Future Food Systems

Smart crop monitoring

Precise phenotyping for improved quality and protected cropping management

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About Future Food Systems

The Future Food Systems Cooperative Research Centre (CRC) is a national initiative created to drive innovation and growth in the agrifood sector by accelerating adoption of STEM technologies and cluster approaches to industry development, resilience and sustainability. It is funded as part of the Australian Government's CRC Program, established to drive industry-led collaborations between researchers and the community to improve the competitiveness, productivity and sustainability of Australian industries, especially in sectors where Australia has a competitive strength.

Citation and authorship

Chelsea Maier, Zhong-Hua Chen, Christopher I Cazzonelli, David T Tissue, Oula Ghannoum (2020) Smart crop monitoring: Precise phenotyping for improved quality and protected cropping management, Future Food Systems, Sydney

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Australian Government
Department of Industry, Science, Energy and Resources

AusIndustry
Cooperative Research Centres Program

Executive Summary

Emerging technology has potential to transform food production, enabling premium crops to be grown virtually anywhere, anytime, with key parameters monitored and inputs controlled precisely and automatically. To realise this vision, however, we must develop automated systems tailored for 21st-century protected-cropping facilities, then simplify these to create affordable, accessible solutions for growers.

Protected cropping (PC) – including low-tech polytunnels; medium-tech facilities enabling some environmental control; and high-tech facilities, such as fully automated glasshouses and indoor vertical-farm facilities – can produce far more food per land area than can field-based horticulture.

These days, it's possible to achieve high crop productivity and quality using environmental-control technology and precision phenotyping, involving image processing and big-data analysis, artificial intelligence (AI) and machine learning (ML). For Australia to move toward realising this vision, however, the technology for monitoring crops and ensuring optimal conditions in protected cropping facilities must be made accessible and affordable to growers.

Automating data collection via remote sensing of crops is integral to the more general automation of facilities that's needed across the sector to reduce reliance on itinerant labour. It is also central to increasing the environmental sustainability of production via the fine-tuning of energy, water and other inputs.

Much of the sensor and phenotyping technology developed to date has been tailored to field and broadacre agriculture, but we can adapt these methods to peri-urban and inner-city greenhouse, glasshouse and vertical farming operations, as outlined in this report.

Advanced, affordable phenotyping solutions for protected cropping

CRC projects involving protected-cropping, AI and ML experts at partner universities UNSW and WSU will develop novel (and adapt existing) sensing, phenotyping and IoT technologies for advanced greenhouse, glasshouse and vertical farm facilities, then simplify these technologies and methods to create affordable, accessible solutions for commercial growers across Australia and further afield.

The development of new phenotyping capability by the Future Food Systems CRC is centred around the National Vegetable Protected Cropping Centre (NVPCC) high-tech glasshouse, part of Western Sydney University (WSU).

Instrumentation will include a mounted imaging system above the crop using LiDAR; fluorescence; hyperspectral, thermal; and red, green, and blue (RGB) imaging to monitor a suite of crop parameters. In addition, cost-effective systems for early detection of hydrocarbon volatiles, phytohormones, microscopic pathogens and insect infestation will be employed to monitor plant health and disease development.

In collaboration with UNSW Sydney, these sensors and imaging tools are being linked via a purpose-built Internet of things (IoT) communication system to enable real-time decision-making.

Collaboration with experts in AI and ML is being established to develop algorithms that can be used to analyse the data and reduce it to simple information and decisions to assist growers. Ultimately, these experts will develop user-friendly software and applications for smart devices that can operate the phenotyping units, visualise data output and make decisions in simple steps in real time.

A phenotyping arm will be multiplexed with harvesting, pollinating and application robots, to be developed with robotics experts based at Queensland University of Technology (QUT). Prototypes will be trialled at WSU and in commercial-production high-tech glasshouses operated by our industry partners.

While these facilities are high-tech and expensive, the data collected will provide critical knowledge enabling us to develop more affordable sensors and simpler phenotyping units, such that commercial industry will need only to collect the required data to make sound, real-time, information-based management decisions.

As yet, these techniques are not widely applied, either in controlled-environment glasshouses or the broader PC industry. Our vision is to develop the technology and capacity that's needed to advance smarter agriculture in Australia's urban and peri-urban areas, then make these advancements available to large-scale polytunnel and high-tech glasshouse operations in these areas.

Current industry context

Australia produces more than 6.7 million tonnes of fruit and vegetables a year (Hort Innovation, 2020). *Table 1* shows the top 10 horticultural crops by value produced in Australia in 2018–2019.

Vegetable	Production ($ millions)	Commonly produced in PC
Capsicum	171.1	✓
Head lettuce	172.8	✓
Cucumber	180.3	✓
Onion	191.2	
Fresh herbs	197.9	✓
Carrot	219.3	
Broccoli/baby broccoli	255.7	
Leafy salad vegetables	396.3	✓
Tomato	674.2	✓
Potato	752.6	

Table 1. Top 10 vegetables produced in Australia by value (in millions of dollars), and those commonly produced in PC facilities

Many of these crops – tomato, capsicum, lettuce, cucumber and herbs – are grown in protected-cropping (PC) facilities, such as greenhouses and glasshouses, which allow growers to control the microclimate and protect crops from disease and excess solar radiation (Hadley, 2017).

Types of PC facilities include low-tech polytunnels, in which only protective coverings are used; medium-tech facilities enabling some environmental control; and high-tech facilities such as fully automated glasshouses and indoor vertical-cropping operations with artificial lighting.

PC production systems have significant advantages over field growing systems, as evidenced by the fact that PC environments typically produce higher yields per area than do field environments (*Figure 1*).

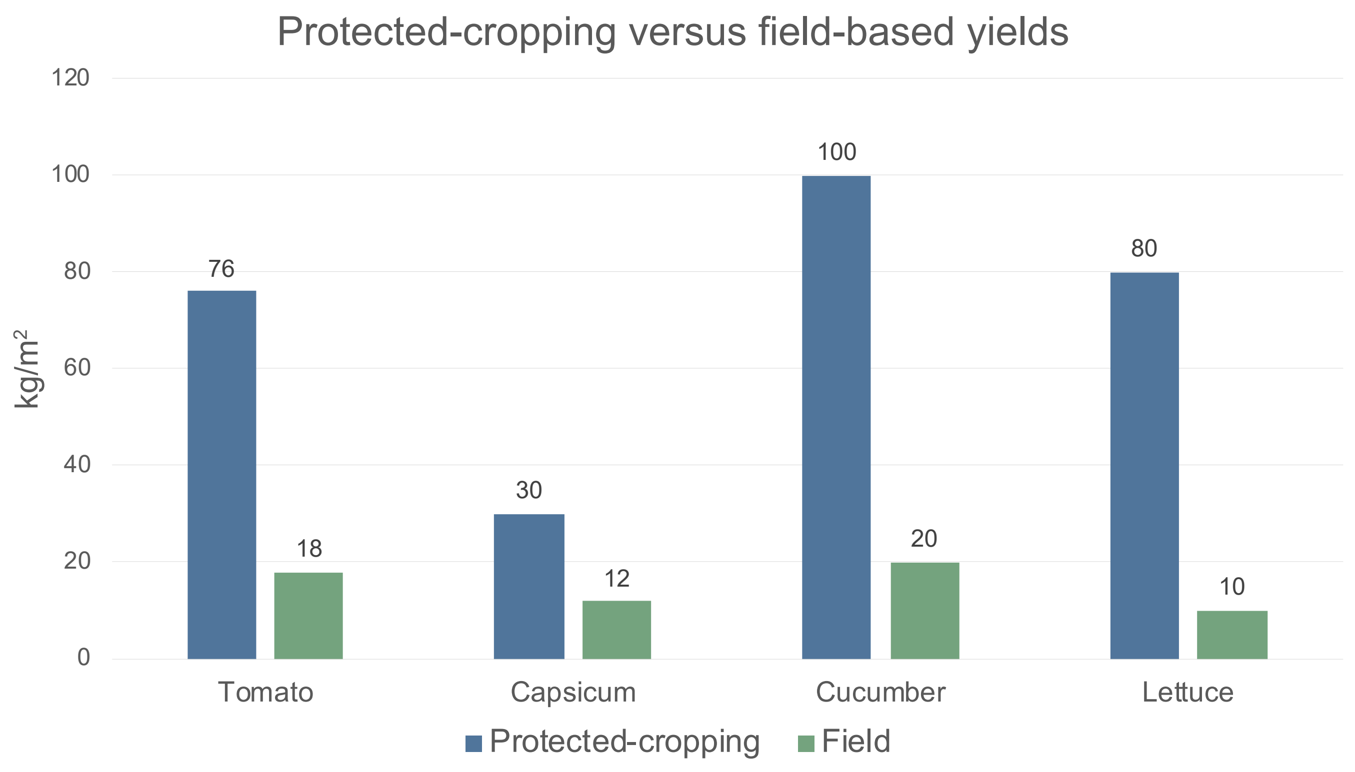


Figure 1. PC-grown crops versus field-based crops (Smith, 2011)

While they tend to be more productive per unit of land area and use less fertiliser and water than field-grown crops, plants grown in PC facilities require more energy per kilogram of produce and higher levels of skilled labour than do field-based production systems (Barbosa *et al*, 2015). The PC industry is researching ways in which to reduce both energy consumption and labour costs. Solutions will come partly from increased automation (such as for harvesting) and partly from real-time phenotyping linked to improved decision-making.

While some technologies are already available for producers, much work remains to be done to adapt and fine-tune sensing and imaging technologies to the needs and conditions of Australia's PC industry, and to develop cost-effective, user-friendly alternatives.

Using phenotyping to advance the protected-cropping industry

A phenotype refers to the observable characteristics expressed as a result of a genotype's interaction with the environment. Plant or crop phenotyping is the science of characterising crop traits such as growth, development, architecture, physiology, health, nutrition and yield.

Non-destructive phenotyping is used to monitor crop health and fruit quality (including plant and fruit nutrient status) and to inform growers about appropriate environmental controls and management strategies, including integrated disease and pest management, for optimal-quality horticultural production.

Already, many plant-phenotyping techniques have been developed for the purposes of breeding, disease detection and improving stress tolerance in field crops (Yang *et al.*, 2013; Humplick *et al.*, 2015; Mahlein, 2016). Phenotyping is also used to monitor plant health, development and fruit quality so growers can take early action to change biotic (disease, insects, etc.) and abiotic (drought, salinity, etc.) conditions and ensure maximum yield.

Plant phenotyping can optimise breeding programs for new varieties that will produce food of high nutritional and aesthetic quality (Li *et al.*, 2014). Appropriate phenotype monitoring can also help growers maximise resource-use efficiency (Fiorani & Schurr, 2013; Riley *et al.*, 2019).

Phenotyping, an essential process in fruit and vegetable production, is particularly important in mitigating the negative impacts of climate change. Going forward, new varieties of heat- and drought-tolerant fruit and vegetables will need to be developed to maintain crop yield and quality.

Currently, assessment of phenotype characteristics relies largely on visual scoring methods deployed by experts, which is time-consuming and can introduce bias via human error (Li *et al.*, 2014). Thus, plant phenotyping has become a field ripe for innovation, with new techniques and technologies needed to hasten breeding programs and help assess quality pre- and post-harvest.

Environmental monitoring: a prerequisite for plant phenotyping

Phenotypic plasticity in response to environmental parameters

High-throughput phenotyping (HTP) platforms have been developed and are being used to collect data for quantitative studies of complex traits related to crop growth, yield, and adaptation to biotic and abiotic stress. Various techniques to assess these traits are available or in development.

Effective phenotyping involves more than assessing crop-related traits; it also requires continuously assessing environmental parameters. Plants' phenotypic expression is highly dependent on environmental conditions; thus the environmental conditions in which a crop is grown must be known and, ideally, controlled, for consistency across a crop cycle.

The environmental conditions that impact crop growth most are: root-zone temperature, moisture and electrical conductivity (EC); light quality and quantity; and air temperature and relative humidity (RH). While some impacts of these environmental parameters on external and internal phenotypic expression are known (Rabbi *et al.*, 2019), others are not. Researchers are continuing to explore the field as better methods of environmental and phenotypic monitoring become accessible.

Root-zone temperature, moisture content and electrical conductivity

Root-zone temperature, moisture and EC play key roles in crop performance. Controlling root-zone temperature is a by-product of maintaining optimal air temperature, while substrate moisture and EC are controlled by irrigation and fertilisation regimes.

Irrigation timing impacts root development in soils and soilless substrates. A moisture-saturated root zone results in poor root development. If early root development is hindered, the plant's ability to produce and bear fruit is reduced because it lacks the root structure required to maintain fruit development.

EC is an indirect measure of nutrient availability. Optimal EC is highly specific to the crop, and is crucial for nutrient uptake. EC that is higher than necessary results in stagnation of nutrient ions. High EC has been related to blossom end rot in tomatoes as, with increasing EC, mass flow is reduced due to less water entering the plant roots (Adams & Ho, 1992). Very low EC, in the case of hydroponic crops, can lead to root cell rupture due to the large imbalance of osmotic pressure across the root membrane.

Light quality and quantity

Light quality and quantity both impact plant development significantly, as light is the main driver in crop production. It is estimated that light quantity is reduced by 30% in glasshouses due to structural shading; this, paired with low light intensity in the winter months, has been linked to low yields and small fruit (Gruda, 2007).

The PC sector has developed cladding material designed specifically not to block solar radiation, as the entire spectrum of solar radiation plays an important role in plant development.

Too little natural light leads to elongation of stems and low fruit yield. In cucumber crops, fruit grown in low light conditions tends to be lighter in colour, and yellows more quickly once harvested (Bakker *et al*, 1995). Misshapen, swollen and hollow tomatoes have also resulted from low light conditions (Gruda, 2007).

In contrast, higher irradiance from the sun results in leaf dehydration and premature shutdown, leading to reduced capacity for photosynthesis and lower crop yield. Excess light can lead to sunscald in a wide range of crops including tomato and capsicum (Gruda, 2007). In lettuce, high-light environments can lead to increased presence of tip burn (Gaudreau *et al*, 1994).

Light quality also influences internal and external phenotypic expression. Plants primarily use 'photosynthetically active radiation' (PAR), made up of wavelengths ranging from 300–700 nm. Exposure to red light has been shown to reduce the bitter flavour in lettuce leaves (Eskins *et al*, 1996), while UV-B exposure causes plants to accumulate secondary metabolites that influence a variety of physiological processes and affect the internal quality of some vegetables (Gruda, 2007).

Temperature and relative humidity

Temperature and RH are important environmental variables that must be maintained for proper crop development and to achieve maximum yield. Closely related environmental parameters, they influence one another. RH is a measure of the percentage of moisture the air can hold as vapour at that particular temperature – hence, as temperature rises, RH falls, and vice versa. Crops also have different microclimate needs at different stages of development. Thus, continuous measurement is necessary to maintain these parameters.

While optimal temperatures for day and night will vary with crop type and variety, the majority of horticulturally produced crops are warm-weather varieties, with their main growing seasons occurring over the summer months. Typically, temperatures between 20 and 30°C and with an RH of 50–80% are desirable; however, each crop variety can have specific requirements. Cucumber, for instance, has been shown to taste sweeter when grown in moderate RH as opposed to high RH and, in general, to produce better-quality, better-looking fruit when grown under moderate-RH conditions (Ali, 2017).

While air temperature is an important parameter, studies have shown that canopy (leaf) temperature may be far more important. As leaf temperature is directly related to transpiration rates, measuring it also provides information about plant water status (Shamshiri *et al.*, 2018).

Sensor technology to monitor environmental parameters

Maintaining consistent environmental conditions is essential for achieving reproducible phenotypic responses from different genotypes. By controlling environmental conditions tightly, ideal plant growth and development can be achieved, enabling the grower to identify and target developmental stages and in turn, identify specific traits.

Moreover, deviations from typical phenotypic expression become more obvious under tightly controlled conditions, so assessing disease, plant health and fruit quality is more straightforward.

Various sensors are available to monitor air temperature, RH, root-zone temperature, moisture and EC, as well as light quantity and quality (*Table 2*). While all these parameters (shade curtains, irrigation etc.) can be monitored individually via computer or smartphone, and their control mechanisms changed manually, integrated hardware and software systems that can manage them automatically are also available.

Summary

In summary, plants have plasticity to alter their phenotypes, exhibiting different external and internal traits depending on their environment. Controlling the environment and capturing data is important throughout the phenotyping process, as antecedent events can result in changes in a plant's progeny – known as the 'memory effect' (Pieruschka & Schurr, 2019). Frequent, high-throughput phenotyping promotes faster acquisition of phenotypic data for correlation with genomic information (Solanke & Kumar, 2013).

In protected cropping, phenotypic expression dictates fruit aesthetic and nutritional quality, pre- and post-harvest, which suggests that two important subjects need to be considered:

- precise control over crop microclimate to maintain desired phenotypic expression across crop cycles; and
- frequent phenotypic surveys of plants and fruit, throughout the cropping cycle and during post-harvest sorting, storage and distribution.

Environmental parameter	Impact on crop	Sensor	Control mechanism	Example
Electrical conductivity (EC)	High: Blossom end rot, nutrient deficiency, reduced yield. Low: Cell rupture.	Slab or soil EC sensors (usually includes temperature and moisture measurements).	Irrigation regimes, pH modification, EC modification of stock solution.	
Root-zone moisture	High: Roots do not develop enough to support full-grown, producing plant. Low: Root die-off and plant dehydration.	Soil moisture probes or slab or soil EC sensors (usually includes temperature and moisture measurements).	Properly timed irrigation, proper landscaping to prevent pooling (slope).	
Root-zone temperature	High: >25°C, NH_4 toxification leading to cell death. Low: 3–11°C, NH_4 uptake stimulates plant growth.	Soil-temperature probes, or TDR probes, that include temperature, moisture and EC measurements.	Shade cloth, irrigation solution temperature, heating pad, heating cables.	
Air temperature	High: Leaf dehydration, earlier stomatal shutdown. Metabolic shutdown due to inability to dissipate heat. Low: Delayed blooming, stunted or slow growth. Large day-night temperature differentials impact fruit set.	Dual air-temperature and relative-humidity probes.	Pad and fan cooling, cold-coil fan cooling, shade cloth to reduce radiant heat, hot-water pipes, hot air via external heat source.	
Relative humidity (RH)	High: Low stomatal conductance, reducing nutrient distribution to plant and fruit. Low: Early stomatal shutdown resulting in reduced photosynthesis.	Dual air-temperature and relative-humidity probes.	Misting system, condensing system, dehumidification.	
Light quality	280 nm: Reduces quantum yield and rate of photosynthesis. 315-400 nm: Promotes pigmentation, thickens plant leaves. 400-440 nm: Promotes vegetative growth. 640-660 nm: Vital for flowering. 740 nm: Increases photosynthesis. (Zwart, 2018)	Spectroradiometer, or a combination of PAR and net radiometer.	Coloured shade cloth, fluorescent films, light supplementation.	
Light quantity	High: Leaf dehydration, sunscald, photodamage and lowered photosynthetic rates. Low: Stem elongation, lower photosynthetic rate, reduced yield, misshapen fruit, reduced shelf life.	PAR sensors.	Shade cloth, light supplementation using light emitting diodes (LEDs).	

Table 2. Environmental parameters and crop impact, listed with available sensor technology and control mechanisms to maintain optimal conditions

Non-destructive phenotyping in protected cropping

Past techniques for assessing crop health, fruit quality and pest/disease status required destructive measurements. But recent advancements in gas chromatography, optical sensors, microwave resonators, spore detection methods and imaging techniques mean that soon, most forms of plant phenotyping will be able to be done harmlessly and rapidly, in real time. Before this can happen, however, emerging phenotyping technologies must be assessed for suitability across various crops, requiring large datasets, AI and ML, and cross-disciplinary collaboration.

Overview

In the past, plant phenotyping techniques have required destructive measurements in order to assess plant health, fruit quality and the presence of pests or disease. However, with the advancement of optical sensors, gas chromatography and other optical analytical methods, plant phenotyping can be done quickly and harmlessly.

Imaging techniques, coupled with computer analysis, provide fast and non-destructive methods by which to evaluate fruit during its development, harvest and post-harvest periods. Use of these technologies started in the 1990s after the development of charge-coupled-device (CCD) and complementary-metal-oxide-semiconductor (CMOS) technologies (Pieruschka & Schurr, 2019). CCD and CMOS sensors are used to measure colour in different food products, from seed to fruit quality (Wu & Sun, 2013; McCraig, 2002). Increasingly, these applications are being used for fruit quality control.

Today, imaging plants is more than taking photographs using RGB cameras; it also includes precise measurement of the wavelengths of photons reflected, absorbed or transmitted by plant tissue. Indeed, each component of a plant cell has wavelength-specific transmittance, absorbance and reflectance properties (Li *et al*, 2014).

Phenotypic imaging techniques span the electromagnetic spectrum and include machine-vision visible imaging, imaging spectroscopy (multispectral and hyperspectral remote sensing), thermal infra-red imaging, fluorescence imaging, 3D imaging and tomographic imaging (magnetic resonance, positron emission and computer tomography).

Primarily, visible imaging techniques are used to measure plant architecture – such as biomass, leaf area, colour, growth dynamics, seed vigour and morphology – and root architecture, as well as leaf disease, yield, and fruit number and distribution. Disease can be detected by the use of fluorescence imaging. Plant temperature and stomatal conductance, related to plant water status and transpiration rate, can be measured by thermal infra-red imaging (Li *et al*, 2014).

Other imaging techniques are also deployed, albeit less often. A microwave resonator can non-invasively determine plant water content, then interpolate the total plant biomass. The dielectric properties of a microwave resonator change when plant material is inserted into the cavity, with this change proportional to the plant's water content. By separating the root and growing media from the plant with a copper plate, researchers were able to monitor intact plants and assess diel growth patterns, allowing for fast, integrative assessment of plant growth, water status and physical attributes. Being able to assess this metric is valuable, as a plant's ability to produce biomass determines its vigour and eventual crop yield (Menzel *et al.*, 2009).

Gas-chromatography with mass spectrometry and proton transfer-reaction spectrometry can be used to identify and quantify volatile organic compounds (VOCs) emitted by a plant. The resulting VOC profile gives valuable information on the plant's stage of growth and whether it is experiencing stress from biotic and/or abiotic sources.

Spore detection methods are also being used as an early warning system for disease. While techniques for microbial identification exist, these require culturing, whereas methods being developed use optical analysis to identify fungal spores in real time (West & Kimber, 2015).

External evaluation of the fruit and edible portions of commercial crops is essential for marketability, further selection of desirable traits and development of proper crop-management practices. As all data must be comparable (Pieruschka & Schurr, 2019), standardisation should be a key aspect of sensor development across the industry as these techniques progress.

Crop growth and yield

Crop canopy (leaf) temperatures can be measured using thermal infra-red imaging – which is useful, given the direct relationship between leaf temperature, stomatal conductance and transpiration rate (leading to evaporative cooling). However, there are technical challenges in adopting this method, as environmental temperature and air movement can impact the measurements (Berger *et al.*, 2010).

RGB/visible measurements are used to assess growth rate, or biomass accumulation. Near infra-red measurements can be used for decreasing leaf water content (Seelig *et al.*, 2008; Seelig *et al.*, 2009).

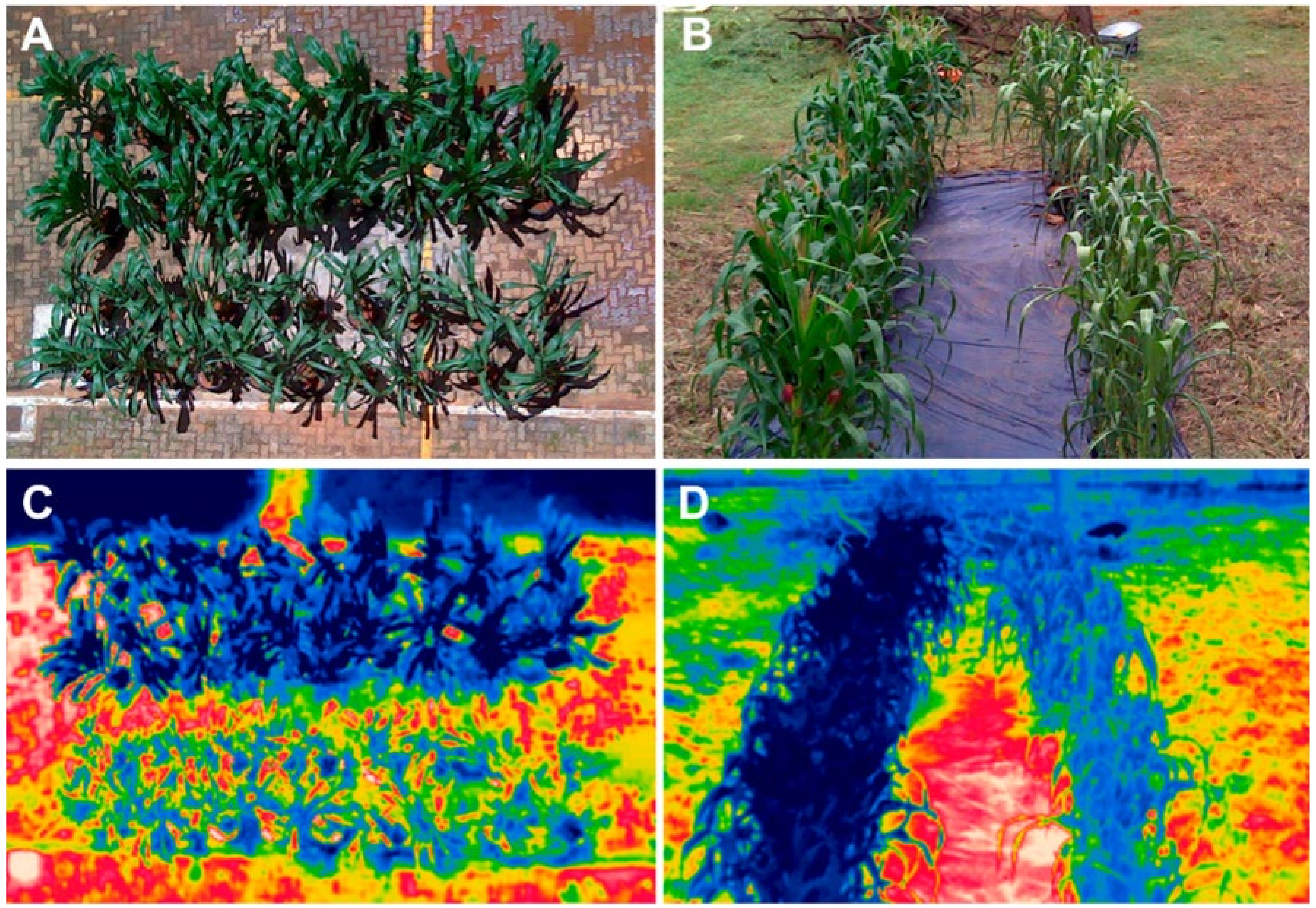


Figure 2. RGB (A, B) and thermal images (C,D) of maize plants taken on the 4th (A,C) and 12th (B,D) day of drought stress. The upper (A, C), and left-hand side (B, D) rows of dark green (RGB) and dark blue (thermal) are control plants, while the lower and right-hand side rows of pale green and light blue are drought-stressed plants (Casari et al, 2019)

Fruit and leaf quality

Hyperspectral imaging for crop quality assessment has recently been developed. Fruit contain different concentrations of nutrients depending on the environmental conditions in which they've developed. Different internal chemical compositions scatter, reflect, absorb and/or emit different wavelengths of electromagnetic energy in specific ways – thus light can be used to characterise the fruit and other organic components of a plant non-destructively (Dale *et al*, 2013).

Plant chlorophyll content is a measure of plant health; it also correlates with carotenoids, nitrogen and maximum green fluorescence. One commonly used, well-tested technique for ascertaining plant chlorophyll content is the normalised difference vegetation index (NDVI). By using near-infra-red (NIR), a plant's NDVI (NIR reflectance–red reflectance/NIR reflectance+red reflectance) can be calculated to estimate plant chlorophyll concentrations (Li *et al*, 2014).

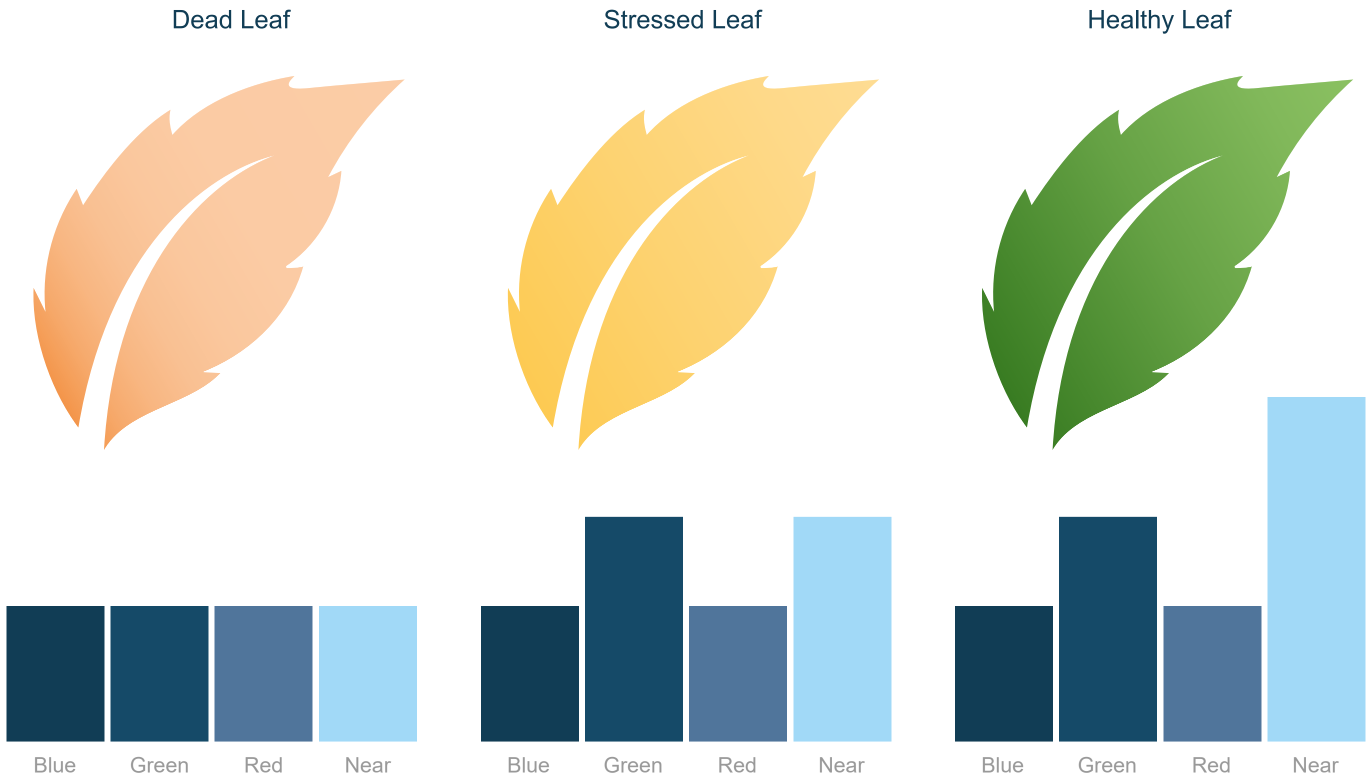


Figure 3. Demonstration of reflected blue (B), green (G), red (R) and near infra-red (NIR) light from dead, stressed and healthy leaves (Caballero et al, 2020)

Fruit and leaf stress can be identified by numerous imaging techniques; however, there are multiple causes for such stress, which could be abiotic or biotic in nature. This is why it is important to model for particular stresses. Applying spatial patterning analyses to multispectral and hyperspectral imaging will greatly improve the determination of likely cause(s) of stress, aiding management decisions (Caballero *et al*, 2020).

Fluorescence measurements are also used to assess chlorophyll content. Fluorescence is related to photosynthetic activity; however, it is limited to an area of 100 cm^2 and is optimised only for planophyll leaves (Woo *et al*, 2008).

Scientists are developing more efficient ways to measure plant chlorophyll content using Google Glass. A leaf is put into a portable illuminating device and two photographs are taken: one under white LEDs; the other under red LEDs. The two photos are sent to a server in under 10 seconds and analysed for chlorophyll content. To date, scientists have successfully calibrated the equipment for 15 species. While these species were deciduous trees, this method could easily be applied to horticultural crops, enabling rapid assessment of plant health in the future (Cortazar *et al*., 2015).

Much of plant-health and fruit-quality monitoring is done using light sensors, and smartphone cameras are starting to become more useful in this realm. Smartphones have also been used to monitor plant stress using the NIR spectrum, by evaluating NDVI. Smartphones have recently had their NIR-blocking filters removed, allowing for the sensing of NIR wavelengths by the CMOS sensor. Chung *et al.* (2018) used an NIR high-pass filter, which allowed for sensing of wavelengths above 800 nm, to collect NIR reflectance, then captured red reflectance without the filter.

Disease

Plant diseases have deleterious effects on the growth and development of crops, which can reduce yields significantly and make the resulting agricultural products unfit for consumption. Globally, plant disease accounts for 10% of reduction in yield (Mutka & Bart, 2015).

Currently, we lack understanding of many plant-pathogen systems and of the physiological mechanisms of disease symptoms in response to pathogen infection (Mutka & Bart, 2015). By using spectral images, which can measure light outside of the visible spectrum, we can quantify disease symptoms invisible to the human eye. Expanding the detection range may allow for earlier detection of diseases, enabling growers to take prompt action to mitigate disease impact.

Plants emit a large array of volatile organic compounds (VOCs), which consist of various chemical classes such as terpenes, fatty-acid derivatives, alcohols, alkanes, alkenes, esters, terpenes, isoprene and acid. Plants emit these compounds from their flowers, fruits, leaves and roots. Constitutive VOCs are those that are controlled largely by genetic and environmental conditions; induced VOCs are those that are highly phenoptically plastic, with their emission affected by abiotic and biotic factors.

Scientists are starting to use real-time 'VOC detection' methods, such as gas chromatography mass spectrometry and proton transfer-reaction spectrometry, to investigate disease and pest presence on crops before visible indications are apparent (Niederbacher *et al*, 2015). In many cases, fungal crop infections that negatively impact crop production are already widespread and difficult to treat by the time they are visible to the naked eye. By using continuous air-sampling techniques, with optical sensors to detect the presence of spores, fungal infection can be detected well before crop performance is impacted (West & Kimber, 2015).

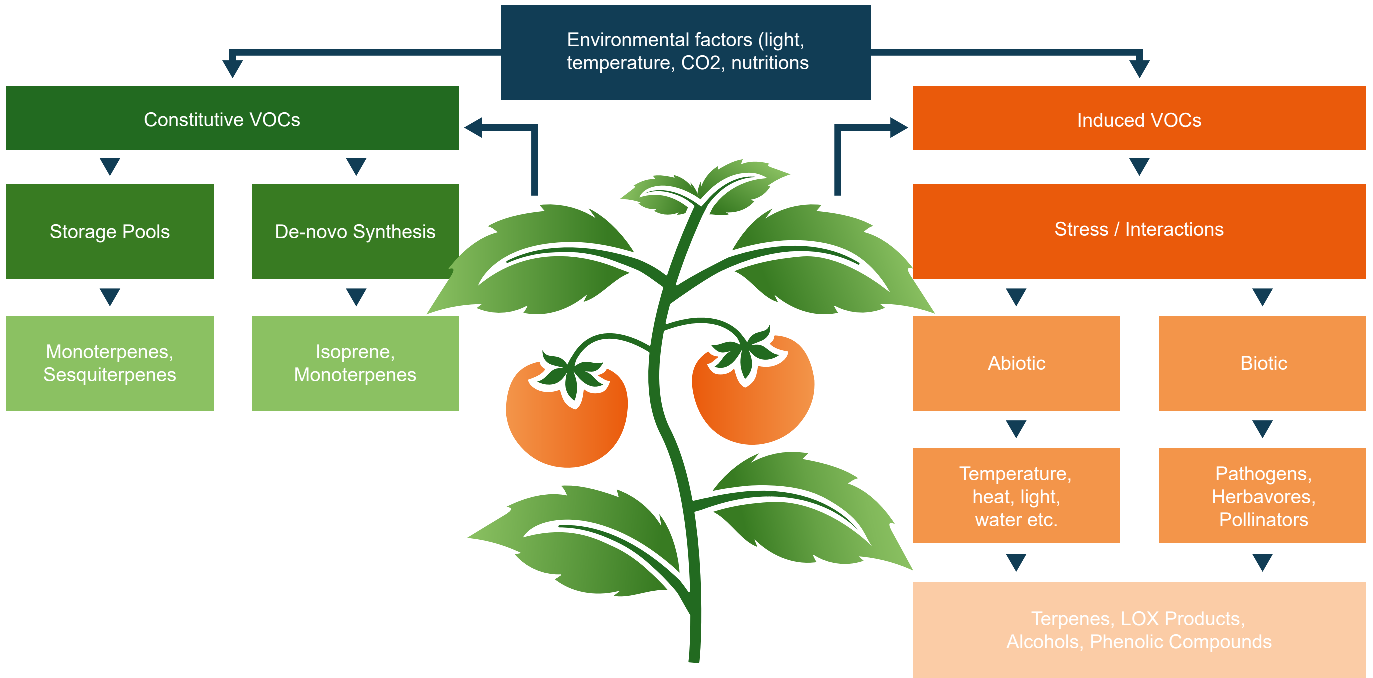


Figure 4. Graphic of constitutive and induced volatile organic compounds (VOCs) and causes (graphic by Niederbacher et al, 2015)

Breeding, new varieties and seeds

Much of the advancement in plant phenotyping has been driven by breeding programs (Fiorani & Schurr, 2013). Research is now aimed toward producing varieties of plants through breeding that will be better adapted to low-input agriculture and resource-limited environments, with pest and disease resistance and drought tolerance.

Seed selection is an important element within breeding programs as seed germination rates and vigour are the two most important measurements for seed performance and thus plant performance. High-throughput seed phenotyping hardware and software technology being developed use machine-learning, image-based technology to assess germination rates and vigour. This technology has been prototyped and tested on a number of crops and will be made commercially available in the near future (SeedGerm, 2018).

Overall, by connecting a plant's genetic make-up (its genotype) to the internal and external characteristics expressed (its phenotype), plants can be selected for high yield and stress tolerance more rapidly, advancing breeding programs and maintaining quality fruit production over a crop cycle.

Increasing breeding efficiency is hugely important for producing high-yielding, disease-tolerant varieties; however, phenotyping is important for monitoring *in situ* plant health and fruit quality in order to make optimal real-time adjustments (Li *et al*, 2014). Accurate phenotyping will help breeders select plants that will adapt better to resource-limiting environments and low-input agricultural systems (Kim, 2020).

Summary

Non-destructive phenotyping techniques are being developed (with some already validated) to assess crop growth, yield, fruit and leaf health status, and disease presence. While many of these techniques are undergoing scientific tests, others are still in initial phases of development. Phenotyping imaging techniques have been validated for specific plant varieties; however, more data are needed to establish whether other varieties can be phenotyped using these technologies (Li *et al*, 2014). The data collected needs to be across growth stage, health status and abiotic and biotic stresses so that specific image signatures can be defined for each plant variety. To validate over such a range of plants will require huge amounts of data capture and analysis, requiring cross-disciplinary collaboration with AI and ML.

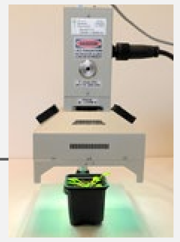
Phenotyping technique	Sensor	Resolution	Phenotype parameters	Examples
Imaging techniques				
Visible light imaging	Cameras sensitive in the visible spectral range	Time series of whole organ or organ parts	Shoot biomass, yield, root architecture, germination rate, morphology, height, size and flowering time	
Fluorescence imaging	Fluorescence cameras and set-ups	Whole shoot or leaf tissue; time series	Photosynthetic status (variable fluorescence); quantum yield; leaf health status; shoot architecture	
Thermal imaging	Near-infra-red cameras	Pixel-based map of surface temperature in the infra-red region	Canopy or leaf temperature; insect infestation of grain	
Near-infra-red imaging	Near-infra-red cameras; multispectral line scanning cameras; active thermography	Continuous or discrete spectra for each pixel in the near-infra-red region	Water content composition parameters for seeds; leaf area index	
Hyperspectral imaging	Near-infra-red instruments, spectrometers; hyperspectral cameras; thermal cameras	Crop vegetation cycles; indoor time-series experiments	Leaf and canopy water status; leaf and canopy health status; panicle health status; leaf growth; coverage density	
3D imaging	Stereo camera systems; time-of-flight cameras	Whole-shoot time series at various resolutions	Shoot structure; leaf angle distributions; canopy structure; root architecture; height	
Laser imaging	Laser scanning instruments with widely different ranges	Whole-shoot time series at various resolutions	Shoot biomass and structure; leaf angle distributions; canopy structure; root architecture; height; stem length	
Gas and volatile organic compound analysis				
Proton transfer-reaction spectrometry	Mass spectrometer	Whole plant or single leaf	Pest presence, abiotic stress indicator	
Gas chromatography with mass spectrometry	Mass spectrometer	Whole plant or single leaf	Pest presence, abiotic stress indicator	
Fungal detection techniques				
Impinger or wet-cyclone	Liquid entrainment for optical analysis	Depends on entrainment method	Size, scatter and pigmentation	
Wide issue bioaerosol spectrometer (WIBS)	Optical sensors	0.8–20 µm	Particle size, symmetry, scatter, fluorescence and absorbance	
Particle fluorescence	Optical sensors	0.5–50 µm	Particle fluorescence	

Table 3. A summary of the phenotyping techniques and their applications. Modified from Li et al, 2014

Conclusions and recommendations for protected cropping

By deploying environmental control systems and rapid real-time phenotyping techniques, Australia's protected-cropping growers can maximise yields, improve crops' aesthetic appeal and reduce losses, giving them a competitive edge in domestic and export markets. Next-gen phenotyping techniques can also help breed varieties better suited to future cropping environments. However, developing emerging phenotyping techniques into cost-effective IoT tailored to indoor cropping requires amassing large datasets to build ML 'libraries', demanding significant collaborative effort and expertise.

By adopting environmental control systems and rapid real-time phenotyping, growers can maximise yields, improve the aesthetic appeal of crops and reduce losses related to biotic and abiotic stresses. This transformation will likely increase their competitive edge in emerging markets for customised, nutritious and provenance-verified quality foods.

To help advance Australia's horticultural industry, it is recommended that growers of different scales implement the use of environmental sensors, climate-control mechanisms and phenotyping techniques. Doing this will assist them greatly in maximising yield, reducing disease impacts and hastening breeding programs to produce new varieties suited for future climates and environments. Fully integrating smart control of growth facilities will also increase flexibility, empowering growers to manage crops remotely.

Key needs for investment from AI and ML developers

Standardisation and data management are key topics for the future of crop phenotyping. Big-data management and protocols will be necessary, as many of the phenotyping techniques explored herein – particularly imaging techniques, require sophisticated post-processing procedures that include self-learning algorithms (Pieruschka & Schurr, 2019) – require the collection of vast amounts of data.

The data generated can be used to build libraries for ML (Lobet *et al.*, 2013). With investment from experts in and developers of AI and ML, post-processing of large datasets can be achieved quickly, with inbuilt management-decision suggestions.

Developing IoT tailored to indoor cropping will greatly facilitate data transfer and analysis as well as decision-making; this is a key research activity of WSU-based activities within the Future Food Systems CRC.

What we plan to do at the National Vegetable Protected Cropping Centre

Collaboration with Future Food Systems CRC partners will enable researchers in high-tech facilities to investigate, develop and test emerging technology that will advance plant phenotyping and ultimately improve crop productivity.

The WSU NVPCC provides an ideal location in which to tightly control environmental parameters and test and develop the various technologies that will ensure accurate assessment of phenotypic variability and maximum crop production.

This facility is one of many that will be used for testing and implementing controlled-environment and high-throughput phenotyping, and its researchers will liaise closely with Future Food Systems industry partners to meet our shared goals of optimising crop production and improving economic returns to growers.

Future Food Systems is in discussion with industry partners keen to test their technology for measuring chlorophyll fluorescence and kinetics, plant reflectance indices, and spectral qualities of natural and artificial light, all of which can inform growers in making optimal management decisions, as previously outlined in this report.

Other phenotyping experts will bring to Future Food Systems their expertise in monitoring diseases and pests, plant health and fruit quality, and the associated management decisions required to ensure maximum crop yield.

Future Food Systems is working with industry partners to develop IoT wireless sensor arrays to increase data-collection resolution in protected-cropping environments. The aim of the system is to collect and transmit only useful data that enables faster, simpler decision-making by growers.

The CRC continues to seek industry partners and research teams that can advance Australian horticulture. With investment from both, we can achieve advancements in agriculture that, potentially, propel Australia into a position of global leadership in this field.

Figure 6. The National Vegetable Protected Cropping Centre, located at Western Sydney University's Hawkesbury campus

Further information

Protected Cropping Toolkit (Protected Cropping Australia, March 2020)
https://protectedcropping.net.au/protected-cropping-toolkit/

A series of practical, informational videos from Protected Cropping Australia, the main industry body for Australia's protected cropping operators, large and small. Topics covered include (list the video titles here).

Reports, publications and fact sheets (Hort Innovation)
https://www.horticulture.com.au/growers/help-your-business-grow/research-reports-publications-fact-sheets-and-more/

Useful information for growers from the peak industry body for Australia's horticulture sector – an estimated 30 per cent of which consists of commercial protected-cropping operations that range from major growers to boutique operations located across all states and territories.

Here, you'll find resources on a broad variety of fruits and vegetables grown by PC operators across Australia, including blueberries, strawberries, rubus (raspberries, blackberries), tomatoes, melons, cucumbers, capsicum, salad (including Asian) greens, herbs, chillies, eggplant and more.

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