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Plant phenomics through proximal remote sensing: A review for improved crop yield

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Abstract
In the present scenario with changing climatic patterns, there is a need to boost crop yield while reducing environmental impact. Traditional breeding methods face limitations in achieving the 2050 target, and new methods are required to facilitate efficient breeding. This review discusses the challenge of feeding the world's growing population, which is expected to reach 9.5 billion by 2050. Plant phenomics is a relatively new interdisciplinary topic that has emerged in this context, aimed at facilitating breeding and enhancing agriculture. Phenotyping, the assessment of attributes significant to commercial plant breeding, is laborious and time-consuming. New approaches, such as speed breeding and precision farming, are being developed to increase the efficiency, precision, and reliability of phenotyping. Plant phenomics involves the collection of complex phenotypic data at an organismal level, and the research and application of tools and techniques to analyse, organize, and store resulting datasets. The article highlights the need for a system that integrates biological functions across genotypes and environments from cellular to the field scale and discusses how high-throughput phenotyping and vegetation indices have been used in agricultural research.

Keywords: Proximal remote sensing, phenomics, phenotyping, diseases, omics, vegetation index, NDVI

Introduction

As stated in the Food and Agriculture Organization's (FAO) Future of Food and Agriculture: Alternative Pathways to 2050 report, the world's population is expected to reach 9.5 billion individuals by 2050 and to feed them, grain sector will need to double, or at the very least, increase by 25% to 70% from current levels [1, 3]. In light of changing climatic patterns, the threat posed by several environmental and biotic elements related to global agricultural production has lately grown increasingly critical [4]. Considering food output must advance by 2.4% annually but the actual growth is limited at 1.3% and yields are stagnating in up to 40 percent, traditional breeding will have difficulty achieving the 2050 target [5]. Anthropogenic changes in climate have resulted in higher Carbon dioxide levels, while temperature stress and erratic rains inevitably lead to severe flooding, droughts, and soil salinity [6]. Despite challenging environmental factors and a small cultivable region, higher output is necessary to provide food security [7]. Utilizing contemporary methods, sustainable development in agriculture must be created to boost crop yield while lowering its environmental [8]. Increased crop breeding is one of the simplest strategies to increase the productivity of the primary food and animal feed crops grown worldwide. The stable potential output of a genotype continues to be crucial for boosting crop yields. Tolerance towards stresses is a crucial feature in the stability of grain yields. Crop scientists will need to efficiently link phenotype to genotype in order for agricultural improvement activities to fulfil the anticipated demand for higher crop production potential in the next decades [9]. Molecular breeding and the expanding availability of affordable Genomic data is a significant technological development that have helped to facilitate this interaction [10]. High-throughput "-omics" have been produced during the past two decades, allowing for the thorough dissection of the genetic component of important traits [11]. However, the lengthy delays in gathering and interpreting multi-dimensional phenotypic data are substantially impeding high-throughput breeding procedures [12]. A recent interdisciplinary topic called plant phenomics (PP) is well known for expediting breeding and enhancing agriculture [13]. To explain the relationship between genes and desirable characteristics, geneticists have proposed the concepts of phenotype and phenomics. The collection of extragenic, non-auto reproductive cell components that made up the set of phenotypes were first referred to as "phenomes" in 1949 [14]. "Crop phenotyping" refers to the approaches and procedures utilized in the conversion of plant phenotype to PP.

A considerably larger concept known as "phenomics" refers to the collection of complex phenotypic data at an organismal level [15]. In a larger sense, phenotyping involves the acquisition and assessment of complex plant features including yield, biotic and abiotic stress tolerance, geometric structure, and other biochemical and physiological aspects. Plant breeding requires the assessment of attributes that are significant commercially [16]. The basic method of manual measuring or scoring used in traditional phenotyping is laborious, time-consuming, and tiresome [17]. Speed breeding and precise farming have raised the bar for phenotyping's efficiency, precision, reliability, and innovation. First, the cornerstone is increased precision and reliable phenotyping. Second, non-destructive, fast and reproducible phenotyping, like senescence dynamics, are becoming more and more in demand [18]. Third, it is hard to assess novel, high-dimensional and hidden phenotypes using conventional techniques [19, 20]. Very detailed and thorough grasp of phenotypic assaying is important in order to correctly describe the adaptation strategies of field crops. Sophisticated techniques use non-destructive remotely sensed data and image processing to provide visual information of an individual's phenotype [21]. Collecting salient information regarding the features of a large population of plants, as well as their micro and macro environment, is one of the primary objectives of plant phenomics that we define as the research and application of the packages of tools and techniques being used. The other two goals are to analyze, organize and store the resulting datasets and to perform simulations that can unravel and imitate the response of plant ideotypes [22]. Morphological and physiological traits may now be frequently and non-destructively measured across entire populations all through the growing period because of advancements in technologies including sensors, information technology (IT) and data extraction. Unmanned aerial vehicles (UAVs) have grown in popularity over the last decade due to their low cost and flexibility in acquiring high-resolution (cm-scale) photographs [23]. These technologies, nonetheless, are still actively being developed. This review provides an overview on plant phenomics, which is the study of plants' morphology, physiology and behavior which are strongly influenced by their environment. Using a variety of techniques, researchers argue for the necessity of a system that integrates biological functions across genotypes and environments from cellular to the field scale. We give an overview of "high-throughput phenotyping (HTP)" and "vegetation indices (VIs)" and discuss how VIs have been used in agricultural research. We review and discuss the most current multi-omics studies that integrate HTP with genetic research in order to guide breeders and scientists in designing a hardy cultivar that can endure climate change and multiple stresses.

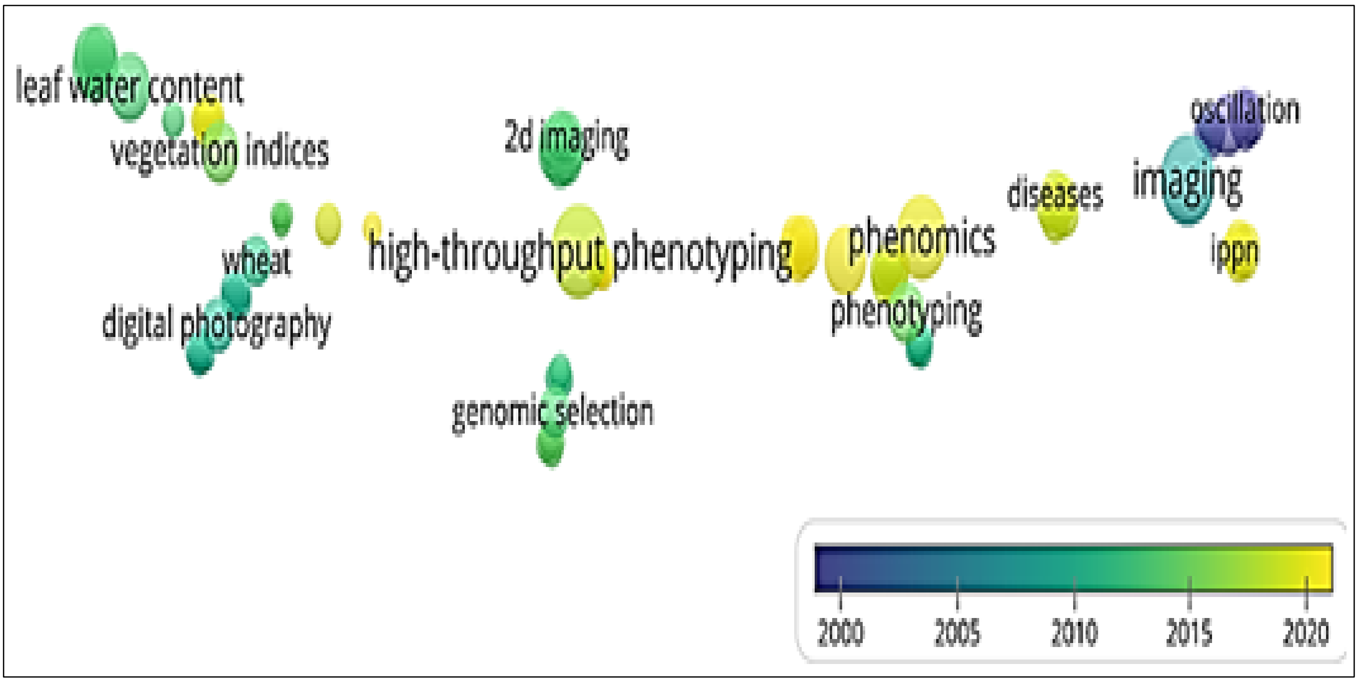

Fig 1: Keywords frequency clustering of research and review papers in the past two decades. Here, bigger font size implies frequent usage, recent keywords trend show higher use of high throughput phenotyping and phenomics

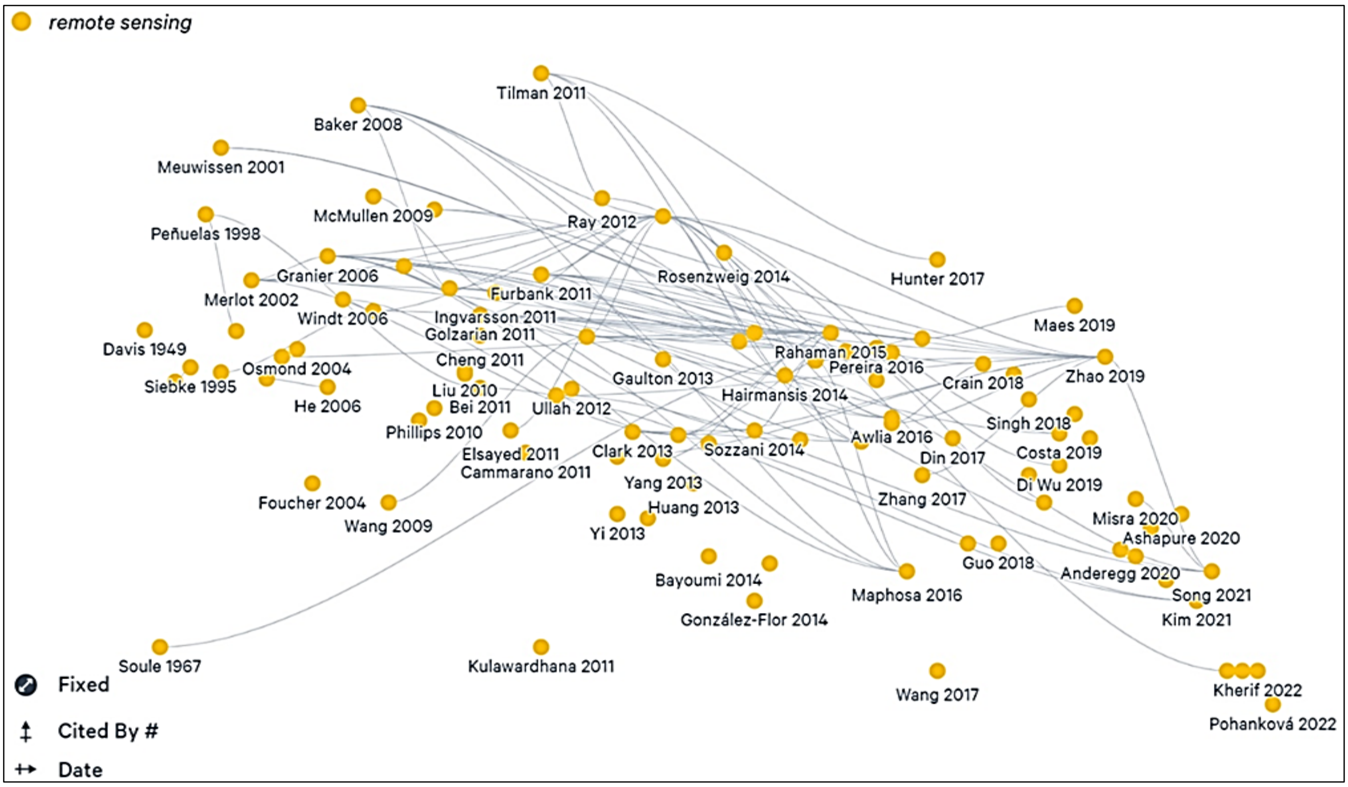

Fig 2: Visualization of reviewed literature based on the publication year and the number of citations

Strategies for plant's phenotypic assessment

Recognizing phenotypic features and their interactions with one another and (or) the surroundings necessitate an accurate and in-depth comprehension of phenotypic plasticity, in both regulated and field setting. Utilizing a powerful software system, various sensors can generate distinctive, multilayer phenotyping datasets [24]. The modern tools for plant biology include image-based plant phenotyping technologies that are coupled with cutting-edge software [25]. Utilizing high-dimensional phenotyping assays calls for standard experimental procedures, calibrated image sensors, and exact evaluations of raw data-processing techniques. The following is a list of the tools that are being utilized for phenotypic assessment of field crops.

Visible Light Imaging (300-700nm)

Plant breeding routinely involves visual examination of characteristics and related phenotypes. Due to its affordability, simplicity of operation and ease of maintenance, visible light-based imaging systems have recently come under more attention. Two-dimensional (2D) digital pictures captured using visible light have been used to quantify shoot-related attributes, leaf architecture, shoot elongation, seed and root morphological characters [26]. Many software provides features like "magic wand" or colour threshold that can easily estimate canopy cover estimates from nadir-view photos. These techniques are employed to assess leaf area index (LAI) and light interception [27]. Images obtained at an angle of 57.5 can provide accurate estimates of LAI [28]. Shape, compactness, solidity and other attributes of an image can be utilised to extract more complex information, such as data on moisture stress [29]. Critical variables for phenotyping, including LAI or panicle length, may be obtained through the examination of the precise reconstruction of the canopy architecture using a stereo camera setup or photos from numerous places [25, 30, 31] used a Lemna Tec 3D Scanalyzer to precisely quantify shoot dry weight in order to test wheat seedlings for salinity stress. From two-dimensional to three-dimensional pictures can be created allowing for the monitoring of root development, morphology and growth by the use of software [32]. Numerous crops have been subjected to various stresses and phenotypes using RGB light utilising PHENOPSIS [33] for drought in Arabidopsis, Lemna Tec [34] for drought stress in barley and salinity stress in maize and rice [35, 36]. During the vegetative phase, when plants might be subjected to environmental stresses such as drought, salt, and high temperatures, phenotypic alterations occur in transpiration rate and plant growth. The ability to quantify traits in both small and large populations using image analysis is an important capability. This makes it possible for us to identify and describe genes that control these desired plant features.

Fluorescence imaging (600-750nm)

Fluorescence is the process through which a substance absorbs light at a specific wavelength and then emits additional low-wavelength light. Fluorescence imaging throws blue light at 500 nm on the plants, and those same plants release red fluorescence light at 600-750 nm. Software is used to picture and analyze the variations in fluorescence, turning them into false-color signals [37]. In phenomics, chlorophyll fluorescence is typically employed to measure a plant's capacity to continue photosynthesis under a variety of environmental situations [37]. Fluorescence imaging may also be used to examine plant metabolite concentration [27], association between photosynthesis and growth stomatal mobility [38], phloem transport [39] while plants are under stress [40, 41]. Blue (440 nm), green (520 nm), red (690 nm) and far-red (740 nm) spectral bands are captured by a single excitation wavelength to create two forms of fluorescence under ultraviolet illumination i.e., red to far-red region and blue to the green region [21]. Its various applications of include resolving variability in photosynthetic rate [42]. The majority of these fluorescence imaging applications are only applicable to model crop seedlings or their single leaves. It necessitates the creation of reliable software for phenotyping and standard operating procedures. In order to assess growth, morphology, colour, and photosynthetic efficiency in rice [35] and *Arabidopsis thaliana* [43] under salt stress as well as to distinguish between cold tolerant variants of *A. thaliana* [44].

Thermal and Infrared Imaging

By using Stefan-Boltzmann equation, infrared thermal imaging enables the viewing of infrared radiation emitted from the object. For imaging, this method takes advantage of the interior molecular motions of infrared-emitting materials [45]. The two primary wavelengths used by infrared imaging systems are near-infrared and far-infrared. Although, the thermal sensitive cameras' have spectral range of 3-14 m [27]. Modern cameras have high thermal sensitivity to measure traits such as canopy temperature depression with greater resolution thanks to advancements in infrared thermal technology. NIR spectroscopy has previously employed in several research to infer crop growth and yield performances of genotypes. This infrared imaging systems offer simultaneous high spatial resolution observations and pictures across broad fields under various environmental circumstances [27]. Additionally, it can assess the canopy temperature, leaf colour and relative chlorophyll content [46-48]. Stomatal behavior under various stress situations has been measured using infrared thermal imaging devices, for instance to track salinity tolerance among wheat varieties [49]. Thermal imaging can monitor the temperature of leaves and canopies to assess the water condition of leaves. Stomatal movement is used to quantify gas exchange since plants often lose heat through transpiration, which causes the plant temperature to rise. In dry conditions, the canopy temperature differential from the ambient air can be utilized as a proxy for the ability to withstand drought.

Spectroscopy imaging

The result of sun light interacting with plants using spectral cameras (Multi or Hyper) is spectral imaging. Hyperspectral imaging separates pictures into bands, resulting in images that contain a considerable portion of the EM spectrum [50]. Plant research has designated distinct spectral zones, such as

1. NDVI (normalized difference vegetation index).
2. CRI (carotenoid reflectance index).
3. PRI (photochemical reflectance index) [22].

Furthermore, when wavelength rises, reflectance falls and absorption increases. This happens as a result of leaf water content, which explains its water condition and aids in estimating canopy water content. This type of spectral reflectance data is used to evaluate vegetation indicators, such as ratios and changes at a certain wavelength and to identify NDVI. Water availability, pigment content and photosynthetically active radiation (PAR) biomass are connected with vegetation indicators, which are used to compute the biomass, chlorophyll content and grain yield in diverse crops [51, 52]. Multispectral and hyper spectral data are commonly utilized to estimate canopy moisture content. These employ infrared water absorption bands to explain different water indices [47, 53]. A double frequency laser, in contrast hand, may be range-resolved to ignore surrounding soil, which would impede spectral EWT measurement. This allows for the estimation of "Equivalent Water Thickness" (EWT) [54]. Aside from basic water indices, high-resolution spectroscopy and wavelet analysis [55-57] can provide a high specificity to canopy moisture content. Moisture contents assessments using reflectance data have indeed been fruitfully linked to water potential on situation [58, 59], but the prediction of water potential under a spectrum of circumstances or plant age group is likely to constantly be somewhat limited, as with any indirect proxy marker [60]. The application of spectroscopic imaging for field phenotyping is well known, however spectral cameras and their associated infrastructure are costly. Because of its higher resolution, hyperspectral imaging is useful in rice for monitoring growth and panicle emergence [61].

Advanced Imaging Technologies

Technological advances, like 3D structural tomography has turned the focus of crop imaging to *in vivo* live imaging. Another technology known as functional imaging focuses on changes in the physiology of a plant to measure performance under stress, such as ChlF imaging and "Positron Emission Tomography" (PET) [42]. "PET" is a non-destructive technique image distribution method that employs positron-emitting radionuclides such as C11, N13 or Fe52 tagged metabolite molecules to transport them [62]. "Magnetic resonance imaging" or "MRI" is a sophisticated imaging method that uses magnetics to create pictures. It may be used to photograph the roots in pots as well as interior physiological activities in living plants [63, 64] used [C11]-labeled CO_2 to demonstrate shoot-to-root carbon fluxes in taproot of sugar beet. MRI may easily detect water dispersion and movement through the conductive tissues in crops including tobacco and castor [65]. By combining MRI and PET technologies, a unique imaging approach for monitoring dynamic shifts in plant functionality and structure is created. The PlantEye (3D laser scanner) was employed for wheat phenotyping in a confined space under control and salt stress conditions. The PlantEye scans plants from above, generating a data cloud from which the system calculates attributes like leaf number and 3D leaf area. Correlations were found between the inspected attributes and conventionally observed leaf characteristics such as area and biomass in wheat under salinity stress [66]. "Forster resonance energy transfer (FRET)" is yet another sophisticated method for capturing images of tiny molecules in live tissue, simply understood as phenotyping at molecular level. This method relies on radiometric fluorescence sensors that are genetically programmed that bind to and measure quantities of the target chemical [67]. A single FRET sensor may be used to identify various routes and complex interactions of the sensor target molecules. A FRET sensor characterizes and expresses the target sensor's cellular/subcellular location and gives data with great precision [68]. FRET has been employed in roots during sugar transport to detect calcium variations with microscopic and real-time spatiotemporal resolution [67]. FRET is an excellent method to answer various fundamental issues about plant development and evolution.

Vegetation indices and high-throughput phenotyping

Most objects, including plants, have 3 reactions to electromagnetic radiation (such as light) that are reflected, transmitted, or absorbed. To put it another way, each substance or plant has a unique spectral signature that can be quantified in three major wavelength regions. VIs is the statistical transformation of the initial spectrum reflectance, and it is derived by measuring and interpreting the incidence and condition of vegetation, such as biomass and canopy characteristics, using two or more wavebands [69]. These indicators enable consistent comparisons of photosynthetic rate and canopy architectural alterations. For the statistical assessment of vegetation cover, stability, and growth pattern, the VIs produced from canopies are an easy and effective technique. They are directly determined with no bias or preconceptions about land cover classification, soil type, or climatic circumstances because they are simple transformations of wavelength bands. VIs aids scientists in tracking seasonal, inter-annual, and long-term structural fluctuations, as well as photoperiodic and biophysical vegetation cover factors [70]. As stated earlier, VIs can anticipate plant development circumstances utilizing a variety of spectrum reflectance bands that are easily captured by spectral cameras, making them particularly useful in HTP. Nevertheless, there is little data on the application of VIs in the farming sector for multi-trait assessment (physiological, biotic, and abiotic), repeated multi-environment evaluation, and massive population assessment. As a result, it is critical to comprehend various VI and HTP applications for crop development. Plants are distinguished from other natural materials by their unique interaction with sun radiation. Plants create energy through photosynthesis and, as a consequence, absorb a lot greater blue and red light. They do, however, powerfully reflect green and near-infrared (NIR) light [71]. Plants are made up of numerous components, such as water, nutrients and pigments, and as a result, they exhibit variances across the spectrum, providing crucial information about the water, nutrient, and pigment levels. For forecasting of plant development conditions, the spectral variation is sometimes referred to as VIs [72]. Several new VIs has been created to analyze the aerial images featured in the literature over the years [73-75]. Most of the vegetative indices produced and published by researchers are widely used in plant science because they are extremely effective in determining different characteristics such as leaf greenness, light usage efficiency, leaf colour, and moisture content [75]. Most vegetative indices is estimated using two or more reflectance wavelengths, which are generally involved in photosynthesis pigment concentration [71]. However, only few of these VIs has been critically compared or evaluated. As a consequence, many selected indicators that are often used in vegetative evaluation and have an association with yield, fitness and moisture content. These are also widely applied in yield prediction. Numerous researchers have published data in various crops using various sensors for multiple studies, which are described in table 1.

Table 1: Achievements of crop studies using remote sensing-based phenotyping techniques

S. No.	Crop	Type of Study Conducted	Type of Sensor	References
1.	Maize	Nitrogen stress	Multispectral	[112]
2.	Maize	Nitrogen stress	Hyperspectral	[113]
3.	Mungbean	Nitrogen concentrations	Hyperspectral	[114]
4.	Pulses	Biophysical trait assessment (biomass, leaf area index)	Hyperspectral	[115]
5.	Wheat	Disease assessment	Hyperspectral	[116]
6.	Grapevines	Disease assessment	Thermal imager	[117]
7.	Maize	Yield prediction	RGB sensor	[118]
8.	Soybean	Yield prediction	Multispectral	[119]
9.	Wheat	Yield prediction	RGB sensor	[120]
10.	Wheat	Protein assessment	Hyperspectral	[121]

The constant progress of breeding techniques allows for a faster rate of genetic improvement [76]. Farmers and breeders have been selecting desirable plants based on phenotypes even before DNA and biomarkers were found. In plant breeding the more crossings and environments utilized for selection; the more likely superior varieties will be discovered. Breeder has to be able to simply and precisely pick the best offspring by phenotyping a large number of lines. To meet anticipated future requirements, the breeding output must be increased. Improvements in high-throughput genotyping have resulted in quick and low-cost genetic knowledge, paving the path for the development of many of recombinant inbred lines for phenotyping large mapping populations and diversity arrays [77]. Although molecular breeding procedures focus primarily on genotypic data, nevertheless, phenotypic data is still required [78]. Likewise, phenotyping is required to categorize promising occurrences in transgenic research [79, 80]. Effective phenotyping is anticipated to be required to capitalize on developments in conventional, molecular and transgenic breeding and assure agricultural genetic enhancement. The need for effective phenotyping approaches has been introduced in a variety of sectors. Phenotypes are often strong indicators of significant biological features such as illness and death [81]. Breeders and molecular biologists feel that improved molecular approaches can only be beneficial in breeding if quantitative characteristics are collected using trustworthy phenotyping techniques [82]. High-performance phenotyping approaches have the potential to change plant breeding by speeding up the generation advancement process [83]. The primary goal is to combine several phenotypic techniques for assessing agronomic characteristics, stress, and aspects that influence crop yield potential to maximize potential and utilize it in development of crop varieties. In general, phenotyping in the plant remains a challenge since the use of methodologies for reliable recording of crucial agronomic features, and crop monitoring have not been fully pushed. The HTP faces various obstacles in this context, including complex/quantitative characteristics, root phenotypic plasticity, environmental influence, multi-location, and replicated trials field plot measurements. It is especially difficult to use the HTP at spatiotemporal resolutions of organ or cellular level and root phenotypes [84]. The discovery of nondestructive, simple, operational, highly reproducible, sturdy, effective, low-cost, and rapid phenotypic instruments is one of HTP's primary difficulties. Furthermore, because HTP generates a large amount of data, storing, maintaining, and analyzing this data, as well as producing useful biological information, are all difficult tasks [85]. To address the aforementioned issues, the use of Vis and Hyperspectral imaging, and their application in plant HTP is recommended by scientists. UAVs have the ability to detect phenotypic trait variations across crops while also allowing for the quick and cost-effective collecting of various information about vegetation across large areas without hurting plants. Vis combined with UAVs is gaining popularity, and interest in adopting these tools for the HTP of various plant species in on a rise among researchers. To archive, manage, and retrieve data there are massive open-source online databases available (PHENOPSIS DB and PhenoFront) [84]. In addition, unique 2D (RootScan) and 3D (RootSlice) tools as well as computational software (RootReader2D and RootAnalyzer) have been created to study plant root features. Recent reviews [86-89] have outlined the many HTP platforms as well as the necessity for a multidomain strategy to overcome the issues that HTP faces. With the progress of HTP, there appears to be little question that plant phenomics faces several issues that must be solved in the near future.

Multi-Omics research using high-throughput phenotyping

Many phenotyping approaches have been widely explored in recent years, including root profiling [90], Deep Learning for abiotic stress [91] and remote sensing and hyperspectral imaging technologies for biotic stresses [92, 93]. The genetic research and plant breeding methods that have previously profited, on the other hand, are rarely acknowledged. Genome selection (GS) selects complicated features controlled by many alleles with tiny effects using DNA markers and statistical modeling. It was originally used in cow breeding [94], however, the recent decrease in sequencing costs, GS is coming forward as a potent tool for evaluating breeding values [95]. Its usefulness is that it can forecast how plants will perform prior to a field test. Massive data from individuals or groups are required to construct a precise and robust prediction model [94]. Markers may now be obtained simply and precisely thanks to the advancement of next-generation sequencing (NGS) technology. However, phenotyping is a major hindrance. High-throughput phenotyping systems have been shown to improve grain crop GS. For example, a UAV remote-sensing unit with an NIR-GB camera has been employed in case of sorghum for high throughput phenotypic characterization particularly for plant height and because of its low expense and ease of operation, it will be a vital tool for marker assisted plant breeding [96]. Wheat GS might leverage data on attributes like canopy temperature and NDVI received by remote sensing to increase the precision of grain production predictions [97]. Furthermore, CIMMYT, Mexico investigated several methods trying to combine dynamic HTP data and 2254 GBS markers of approximately 1200 advanced lines of wheat and discovered that genomic selection techniques are a feasible way to enhance the genetic advance and choose higher-yielding cultivars effectively [98]. Investigating biologically relevant phenotypic information from multidimensional phenotypes. For modest preliminary studies, basic predictive methods are mostly sufficient [99]. On the other hand, pointed out that phenotypic tasks like yield prediction benefit from high-dimensional and nonlinear modelling techniques. However, ML (Machine Learning) techniques typically require manually created features, and despite the emergence of huge data, their performance has not considerably improved [100]. A new paradigm in phenomics analysis has been introduced by “Deep Learning” (DL), a sub-branch of machine learning (ML) that can tackle increasingly difficult phenotypic tasks by automatically extracting features from large datasets. For instance, hundreds of photos of the wheat plants may be used to recognize and count number of ears [101, 102]. The requirements for the quality and volume of data are frequently stricter for deep learning-based methods. Crop development simulations can simulate the interactions between crop genetic background, variations in macro-micro environments, and package and practices through which they can accurately predict plant stress reactions [103], predict the impacts of climatic stresses on grain production [104], assess the behavior of varieties in a particular environment [105] and explain how the interaction of Genotype x Environment affects crop yield [106]. Crop Growth Models might therefore offer assistance for high-tech farming, variety identification, and optimizations of agricultural resources [107].

The two main categories of multi-omics analytic pipelines are phenomics to genomics and genomics to phenomics. Quantitative trait loci (QTLs) may be found and potential genes or networks identified by combining the “-omics” techniques and employing GWAS for various periods and settings [7]. Following that, ideal traits (ideotypes) can be generated by genetic modification. Rapid and precise analysis of phenomics data has the potential to significantly advance the integration of multi-dimensional molecular mechanisms from plant genes to phenotypes, thereby enhancing our comprehension of the plants processes. Multi-omics includes genomic, transcriptomic, proteomic, epigenomic and metabolomics studies [13]. Multi-omics investigations have been accelerated using PRS-based phenomics for finding new genetic markers, screening superior varieties and speeding up breeding. The dynamic, and non-destructive phenotyping offers phenomics data for GWAS studies, enabling quick discovery of the genes linked to significant agronomic characteristics [108]. For instance, 739 attributes from 235 germplasm accessions were collected using a micro-CT-RGB imaging technology. Two of the 402 substantially related loci, each associated with yield and vigour, helped in the selection of cultivars with high grain yield [109, 110] evaluated phenotypic traits of maize using an autonomous HTP technique and found 1000 QTLs and three hotspots. They developed a novel method for choosing superior maize varieties and highlighted the genetic structure of maize development. This phenotyping platform has shown that high-quality genetic selection is feasible. A collection of several thousand tobacco mutants was successfully evaluated for 18 stable genetic mutations using phenomics data [111]. It has been demonstrated that the pairing genomic and phenomic data can aid breeders in identifying and choosing high-quality wheat genotypes by utilizing dynamic phenotyping data for genetic analysis to evaluate ideal wheat cultivars under heat and drought environments. In conclusion, PRS provides phenotyping methods and phenomics expertise to pave the way for multi-omics investigations. Data processing and modelling techniques may be used to extract morphological, physiological, and productivity-related attributes from multi-spatial, multi-temporal, and multi-spectral data. Multifaceted phenotypes may be integrated using data which can also convert data into phenomics knowledge. Although there are still numerous difficulties, “Proximal Remote Sensing based Plant Phenomics” offers unmatched prospects as a gateway for multi-omics research.

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References
1. Hunter MC, Smith RG, Schipanski ME, Atwood LW, Mortensen DA. Agriculture in 2050: Recalibrating Targets for Sustainable Intensification. Bioscience. 2017 Apr 1;67(4):386-91. Available from: https://doi.org/10.1093/biosci/bix010
2. Joshi R, Wani SH, Singh B, Bohra A, Dar ZA, Lone AA, *et al*. Transcription Factors and Plants Response to Drought Stress: Current Understanding and Future Directions. Front Plant Sci; c2016. p. 7.
3. FAO. The Future of Food and Agriculture-Alternative pathways to 2050. Rome; c2018.
4. Pereira A. Plant Abiotic Stress Challenges from the Changing Environment. Front Plant Sci; c2016. p. 7. Available from: https://www.frontiersin.org/articles/10.3389/fpls.2016.01123
5. Ray DK, Ramankutty N, Mueller ND, West PC, Foley JA. Recent patterns of crop yield growth and stagnation. Nat Commun. 2012 Jan;3(1):12-93.
6. Rosenzweig C, Elliott J, Deryng D, Ruane AC, Müller C, Arneth A, *et al*. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proceedings of the National Academy of Sciences. 2014;111(9):3268-73. Available from: https://doi.org/10.1073/pnas.1222463110
7. Furbank RT, Tester M. Phenomics-technologies to relieve the phenotyping bottleneck. Trends Plant Sci. 2011;16(12):635-44. Available from: https://www.sciencedirect.com/science/article/pii/S1360138511002093
8. Chawade A, Armonienė R, Berg G, Brazauskas G, Frostgård G, Geleta M, *et al*. A transnational and holistic breeding approach is needed for sustainable wheat production in the Baltic Sea region. Physiol Plant. 2018 Dec;164(4):442-51. Available from: https://doi.org/10.1111/ppl.12726
9. Tilman D, Balzer C, Hill J, Befort BL. Global food demand and the sustainable intensification of agriculture. Proceedings of the National Academy of Sciences. 2011 Dec 13;108(50):20260-4. Available from: https://doi.org/10.1073/pnas.1116437108
10. Ingvarsson PK, Street NR. Association genetics of complex traits in plants. New Phytologist. 2011 Mar;189(4):909-22. Available from: https://doi.org/10.1111/j.1469-8137.2010.03593.x
11. Roitsch T, Cabrera-Bosquet L, Fournier A, Ghamkhar K, Jiménez-Berni J, Pinto F, *et al*. Review: New sensors and data-driven approaches-A path to next generation phenomics. Plant Science. 2019 May 1;282:2-10.
12. Großkinsky DK, Svensgaard J, Christensen S, Roitsch T. Plant phenomics and the need for physiological phenotyping across scales to narrow the genotype-to-phenotype knowledge gap. J Exp Bot. 2015 Sep 1;66(18):5429-40. Available from: https://doi.org/10.1093/jxb/erv345
13. Watt M, Fiorani F, Usadel B, Rascher U, Muller O, Schurr U. Phenotyping: New Windows into the Plant for Breeders. Annu Rev Plant Biol. 2020 Apr 29;71(1):689-712. Available from: https://doi.org/10.1146/annurev-arplant-042916-041124
14. Davis BD. The Isolation of Biochemically Deficient Mutants of Bacteria by Means of Penicillin. Proceedings of the National Academy of Sciences. 1949 Jan;35(1):1-10. Available from: https://doi.org/10.1073/pnas.35.1.1
15. Soule M. Phenetics of Natural Populations I. Phenetic Relationships of Insular Populations of the Side-Blotched Lizard. Evolution (N Y). 1967;21(3):584-91. Available from: http://www.jstor.org/stable/2406618.
16. Costa C, Schurr U, Loreto F, Menesatti P, Carpentier S. Plant Phenotyping Research Trends, a Science Mapping Approach. Front Plant Sci; c2019. p. 9. Available from: https://www.frontiersin.org/articles/10.3389/fpls.2018.01933
17. Dhondt S, Wuyts N, Inzé D. Cell to whole-plant phenotyping: the best is yet to come. Trends Plant Sci. 2013 Aug 1;18(8):428-39.
18. Anderegg J, Yu K, Aasen H, Walter A, Liebisch F, Hund A. Spectral Vegetation Indices to Track Senescence Dynamics in Diverse Wheat Germplasm. Front Plant Sci; c2020. p. 10. Available from: https://www.frontiersin.org/articles/10.3389/fpls.2019.01749
19. Xiao F, Xiao F, Li W, Xiao M, Yang Z, Cheng W, *et al*. A novel light interception trait of a hybrid rice ideo-type indicative of leaf-to-panicle ratio. Field Crops Res. 2021 Dec 1;274:108-338. Available from: https://dx.doi.org/10.1016/j.fcr.2021.108338
20. Liu F, Song Q, Zhao J, Mao L, Bu H, Hu Y, *et al*. Canopy occupation volume as an indicator of canopy photosynthetic capacity. New Phytologist. 2021 Oct;232(2):941-56. Available from: https://doi.org/10.1111/nph.17611
21. Rahaman MdM, Chen D, Gillani Z, Klukas C, Chen M. Advanced phenotyping and phenotype data analysis for the study of plant growth and development. Front Plant Sci; c2015. p. 6. Available from: https://www.frontiersin.org/articles/10.3389/fpls.2015.00619
22. Fiorani F, Schurr U. Future Scenarios for Plant Phenotyping. Annu Rev Plant Biol. 2013;64(1):267-91. Available from: https://doi.org/10.1146/annurev-arplant-050312-120137
23. Akash Barela, Sunny Thakur, Surbhi Pachori, Shivangi Rahangdale, Vinod Kumar Goyal, Sumit Kakade, *et al*. Applications of proximal remote sensing in agriculture: A review. The Pharma Innovation Journal. 2023;12(2):1124-30.
24. Sozzani R, Busch W, Spalding EP, Benfey PN. Advanced imaging techniques for the study of plant growth and development. Trends Plant Sci. 2014 May;19(5):304-10. Available from: https://doi.org/10.1016/j.tplants.2013.12.003

25. Paproki A, Sirault X, Berry S, Furbank R, Fripp J. A novel mesh processing-based technique for 3D plant analysis. BMC Plant Biol. 2012;12(1):63. Available from: https://doi.org/10.1186/1471-2229-12-63
26. Fahlgren N, Gehan MA, Baxter I. Lights, camera, action: high-throughput plant phenotyping is ready for a close-up. Curr Opin Plant Biol. 2015 Apr 1;24:93-9. Available from: https://www.sciencedirect.com/science/article/pii/S1369526615000266
27. Li Zhang, Huang. A Review of Imaging Techniques for Plant Phenotyping. Sensors. 2014 Oct 24;14(11):20078-111.
28. Baret F, De Solan B, Lopez-Lozano R, Ma K, Weiss M. GAI estimates of row crops from downward looking digital photos taken perpendicular to rows at 57.5° zenith angle: Theoretical considerations based on 3D architecture models and application to wheat crops. Agric For Meteorol. 2010 Oct 15;150(11):1393-401.
29. Foucher P, Revollon P, Vigouroux B, Chassériaux G. Morphological Image Analysis for the Detection of Water Stress in Potted Forsythia. Biosyst. Eng. 2004;89(2):131-8. Available from: https://www.sciencedirect.com/science/article/pii/S1537511004001163
30. Huang C, Yang W, Duan L, Jiang N, Chen G, Xiong L, *et al*. Rice panicle length measuring system based on dual-camera imaging. Comput Electron Agric. 2013;98:158-65. Available from: https://www.sciencedirect.com/science/article/pii/S0168169913001841
31. Golzarian MR, Frick RA, Rajendran K, Berger B, Roy S, Tester M, *et al*. Accurate inference of shoot biomass from high-throughput images of cereal plants. Plant Methods. 2011;7(1):2. Available from: https://doi.org/10.1186/1746-4811-7-2
32. Clark RT, Famoso AN, Zhao K, Shaff Jone, Craft EJ, Bustamante CD, *et al*. High-throughput two-dimensional root system phenotyping platform facilitates genetic analysis of root growth and development. Plant Cell Environ. 2013;36(2):454-66. Available from: https://doi.org/10.1111/j.1365-3040.2012.02587.x
33. Granier C, Aguirrezabal L, Chenu K, Cookson SJ, Dauzat M, Hamard P, *et al*. PHENOPSIS, an automated platform for reproducible phenotyping of plant responses to soil water deficit in Arabidopsis thaliana permitted the identification of an accession with low sensitivity to soil water deficit. New Phytologist. 2006;169(3):623-35. Available from: https://doi.org/10.1111/j.1469-8137.2005.01609.x
34. Honsdorf N, March TJ, Berger B, Tester M, Pillen K. High-Throughput Phenotyping to Detect Drought Tolerance QTL in Wild Barley Introgression Lines. PLoS One. 2014;9(5):e97-047. Available from: https://doi.org/10.1371/journal.pone.0097047
35. Hairmansis A, Berger B, Tester M, Roy SJ. Image-based phenotyping for non-destructive screening of different salinity tolerance traits in rice. Rice. 2014;7(1):16. Available from: https://doi.org/10.1186/s12284-014-0016-3
36. Ge Y, Bai G, Stoerger V, Schnable JC. Temporal dynamics of maize plant growth, water use and leaf water content using automated high throughput RGB and hyperspectral imaging. Comput Electron Agric. 2016;127:625-32. Available from: https://www.sciencedirect.com/science/article/pii/S0168169916305464
37. Weirman; c2010. Final_Phenomics_for_word_with_image.doc.
38. Cardon ZG, Mott KA, Berry JA. Dynamics of patchy stomatal movements, and their contribution to steady-state and oscillating stomatal conductance calculated using gas-exchange techniques. Plant Cell Environ. 1994 Sep;17(9):995-1007. Available from: https://doi.org/10.1111/j.1365-3040.1994.tb02033.x
39. Siebke K, Weis E. Assimilation images of leaves of *Glechoma hederacea*: Analysis of non-synchronous stomata related oscillations. Planta. 1995;196(1):155-65. Available from: https://doi.org/10.1007/BF00193229
40. Osmond B, Ananyev G, Berry J, Langdon C, Kolber Z, Lin G, *et al*. Changing the way we think about global change research: Scaling up in experimental ecosystem science. Glob Chang Biol. 2004 Apr;10(4):393-407. Available from: https://doi.org/10.1111/j.1529-8817.2003.00747.x
41. Chaerle L, Van der Straeten D. Seeing is believing: imaging techniques to monitor plant health. Biochemical ET Biophysical Acta (BBA) - Gene Structure and Expression. 2001;1519(3):153-66.
42. Baker NR. Chlorophyll Fluorescence: A Probe of Photosynthesis *in vivo*. Annu Rev Plant Biol. 2008 Jun 2;59(1):89-113.
43. Awlia M, Nigro A, Fajkus J, Schmoeckel SM, Negrão S, Santelia D, *et al*. High-Throughput Non-destructive Phenotyping of Traits that Contribute to Salinity Tolerance in Arabidopsis thaliana. Front Plant Sci; c2016. p. 7.
44. Mishra A, Heyer AG, Mishra KB. Chlorophyll fluorescence emission can screen cold tolerance of cold acclimated Arabidopsis thaliana accessions. Plant Methods. 2014 Dec;10(1):38. Available from: https://doi.org/10.1186/1746-4811-10-38
45. Kastberger G, Stachl R. Infrared imaging technology and biological applications. Behavior Research Methods, Instruments, & Computers. 2003 Aug;35(3):429-39. Available from: https://doi.org/10.3758/BF03195520
46. Merlot S, Mustilli AC, Genty B, North H, Lefebvre V, Sotta B, *et al*. Use of infrared thermal imaging to isolate Arabidopsis mutants defective in stomatal regulation. The Plant Journal. 2002 Jun;30(5):601-9.
47. Jones HG, Serraj R, Loveys BR, Xiong L, Wheaton A, Price AH. Thermal infrared imaging of crop canopies for the remote diagnosis and quantification of plant responses to water stress in the field. Functional Plant Biology. 2009 Nov 5;36(11):978-89.
48. Munns R, James RA, Sirault XRR, Furbank RT, Jones HG. New phenotyping methods for screening wheat and barley for beneficial responses to water deficit. J Exp. Bot. 2010 Aug;61(13):3499-507. Available from: https://doi.org/10.1093/jxb/erq199
49. Tarek Youssef Bayoumi, Salah El-Hendawy, Mohamed Sabry Hamada Yousef. Application of infrared thermal imagery for monitoring salt tolerant of wheat genotypes. Journal of American Science. 2014;10(12):227-34.
50. Yang W, Duan L, Chen G, Xiong L, Liu Q. Plant phenomics and high-throughput phenotyping:

accelerating rice functional genomics using multidisciplinary technologies. Curr. Opin Plant Biol. 2013;16(2):180-7.
51. Peñuelas J, Filella I. Visible and near-infrared reflectance techniques for diagnosing plant physiological status. Trends Plant Sci. 1998 Apr 1;3(4):151-6.
52. Din M, Zheng W, Rashid M, Wang S, Shi Z. Evaluating Hyperspectral Vegetation Indices for Leaf Area Index Estimation of *Oryza sativa* L. at Diverse Phenological Stages. Front Plant Sci; c2017. p. 8.
53. Yi Q Xiang, Bao A Ming, Wang Q, Zhao J. Estimation of leaf water content in cotton by means of hyper spectral indices. Comput Electron Agric. 2013 Jan 1;90:144-51.
54. Gaulton R, Danson FM, Ramirez FA, Gunawan O. The potential of dual-wavelength laser scanning for estimating vegetation moisture content. Remote Sens. Environ. 2013 May 15;132:32-9.
55. Cheng T, Rivard B, Sánchez-Azofeifa A. Spectroscopic determination of leaf water content using continuous wavelet analysis. Remote Sens Environ. 2011 Feb 15;115(2):659-70. Available from: https://www.sciencedirect.com/science/article/pii/S0034425710003147
56. Ullah S, Schlerf M, Skidmore AK, Hecker C. Identifying plant species using mid-wave infrared (2.5-6μm) and thermal infrared (8-14μm) emissivity spectra. Remote Sens Environ. 2012;118:95-102.
57. Ullah S, Skidmore AK, Groen TA, Schlerf M. Evaluation of three proposed indices for the retrieval of leaf water content from the mid-wave infrared (2-6μm) spectra. Agric For Meteorol. 2013 Apr 15;171-172:65-71.
58. De Bei R, Cozzolino D, Sullivan W, Cynkar W, Fuentes S, Dambergs R, *et al*. Non-destructive measurement of grapevine water potential using near infrared spectroscopy. Aust. J Grape Wine Res. 2011 Feb;17(1):62-71. Available from: https://doi.org/10.1111/j.1755-0238.2010.00117.x
59. Elsayed S, Mistele B, Schmidhalter U. Can changes in leaf water potential be assessed spectrally? Functional Plant Biology. 2011;38(6):523-33.
60. Jones HG. The use of indirect or proxy markers in plant physiology. Plant Cell Environ. 2014 Jun;37(6):1270-2.
61. Liu J, Pattey E. Retrieval of leaf area index from top-of-canopy digital photography over agricultural crops. Agric For Meteorol. 2010 Oct 15;150(11):1485-90.
62. Kiyomiya S, Nakanishi H, Uchida H, Tsuji A, Nishiyama S, Futatsubashi M, *et al*. Real Time Visualization of 13N-Translocation in Rice under Different Environmental Conditions using Positron Emitting Tracer Imaging System1. Plant Physiol. 2001 Apr;125(4):1743-53. Available from: https://doi.org/10.1104/pp.125.4.1743
63. Borisjuk L, Rolletschek H, Neuberger T. Surveying the plant's world by magnetic resonance imaging. The Plant Journal. 2012 Apr;70(1):129-46.
64. Jahnke S, Menzel MI, Van Dusschoten D, Roeb GW, Bühler J, Minwuyelet S, *et al*. Combined MRI-PET dissects dynamic changes in plant structures and functions. The Plant Journal. 2009 Aug;59(4):634-44.
65. Windt CW, Vergeldt FJ, De Jager PA, Van ASH. MRI of long-distance water transport: a comparison of the phloem and xylem flow characteristics and dynamics in poplar, castor bean, tomato and tobacco. Plant Cell Environ. 2006;29(9):1715-29. Available from: https://doi.org/10.1111/j.1365-3040.2006.01544.x
66. Maphosa L, Thoday-Kennedy E, Vakani J, Phelan A, Badenhorst P, Slater A, *et al*. Phenotyping wheat under salt stress conditions using a 3D laser scanner. Isr J Plant Sci. 2017 Dec 6;64(3-4):55-62. Available from: https://brill.com/view/journals/ijps/64/3-4/article-p55_55.xml
67. Jones AM, Danielson JÅH, Manoj Kumar SN, Lanquar V, Grossmann G, Frommer WB. Abscisic acid dynamics in roots detected with genetically encoded FRET sensors. Amasino R, editor. Elife. 2014 Apr 15;3:e01-741. Available from: https://doi.org/10.7554/eLife.01741
68. Okumoto S, Jones A, Frommer WB. Quantitative Imaging with Fluorescent Biosensors. Annu Rev Plant Biol. 2012 Jun 2;63(1):663-706.
69. Rahman AF, Gamon JA, Sims DA, Schmidts M. Optimum pixel size for hyperspectral studies of ecosystem function in southern California chaparral and grassland. Remote Sens Environ. 2003 Feb 1;84(2):192-207.
70. Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ. 2002;83(1):195-213.
71. Kim J, Kim KS, Kim Y, Chung YS. A short review: Comparisons of high-throughput phenotyping methods for detecting drought tolerance. Sci. Agric; c2021. p. 78.
72. Kokhan. Application of vegetative indexes derived from satellite images IRS-1D LISS-III for determination of crop status. Space Science and Technology. 2011;17:58-63.
73. Cammarano D, Fitzgerald G, Basso B, O'Leary G, Chen D, Grace P, *et al*. Use of the Canopy Chlorophyl Content Index (CCCI) for Remote Estimation of Wheat Nitrogen Content in Rainfed Environments. Agron J. 2011 Nov;103(6):1597-603.
74. Tedesco-Oliveira D, Pereira da Silva R, Maldonado W, Zerbato C. Convolutional neural networks in predicting cotton yield from images of commercial fields. Comput. Electron Agric. 2020 Apr 1;171:105-307.
75. Yue J, Yang G, Tian Q, Feng H, Xu K, Zhou C. Estimate of winter-wheat above-ground biomass based on UAV ultrahigh-ground-resolution image textures and vegetation indices. ISPRS Journal of Photogrammetry and Remote Sensing. 2019 Apr 1;150:226-44. Available from: https://www.sciencedirect.com/science/article/pii/S0924271619300619
76. Phillips RL. Mobilizing Science to Break Yield Barriers. Crop Sci. 2010;50(S1):S-99-S-108. Available from: https://doi.org/10.2135/cropsci2009.09.0525
77. McMullen MD, Kresovich S, Villeda HS, Bradbury P, Li H, Sun Q, *et al*. Genetic Properties of the Maize Nested Association Mapping Population. Science. 1979, 2009;325(5941):737-40. Available from: https://doi.org/10.1126/science.1174320
78. Jannink JL, Lorenz AJ, Iwata H. Genomic selection in plant breeding from theory to practice. Brief Funct Genomics. 2010 Mar 1;9(2):166-77.
79. Gaudin ACM, Henry A, Sparks AH, Slamet-Loedin IH. Taking transgenic rice drought screening to the field. J Exp. Bot. 2013;64(1):109-17.
80. Saint Pierre C, Crossa JL, Bonnett D, Yamaguchi-Shinozaki K, Reynolds MP. Phenotyping transgenic

wheat for drought resistance. J Exp. Bot. 2012;63(5):1799-808. Available from: https://doi.org/10.1093/jxb/err385
81. Houle D, Govindaraju DR, Omholt S. Phenomics: the next challenge. Nat Rev Genet. 2010;11(12):855-66. Available from: https://doi.org/10.1038/nrg2897
82. Araus JL, Slafer GA, Royo C, Serret MD. Breeding for Yield Potential and Stress Adaptation in Cereals. CRC Crit Rev Plant Sci. 2008 Nov;27(6):377-412. Available from: https://doi.org/10.1080/07352680802467736
83. Cabrera-Bosquet L, Crossa J, Von Zitzewitz J, Serret MD, Luis Araus J. High-throughput Phenotyping and Genomic Selection: The Frontiers of Crop Breeding Converge F. J Integr Plant Biol. 2012 May;54(5):312-20. Available from: https://doi.org/10.1111/j.1744-7909.2012.01116.x
84. Zhao C, Zhang Y, Du J, Guo X, Wen W, Gu S, *et al*. Crop Phenomics: Current Status and Perspectives. Front Plant Sci., 2019, 10.
85. Ates, Bukowski. 22 Global Soybean Stocks Fall in Tandem with South American Production Economic Research Service| Situation and Outlook Report Domestic Outlook International Outlook; c2021-2022.
86. Burton AL, Williams M, Lynch JP, Brown KM. Root Scan: Software for high-throughput analysis of root anatomical traits. Plant Soil. 2012 Aug;357(1):189-203. Available from: https://doi.org/10.1007/s11104-012-1138-2
87. Chopin J, Laga H, Huang CY, Heuer S, Miklavcic SJ. Root Analyzer: A Cross-Section Image Analysis Tool for Automated Characterization of Root Cells and Tissues. PLoS One. 2015;10(9):e013-7655. Available from: https://doi.org/10.1371/journal.pone.0137655
88. Jeudy C, Adrian M, Baussard C, Bernard C, Bernaud E, Bourion V, *et al*. Rhizo Tubes as a new tool for high throughput imaging of plant root development and architecture: test, comparison with pot grown plants and validation. Plant Methods. 2016 Dec;12(1):31. Available from: https://doi.org/10.1186/s13007-016-0131-9
89. Song P, Wang J, Guo X, Yang W, Zhao C. High-throughput phenotyping: Breaking through the bottleneck in future crop breeding. Crop J. 2021 Jun 1;9(3):633-45. Available from: https://www.sciencedirect.com/science/article/pii/S2214514121000829
90. Atkinson JA, Pound MP, Bennett MJ, Wells DM. Uncovering the hidden half of plants using new advances in root phenotyping. Curr. Opin. Biotechnol. 2019;55:1-8. Available from: https://www.sciencedirect.com/science/article/pii/S0958166918300521
91. Singh AK, Ganapathysubramanian B, Sarkar S, Singh A. Deep Learning for Plant Stress Phenotyping: Trends and Future Perspectives. Trends Plant Sci. 2018 Oct 1;23(10):883-98.
92. Maes WH, Steppe K. Perspectives for Remote Sensing with Unmanned Aerial Vehicles in Precision Agriculture. Trends Plant Sci. 2019 Feb 1;24(2):152-64.
93. Mahlein AK, Kuska MT, Behmann J, Polder G, Walter A. Hyperspectral Sensors and Imaging Technologies in Phytopathology: State of the Art. Annu Rev Phytopathol. 2018 Aug 25;56(1):535-58. Available from: https://doi.org/10.1146/annurev-phyto-080417-050100
94. Meuwissen THE, Hayes BJ, Goddard ME. Prediction of Total Genetic Value Using Genome-Wide Dense Marker Maps. Genetics. 2001 Apr;157(4):1819-29. Available from: https://doi.org/10.1093/genetics/157.4.1819
95. Taylor JF. Implementation and accuracy of genomic selection. Aquaculture. 2014;420-421:S8-14.
96. Watanabe K, Guo W, Arai K, Takanashi H, Kajiya-Kanegae H, Kobayashi M, *et al*. High-Throughput Phenotyping of Sorghum Plant Height Using an Unmanned Aerial Vehicle and Its Application to Genomic Prediction Modeling. Front Plant Sci; c2017. p. 8. Available from: https://www.frontiersin.org/articles/10.3389/fpls.2017.00421
97. Rutkoski J, Poland J, Mondal S, Autrique E, Pérez LG, Crossa J, *et al*. Canopy Temperature and Vegetation Indices from High-Throughput Phenotyping Improve Accuracy of Pedigree and Genomic Selection for Grain Yield in Wheat. G3 Genes | Genomes | Genetics. 2016 Sep 1;6(9):2799-808. Available from: https://doi.org/10.1534/g3.116.032888
98. Crain J, Mondal S, Rutkoski J, Singh RP, Poland J. Combining High-Throughput Phenotyping and Genomic Information to Increase Prediction and Selection Accuracy in Wheat Breeding. Plant Genome. 2018 Mar;11(1):170-043.
99. Ashapure A, Jung J, Chang A, Oh S, Yeom J, Maeda M, *et al*. Developing a machine learning based cotton yield estimation framework using multi-temporal UAS data. ISPRS Journal of Photogrammetry and Remote Sensing. 2020 Nov 1;169:180-94. Available from: https://www.sciencedirect.com/science/article/pii/S0924271620302628
100. Guo Q, Jin S, Li M, Yang Q, Xu K, Ju Y, *et al*. Application of deep learning in ecological resource research: Theories, methods and challenges. Sci. China Earth Sci. 2020 Oct;63(10):1457-74. Available from: https://doi.org/10.1007/s11430-019-9584-9
101. Jiang Y, Li C. Convolutional Neural Networks for Image-Based High-Throughput Plant Phenotyping: A Review. Plant Phenomics 2023; c2020. Available from: https://doi.org/10.34133/2020/4152816
102. Misra T, Arora A, Marwaha S, Chinnusamy V, Rao AR, Jain R, *et al*. Spike Seg Net-a deep learning approach utilizing encoder-decoder network with hourglass for spike segmentation and counting in wheat plant from visual imaging. Plant Methods. 2020 Dec;16(1):40. Available from: https://doi.org/10.1186/s13007-020-00582-9
103. Tang L, Zhu Y, Hannaway D, Meng Y, Liu L, Chen L, *et al*. Rice Grow: A rice growth and productivity model. NJAS: Wageningen Journal of Life Sciences. 2009 Dec 1;57(1):83-92.
104. Pohanková E, Hlavinka P, Kersebaum KC, Rodríguez A, Jan Balek, Bednařík M, *et al*. Expected effects of climate change on the production and water use of crop rotation management reproduced by crop model ensemble for Czech Republic sites. European Journal of Agronomy. 2022 Mar 1;134:126-446.
105. Lamsal A, Welch SM, Jones JW, Boote KJ, Asebedo A, Crain J, *et al*. Efficient crop model parameter estimation and site characterization using large breeding trial data sets. Agric Syst. 2017 Oct 1;157:170-84.

106. Messina CD, Technow F, Tang T, Totir R, Gho C, Cooper M. Leveraging biological insight and environmental variation to improve phenotypic prediction: Integrating crop growth models (CGM) with whole genome prediction (WGP). European Journal of Agronomy. 2018;100:151-62.
107. Kherif O, Seghouani M, Justes E, Plaza-Bonilla D, Bouhenache A, Zemmouri B, *et al*. The first calibration and evaluation of the STICS soil-crop model on chickpea-based intercropping system under Mediterranean conditions. European Journal of Agronomy. 2022 Feb 1;133:126-449.
108. Guo Z, Yang W, Chang Y, Ma X, Tu H, Xiong F, *et al*. Genome-Wide Association Studies of Image Traits Reveal Genetic Architecture of Drought Resistance in Rice. Mol Plant. 2018 Jun 4;11(6):789-805.
109. Wu D, Guo Z, Ye J, Feng H, Liu J, Chen G, *et al*. Combining high-throughput micro-CT-RGB phenotyping and genome-wide association study to dissect the genetic architecture of tiller growth in rice. J Exp. Bot. 2019 Jan 7;70(2):545-61.
110. Zhang X, Huang C, Wu D, Qiao F, Li W, Duan L, *et al*. High-Throughput Phenotyping and QTL Mapping Reveals the Genetic Architecture of Maize Plant Growth. Plant Physiol. 2017;173(3):1554-64. Available from: https://doi.org/10.1104/pp.16.01516
111. Wang D, Wang S, Chao J, Wu X, Sun Y, Li F, *et al*. Morphological phenotyping and genetic analyses of a new chemical-mutagenized population of tobacco (*Nicotiana tabacum* L.). Planta. 2017 Jul;246(1):149-63. Available from: https://doi.org/10.1007/s00425-017-2690-z
112. Miao Y, Mulla DJ, Randall GW, Vetsch JA, Vintila R. Combining chlorophyll meter readings and high spatial resolution remote sensing images for in-season site-specific nitrogen management of corn. Precis. Agric. 2009 Feb;10:45-62.
113. Cilia C, Panigada C, Rossini M, Meroni M, Busetto L, Amaducci S, *et al*. Nitrogen status assessment for variable rate fertilization in maize through hyperspectral imagery. Remote Sens. 2014;6:6549-6565.
114. Rama Rao N, Garg PK, Ghosh SK, Dadhwal VK. Estimation of leaf total chlorophyll and nitrogen concentrations using hyperspectral satellite imagery. J Agric. Sci. 2008 Feb;146(1):65-75.
115. Thenkabail PS, Mariotto I, Gumma MK, Middleton EM, Landis DR, Huemmrich KF. Selection of hyperspectral narrowbands (hnbs) and composition of hyperspectral twoband vegetation indices (HVIS) for biophysical characterization and discrimination of crop types using field reflectance and hyperion/EO-1 data. IEEE J Sel. Top. Appl. Earth Obs. Remote Sens. 2013;6(2):427-439.
116. Franke J, Menz G. Multi-temporal wheat disease detection by multi-spectral remote sensing. Precis. Agric. 2007 Jun;8:161-172.
117. Stoll M, Schultz HR, Baecker G, Berkelmann-Loehnertz B. Early pathogen detection under different water status and the assessment of spray application in vineyards through the use of thermal imagery. Precis. Agric. 2008 Dec;9:407-417.
118. Geipel J, Link J, Claupein W. Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system. Remote Sens. 2014 Oct 27;6(11):10335-10355.
119. Du M, Noguchi N. Monitoring of wheat growth status and mapping of wheat yield's within-field spatial variations using color images acquired from UAV-camera System. Remote Sens. 2017;9:289.
120. Lobell DB, Thau D, Seifert C, Engle E, Little B. A scalable satellite-based crop yield mapper. Remote Sens. Environ. 2015;164:324-333.
121. Wang ZJ, Wang JH, Liu LY, Huang WJ, Zhao CJ, Wang CZ. Prediction of grain protein content in winter wheat (*Triticum aestivum* L.) using plant pigment ratio (PPR). Field Crop. Res. 2004 Dec 8;90(2-3):311-321.