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REVIEW ARTICLE

Advances in Plant Phenotyping Tools for Agricultural Sustainability

Anjali Bhardwaj[1], Shikha Chaudhary[2]

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ABSTRACT

The continuously rising population of the world and decreasing land for agriculture are highlighting the issue of sustainable agriculture and food security. The ancient methods of crop improvement require manual labour and time. The plant phenotyping techniques are providing a helping hand to plant breeders as they study plant phenotypes using imaging, aerial vehicles, sensors, robots, crop models etc. these tools accurately measure the visible traits of the plant such as plant height, physiology and response to stress in different conditions and thus speed up the crop breeding researches. The research is entering a new phase of development in which phenotyping is combined with machine learning, artificial intelligence, predictive crop models to support decision making in sustainable agriculture. The current review discusses the use of phenotyping tools in agriculture and the challenges that are still limiting the use of these novel techniques in agriculture and the possible solutions.

KEYWORDS

• Phenomics • Agricultural sustainability • Food security • Imaging tools • Machine learning • Remote sensing

INTRODUCTION

Agriculture must advance beyond conventional breeding and phenotypic evaluation techniques in order to become quicker, more accurate, and more data-driven in this accelerating pace of rising global food demands and increasingly unpredictable settings brought on by climate change. Phenomics, the high-throughput measurement of phenotypes; the observable characteristics of plants or crops, often under various environmental conditions, is one of the promising frontiers in this evolution to understand how genotype, environment, and their interaction shape yield, stress resilience, quality traits.[109] The conventional breeders

AUTHOR'S AFFILIATION:

[1] Assistant Professor, Department of Botany, Pandit Sant Ran Government College, Baijnath, Himachal Pradesh, India.

[2] Assistant Professor, Department of Botany, Government Degree College, Roopnagar, Punjab, India.

CORRESPONDING AUTHOR:

Anjali Bhardwaj, Assistant Professor, Department of Botany, Pandit Sant Ran Government College, Baijnath, Himachal Pradesh, India.

E-mail: bhardwajanjali96@gmail.com

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depended upon conventional phenotyping which needs time, resources, laborious as they were based on morphology, touch and taste of the crop and also required sampling of a large population of crop plants.[58] Plant phenomics depends upon three major steps: target trait detection, data speculation and computation to assist decision making. To capture, handle, and analyze extensive phenotypic data in controlled and field settings, phenomics tools combine advanced imaging, sensor technologies, robotics, and computational pipelines. Plant development, physiology, architecture, health, and other functional characteristics can be regularly, non-destructively, and multiscale monitored with these methods.[109;116] The use of imaging techniques allows researchers to understand and evaluate complex traits like yield under unfavourable environmental conditions. The sensory equipments have a broad range of utilization in agriculture to decipher the physiological changes under stress conditions and to control experimental setups in the growth chambers, labs and fields.[58] Furthermore, phenomics fills a significant gap between breeding and crop improvement which ultimately depends on features displayed in real conditions and genomics, which can catalogue genetic potential. By combining genotyping and phenotyping it is possible to gain thorough understanding into the gene expression and it's response to varied environmental conditions.[58] Phenomics aids in the identification of advantageous alleles, speeds up selection, and enhances performance prediction under stress (both biotic and abiotic) by providing accurate trait quantification and temporal resolution).[109;65] Nevertheless, there are difficulties in putting phenomics techniques into practice. These include the high cost or complexity of sensors and platforms; the need for standardization; handling, storage and analysis of large, high-dimensional datasets; adapting tools to diverse environments and crops; and ensuring that tools developed under controlled or experimental conditions translate well to the field.[116;149] Phenomics tools represent a transformative approach in modern agriculture as they offer the potential to make crop improvement faster, more precise, and more responsive to environmental stresses, but realizing that potential will require overcoming technological, analytical, and logistical hurdles.

VARIOUS TOOLS USED IN PHENOMICS

Deep learning platforms

Phenotyping has been made automated with a variety of "phenotyping platforms," which are hardware and software solutions that include plant installation, phenotyping conditions standardisation, picture and sensor registration, and online processing. Plant cultivation boxes, measuring tools, plant calibration and movement systems, cameras, sensors, automated watering, lighting, and microclimate management systems, computer-based process control systems, information processing and storage, servers, and software for more in-depth image analysis based on machine vision and learning systems are some examples of phenotyping platforms.[37]

Artificial neural networks provided the basis for deep learning, a branch of machine learning that deals with extracting meaningful patterns and observations from large datasets. Deep learning has become a potent method for handling difficult data analysis problems. Deep convolutional neural networks (CNNs) are one of its many topologies that work especially well for computer vision applications. Ubbens and Stavness[133] presented Deep Plant Phenomics, a deep learning framework for image-based plant phenotyping, and used three phenotyping tasks from earlier research to show how effective it is. Because deep learning platforms increase the accuracy, efficacy, and scalability of phenomic investigations, they are essential tools in modern phenomics research. Another deep learning tool is TensorFlow, which analyzes phenotypic images (such plant growth or disease indicators) and builds prediction models based on large datasets. The TensorFlow framework was used to create and train the models for estimating sorghum yield in field conditions.[119] PyTorch is another deep learning platform that is useful for creating original models for complex phenotypic data analysis, object detection in photos, and picture classification. Dong *et al*.[39] measured Lactuca sativa phenotypic parameters using PyTorch and image deep learning. Dhakal,[38] used a spectroscopy-based machine learning method to identify the best time to harvest edamame (*Glycine max*).

Deoxynivalenol (DON) concentrations in wheat kernels may be measured in a high-throughput manner using hyperspectral imaging in conjunction with computer vision and machine learning techniques.[38] Togninalli *et al*.,[131] presented a versatile deep learning system called PheGeMIL (Phenotype-Genotype Multiple Instance Learning), which employs multichannel, temporal inputs to forecast grain production more accurately in spring wheat. The yield prediction algorithms hold the potential to enhance breeding initiatives and expedite the release of enhanced cultivars. DIRT, LemnaTec, Photon Systems Instruments, QubitPhenomics, Phenomix, Phenospex, Delta-T Devices Ltd., Heinz Walz, WPS, CropDesign, WIWAM, Rothamsted Research, and VBCF are other commonly used phenomics platforms.

Different phenomic softwares are also available for data storage and metadata analysis to assist high-throughput phenotyping. For instance, **Tomato Analyzer** is used for assessing fruit shape and morphological characteristics in tomatoes.[20] **TraitCapture** enables the simulation of regional variety trials to preselect genotypes with improved productivity under challenging environmental conditions.[21] **PlantPAD** serves as a platform for analyzing plant diseases through image-based approaches.[40] **Precision Plots Analyzer (PREPs)** facilitates the acquisition of phenotypic traits at the microplot level from orthomosaic and digital surface model (DSM) images produced using Structure-from-Motion/Multi-View-Stereo (SfM-MVS) technologies.[57] Similarly, **Pheno-Mapper** provides an interactive environment for exploratory analysis and visualization of widespread phenomics datasets[163] (Table 1).

Table 1: Various softwares and machine learning tools used in plant phenomics

Tools	Traits	References
4D Root	Root traits: Root volume, depth, length, and area of the main and lateral root etc.	51
Root Analyzer	Root anatomy	29
Rhizo Pot	Root morphology, root growth rate, and lifespan analysis	161
GT-Root S	Root architecture	19
GiA Roots	Root architecture	43
Root Reader 2D	Root growth and development	30
Root Graph	Characterisation of root traits	23
Root Nav	Quantification of root system architecture	106
Root Scape	Root architecture	114
ARIA	Seedling root analysis in maize	96
GLO-Roots	Root architecture	111
Autoroot	Measurement of root traits	105
Root Scan	Measurement of root traits	22
Rootnet	Measurement of root traits	152
Rhizo Vision	Measurement of root traits	121
GlyPh	Plant growth and water use	101
Rotated Stomata Net	Stomata phenotype analysis	150
rosett R	seedling area and growth	132
Leaf-GP	Arabidopsis and wheat leaf	162
Canopeo	Analyse ground cover fraction	48
Shiny Fruit	Fruit phenotyping	27
Phenocave	For controlled growth conditions	70
PREPs	Analyse field images for crop cover	57
HSI-PP	Hyperspectral plant imaging	41
Gras VIQ	Vein number and morphology of grass	115
Grid Free	Grain counting and measurement	55
Seed Germ	Seed imaging	32
Seedscreener	Wheat germplasm phenotyping	145

table cont....

Tools	Traits	References
ear unwrapper	Disease detection in maize	56
Septo Sympto	Septoria tritici blotch disease analysis	85
CellProfiler	Cell image analysis	26
My Root	Primary root length	14
Mu See Q	Seed morphology	87
Rhizo Chamber	Root growth	143
My Root 2.0	Primary root length	47

Crop growth models

In the subject of phenomics, numerous models are employed to assess and decipher the vast amount of data obtained from phenotypic measurements. These models aim to increase our understanding of plant growth, development, and adaptability by bridging the gap between genotype and phenotype. The WOFOST simulation model can be applied to analyze field crop growth and productivity under a range of soil and meteorological conditions. The physical growth and yield of annual crops, which are impacted by weather, crop species, soil type, and hydrologic conditions, are best described by the model.[134]

Numerous crops, including wheat,[144] chilli pepper,[126] maize,[112] sugarcane,[2] potatoes,[(67)] etc., have had their yields estimated using this model. The Australian Agricultural Production Systems Research Unit created the modular modeling framework known as the Agricultural Production Systems Simulator (APSIM) to model and explore the biophysical processes that take place in agricultural systems. APSIM was originally designed as an agricultural systems simulator that would associate accurate yield estimation in response to management with the forecasting of farming practices' long-term effects on the soil resources like dynamics of soil organic matter, erosion, acidification, etc. It was demonstrated that the best management techniques for nitrogen fertilizer and water regime could be determined by using the AQUACROP and APSIM models. In arid regions, these models were used to increase wheat yield and conserve water. Another popular crop simulation model is the Decision Support System for Agrotechnology Transfer (DSSAT), which forecasts crop growth, development, and yield as influenced by soil–plant–atmosphere–management interactions. For researchers looking to more accurately and robustly estimate biomass and leaf area, this model is a useful tool. Singh[123] improved the predictive power of crop growth models by creating a biomass and leaf area estimation model using the Bayesian Least Absolute Shrinkage and Selection Operator (BLASSO) machine learning technique. The following **Table 2** shows a list of various crop growth models with their respective applications in agriculture.

Table 2: Various crop growth models used in plant phenomics

Crop growth models	Applications	References
EPIC	Estimate soil productivity, crop yield	142
CROPGRO	Plant C balance, plant water balance, soil plant N balance	18
AquaCropR	Optimate sowing dates	25
SVAT	Crop yield, water use efficiency	90
MISCANFOR	Yield	49
SAFY	Growth monitoring and yield estimation in wheat	81
DSSAT	Maize yield prediction	33
MONICA	Growth, soil moisture and nitrogen dynamica	93
SIMPLE	Growth and yield	160
AFRCWHEAT2, CERES-Wheat, SWHEAT	Wheat crop growth	104
Noah-MP	Leaf area index	76
WRF3. 3-CLM4crop	Crop growth and management	79

table cont....

Crop growth models	Applications	References
PNUTGRO	Crop C,N and water balance of peanut	45
STICS	Biomass, yield, leaf area index	62
SALUS	Impact of agronomic management on crop yields, C,N dynamics	11
SIMRIW-RS	Yield in rice	82
SUCROS	Cotton	158
WOFOST, SCOPE	Growth and yield	94
OPUS	Crop growth, soil water and nitrogen balance	141
ORYZA	Rice yield estimation	122
Web InfoCrop	Growth and yield of wheat	66
OILCROP-SUN	development, growth, and yield model of sunflower	137
GRAMI	Wheat yield	97
PROSAIL	Biomass of rice	138
Sentinel-2	Trophication measurement	72
YOLOX	Maize tassels	125
MSFNet	Crop monitoring, yield prediction and irrigation management	53
fAPAR	Crop growth monitoring and yield estimation	80
LINTUL	Development and growth of potato	50
MODIS	Maize grain tield estimation	118
IVINE	Phenology and physiology of grapevine	5

Remote sensing

Thanks to technological breakthroughs in the areas of sensors, information technology (IT), and data extraction, morphological and physiological features may now be assessed regularly and nondestructively over the course of a population's growth period. Unmanned aerial vehicles (UAVs) have grown in popularity over the last ten years due to their affordability and versatility in capturing high-quality images. Nevertheless, there is active development of these technologies.[129] Data collection without physical contact is known as remote sensing technology. It provides fresh insight into plant phenotyping and has been applied extensively in geoscience and engineering. The use of sensors in close proximity to plants is known as proximal sensing (PS), and it includes methods such as magnetic resonance imaging (MRI) and computed tomography (CT). Remote sensing (RS), on the other hand, describes the use of sensors that are not in close proximity to plants. This includes imaging from space and aircraft, such as drones and satellites.[127] High-resolution data can provide useful spectral characteristics of crops associated with performance variables such as seed yield for these applications. Depending on the stage of crop growth, high-resolution satellite imaging has become a useful tool for assessing seed output at the breeding plot level. The potential of these technologies for accurate yield estimation has been shown by studies assessing UAS-based multispectral features and high-resolution satellite data in field pea. Additionally, a multi-source image fusion method called pan-sharpening improves satellite spatial resolution and can help plant breeders evaluate past crop performance using satellite imagery that has been preserved. Additionally, it makes it easier to explore hyperspectral satellite images for field-based phenomics applications by hyper-sharpening it. Furthermore, crop growth dynamics and temporal variability can be efficiently captured using multi-temporal data fusion.[84] Plant phenomics is using Light Detection and Ranging (LiDAR), a potent remote sensing technique, more and more. In order to precisely measure distances and produce comprehensive three-dimensional structural information of plants and canopies, it emits laser pulses toward a target and analyzes the reflected light.[74] LiDAR-based plant phenotyping can yield a multitude of useful information for crop management and plant condition diagnostics at all levels, from the leaf to the canopy. For example, non-destructive evaluation of water stress in plants is frequently challenging; however, LiDAR-based methods, which estimate each leaf area and inclination, angle to quantify the degree of leaf droop, have demonstrated promising results in this area.[52] Compared to traditional RGB imaging, LiDAR-derived data offer distinct advantages by overcoming certain limitations such as over or underexposure caused by variations in ambient light and shadows, which can adversely affect image quality and data accuracy.[36] Furthermore, Jimenez-Berni *et al*.[64] demonstrated the successful application of LiDAR technology under field conditions for the non-destructive and precise quantification of canopy height, ground cover, and above-ground biomass in wheat.

Drones

Drone assistance via UAV In addition to being utilised in biotic and abiotic stress assessment in plants, is also employed in qualitative phenotyping for features like leaf nitrogen content and quantitative phenotyping for traits like plant height, biomass, and leaf area index. Currently, using UAVs (drones) for pesticide spraying in open fields and observation is rather common. As an emerging area of study, the use of UAVs (drones) for phenotyping is still in early stages.[100] Utilising UAV imagery in conjunction with precision phenotyping, breeders may get data on the growth and development state of plants. Plant number or density is one of the targeted features in image-based precision phenotyping. It has been utilised to quantify field emergence and create precise estimates of ultimate yield characteristics. Typically, RGB cameras are employed for measurement.[44] Drones were utilized to estimate the number of tillers grown in a field of wheat.[117] Unmanned aerial vehicles (UAVs) with multispectral (MS) cameras can be used to track changes in the vegetation index (VI) both spatially and temporally. The three primary types of UAVs are fixed-wing, rotary-wing, and hybrid drones, often known as Vertical Takeoff and Landing (VTOL) drones. Technologies for unmanned aerial vehicles offer a compelling opportunity to reduce the time, effort, and cost associated in collecting field phenotypes and data. However, the study subject matter, target species, and relevant characteristics determine which system and which sensors to utilise.[44] In recent years, UAV-based remote sensing has been used to measure soil organic matter, identify soil characteristics, and help control the salinity effect, which lowers the amount of organic carbon in the soil.[139] UAV-based sensing techniques have been used to identify a number of diseases, including powdery mildew,[3,78] stem rust,[1] rice bacterial infection,[108] pine wilt,[24] and Verticillium wilt in cotton plant disease.[73,61]

Robotics

Robotics in plant phenomics is a quickly emerging discipline that studies and analyzes large-scale plant traits and characteristics using automation and robotics technologies. In addition to collecting data on plant growth and development, which is crucial for optimizing crop management, autonomous vehicles, also referred to as field robots, can navigate fields to monitor plant health, identify pests, and apply treatments. They can also measure environmental parameters like soil moisture, temperature, and light conditions.[153] In essence, autonomous tractors are Unmanned Ground Vehicles (UGV) with sensors and actuators that make it easier to monitor crops, irrigate them, harvest them, and control diseases.[75] Cho *et al*.[28] created a smart farm robot that can accurately measure plant growth metrics in order to achieve more robust and accurate distinction of target plants from surrounding vegetation. Using the combined information from RGB and depth images, this system combines object detection, image fusion, and data augmentation approaches to improve measurement reliability and detection accuracy. Weed control is a crucial part of agricultural production. Effective weeding can increase crop productivity and quality. However, traditional weeding methods often neglect environmental protection and weeding quality. Jiang *et al*.[61] developed a weeding method that uses herbicides only after weed tissue has been harmed in order to get around these problems. To assess the efficacy of automated weed control methods, an intelligent intra-row weeding robot was created. The robot demonstrated its excellent precision and potential for sustainable, automated crop management in field trials, achieving a weed removal efficiency of 90.0% with only 1.9% crop damage in maize and a weed removal efficiency of 94.5% with 0.8% crop damage in Chinese cabbage. Through the use of more comprehensive, broad, and efficient assessments of plant characteristics, a crucial component of advancing in the domains of agriculture and plant science, robotics is generally transforming the field of plant phenomics.

Imaging tools

Visible imaging

Novel imaging technologies greatly aid quantitative measurement; yet, as part of optimal practices for plant phenotyping, standardised experimental techniques are required. These include imaging sensor calibration and a clear specification of raw data processing processes. Multidimensional and multiparameter data may be visualised thanks to the great resolution of modern imaging methods. Under both **controlled environmental conditions** (such as growth chambers and greenhouses) and **field environments**, **imaging techniques** are widely employed in plant phenotyping to measure complex traits associated with **growth, yield, and stress responses**. Different wavelengths of imaging are used in different aspects of plant phenotyping.[71] The primary elements of plant architecture that are measured by visible imaging include image-based projected biomass,[77] leaf area,[46] seedling vigor, seed morphology,[32] root architecture,[99] leaf disease severity assessments,[16] yield, and fruit number and distribution.[159] Paproki *et al*.[98] developed a 3D imaging technique with a mean absolute error of less than 10% for high throughput analysis of cotton stem height, leaf breadth, and leaf length. In a related study, An *et al*.[4] quantified the 2D and 3D leaf areas in Arabidopsis thaliana using innovative photogrammetry and computer vision methods. They then used the 2D measurements to examine nastic leaf movements and diurnal growth cycles.

Hyperspectral imaging

Hyperspectral imaging (HSI) is an emerging method that enables more detailed characterization of plant performance and environmental interactions by simultaneously detecting characteristics over a wide range of wavebands. A rapid, non-invasive, high-throughput method of remote sensing plant phenotyping collects and merges spectral (λ) and spatial (x, y) data to produce a 3D data matrix called a "hyperspectral data cube" (hypercube). HSI is a nondestructive technique based on how light interacts with plant tissues and their biological components.[120] The ability of HSI to gather both spatial and complete spectrum data allows for the extraction of both physiological and structural information about plants. The five primary components of a typical HSI system are the light source, objective lenses, hyperspectral sensor, image spectrograph, and computer.[88] It has been applied to the detection of early abiotic stress,[8] disease,[13] root phenotyping,[17] nitrogen status,[10] heavy metal stress,[155] and salt stress.[42]

Fluorescence imaging

When a material absorbs light at one wavelength and emits it at another, this phenomenon is known as fluorescence. The dynamics of this emission, which is extremely sensitive to the spectrum region of the fluorescent signal, are captured by fluorescence imaging systems. To detect fluorescence, these systems usually use pulsed light sources or cameras with particular spectral cutoff filters. For instance, fluorescence is released in the 600–750 nm region when plants are exposed to blue light (>500 nm). Researchers can visually detect and examine changes in fluorescence patterns by recording these emissions and using computer software to create false-color images.[110] Chlorophyll fluorescence is frequently employed in plant phenomics to track changes in photosynthetic performance, offering insights into how various genes or environmental conditions affect photosynthetic efficiency, especially in young plants. Commercial tools that assess particular fluorescence properties linked to stress reactions, including pulse amplitude modulated (PAM) fluorometers, have been developed for this purpose.[68] Furthermore, chlorophyll fluorescence imaging is a useful method for high-throughput phenotyping since it allows for the early detection of biotic and abiotic stressors,[91] disease detection,[102] photosynthesis monitoring,[35] rice stress identification,[156] wheat water deficit stress tolerance,[7] Arabidopsis salt stress detection,[130] protein imaging in canopies,[113] sorghum chlorophyll content analysis,[157] and plant tissue culture.[15]

Infra-red thermal imaging

Infrared thermography can be used for high-throughput phenotyping based on the heat produced in stressed plants.[92] Infrared technology can be used to statistically monitor the growth of stressed plants over time by combining careful image acquisition, image processing, and color classification. For the assessment of stressed plants, IR thermal sensing can provide rapid, thorough, and effective phenotyping. Because it releases more infrared radiation, plants with less water typically have higher temperatures. An infrared camera (IR) may detect this radiation in the same way that a standard camera detects visible light. In a controlled environment, an infrared camera with software can detect the water condition of a leaf based on its reflected heat generation. The average temperature and color pattern of plants and leaves may serve as markers of heat generation brought on by stress.[69] IR thermography has been used as a selection technique to identify genotypes of maize that are resistant to water stress.[164] Thermal imagers measure surface temperatures using the Stefan-Bolzmann equation, which asserts that the emission of long-wave infrared radiation varies as a function of surface temperature. As transpiration increases, the surface temperature of crop canopies decreases due to evaporative cooling. One of the factors influencing transpiration rate is stomatal aperture. Therefore, changes in leaf or canopy temperature provide a valuable signal of stomatal conductance, an important indicator of many stress responses.[107] Vasseur *et al*.[136] state that a variety of information about plant metabolism, ecological strategies, response to the environment and functioning can be obtained by combining deep learning with near-infrared spectroscopy (NIRS). It has been demonstrated that NIRS is an accurate and practical method for estimating cereal flour composition. These sophisticated phenotyping methods can offer comprehensive insights into the biochemical structure of individual seeds, including protein and starch levels, amino acid profiles, and lipid composition, in addition to structural and physiological characteristics.[34] Additionally, infrared thermography (IRT) has been utilized to track transpiration dynamics and leaf temperature in stressed plants; Wedeking *et al*.[140] used IRT to evaluate Beta vulgaris plants under escalating drought stress.

Magnetic resonance imaging (MRI)

A powerful magnetic field is delivered to the target sample during 3D imaging using magnetic resonance imaging (MRI). Under specific conditions, some atomic nuclei particularly hydrogen nuclei absorb and release radio frequency energy. When hydrogen atoms are excited by radio wave pulses, they produce signals that nearby antennas can detect. The magnetic field, which maps hydrogen atoms and so water, allows these signals to be localized.[128] Using MRI-PET-based imaging, scientists have been able to map the movement of carbon from leaves to certain roots.[59] MRI has been utilized in root phenomics in wheat to identify seminal and lateral roots, and characteristics such as root and shoot emergence times, total root length, angle, and depth were noted.[103] Additionally, xylem embolism development has been visualized and quantified using it.[86] The precise anatomical components of the plants could be measured at a scale smaller than one millimeter using MRI.[60] Additionally, MRI can be utilized noninvasively to investigate the detection of plant diseases.[124]

Computed tomography (CT)

Using a highly sensitive detector and a correctly collimated X-ray beam, CT scans one part of the object at a time to rebuild it in three dimensions. Tomographic imaging allows for accurate monitoring and screening of plant physiological performance. In recent years, CT imaging has been used in the agricultural sector for quality control and inspection of a variety of food items and agricultural materials.[95] The number of tillers on rice plants is determined using X-ray computed tomography (CT) scanners.[151] A thorough pipeline was developed to automatically interpret CT scans and extract 22 rice grain traits.[54] As demonstrated by Xu *et al*.,[146] 3D CT image analysis of plant roots has a long history. Van Harsselaar *et al*.[135] used X-ray CT to monitor potato tuber growth under stress from beginning to harvest. The disadvantages of CT are its high cost and long scanning times.[95] Plant root phenotyping can also be accomplished with CT.[9]

Positron emission tomography (PET)

PET imaging involves injecting radioactive tracers into living plants and tracking radiolabeled compounds inside their tissues. By recording dynamic changes in metabolic activity and nutrient transport in real-time, it makes it possible to visualize and analyze physiological responses.[63] The combined use of PET and CT technologies combines the newly assimilated 11C with the observed morphology and provides simultaneous spatial and temporal root architecture data.[147] Miyoshi *et al*.[89] used PET imaging and an 11C tracer to measure photosynthate translocation to roots in rice plants. MRI-PET imaging has allowed researchers to track the movement of carbon from leaves to certain roots.[59] However, PET imaging has a lower spatial resolution than X-ray CT and MRI, making it more difficult to discern small-scale structures and minute anatomical details in plant tissues. Finding appropriate isotopes that plants may safely absorb without changing their physiology can be challenging because the biological data obtained by PET also depends on the tracer selected. Operating and maintaining CT, MRI, and PET imaging systems can be expensive and need specialized knowledge.[63]

CHALLENGES IN PHENOMICS

Plant phenotyping techniques are a highlighted topic in the current scenario because of its multi-use but still this field is experiencing obstacles. Despite of its use, phenomics has many challenges like high implementation cost, limited accessibility, lack of standardization and reproducibility. Most of the phenotyping techniques are not meant for field implementation as they are optimized for controlled environments. The genomic selection models are failed to apply for genotype*environment interactions which limits its role.[6] The phenotyping on cellular scale or microphenotyping requires more sophisticated techniques as the picture processing is a major challenge.[12] Also there are multiple challenges in the use of phenomics for disease detection. Hence it is important to conduct ethical and regulatory researches for developmental strategies for studies on diseases based on phenomics.[154] Another challenge in phenotyping is the data storage and management as the phenotyping techniques generate a large amount of data along with the pictures. Researchers are more aligned towards the development of sensors and techniques but the real problem emerged is data management and processing. However, the novel AI based methodologies have power to address these challenges in the field of image based phenotyping but need further validations.[6] As comared to shoot phenotyping, root phenotyping poses a major challenge especially in ground.[148] The environment dependent traits are still hard to assess. The environmental variables like cloud cover, winds, sunlight intensity and shifting angles all pose difficulties in automated phenotyping and also impact the traits. The machine learning models are also not precise and accurate in capturing and predicting the intricate interactions between genotype, phenotype and environment.[83] Additionally, the adoption of phenotyping techniques in many research experiments is slowed down because of the unavailability of qualified persons and specialists. There is a need of advanced statistical and computational models to link genomics to phenomics which still lacks interoperability.[31] Another challenge in the field of phenomics is to establish phenomic research centers on a wide scale which can educate, train individuals in this field and conduct research also. There is a vital need of international cooperation in this field to promote the development and use of phenomics.[154] All these challenges need to be addressed for the use of phenomics in agriculture and food security.

CONCLUSION

Plant phenotyping has covered a long journey from visible evaluations to the use of sensors, robots, machine learning and artificial intelligence. Phenotyping techniques are aiding researchers in data measurement of different plant traits, disease detection, harvesting etc which were otherwise laborious. By using these techniques, scientists are able to achieve their aim of improving crop quality and quantity, developing climate resilient or stress tolerant varities. Some of the issues are still there which are limiting the use of these techniques including high cost, the issue of big data, the gap between genotype and phenotype and its potential use only in controlled conditions and not in the field. These issues can be addressed by standardizing data, integration of AI, skilled professionals and international research collaborations so that the phenotyping can be used in its fullest for developing climate resilience crops and providing nutritional security to the world.

Declarations

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