizes how advances in plant phenomics status and dynamic changes across many spatial-temporal scales and disciplines in agriculture have enhanced agriculture research. It looks at how these phenotyping and modeling techniques have helped breeders improve their methods. Finally, it notes that while the above-mentioned phenotyping developments have solved certain breeding and management concerns, there are still obstacles to overcome. It discusses anticipated developments in low-cost, high-spatial-resolution, multi-functional facilities, multi-dimensional applications with algorithm attempts, open-source, and big data that will transform our understanding of plant phenotyping, modeling, and breeding and management.

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