Field Phenotyping for the Future

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Abstract

Global agricultural production has to double by 2050 to meet the demands of an increasing population and the challenges of a changing climate. Plant phenomics (the characterization of the full set of phenotypes of a given species) has been proposed as a solution to relieve the "phenotyping bottleneck" between functional genomics and plant breeding studies. In this review, we survey current approaches and describe recent technological and methodological advances for phenotyping under field conditions and discuss the prospects for these emerging technologies in addressing the challenges of future plant research.

Keywords

Field phenotyping, phenomics, sensors, phenotyping platforms

1.1 Introduction

A doubling of global agricultural production is required by 2050 to meet the demands of an increasing population and the challenges of a changing climate (Alexandratos and Bruinsma, 2012). This production increase will need to be met by more intensive use of the same land area through the priority process of sustainable intensification. An aspect of this requires a hastening of the plant breeding effort to deliver increased potential yields. However, potential yields are not always achieved on farm, and growing attention is paid to the stagnation of crop yields on farm (Ray et al., 2012). Elements of understanding and driving both plant breeding gain and on-farm productivity rely on the accurate capture of the phenotypic response and performance. At its broadest this encompasses harvestable yield and crop quality, as well as agronomic, biotic and abiotic stress tolerance characters. At a finer scale it involves the precision analysis of phenotypes for the dissection of underlying plant processes.

Much progress has been made over the past decade in decoding and describing the genetics of key plant species. This encompasses the development of molecular markers for use in marker-assisted selection to accelerate breeding gain through to the generation of whole genome assemblies giving unprecedented insight into the genomes of crop species. These advances have also been enabled with rapid advances in bioinformatics and the development of software tools and other computational resources to allow the extraction and application of genetic and genomic data.

In comparison, developments in the detailed understanding of plant phenotypes has been slow. The field of plant phenomics (the characterization of the full set of phenotypes of a given species) has been proposed as a solution to relieve the so-called “phenotyping bottleneck” between functional genomics and plant breeding studies (Furbank and Tester, 2011). This encompasses both the capture of plant phenotypes using a range of methodologies and the accurate and timely extraction, analysis and application of the resulting data. Although relatively well developed in controlled conditions (Bai et al., 2016), progress in understanding and interrogating complex phenotypes at the field level remains slow. In this review, we survey recent advances in phenotyping under field conditions and discuss the prospects for these emerging technologies in addressing the challenges of plant research for the future.

1.2 Traditional field phenotyping approaches

Through the empirical selection of favourable individuals for harvest, consumption and replanting, early farmers employed the most traditional of phenotyping approaches: physical appearance of a plant in its environment. Early selection led to the subsequent domestication of many crop species. Studies in barley have shown the spread of favourable mutations modifying response to the seasonal daylength queue for the initiation of reproductive development supported the Neolithic spread of the crop for cultivation (Jones et al., 2008). Farmers and breeders have continued to use phenotypic selection in an environment, or series of environments, through time. Beyond domesticating wild species this has allowed in particular, for the optimisation of key adaptive traits, including flowering time to ensure maximum yields in a given region. Driven by physical appearance as the result of both genetic and environmental effects, this process has indirectly selected a complex of underlying genetic controllers. Modern plant science and breeding still rely on traditional phenotyping tools. This ranges from simple measurements of growth (e.g., height), time series measurements of the appearance of development stages (e.g., vegetative and reproductive development), comparative numerical scores or indices (e.g., for assessment of pest or pathogen infection) through to assessment of agronomic performance (e.g., yield, biomass) and predictive tests (e.g., for end-use quality traits). When employed at scale and with sufficient replication, many of these traits can be assessed reliably, supporting subsequent selection or analysis. This is particularly true for simple traits that have a high heritability (Hallauer et al., 2010).

Estimation of the genotypic value of a large number of selection candidates (in plant breeding) or cultivars to be recommended to farmers (in variety testing and agronomy) is central to breeding and/or crop production (Piepho et al., 2008). Heritability is a driver of this estimation: defining the degree to which phenotypic variance is a result of genetic variation. Irrespective of the means of generating phenotypic data, its heritability will impact the degree to which it can be used as a selection or trait discovery tool.

Confounding this is genotype-by-environment interactions, which have been reviewed extensively elsewhere (e.g. Yan & Hunt, 2010). The magnitude of climate change effects on crops are likely to be, in part, cultivar dependent, necessitating practical solutions to tailor selective breeding to changing regional patterns (Trnka et al 2014). In order to reliably devise production strategies under future climatic uncertainty, trade-offs to physiologically-based plant processes and productivity across environments need to be accurately characterised which expands the need for development and application of accurate and high-throughput field phenotyping capabilities.

1.3 High-throughput field phenotyping platforms

High-throughput plant phenotyping can be delivered in the field via a variety of platforms, across a range of scales (see Figure 1 for examples) and using a diverse array of sensor modalities (Araus and Cairns, 2014). Platforms can be broadly classified as those operating at ground-level (both above and below the soil surface) and those operating aerially (air- or space-borne). The appeal of these platforms is the increased throughput and impartiality with which they collect data when compared to traditional field approaches.

1.3.1 Above-ground phenotyping platforms

In comparison to phenotyping under controlled conditions, where the movement of either sensors or plants can be automated to increase throughput, ground-based plant field phenotyping requires either a network of fixed sensors or a system to move sensors over the crop. The simplest systems operate at the lowest spatial resolution (single plants or experimental plots) and consist of fixed platforms typically monitoring the local environment and imaging crop development using visible light cameras (Naito et al., 2017; Zhou et al., 2017). These systems have the advantage of being relatively inexpensive, allowing deployment of multi-unit networks to increase throughput to the whole-field level (Zhou et al., 2017).

Multiple plots can be assessed using mobile platforms, the simplest of which are wheeled buggies or “phenocarts”- hand-propelled platforms capable of deploying heavier sensor payloads than can be carried by an individual user (White and Conley, 2013). Motorised versions of the cart design have been developed that, although still requiring an operator, allow high-throughput positioning of sensor arrays across an experimental field (Deery et al., 2014; Jimenez-Berni et al., 2018). Fully-autonomous ground vehicles (ranging in size from small robots capable of navigating between row crops to tractor-sized vehicles) offer the promise of unattended field monitoring and have been the focus of much recent research (Shafiekhani et al., 2017; Underwood et al., 2017; Burud et al., 2017; Grimstad and From, 2017). Trailer or tractor-mounted systems have the benefit of utilising precision agriculture platforms already present at most field sites and have been extensively used for row crops (Comar et al., 2012; Busemeyer et al., 2013; Fernandez et al., 2017; Tanger et al., 2017). Drawbacks of tractor-based systems (and heavier autonomous ground vehicles) are that they cannot be deployed in adverse weather or soil conditions and that repeated traversing of the field may lead to unwanted soil compaction, impacting plant development (Virlet et al., 2017).

Compaction can be avoided by use of larger versions of fixed platforms (often termed “phenotyping towers” or “phenotowers”, Figure 1) which can be either installed on a temporary basis or fixed in position (Ahamed et al., 2012; Shafiekhani et al., 2017; Naito et al., 2017). Crane or gantry installations can accurately and repeatedly position heavy sensor payloads along the three axes of a research field (Virlet et al., 2017). However, the size of field used in such systems is relatively small, making this an expensive approach for multi-site trials (Fernandez et al., 2017). Cable- or zip-line platforms (Kirchgessner et al., 2017) generally have a lower payload than fixed gantries, but may be repositioned across multiple sites as required.

1.3.2 Aerial phenotyping platforms

There are four main platforms for aerial deployment of phenotyping sensors: dirigibles (airships and blimps), drones (unmanned aerial vehicles), manned aircraft, and satellites; each having its own benefits and drawbacks. Dirigibles, whilst able to carry a heavy payload, have slow airspeeds and a lack of stability in high winds (Leibisch et al., 2015). Drones, both rotor and fixed wing, have the ability to fly at lower altitudes and speeds allowing for higher resolution images, making them suited for trials with smaller plots (~1m^2) such as wheat nursery trials (Herwitz et al., 2004; Link et al., 2013). Drones are less expensive than other aerial systems and require smaller landing/take off areas, allowing them to be used in numerous locations. The disadvantage of drones is a limited payload capacity (<20 kg and much lower in most models) and flight time, reducing the type and number of sensors that can be carried (Yang et al., 2017). Drone flights are also limited by weather conditions, with flights ideally performed in good weather (clear, still, dry days) similar to the conditions required for application of agronomic inputs. As such, drone flight days can be limited for field trials in temperate climates and have to be organised so as not to disrupt other field activities.

Manned aircraft have a far greater carrying capacity compared to drones and can cover larger areas in comparable flight times. This allows data from entire trial stations to be collected in one flight with numerous sensors. Manned aircraft can also operate in more challenging conditions than drones. Whilst conditions should ideally still be cloudless, manned aircraft are more stable and therefore less affected by the wind. They also fly at higher altitudes and thus do not interfere with other farming practices occurring at the same time. These advantages, however, come at the cost of resolution with most aircraft-mounted sensors operating at one pixel per 1 m^2 compared to 0.05 to 0.15 pixels per m^2 for drones. As the aircraft is travelling at a higher speed, image blur can be an issue making image stitching for orthomosaics more challenging (Herwitz et al., 2004; Link et al., 2013). This limits the type of trial aircraft can be used for (a maximum plot size of ~8m^2 which precludes nursery trials) and lessens the ability to capture within-plot variations which can be key to explaining some results. The initial set up cost and logistics of deploying manned aircraft make it unlikely that many organisations will develop in-house solutions but for larger scale field trials (>1 ha) data from subcontracted manned aircraft is now comparable in cost to subcontracted data collected using drones.

Satellites are not ideally suited for plant field phenotyping research despite being the cheapest source of data on the market (Lelong et al., 2008). Satellite imagery is lower-resolution than other aerial techniques and as the platforms are in orbit, sensor choice is fixed. The WorldView-3 Earth observation satellite (worldview3.digitalglobe.com), which provides publicly-available data, carries a multispectral camera with a resolution of 1.24 m^2. For most satellite-deployed sensors, cloud cover prevents effective capture of trials data. Despite these current limitations, satellite-based phenotyping platforms will probably be a viable option in the future as sensor resolution increases and cloud penetrating sensors are deployed allowing for regular, reliable collection of high quality data.

1.4 Sensors for phenotyping

The characteristics of each platform determine the sensors that can be employed (Table 1). For example, sensors utilising line-scanning for data acquisition obviously cannot be used on static platforms. Whilst most sensors have models that can be deployed on both ground and aerial based platforms, the quality of sensor and the information collected can vary dramatically. Features such as maximum payload, positioning precision, field of view, and distance above crop will determine the appropriate sensors for each scale of platform.

<Table 1 here>

The simplest sensors are visible light (400-700 nm) cameras (often termed RGB imaging) that can be deployed at every scale of platform, producing two-dimensional (2D) colour images. Using visible light cameras on ground based platforms allows the analysis of individual plants and plots. A drawback of 2D imaging is occlusion caused by overlapping leaves in older plants and difficulties in image segmentation of plant material from soil, making estimations of biomass inaccurate (Fiorani and Schurr, 2013). Imaging using multiple cameras allows reconstruction of three-dimensional (3D) features, though rarely at the resolution seen in controlled condition platforms. A high resolution RGB camera mounted on a drone or a manned aircraft can provide a range of useful phenotypic data at plot level (1 m^2 and above). As with ground based platforms, images from drone-mounted RGB cameras can be used to measure basic traits such as height and crop cover, allowing assessment of traits such as lodging and leaf area index (Bendig et al., 2014). As drones can cover large areas quickly, RGB cameras can be deployed as agronomic tools in field phenotyping trials. Visual assessments of the previous crop before the trial crop is planted will identify any areas of the field that are performing badly or are lacking nutrients allowing researchers to intervene to provide the most homogeneous trial environment possible and limiting any confounding effect of environment (Zaman-Allah et al., 2015).

A key step in the analysis of image sensor data from aerial (and some ground based platforms) is the production of an orthomosaic image (“orthoimage”), also termed a digital elevation/surface model depending on the sensor. Obtaining an orthoimage is a multi-stage process. Firstly the inspection and distortion characteristics of the camera and lens is required before images can then be manipulated to ensure consistency of brightness, grayscale, and texture (Yang et al., 2017). This is usually achieved by placing ground control points at fixed points in the field of known colour and texture (Richards, 1999). Finally, images are stitched together based on feature points within the images, in combination with aerial triangulation data (Colomina and Molina, 2014) to produce a mosaic. It is from these mosaics that the reflectance of certain light bands can be extracted from pixels in specific locations and compared over a large area (Figure 2).

By combining RGB and near infrared (780 – 2500 nm) cameras (or by using a dedicated multispectral camera), various vegetation indices (VIs) can be determined (Yang et al, 2017). The accuracy of phenotype prediction using these indices varies depending on the stringency during VI development and the population being assessed. In many cases of VI development, the accuracy of phenotype prediction is assessed by correlating against a phenotype quantified using traditional methods. Whilst this method can be effective, it can be confounded by issues facing all correlations; sample size, measurement errors, homogeneity of the sample, identification of outliers and hidden variables. It is for this reason that trials phenotyped using VIs should initially have a subset of plots assessed by traditional methods for validation. Multispectral sensors represent the next level of technology from RGB cameras and are widely used in both academic and commercial field trials as they are more effective at segmenting green plant material from soil. As a result, multispectral cameras are better at predicting plant height, crop cover and predicting crop yield than RGB cameras (Yang et al, 2017). True hyperspectral cameras (those which measure continuous and contiguous ranges of wavelengths) have traditionally been very expensive line-scanning devices more suited for laboratory use (Fiorani and Schurr, 2013). A new generation of lighter, relatively cheaper devices has made incorporation into field phenotyping platforms possible, although the large amounts of data such cameras produce pose an analysis bottleneck when mounted on ground based platforms. On aerial platforms, hyperspectral cameras present a step-change in information and quality of prediction compared to multispectral models. Currently, hyperspectral cameras are mainly used to identify and accurately measure traits that could potentially be identified using a multispectral camera, e.g., nitrogen content and biomass, chlorophyll content, water content and photosynthetic parameters (Yang et al., 2017). Researchers have also developed novel assessment methods that previously were not possible with multispectral sensors. For example, Zarco-Tejada et al. (2013) has identified leaf carotenoid content in vineyards whilst Uto et al. (2013) were able to identify chlorophyll density, not just chlorophyll content, in rice paddies.

Thermal imaging in the field, whether deployed on the ground or in the air, usually employs long-infrared (9000 – 14000 nm) sensors and can quantify useful functional traits such as water stress (Gonzalez-Dugo, 2013), disease (Nilsson, 1991), stomatal conductance, and transpiration rate (Baluja et al., 2012). Thermal sensors require calibration and correction for ambient temperature, wind speed and solar radiation which may confound time course imaging (Sugiura et al., 2007; Deery et al., 2014). As with RGB imaging, segmentation of plant thermal signals from that of the soil is difficult in sparse canopies (Li et al., 2014) which can be problematic as most thermal phenotyping requires a high accuracy (< 0.5°C).

LiDAR (light detection and ranging) is an active sensor technology that can quantify ground cover, canopy height and above-ground biomass. Modern LiDAR units are light enough to be used on most ground and aerial platforms (Grimstad and From, 2017; Virlet et al., 2017). Despite its expense and relative complexity, LiDAR offers several advantages over RGB imaging - it is insensitive to ambient light changes and produces a direct measurement of canopy architecture (Jimenez-Berni et al., 2018). LiDAR mounted on aerial platforms lacks the accuracy to correctly measure canopy architecture of short crops, limiting its utility during earlier growth stages when assessing architecture is important. This limitation, coupled with the high cost and image processing requirements has meant that LIDAR has not yet been extensively deployed on aerial based platforms for crop phenotyping.

Synthetic-aperture radar (SAR) is a promising technology based on detection of radar echoes to produce high-resolution three-dimensional images even in bad weather (Wang et al., 2014). SAR sensors are currently too large and expensive to readily be deployed on drones and manned aircraft and as such are mainly used on satellites making the resolution currently too low for monitoring small plot crop trials.

1.5 Below-ground phenotyping

Phenotyping for below-ground traits in the field has seen comparatively less advancement than above ground sensors and platforms, largely due to the difficulties associated with imaging and data capture (Atkinson et al., 2018).

Classical destructive techniques such as digging trenches to directly observe and quantify roots (Voss-Fels et al., 2018), soil coring and root washing (Frasier et al., 2016) or soil monolith sampling (Kuchenbuch et al., 2009) are still widely used. Although these methods provide high levels of detail, the time taken to physically remove soil and quantify samples makes them inherently low throughput. The core-break method, another longstanding technique, increases the throughput of coring and root washing by breaking/slicing soil core samples at set intervals and only quantifying the visible roots revealed by each break, as a representation of root biomass at each interval (Kuecke et al., 1995). This method has recently been improved and partially automated by employing UV illumination and fluorescence spectroscopy. The fluorescence images have significantly enhanced soil-root contrast when compared to RGB, allowing for automated image processing and quantification (Wasson et al., 2016).

Rhizotrons, usually defined as any type root observation chamber with a transparent window, come in a variety of forms and sizes. Traditionally, a rhizotron refers to an underground laboratory dug into a field with transparent viewing windows such as the EMR Rhizolab (NIAB EMR, 2018), allowing the soil profile and any roots contacting the observation window to be studied and quantified. The term is also used for lab installations where roots are grown in artificial soil-filled boxes or between plates with transparent or removable covers such as the GROWSCREEN-Rhizo platform (Nagel et al., 2012). Minirhizotrons are the most common type of field-deployed rhizotron consisting of a transparent cylinder inserted into the soil, into which an imaging device can be lowered to quantify the soil and roots contacting the cylinder walls (Chen et al., 2018; Liu et al., 2018a; Herbrich et al., 2018). The main advantage of a minirhizotron is that a single imaging device can be used in multiple tubes, with the limitation on throughput being deployment of the tubes themselves rather than imaging/data acquisition. Their main disadvantage is that tube installation often causes artefacts in the soil, with a period of 6-12 months between installation and data capture being recommended to allow some of the disturbances to dissipate (Johnson et al., 2001).

The crown root phenotyping technique “shovelomics” (Trachsel et al., 2011) is becoming a widely adopted method due to its relatively high throughput. The protocol, originally designed for maize, involves manual excavation of the crown root system and quantification of a number of key root architectural traits such as crown root number and angle. These traits can be quantified directly from the excavated crown, or from images using automatic image analysis software such as DIRT (Bucksch et al., 2014) and REST (Colombi et al., 2015). Although automated image analysis has increased overall throughput of the method, the rate-limiting step is still the manual excavation of the crown root system. Automation of this process is being addressed by the DEEPER project at Pennsylvania State University, part of the ARPA-E funded ROOTS program. Field-deployable systems for root phenotyping using several other sensor technologies (X-ray computed tomography, magnetic resonance imaging, thermoacoustic imaging) are also being developed as part of the same program (ARPA-E, 2018).

Geophysical sensors, more commonly utilised in archaeology and engineering, have seen significant advancement in recent years and are now commonly used in soil and root profile phenotyping. Electrical Resistance Tomography (ERT) can be used to quantify soil structure and water profiles by measuring electrical resistivity via arrays of probes inserted into the soil. ERT is an indirect method to quantify root activity via mapping soil drying caused by plant water uptake (Srayeddin and Doussan, 2009). ERT has been employed to analyse large diameter root profiles (e.g. trees (Amato et al., 2008)) but is starting to see adoption in crop phenotyping (Srayeddin and Doussan, 2009; Whalley et al., 2017). Although ERT has advantages such as non-destructive data collection, its throughput is limited by the number of probe arrays that can be placed and maintained in the field throughout the season.

Electromagnetic inductance (EMI) measures soil electrical conductivity and can be used to quantify root activity by measuring soil water profiles in a similar fashion to ERT. EMI collects data at a significantly higher throughput compared to ERT as it does not require probe arrays or direct contact with the soil (Shanahan et al., 2015), requiring a single sensor for measurement of multiple plots (or even fields) in reasonably quick succession. However, EMI has a lower spatial resolution than ERT, and also requires data calibration using a second method such as penetrometer mapping (Whalley et al., 2017).

Neutron probes also quantify soil water content and are used as an indirect measure of root activity in a similar fashion to EMI and ERT. A radioactive source is placed on the soil surface or lowered into an access tube and emits fast neutrons into the soil which interact with hydrogen atoms in water, thermalizing and scattering the neutrons. These thermalized neutrons can then be quantified as an estimate of water content. Neutron probes are a widely accepted method for measuring soil water content (Whalley et al., 2017) and are frequently used in root phenotyping e.g. (Zhang et al., 2016), but are limited in terms of throughput as they require access tubes in the soil and extra handling precautions associated with the use of a radioactive source.

Ground penetrating radar (GPR) maps sub-surface structures by measuring reflection, refraction, and scattering of pulses of high-frequency radio waves, with a similar data collection throughput to EMI. GPR does not currently have the resolution to detect individual objects less than 2 mm in diameter, but has previously been used to quantify larger diameter tree roots (Liu et al., 2016). Despite spatial resolution limitations, it has recently been demonstrated that GPR can detect bulk root biomass in wheat and sugarcane, although with limited ability to detect differences between genotypes (Liu et al., 2018b).

1.6 Conclusions and Future Perspectives

The adoption of high-throughput technologies has generated a potential new bottleneck in the phenotyping pipeline – the handling, management and analysis of very large amounts of data. Whilst challenging to manage, such large datasets also offer opportunities for modelling and machine learning analyses (Coppens et al., 2017). Machine learning represents a solution to the problem of analysing large image datasets, with automated feature detection capable of producing highly accurate results. For example using a deep machine learning approach, wheat spikes and spikelets have been identified in complex images with >95% accuracy (Pound et al., 2017). As more datasets are produced and made publically available, the accuracy of such techniques will increase. Modelling approaches are capable of fully utilising the large amount of sensor data to provide more reliable phenotype predictions than vegetation indices (Jin et al., 2018). Crop modelling describes phenotypes or crop growth traits as functions of various metadata, both genetic and environmental. One of the main limitations of these models has been a lack of (or unreliable) spatial data. Field-deployed sensors offer the opportunity to collect reliable and accurate spatial descriptors of soil properties and canopy phenotypes of crops (reviewed in Jin et al., 2018 and Kasampalis et al., 2018). From this data predictive models for the phenotype of interest can be developed for use in future studies. As with machine learning, subsequent trials will provide more data to further improve model accuracy and predictive power.

The recent advances in plant phenotyping approaches under field conditions reviewed above offer the promise of high-throughput collection of phenotypic data and unbiased quantification of novel traits for functional analyses and assessment of field performance. Such platforms have been widely adopted by research organisations and are being more slowly adopted by plant breeders as the technology matures and the benefits are proven. Ground based platforms with new sensor modalities allow researchers to study many aspects of plant development at a level of detail not previously possible. Aerial sensors offer the opportunity to non-destructively assess traits such as photosynthetic activity and water stress at regular intervals over large scale field trials. For many years, root system traits have been less studied by field researchers due to a lack of suitable techniques; new below-ground techniques and sensors have made it possible to assess various aspects of root growth *in agri*, informing new selection criteria for crops for sustainable farming systems.

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Figure Legends

Figure 1. Field phenotyping platforms. Adapted from (Shakoor et al., 2017).

Figure 2. Orthoimage of a large-scale wheat field trial compiled from images captured by a drone using RGB and multispectral cameras (NIAB, *unpublished*). (a) RGB camera image. (b) Plots overlaid with a heat map showing Normalized Difference Vegetation Index (NDVI) for each plot calculated from multispectral camera data. Scale bar: 20m.

Table 1. Sensors deployed in field phenotyping (adapted from Yang et al., 2017).

Sensor	Spectral bands	Wavelength range (typical)	Potential applications	Advantages	Disadvantages
Digital camera	Red Green Blue	400 – 700 nm	Leaf colour, plant height, lodging, canopy cover, intercepted radiation, LAI, 3D structure, leaf angle	Low cost, light weight, convenient operation, simple data processing	Low radiometric resolution, lack of proper calibration
Multispectral camera	Red Green NIR	490 -~920 nm	See above and leaf nitrogen content, yield, chlorophyll, biomass, weed emergence	Low cost, flexibility	Fewer bands, low spectral resolution, discontinuous spectra
Hyperspectral camera	100-1600	250-2500 nm	See above and net photosynthesis, nitrogen, chlorophyll, disease detection	More bands, higher spectral resolution	Expensive, complex data processing, sensitive to weather
Thermal imager	Long IR	7.5–13 µm	Canopy temperature, stomatal conductance, water potential	Indirect determination of crop growth status under abiotic and biotic stress	Sensitive to weather, frequent calibration, difficult to eliminate the influence of soil
LIDAR	UV Visible NIR	532-1550	Plant height, biomass	Rich point cloud information, acquisition of high precision 3D canopy structure	High cost, data processing
Synthetic Aperture Radar	-	1-1000 mm	Crop identification, crop acreage monitoring, key crop trait estimation and yield prediction	Collects data even in cloudy weather	High cost, data processing, Mainly limited to satellites therefore only used for large plot work
Ground Penetrating Radar	Ultrawideband 0 – 1000 MHz	-	Detection of root bulk root biomass or large diameter tree roots	High throughput	Cannot detect fine roots, limited ability to detect genotypic differences

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Figure 1.

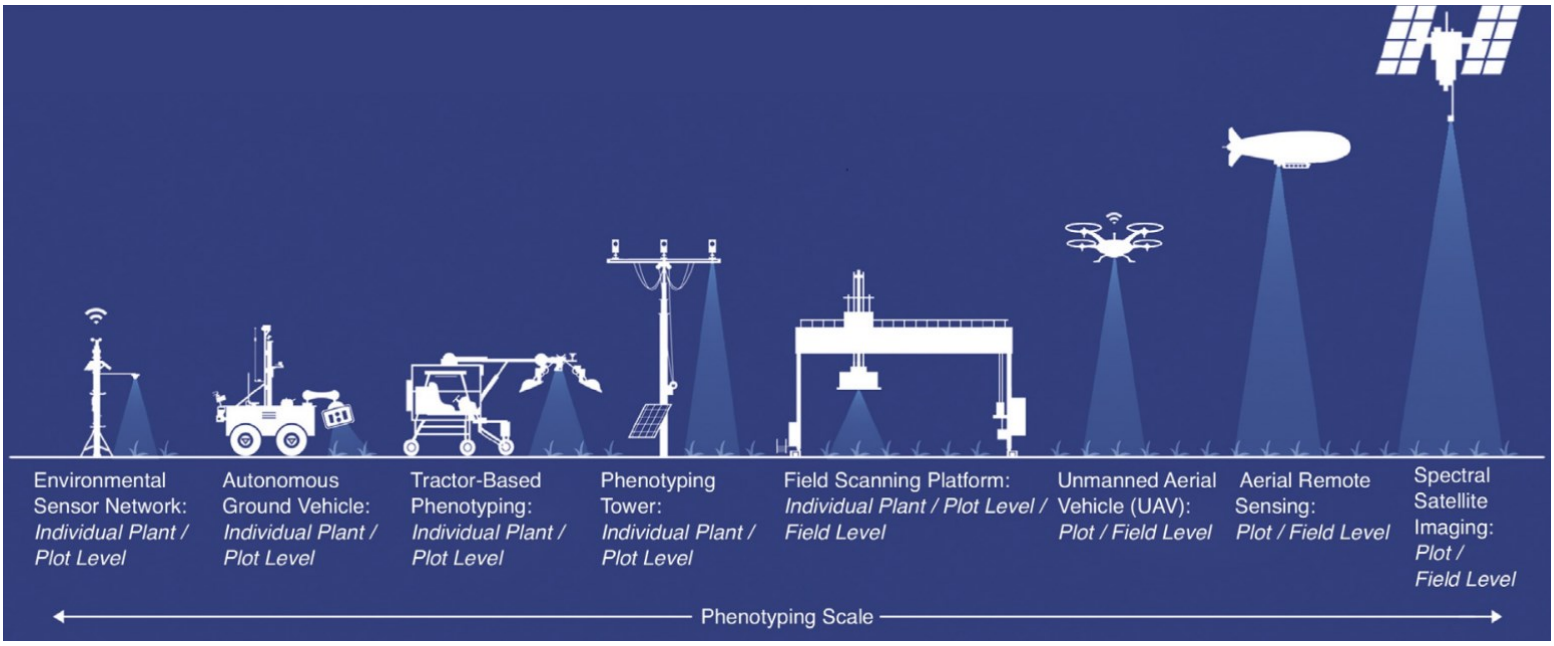

Figure 2.