Phenomics: Next Generation of Agronomical Trait for Agriculture Crops

Abstract

Agriculture now has facing different type of challenges to overcome by high through output technology with their management with respect to crops. The United Nations has established seventeen goal to achieve zero hunger and malnutrition by 2030, ensuring that people especially children have sufficient and nutritious food throughout the year. Plants phenotypes are affected by complex interactions of genome × environment × management they determine phenotypic variability by genetic components. Plant Phenomics is next generation phenotyping technology, play a vital role to study of plant growth, architecture, performance, and composition using high-throughput methods of data acquisition and analysis and overcome challenges in crop production. It is a correlation of gene function, plant performance and environmental response, with high resolution. The external phenotype is determined by the sum of the complex interactions of intracellular regulatory networks to control metabolic pathways and that is reflected in physio-chemical as well as morphological phenotype. Phenomics is the field of image-based analysis, non-destructive, phenotyping that permit to characterization of plant traits.

Keywords: Phenomics, Physio-chemical, Genes and Environment, Gene performance, and metabolic pathways

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I. INTRODUCTION

Phenomics is new branch of biology which deals with a set of characters (phenome) belonging to a particular organism. Phenomics involves analyzing phenotypes in a high-throughput manner by examining an organism's morphological, physiological, and biochemical traits (Kiran, *et al*., 2019), and linking these traits with genetic, epigenetic, and environmental factors (Deshmukh *et al*., 2014). When applied to plants, phenomics focuses on understanding plant growth, performance, and composition. Tolerant plants exhibit specific traits in genomics, transcriptomics, proteomics and metabolomics. Consequently, integrating phenomics integrated with other omics approaches provides huge insight for the understanding of how cellular biochemical or biophysical processes lead to the final phenotype. Plant phenotypes are inherently complex because they arise from the interaction of genotypes with a numerous environmental factor (Bilder *et al*., 2009).

Phenotyping have been widely used to screening collections of germplasm in order to predict phenotype based on genetic markers (Kumar *et al.*, 2023). Nowadays, many of nondestructive methods that can be utilized for the basic phenotyping comparison like fluorescence imaging systems. Humplik *et al.* (2015) employed hyperspectral imaging, thermo-imaging and chlorophyll fluorescence imaging as high throughput platforms for plant phenotyping. With advancement in high throughput tools to analyzing the total plant phenome has become easier as well as accurate. Using the noninvasive methods throughout the life cycle, we can measure plant growth and morpho-physiological parameters to screen the plant vigor which can help us to link the phenotypic data obtained under various stress or multiple environmental conditions. Hairmansis *et al*. (2014) used a noninvasive image-based phenotypic method to check the differences in shoot area under salinity stressed and control conditions, contrasting rice varieties such as IR64 and Fatmawati. Accurately measure diverse traits of an increasingly large number of plants to help plants to adapt to resource-limiting environment and low-input agriculture. Variation in the shoot area of the cultivars Fatmawati and IR64 under control and 50, 75, and 100 $mmolL^{-1}$ NaCl concentration indicates a variation in tissue tolerance mechanisms between the cultivars.

Phenomics has also advanced to develop other high-throughput phenomics technologies, a few of which include plant response to biotic and abiotic stresses (Matouš *et al*., 2006; Chaerle *et al*., 2007; Jones *et al*., 2009; Sirault *et al*., 2009; Berger *et al*., 2010; Munns *et al*., 2010; Furbank and Tester, 2011; Kumar, *et al*., 2022), dissecting dynamic changes in plant structure and

functions (Jahnke *et al*., 2009), multi-sensor stress catalog (Chaerle *et al*., 2009), or module for handling large-scale phenotyping and genotyping data (Jung *et al*., 2011), which is beyond the scope of this chapter to provide procedural and technical details (Lenk *et al*., 2007). Nonetheless, we highlight their applications in agriculture including in plant breeding to developing cultivars with better adaptation to stress-prone environments.

II. DEVELOPMENTAL STAGE OF PHENOMICS CANTER

International Plant Phenotyping Network is an association representing the major plant phenotyping centers. IPPN aims to provide all relevant information about plant phenotyping. The goal is to increase the visibility and impact of plant phenotyping and enable cooperation by fostering communication between stakeholders in academia, industry, government, and the general public.

1. Austrian Plant Phenotyping Network (APPN)
2. Australian Plant Phenomics Facility (APPF)
3. China Plant Phenotyping Network (CPPN)
4. German Plant Phenotyping Network (DPPN)
5. Phen-Italy
6. PHENOME - The French plant phenomics network

3. Type of Phenomics: Phenomics classified in two group broad group

III. FORWARD AND REVERSE PHENOMICS (II) CONVENTIONAL AND HIGH THROUGH OUTPUT PHENOMICS

1. Forward and Reverse Phenomics

The phenomics is the study of the phenome aiming to characterize phenotypes in a rigorous and formal way to link with the associated genes and alleles (gene variants). Phenomics deals with study of plant growth & development, performance, composition, correlation of genetic, epigenetic, and environmental factors. Forward phenomics uses phenotyping tools to 'sieve' collections/ selection of germplasm for desirable traits. Heat stress imposing during the critical phases of plant development; during this period, an effective photochemical quantum yield of photosystem II (YII) performance was monitored across set of genotypes (Brito *et al*, 2019).

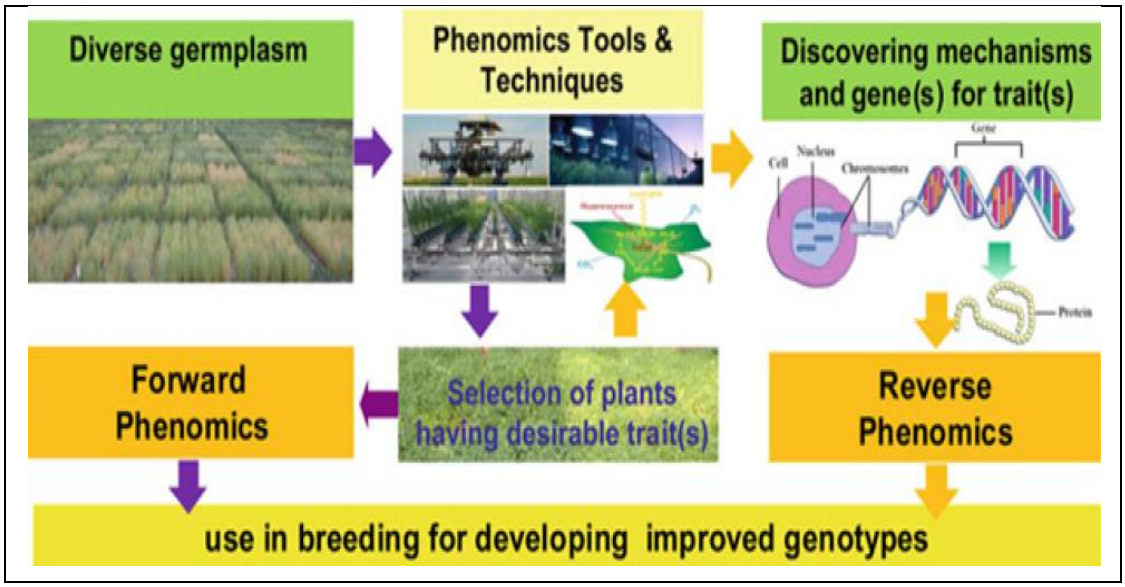

Figure 1: In this figure depicted the forward phenomics as well as reverse phenomics and we are reached to ultimate goal of improved the genotype for the enhance the yield and other agronomics traits (Source; Kumar, *et al*., 2015).

The screen could be high-throughput and fully automated and low resolution, followed by higher-resolution, lower-throughput measurements. Reverse phenomics is the detailed dissection of traits shown to be of value to reveal mechanistic understanding and allow exploitation of this mechanism in new approaches. This can involve reduction of a physiological trait to biochemical or biophysical processes and ultimately expression of genes/genes variants.

2. Classical or Conventional Phenotyping

Conventional Phenotyping is also known as traditional phenotyping. The traditional phenotyping is a companied with lots of bottlenecks to justify the experiments which cause the hindrance in the research programme and also time consuming and labor intensive. The whole phenotyping of the larger plot is quite difficult and if done which may be not precise. The traditional phenotyping is done by visual screening which cannot be useful for physiological and biochemical characteristic. Some of the biochemical characterization includes destructive assay (Kiran *et al*., 2019). The conventional phenotyping is error prone so the precise justification is difficult for the experiment. This is the reason of evolving the science of phenotyping.

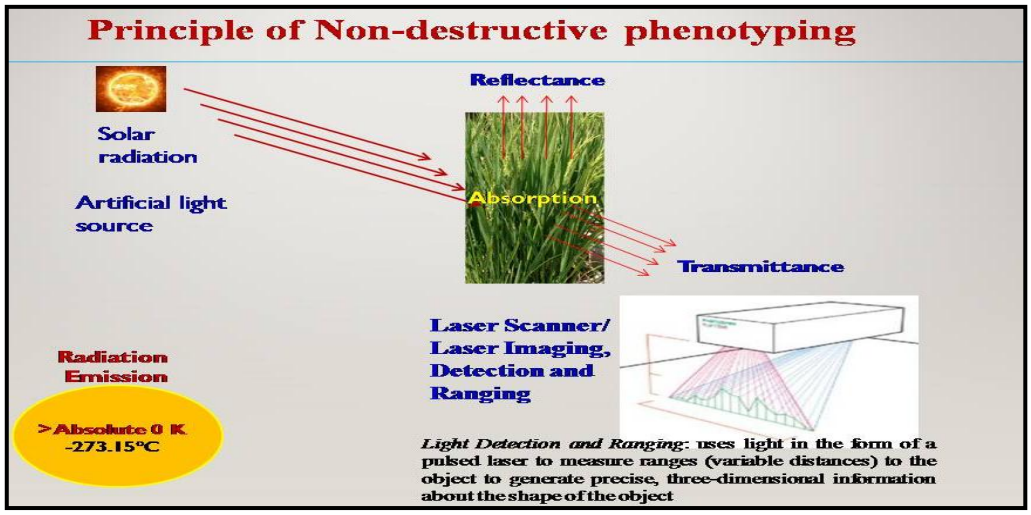

Figure 3: This picture depicted the mechanism of non-conventional phenotyping.

Image-based phenotyping or Nonconventional Phenotyping

1. These approaches are noninvasive and nondestructive.
2. As a result, the same plants can be imaged in a sequence throughout the life cycle/experiment to measure dynamic traits like growth & developments.
3. The image-based assays are sensitive, especially when a high-resolution camera (>1 megapixel) is used.
4. They are relatively easy to perform.
5. The whole plant, plot, or even the entire field can be included in a single image.
6. Therefore, analysis of a single image would allow quantification of several traits.
7. The digital images can be stored in databases and reanalyzed later using an improved image-processing algorithm or to evaluate some new questions/hypotheses.

List of Different Wavelength Based Sensorsused in Plant Phenotyping

1. γ-ray (Positron emission tomography)	2. X-ray (Computed tomography Scan)
3. Ultra-Violet (UV) Fluorescence	4. Visual (400-700nm)
5. Near-Infrared (NIR) (700-1700nm)	6. VNIR, Hyperspectral (400-1000nm)
7. SWIR, Hyperspectral (1000-2500nm)	8. Infrared (IR) Thermal (8 -16 μm)
9. Chlorophyll Fluorescence (Photosynthetic efficiency)	10. Bioluminescence
11. Fourier transform infrared spectroscopy (FTIR)	12. Radiowaves (MRI)

Table 3: Different types of electromagnetic radiation captured by different types of cameras with their exposure time in per second and their application.

Camera type	Spectral sensitivity	Exposures per second	Application
RGB Camera	Visible, 400-950 nm (with filters 400-700nm)	17	Morphological & growth phenotyping; node number, leaf length, morphology, growth phase, nutrient deficiency, disease, & senescence analysis
Fluorescence camera	Same as RGB	17	Low light condition; excitation, blue light (<500 nm); stress identification and quantification, photosynthesis & chlorophyll content
NIR camera	900-1700 nm	30	Root imaging, water distribution & dynamics, especially in response to drought
IR camera	8000-14000 nm	40	Temperature (within leaves & between plants) stomatal conductance; Drought , heat etc stress studies
Hyperspectral camera	Reflectance in visible to NIR range	-	Pigment composition, nitrogen use efficiency, other biochemical features

a) Visual Imaging

Digital imaging in the visible wavelength (400–700 nm) is called visual imaging. It is one of the simplest and slightly useful methods of imaging, which provides information as size of plant parts as well as color. This information allows quantitative measurement of growth, senescence, nutrient deficiencies, pathogen infections, and the consequences of stress-response mechanisms. In addition, it allows identification of the type of stress likely to be responsible for the observed changes. For example, visual imaging permits the separation of the various responses of plants to salinity stress into the following two categories: salt-dependent responses and salt independent responses. The stomata close soon after exposure to high salt concentration, and plant growth and development inhibited quickly; this inhibition is dependent of salt accumulation

in plant tissues. Later, leaf senescence begins in response to salt accumulation. The separation of leaf areas into yellow and green areas allows quantitative assessment of senescence. Visual imaging also allows phenotypic analysis of large plant populations for mutant isolation or linkage mapping. Time-lapse visual imaging permits the estimation of growth rate and visualization of effectiveness of the strategies to limit insect damage. Visual images are generally used as reference images in conjunction with other imaging techniques. The visual images to be used as reference are acquired either at the same time or just before the acquisition of the other types of images (Chaerle and Van Der Straeten 2001).

b) Near Infrared Imaging (NIR imaging)

The reflectance is high in the NIR region, exclusively between 800-1,300 nm. The reflectance declines beyond 1,300 nm due to absorption by tissue water: there are three characteristic water absorption bands at 1,450, 1,930, and 2,500 nm. The NIR region reflectance can be measured/imaged and used for various analyses, including calculation of some useful indices like water index, normalized difference vegetative index (NDVI), etc. These indices make the reflectance data nearly independent of sunlight intensity. Sequences of NIR images can be analyzed to determine leaf growth and leaf growth rate (Bilder, (2008); Finkel, (2009); Furbank, (2009)). Multispectral imaging enables the detection of alterations in leaf angles of plants generated by various factors like drought stress since leaf angle alterations also change the sunlight reflection pattern. Further, information about the contents of various pigments like chlorophylls, carotenoids and xanthophylls, photosynthetic activity, and water content can be obtained from multispectral imaging (Ollinger 2011; Chaerle and Van Der Straeten 2001). The changes in chlorophyll and/or nitrogen content(s) of the leaf, and in water status and health of the tissue lead to characteristic alterations in leaf color. Even slight differences in leaf color can be detected by measuring reflectance at different wavelengths. The issues relevant to the use of NIR reflectance for routine phenotyping concern the cost, management, analysis, and interpretation of the huge amounts of data; researchers are beginning to address these issues (Fiorani and Schurr 2013).

The use of hyperspectral reflectance spectroscopy in plant breeding has been rather limited due to various reasons, including its dependence on solar radiation. But LED-based easy-to-use portable spectrometers for measuring NDVI are in common use. NDVI is perhaps the most extensively used vegetation index for assessing the responses of plants to drought, salinity, and

nutrient deficiency stresses and to predict yield in the field. NDVI is estimated as follows (Ollinger 2011):

$$NDVI = R_{NIR} - R_{red} / R_{NIR} + R_{red}$$

Where,
R_{NIR} and Rred denote reflectance in the NIR (at 800 nm) and red (at 680 nm) regions of the spectrum, respectively.

Theoretically, NDVI values can range between ⁻1.0 and +1.0. In general, healthy plants show higher NDVI values than unhealthy plants. NDVI is often directly related to photosynthetic activity, chlorophyll content, leaf area index, biomass, and yield. Sometimes, the ratio vegetation index (RNIR/Rred) is also used, but NDVI is considered more desirable.

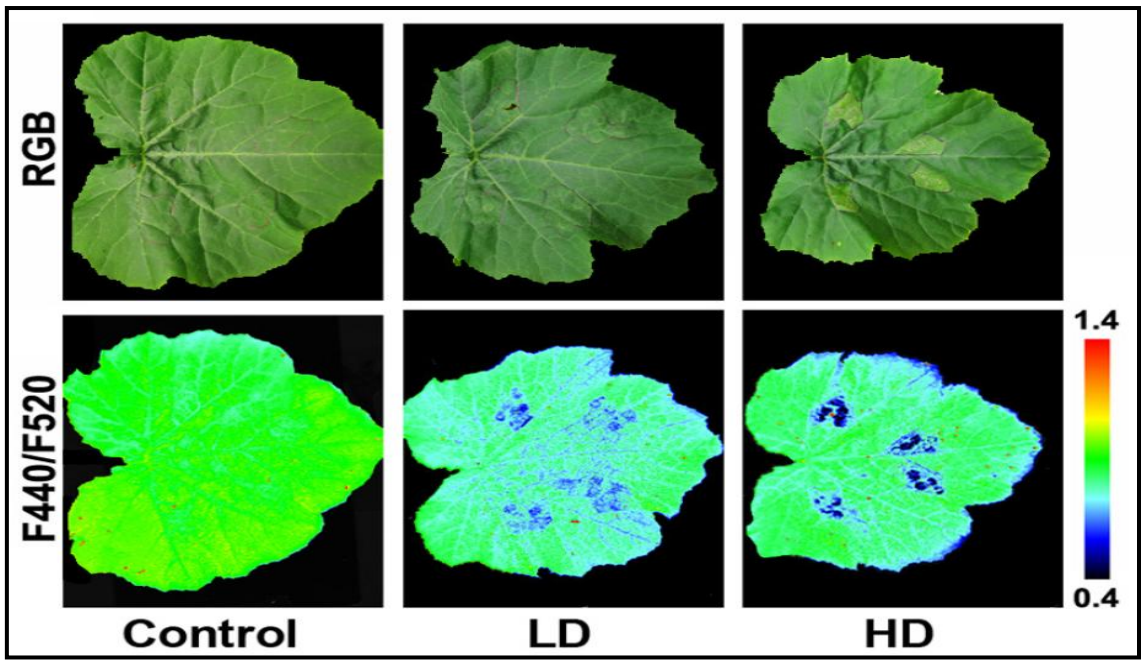

Figure 4: Auto-fluorescence images: blue (F440), green (F520), red (F680), and far red (F740) regions. Standard F440/F520 images of mock-control, LD, and HD-inoculated zucchini leaves at 3 dpi (soft-rot, caused by *Dickeya dadantii*), and their corresponding RGB images (Source: **Pérez-Bueno *et al.* 2016.** Front. Plant Sci. 7:1790).

c) Fluorescence Imaging

When a molecule absorbs light at a specific wavelength and subsequently emits light at a longer wavelength, this phenomenon is known as fluorescence, and

such molecules are called fluorophores or fluorescent molecules. If fluorescence occurs due to an endogenous molecule like chlorophyll or xanthophyll in plants, it is referred to as autofluorescence. In situations where autofluorescence is not available or practical, an exogenous fluorophore must be supplied, or a transgene expressing a fluorophore needs to be introduced into the plants. By illuminating these fluorophores with light of the appropriate wavelength, the resulting fluorescence can be observed at various levels, such as cells (using a fluorescence microscope), organs, whole plants, or canopies, and measured using a fluorometer (Yang, *et al*., 2020).

Fluorometers Come in Two Types: imaging and non-imaging. Imaging fluorometers acquire images of fluorescing objects through a fluorescence imaging system, which includes a light source for homogeneous illumination of the target surface, a fluorescence detector, and a computer to control data acquisition and analysis. Blue or short-wavelength red light is commonly used to excite chlorophyll fluorescence. UV illumination can detect both blue-green fluorescence and chlorophyll fluorescence. However, using UV radiation to excite chlorophyll fluorescence can be problematic if UV-absorbing substances are present in the plant epidermis.

To measure chlorophyll fluorescence in the field, plants must either be completely shielded from sunlight using a box or strong lasers are used to induce fluorescence. Typically, light sources operate in a pulsed mode to eliminate interference from ambient and reflected light. Illumination is generally provided by LEDs (light-emitting diodes) or Xenon/halogen lamps with band-pass filters.

Monochrome CCD cameras are employed to capture fluorescence images. These cameras operate in synchrony with light pulses and are equipped with appropriate filters to ensure proper imaging. For example, a red filter is used to block all light below 650 nm for detecting chlorophyll fluorescence. To detect low fluorescence signals, such as in imaging F0, a cooled CCD camera is utilized. Newly developed modulated imaging systems, like FluorCams (www.psi.cz), can capture up to 50 images per second. These images display the fluorescence characteristics of entire leaves or plants, with each pixel representing a distinct measurement. Successive images taken over time enable the estimation of the leaf area and growth rate. Fluorescence imaging can be used to analyze various physiological processes, including photosynthesis, gene expression, signaling pathways, and plant-microbe interactions. It is also useful for identifying early effects of biotic and abiotic stresses, such as water stress and insect attacks.

Non-imaging fluorometers, such as portable handheld fluorometers like plant efficiency analyzers (PEA), measure fluorescence from small leaf areas. The leaf area to be monitored is first dark-adapted by covering it with a specially designed clip for a few minutes. Once the clip is removed, the area is exposed to a saturating flash of light, and the resulting fluorescence is recorded over a few seconds. Modern fluorometers are typically modulated and tuned to detect only the fluorescence excited by their own light sources, allowing measurements to be taken even in full sunlight. Non-imaging fluorescence measurements are extensively used to characterize leaf tissues and determine chlorophyll content in leaves, seeds, and other plant parts. For instance, seed chlorophyll content has a significant negative correlation with germination potential in cabbage. Therefore, cabbage seed lots can be classified into high and low germination potential groups based on chlorophyll fluorescence.

d) Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) enables nondestructive, high-resolution visualization of the distribution of bound and free water, which indicates the spatial organization of organs and tissues. For example, proton-MRI microscopy has been used for nondestructive imaging of fruit development. But the findings from in vivo MRI imaging need to be verified by studies using other microscopic techniques. There is a rapid increase in proton-MRI signal as a result of tissue freezing. Therefore, MRI permits localization of frozen and unfrozen water in tissues and identification of healthy and frost-damaged tissues. Since MRI data acquisition is slow, thermography is preferable for monitoring more rapid events during freezing. MRI can be used to determine the effect of environmental conditions on water distribution within plants, and analytical tools for determining water content from MRI data have been developed. But MRI cannot be used to screen plant populations. Efforts are being made to combine MRI with positron emission tomography (PET) for investigating the structures of plants and their transport processes. However, MRI–PET data analysis remains a challenging task (Jahnke *et al*. 2009).

e) Multi-sensor Monitoring Approaches

In a multi-sensor approach, images of the same object are captured using different sensors, e.g., visible and thermal sensors, or a combination of visible, thermal, and fluorescence sensors. During image analysis, the images from different sensors are laid over each other with the help of predetermined reference points within the concerned images. This greatly facilitates separation of the imaged object from the background materials. A combination of two or

more imaging methods might generate more phenotypic information of greater reliability (Chaerle *et al*. 2009). Hyperspectral imaging to estimate amount of 15 elements viz. B, C, Ca, Cd, Cu, Fe, K, Mg, Mo, Mn, N, Na, P, S, Zn in grain in high-throughput in the wild barley nested association mapping (NAM) population HEB-25, comprising 1,420 BC1S3 lines derived from crossing 25 wild barley accessions with the cultivar 'Barke' (Herzig *et al*., 2019). The individual imaging techniques can reveal the symptoms of a wide range of stresses at an early stage, but the use of images from multiple sensors may permit the identification of the stress responsible for the observed symptoms. For example, leaf chlorophyll content decreases in response to both water stress and nitrogen deficiency; this change is readily detected by fluorescence imaging (Singh, & Singh, 2015). However, water stress also leads to stomatal closure; this in turn leads to increased leaf/canopy temperature, which is easily detected by thermography. In contrast, nitrogen deficiency does not affect stomatal closure so that there is no change in leaf/canopy temperature. Therefore, a combination of fluorescence and thermal imaging would allow the determination of whether water stress or nitrogen deficiency is the real cause of the observed decrease in chlorophyll contents of the test plants. Clearly, the optimal combination of different sensors would depend on the physiological effects of the different stresses that are to be distinguished.

f) Modern Field Phenotyping Opens New Avenues for Selection

Another area of at least equal importance is phenomics, that is, the phenotypic evaluation of the plants. In plant breeding new variation is generated by crosses among selected parental lines. To identify superior genotypes, several thousand or rather tens of thousands of genotypes must be evaluated in field trials each year (Houle *et al*., 2010). Phenotyping is therefore the central pillar on which selection gain in plant breeding is based. However, in contrast to genomics, phenotyping has seen only little improvements in the last decades, despite the importance of accurately assessing the phenotype of crops. The phenotyping methods currently available to plant breeders are often based on visual scorings, are labor- and time-intensive, expensive, not objective, and sometimes destructive (Kumar, *et al*., 2016). Furthermore, many traits that will become important in the future, for example, improvement of traits related to raw materials for industrial purposes, cannot be assessed with classical approaches at all. Phenotyping is therefore currently considered a major bottleneck of plant breeding (Furbank and Tester, 2011; White *et al*., 2012; Cobb *et al*., 2013). Great potential to alleviate this problem and to take phenotyping to the 21st century lies in precision phenotyping, that is, the use of sensor technology to assess traits and plant characteristics on plants and in plant stands (Montes *et al.*, 2007).

Role of Nanotechnology in Phenomics

Nanobiotechnology embrace significant potential to developing smart plant sensors that relate with electronic devices for enhance plant productivity, and improving quality. By optimizing and automating the allocation of water and agrochemical, and enabling high-throughput chemical phenotyping in plants, this technology objectives to address major challenges in agricultural industry, like reducing crop loss due to environmental and pathogen-related stresses, improving water/ resource use efficiency, and choosing optimal plant traits. To achieve this, innovative technologies are required for accurately monitoring plant physiological and developmental responses to their microenvironment in real-time, with high spatial and temporal resolution.

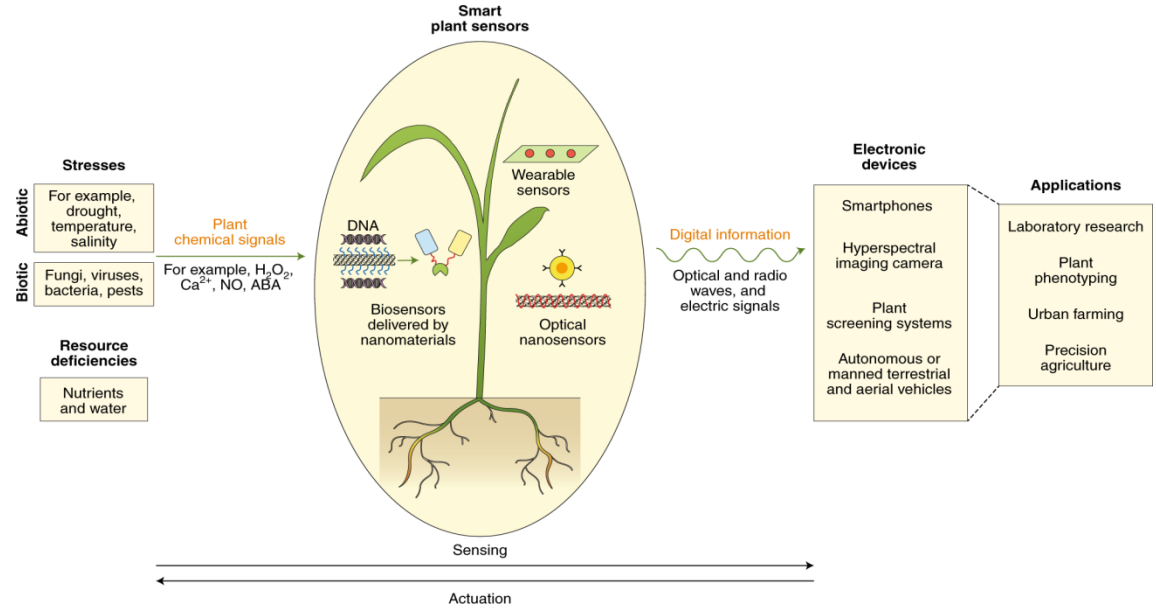

Figure 5: Nanobiotechnology approaches enable research and development of smart plant sensors that communicate plant chemical signals to agricultural and phenotyping equipment. Optical nanotechnology-based sensors interfaced with plants allow the translation of plant chemical signals into electric signals, which can be detected by electronic devices. Machines with the capacity to decode spatiotemporal patterns of plant chemical signals will allow smart nanobiotechnology-based sensors (Behrendt *et al*., 2020) to actuate agricultural devices for optimizing the plant environment. (Source: Giraldo *et al*., 2019).

Nanomaterials play a crucial role in converting plant chemical signals into digital information, which can then be monitored by remote electronic devices. This discussion focuses on the design and integration of smart

nanobiotechnology-based sensors that can detect plant signaling molecules related to health status and transmit this information to agricultural and phenotyping devices through optical, wireless, or electrical signals. We also explore how nanomaterial-mediated delivery of genetically encoded sensors can serve as tools for the research and development of smart plant sensors. Furthermore, we evaluate the performance parameters of these sensors in plants, such as resolution, sensitivity, accuracy, and durability, including in vivo optical nanosensors and wearable nanoelectronic sensors (Giraldo *et al*., 2019). Finally, we present an integrated and forward-looking perspective on how nanotechnology can enable smart plant sensors to communicate with and actuate electronic devices for the monitoring and optimization of individual plant productivity and resource use.

Public Datasets

Developing and sharing datasets publicly is crucial for research in image-based plant phenotyping because it provides the broader computer vision research community with access to datasets they typically cannot generate. Standard datasets also offer a common basis for comparing the performance of plant phenotyping algorithms. Here is a brief summary of some publicly available datasets:

Leaf Segmentation Challenge (LSC) Dataset: This dataset is designed to improve the state of leaf segmentation, counting, and tracking of rosette plants. It includes images of two plant species, Arabidopsis thaliana and Nicotiana tabacum, organized into three subsets. Subsets A1 (Ara2012) and A2 (Ara2013) contain top-view time-lapse images of Arabidopsis thaliana rosettes with 150 and 5048 images, respectively (Pieruschka, *et al.*, 2019). Subset A3 (Tobacco) includes top-view stereo image sequences of Nicotiana tabacum plants captured hourly for 30 days (Bilder, (2008); Finkel, (2009); Furbank, (2009)). The dataset is available at [CVPPP2014-challenge] (http://www.plant-phenotyping.org/CVPPP2014-challenge).

Michigan State University Plant Imagery Dataset (MSU-PID): This dataset consists of images of Arabidopsis (2160 × 4) and bean (325 × 4) captured with four types of calibrated cameras: fluorescent, infrared, RGB color, and depth sensor. It supports research in leaf segmentation, leaf counting, leaf alignment, leaf tracking, and 3D leaf reconstruction. A subset is annotated for ground-truth for leaf tip location, leaf segmentation, and leaf alignment. The dataset is available at [MSU-PID] (http://cvlab.cse.msu.edu/multimodality-imagery-database-msu-pid.html).

Panicoid Phenomap-1: This dataset aims to stimulate the development and evaluation of holistic phenotypes of panicoid grain crops. It includes visible light image sequences of 40 genotypes from five panicoid grain crops: maize, sorghum, pearl millet, proso millet, and foxtail millet (Kumar *et al*., 2016). Images are captured by the Lemnatec scanalyzer high-throughput plant phenotyping facility at the University of Nebraska-Lincoln (UNL), USA.

University of Nebraska-Lincoln Component Plant Phenotyping Dataset (UNL-CPPD): Introduced to spur research in leaf detection and tracking, leaf segmentation, and the evaluation of holistic and component phenotypes for maize and cereal crops with similar architecture, such as sorghum. The dataset includes human-annotated ground-truth along with the original image sequences to facilitate image-based component phenotyping analysis.

Komatsuna Dataset: This dataset contains images of early growth stages of Komatsuna plants with a leaf annotation tool to support 3D plant phenotyping analysis, such as leaf segmentation, tracking, and reconstruction. Five Komatsuna plants are imaged every 4 hours for 10 days using an RGB camera (Multiview dataset) and an RGB camera fitted with a structured light depth camera (RGBD dataset). The dataset is available at [Komatsuna] (http://limu.ait.kyushu-u.ac.jp/~agri/komatsuna/).

University of Nebraska-Lincoln 3D Plant Phenotyping Dataset (UNL-3DPPD): This dataset includes images of 20 maize and 20 sorghum plants from 10 side views to support 3D plant phenotyping research. Plants were imaged once per day using the visible light camera of the UNL Lemnatec Scanalyzer 3D high-throughput phenotyping facility. It can be downloaded from [Plant Vision] (http://plantvision.unl.edu/).

Deep Phenotyping Dataset: This dataset contains 22 successive top-view image sequences of four Arabidopsis accessions (Sf-2, Cvi, Landsberg, and Columbia), captured once daily to study temporal phenotypes for accession classification using convolutional neural networks (CNN), recurrent neural networks, and long-short term memory (LSTM) (Bilder, (2008); Finkel, (2009); Furbank, (2009)). The dataset is augmented by rotating each image by 90°, 180°, and 270° to prevent overfitting while training CNNs. It is available at [Figshare] (https://figshare.com/s/e18a978267675059578f).

Application of Plant Based Phenomics

1. Rapid identification of stresses in plant population
2. Rapid and efficient screening for mutants
3. Evaluation of phenotyping effect of uncharacterized transgenes.
4. Detection and monitoring of disease epidemics in field.
5. Detection of root attack by fungi, nematodes, insect and other pathogens,
6. Modeling of biomass and green energy production.
7. These techniques would be cooperative in the understand various physiological developments underlying specific plant functions.
8. They would facilitate screening of germplasm, collection of germplasm, identification of accessions with the genes of interest.
9. The Phenomics approaches would also facilitate the selection of superior /desired genotypes from breeding populations.
10. They would ultimately, allow the huge genomic information to be reliably related to specific phenotypes.
11. Permit a systematic study of the pleiotropic effect of the genes.
12. It might become feasible to precisely predict the phenotypic effect of the changes at DNA Sequence level.
13. The above developments would enable a planned and precise use of the available genetic diversity for crop improvement to achieve increased agricultural productivity.

IV. CONCLUSION

Phenomics technologies are transforming the field by enhancing reproducibility and unbiased data acquisition in both basic and applied research. A successful approach involves integrating sensors with wavelength and image acquisition capabilities to accurately identify the items under analysis. Much work has been done in indoor setups, where controlled conditions can be created to obtain high-quality images suitable for further processing. Outdoor setups, however, pose challenges due to limitations in image acquisition devices and uncontrolled conditions that directly affect image quality. New technologies, such as high-definition LIDAR and multi-hyperspectral cameras, hold great potential for improvements, particularly in outdoor environments.

Preprocessing and segmentation are crucial aspects of data treatment and acquisition that require careful design to avoid distortions and ensure reproducibility. Since images are machine-produced data, and image types and processing procedures can vary widely, standardizing image capture, preprocessing, and segmentation processes is important. Additionally, there is

no single procedure for image analysis that can be deemed the best choice; researchers must evaluate different algorithms to develop an optimized procedure for their specific setup. It is expected that databases with raw images will eventually become standard in phenomics, similar to how NCBI and Uniprot are essential in genomic and proteomic projects. With the decreasing cost of hyperspectral devices, new experiments may generate larger datasets, necessitating artificial intelligence-based data analysis to provide researchers with interpretable results. Like other omics approaches, a convergence of standard procedures is anticipated, making the current diverse literature more cohesive. Despite the diversity, the basic processes described here are shared among different experimental setups and data analysis pipelines.

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