Advances in high-throughput crop phenotyping using unmanned aerial vehicles (UAVs)

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Advances in high-throughput crop phenotyping using unmanned aerial vehicles (UAVs)

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1 Introduction

Over 10 years ago, unmanned aerial vehicles (UAVs) were seen as bringing about a new era in agriculture (Zarco-Tejada, 2008). Seen from today's perspective, the biggest impact in the application of UAVs in agriculture can be seen in high-throughput field phenotyping. Field phenotyping refers to a quantitative description of a plant's phenotype – that is, its anatomical, ontogenetical, physiological and biochemical properties – in its natural environment (Walter et al., 2015). In the context of breeding, where hundreds or even thousands of different genotypes need to be screened for their effect on plant traits and performance, high-throughput field phenotyping allows the timely and rapid screening of multiple traits in the early stages of breeding. This offers the potential to reduce the duration of breeding cycles and avoid loss of potentially important alleles due to linkage drag (Araus and Cairns, 2014; Furbank and Tester, 2011; Rebetzke et al., 2019).

Since UAV systems have matured as remote sensing platforms (Aasen et al., 2018), almost all the 'big players' in the area of field phenotyping (research groups, companies and other organizations) have started to use UAVs for

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measurement (see reviews by Araus et al., 2018; Cendrero-Mateo et al., 2017; Hund et al., 2019a; Rebetzke et al., 2019; Tardieu et al., 2017). This has led to increasing adaption of remote sensing technologies by agronomists, reflected in an exponential increase in publications (Fig. 1), which has helped significantly in relieving the phenotyping bottleneck.

This is a welcome trend since the potential of remote sensing has long been underexplored in agricultural sciences. However, using UAV technologies also comes with challenges since not every agronomist has a background in remote sensing or image processing. Additionally, some companies can underplay the challenges in flying a particular UAV-mounted sensor for reliable trait extraction. This chapter discusses approaches to UAV remote sensing and data analysis for high-throughput field phenotyping and ecophysiological research.

2 Remote sensing tools: unmanned aerial vehicles and flight protocols

2.1 UAVs

A typical field phenotyping set-up may involve a couple of hundred to several thousand plots. These consist of patches of crop canopies with uniform conditions, ranging in size from single plants/rows to machine harvestable yield plots of a few metres. Each plot needs to be screened. Unmanned aerial vehicle remote sensing combines the potential of capturing highly spatially resolved data with

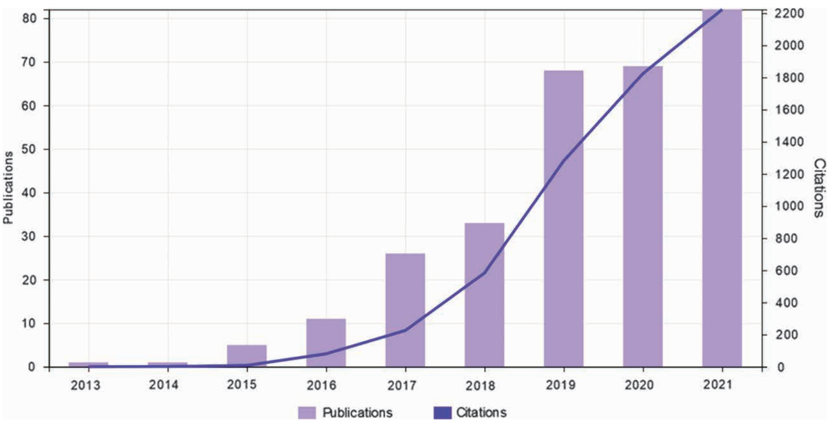

Figure 1 Number of publications and citations with the topics field phenotyping and UAVs. Please note that only publications and citations until August 2021 are shown. Ts = (UAV* or UAS* or 'unmanned aerial vehicle*' or 'unmanned aerial system*' or 'unmanned aircraft system*' or 'RPAS' or 'remotely piloted aircraft system') and (phenotyping or 'field phenotyping' or 'field-phenotyping') and Articles or Review Articles or Early Access (Document Types) and Articles or Review Articles or Book Chapters (Document Types).

high throughput and a wide choice of sensors. In contrast to UAVs, handheld measurement tools are lower cost, easy to set up and highly flexible (Aasen et al., 2020; Perich et al., 2020). They have been supplemented by phenotyping stations (e.g. where arrays of sensors are mounted on gantries which scan plots from above) such as the 'Field Phenotyping Platform' (FIP) at ETH Zürich in Switzerland (Kirchgessner et al., 2017), the 'Field Scanalyzer' in Rothamsted in the UK (Virlet et al., 2017) and similar stations elsewhere (see e.g. Hund et al., 2019b). These technologies arguably have the best ground sampling distance (GSD) in optimizing image resolution. However, sampling large field experiments with such devices is in most cases impractical due to the high running costs and the length of time needed to sample a whole experiment with potentially hundreds of plots. Changes in environmental conditions during the sampling period can also distort the results, for example, in the case of thermal and spectral measurements (Deery et al., 2016; Perich et al., 2020; Sagan et al., 2019) (Fig. 2).

In contrast to phenotyping stations, UAVs have relatively low set-up and running costs. Additionally, the size of the coverable area is only limited by the flight time of the carrier system and can be extended by combining imagery from multiple flights (Perich et al., 2020) or by adjusting the flight height at the expense of lowering the GSD. While fixed-wing UAVs are more efficient when it

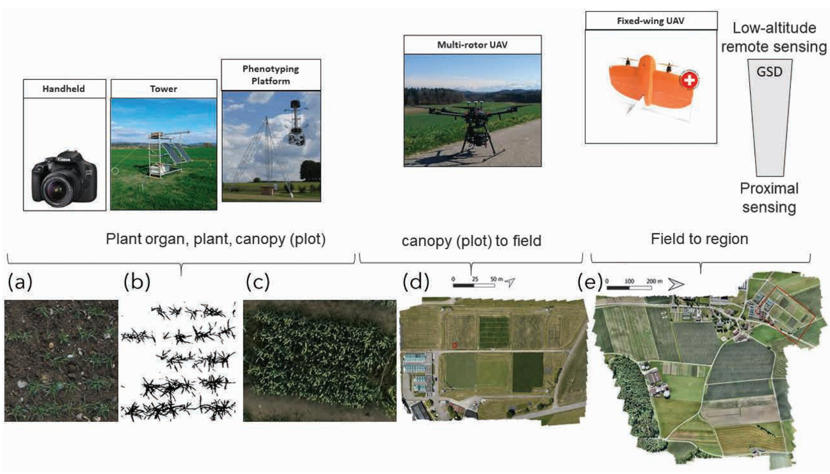

Figure 2 UAV sensing systems in comparison with other field phenotyping approaches regarding coverage and ground sampling distance (GSD). (a) and (b) are images taken with the field phenotyping platform (FIP) with 0.0005 m GSD and a segmentation of leaves using the method of (Zenkl et al., 'in review'). (c) is the area of a plot extracted from a multi-rotor UAV flying at 30 m above ground altitude (AGA) with 0.003 m GSD. (d) is an orthomosaic with an extent of 2 ha and a GSD of 0.008 m generated from a multi-rotor UAV flying at 80 m AGA. The red rectangle marks the area of (c). (e) is an orthomosaic with an extent of approximately 60 ha and a GSD of 0.013 m generated from a fixed-wing UAV flown at 110 m AGA. The red rectangle marks the area of (d).

comes to aerial coverage, multi-rotor systems are more flexible when it comes to flight trajectory. Multi-rotor UAVs also have greater payload potential than fixed-wing UAVs, making it possible to mount a wide range of spectral, thermal, RGB or LiDAR sensors (Aasen et al., 2018; Yang et al., 2017; Lucieer et al., 'in preparation').

Unmanned aerial vehicles can measure traits of interest with relative ease across several hectares in a couple of minutes. The exact coverage over time depends on the GSD necessary to extract the trait of interest. Frequent measurements can be made with no disturbance of the soil or plants. Measurements can also potentially be undertaken by non-experts since flight paths and data capture can be programmed. Unmanned aerial vehicles also allow measurements in multiple locations. Key to repeatable and reliable trait extraction are well-established flight (cf. Section 2.2) and trait extraction protocols (cf. Section 3).

2.2 Flight protocols

Defining UAV measurement protocols can be complex. It requires a good understanding of the sensing system, data processing and analysis (Aasen et al., 2018). Moreover, optimizing measurement results and flight time requires additional infrastructure such as georeferencing ground control points (GCPs) or radiometric ground control points (RCPs). Finally, the flight plan and sensing equipment (flight height, flight speed, angular composition of data, focal length, image resolution, exposure time) need to match the requirements given for the trait of interest (ground sampling distance and motion blur). There are several tools available to help with configuring flight parameters and equipping the area of interest, for example, with GCPs or RCPs (Roth et al., 2018b).

3 Major plant traits that can be extracted using unmanned aerial vehicle remote sensing

The following section discusses some important traits for field phenotyping. Topics are arranged across the growing period from germination to senescence. The discussion ranges from basic feature extraction techniques to their application in an ecophysiological and breeding context.

3.1 Canopy cover and leaf area index

There are different terms to describe plant canopies. Canopy cover describes how well a plant canopy covers the soil. A physiologically more relevant term is leaf area index (LAI) which describes total leaf coverage per unit of ground surface area. The LAI can reach values well above one (e.g. around six for wheat at the end of the vegetative stage) if multiple layers of leaves in a canopy cover a given ground area. It is challenging to measure the LAI nondestructively as soon as multiple leaf layers overlap. Even in the early season, where there are few overlaps, it is not straightforward to estimate LAI. Leaves are often not planar and grow at a certain inclination angle, leading to a complex 3D geometry. This makes it difficult to estimate a correct leaf area; oblique viewing geometries (e.g. towards the edge of an image) may introduce biases due to perspective distortion.[1] Keeping these constraints in mind, two major approaches are used to estimate leaf area:

1 image-based leaf-from-soil segmentation; and
2 absorption-based proxy measurements.

These are discussed in the following sections.

3.1.1 Leaf area estimation by image segmentation

Image segmentation-based leaf area estimation is based on differentiating between 'green' leaf pixels and 'brown' soil pixels using some kind of classification programme. The ratio of 'green' to total pixels is expressed as the canopy cover. These ratios are also referred to as fractional cover or green cover. Besides the constraints already mentioned, the precision of this method of measurement relies on the ability to differentiate 'green' from 'brown' pixels in the image. The GSD and motion blur need to be tuned to reach the necessary precision (Hu et al., 2019; Roth et al., 2018b). This is relative to the organ (leaf) size and is thus crop specific (cf. Fig. 3). Moreover, shadows and overexposure of reflecting leaf parts can compromise the precision of classification.

Decision tree-based segmentation techniques are often used to segment 'green' plant material from the background (e.g. soil and stones). Examples of these classifiers are Random Forest classifiers (in their simplest form using Otsu thresholding to create a binary image) (Torres-Sánchez et al., 2014). These segmentation techniques are used in combination with different colour space transformations to make classification more robust (Roth et al., 2018a, 2020). The most recent segmentation approaches also include information about neighbouring pixels for more precise classification. A recent study by Zenkl et al. ('in review') has compared different segmentation approaches for very-high-resolution RGB images (0.003 m) of the *Eschikon Wheat Segmentation Dataset*. The study concluded that a deep learning-based approach outperformed other machine learning methods using Support Vector Machines and/or

1 The curious reader may grab his/her rubber boots, go to a crop field and look at the same spot from right above the spot and a few metres aside from it.

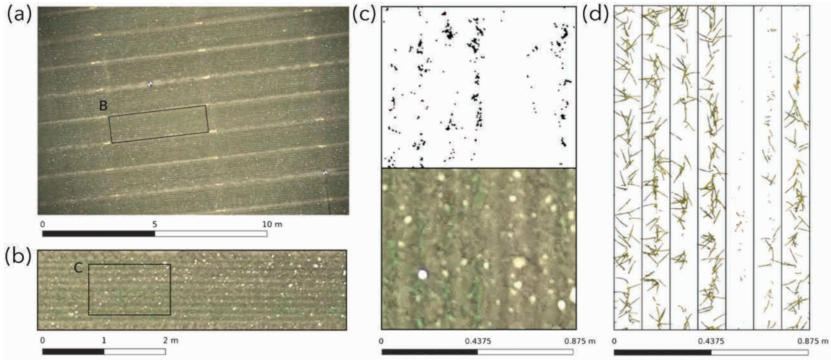

Figure 3 Example of UAV image of wheat (a, b, c) with a GSD of 3 mm per pixel that covers an area of approximately 13 × 9 m in comparison to an image captured with the field phenotyping platform (FIP) of ETH Zurich with a GSD of 0.3 mm per pixel that covers an area of approximately 0.9 × 1.2 m (d), both taken at 12 November 2018 one month after sowing. Illustrated are the original RGB images (a), the shape of the yield plot (b), a subsample of the plot where a Random Forest segmentation approach was applied (Roth et al., 2020) (c) and the same subsample in a FIP image where a deep learning semantic segmentation was applied (Zenkl et al., 'in review') (d).

Random Forest. Most methods are able to assign degrees of uncertainty to the prediction, which means these uncertainties can be taken into account in subsequent processing steps (Roth et al., 2021). However, performing such studies requires well-annotated datasets such as the *Eschikon Wheat Segmentation Dataset* (Zenkl et al., 'in review').

Another 'trick' that can be used to improve leaf area estimation by image segmentation is to make full use of information from multiple overlapping images captured from different angles. Such images are often acquired sequentially by UAVs flying with a constant velocity over a canopy and taking images at equidistant time intervals. Objects on the ground are then captured from slightly different angles in subsequent images. This so-called multiview imaging combines complementary information in these images to improve prediction of leaf area (Roth et al., 2018a, 2020). Nevertheless, all segmentation-based methods reach their limit of accuracy as soon as full canopy closure is reached.

3.1.2 Absorption-based leaf area estimation

A different approach is to use the absorption of plant matter (the change in reflection from a plant surface) to measure the plant material in an area of interest. This approach is particularly useful when the GSD is not sufficient to discriminate plants from the soil background.

This approach has a long history in remote sensing. Several methods and algorithms can be used to generate models for plant trait retrieval from spectral data. Parametric regression methods, such as vegetation indices (VIs), of which the best known is the normalized difference vegetation index (NDVI) (Rouse, Jr. et al., 1974), combine information from several wavelength bands. Linear nonparametric regression methods [sometimes called chemometric techniques; Atzberger et al. (2010)], such as principle component analysis and partial least square regression, take into account the full spectrum. More recently, nonlinear nonparametric methods, often referred to as machine learning regression algorithms (MLRAs), are increasingly being applied in remote sensing. Examples include decision trees (e.g. Random Forest), artificial neural networks and kernel-based regression (e.g. Gaussian process regression) methods. Their main advantage is that they can capture nonlinear relationships without needing to know the underlying data distribution, and hence without assuming a particular probability density distribution. Thus they are perfectly suited to spectroscopic data and have been shown to outperform other methods [for more detailed information, please refer to the reviews of Verrelst et al. (2015, 2019)].

The general advantage of spectral data-based approaches is that they can increase throughput significantly since absorption-based approximation of plant traits does not depend on very high GSD to segment objects. Consequently, they make it possible to fly UAVs higher and faster. They can also measure the amount of plant matter even when multiple layers of leaves overlap. The disadvantage, however, is that, if absolute values from one day to another or one field to another are to be compared, radiometrically and spectrally calibrated devices need to be used. A review on the current state of the art in UAV spectral remote sensing is provided by Aasen et al. (2018). When only relative differences at one location are needed, uncalibrated systems can be used as long as the image-capturing settings and conditions remain constant (Rasmussen et al., 2016).

Structural properties of the canopy such as leaf angles also have an impact on the apparent spectral reflectance of a canopy and may bias the retrieval of plant traits (Wan et al., 2021; e.g. Zou et al., 2018; Zou and Mõttus, 2015). The empirical relationship between spectral reflectance indices and plant traits is not always comparable across years and phenological stages (Aasen et al., 2014; Gnyp et al., 2013). To the authors' knowledge, the robustness of measurements across different genotypes has not yet been assessed. Caution must be exercised when using empirical models for plant trait retrieval from spectral data – particularly in the context of breeding, where structural properties of new varieties are unknown. Inverting physically based radiative transfer models may be a way forward since this procedure builds on mechanistic relationships between spectral formation and biophysical and structural plant traits (Verrelst et al., 2015).

3.2 Plant emergence, density and tillering

An important driver of yield is the number of shoots that bear harvestable organs. This number is limited by two parameters:

1. by the number of plants per area (which itself is the product of sowing density and germination rate); and
2. by the branching rate (often called tillering rate).

Estimating the number of plants per area as well as the number of tillers per area makes it possible to determine the germination rate, tillering rate and related dynamics parameters. Corresponding high-throughput approaches are thus of significant interest in UAV-based field phenotyping.

Monitoring the development of plants and tillers is usually done early in the season when canopies establish. Coverage-based and counting approaches have been used to assess the early growth phase.

Coverage-based approaches use some kind of metric to assess the greenness within an area of interest and are therefore closely related to canopy cover and leaf area approaches (cf. section 2.2). They consequently measure the totality of the canopy and are unable to distinguish tillers from main shoots. They can only estimate the number of tillers and not the number of plants (Phillips et al., 2004; Scotford and Miller, 2004). In addition, coverage-based estimation approaches are based on empirically determined parameters and may therefore be biased by genotype and environment variances that are unrelated to tiller density. On the positive side, coverage-based approaches require a relatively low GSD. To overcome the limitations of pure coverage-based approaches, while working with low GSDs, Roth et al. (2020) used a multiview approach to harvest the information contained in multiple overlapping images to improve the prediction of plant and tiller count estimation.

Counting approaches overcome the limitations of coverage-based approaches by identifying and counting visible plant organs such as leaves. Consequently, those approaches require GSDs that make it possible to clearly separate tiny plant organs in early growth stages from the soil and from each other. In the case of wheat, this typically demands GSD < 0.5 mm per pixel (Roth et al., 2020). Both handcrafted feature extraction and machine learning approaches have proved to be useful to estimate plant densities (Liu et al., 2017, 2018). Transferred to UAV data, those approaches require collecting images while flying at very low heights (Jin et al., 2017) and consequently at low speed to avoid motion blur, which significantly decreases their suitability in large-scale breeding experiments.

3.3 Plant height, growth and lodging

Plant height has become a standard trait extracted by UAV remote sensing. Hoffmeister et al. (2010) introduced the concept of crop surface models (CSMs) later refined by Tilly et al. (2014) to track plant growth. Crop surface models has been adapted for use in UAV remote sensing by Bendig et al. (2013, 2014, 2015). Lodging – which is characterized by a depression in plant height – can be detected using UAV sensing. Plant growth information can then be used, for example, to investigate the interaction of environmental variables, genetic information and stem elongation (Kronenberg et al., 2017, 2021).

Laser scanning and image-based approaches are available for use in UAV systems to extract plant height. Image-based approaches have become popular since they can be used with cheaper and lighter equipment. With photogrammetric algorithms, overlapping 2D images can be aligned and the 3D geometry of an object can be reconstructed using the central projection imaging model (Leuhmann et al., 2014). Particularly important for UAV remote sensing has been the development of the Structure from Motion (SfM) technique within the field of computer vision and its combination with digital photogrammetry (Colomina and Molina, 2014; Eltner and Schneider, 2015). Advances in image matching in digital photogrammetry (Gruen, 2012), orientation (Remondino et al., 2012) and the process of dense 3D point cloud generation allow the reconstruction of surfaces in very high resolution (Haala, 2013).

The drawback of SfM is that, in contrast to active remote sensing systems such as laser scanners, only points visible in at least two images can be reconstructed (Fig. 4). In practice, SfM can barely penetrate the canopy (Harwin and Lucieer, 2012). However, since structural traits are gaining increasing attention, UAV laser-scanning-based approaches hold great potential for field phenotyping applications. With the availability of 2D spectral images, spectral and 3D data can be captured at the same time (Aasen et al., 2015).

3.4 Biomass

Biomass is an important trait, for example, in the context of the harvest index. However, because the measurement is both labour-intensive and destructive, it is often only measured once a season if at all. With remote sensing-based approaches, biomass can now be estimated nondestructively multiple times a season. This makes it possible to investigate dynamic growing patterns such as response to temperature or other environmental parameters.

Structural and spectral approaches have shown great potential in estimating biomass throughout the season (Aasen and Bareth, 2018; Bendig

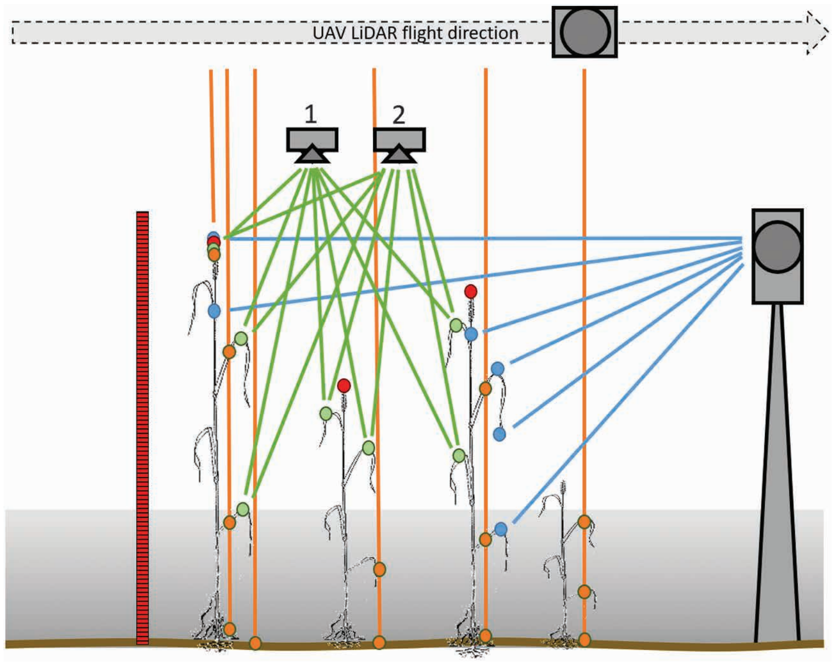

Figure 4 Schematics of plant height estimated with a ruler (red), (single-return) terrestrial laser scanner (blue), UAV (multi-return) laser scanning moving across the area (orange) and structure from motion with two camera positions (green). The active laser scanning systems can penetrate the shade (grey area). Adapted from Aasen (2016).

et al., 2015; Tilly et al., 2015). Structural approaches are mainly based on empirical relationships between biomass and plant height. From a theoretical perspective, one can be sceptical about the robustness of this approach across genotypes and seasons since the relationship of height to biomass may vary between genotypes and due to environmental influences. Extracting the mean plant height per plot represents a massive reduction in dimensionality if working with 3D point clouds as a source. Approaches that include other canopy-related information, for example, canopy roughness (Herrero-Huerta et al., 2020), may lead to improved biomass estimations based on structural data.

Biomass estimation based on spectral data is very common in remote sensing and is now frequently undertaken in field phenotyping applications. Empirical relationships are established between the absorption of an area covered by plants – often measured by means of vegetation indices – and biomass (Aasen et al., 2014; Bendig et al., 2015; Erdle et al., 2013; Fu et al., 2014; Gnyp et al., 2014; Hansen and Schjoerring, 2003; Prabhakara et al., 2015; Tilly et al., 2015). Light absorption is closely related to the amount of absorbing plant matter (cf. Section 3.1.2). From a theoretical point of view, this relationship is more robust than the relationship of plant height to biomass. However, as with LAI, the retrieval of biomass data based on empirical relationships with spectral data may not be robust across genotypes, phenological stages and different years. The use of inversion of physiology-based radiative transfer models in combination with nonparametric machine learning may be a way forward (cf. Section 3.1.2).

3.5 Flowering, fruiting and yield estimation

Flowering and fruiting can be easy to detect for some crops – such as flowering in rapeseed – or very challenging – as in the case of flowering in wheat. Direct and indirect approaches have been used to determine flowering and fruiting.

An indirect method is to monitor the change in colouration of the canopy that indicates that reproduction organs are appearing. A direct approach is to directly detect these organs with image processing techniques. There have been several attempts at direct measurement using traditional, handcrafted features (Guo et al., 2015). With the advent of deep learning, this approach has been largely automated. Today convolutional neural networks can be used to segment plants from soil even in challenging conditions (Zenkl et al., 'in review'), detect and even count flower heads (Gallmann et al., 2022) and wheat ears (David et al., 2020). The publications by David et al. (2020, 2021) are particularly interesting since they represent a worldwide initiative by many institutions to compile a dataset called the *Global Wheat Head Dataset* that now serves as a benchmark dataset for the global machine learning community.

However, for the direct detection approach to work, the GSD needs to be relatively low. This may reduce throughput due to the necessity to lower the flight altitude in order to achieve the necessary resolution. Luckily camera technology is developing fast and current very high-resolution camera systems with 100 megapixels are making it possible to take images at higher altitudes (Lucieer et al., 'in preparation').

Differences in flowering between genotypes can also happen within only a few days, requiring a high frequency of sensing. This might be feasible for permanently manned research stations, but may be particularly suitable for remote field solutions such as PhenoCam which automatically capture images at regular intervals with a camera mounted on a tower (Aasen et al., 2020).

3.6 Senescence

Senescence – the gradual deterioration of all physiological processes – is a developmental process which overlaps with the reproductive phase in annual crop plants. Senescence might reduce crop yield when it is induced prematurely under adverse environmental conditions. On the other hand, a number of studies found that, among so-called 'stay-green' phenotypes, some are functional stay-green plants with increased productivity due to prolonged carbon assimilation (Gregersen et al., 2013).

Since the process of senescence is related to the decolourization of leaf tissue, it is traditionally rated as the ratio of decolourized individual leaves (e.g. flag leaf in wheat) over the whole canopy (Pask et al., 2012). Digital methods follow this approach and quantify canopy colour. (Burkart et al., 2018) used the green-red vegetation index to extract canopy greenness from UAV RGB images across two vegetation periods and could identify different growth stages, including ripening/senescence. Other approaches build on spectral data (Anderegg et al., 2020) and may be used in flying platforms in the near future.

3.7 Canopy temperature

Plants interact with the surrounding environment through carbon, water and energy-exchange processes, maintaining an equilibrium that permits them to grow and adapt to variable growing conditions. Due to the transpiration cooling effect of water leaving the stomata, this energy exchange, among other processes, affects the temperature of foliage. Based on this relationship, many researchers have taken canopy temperature as a proxy for the water status of plants and associated traits such as yield (Li et al., 2019; Lopes and Reynolds, 2010; Rebetzke et al., 2013; Reynolds et al., 1994).

Since field measurements are time consuming and often result in low repeatability if environmental conditions change during the measurement (Deery et al., 2016), airborne thermography (including with UAVs) has gained in popularity. It allows the assessment of canopy temperature in large breeding or genetic experiments in a short time, with improved repeatability compared to manual plot-by-plot measurements (Deery et al., 2016, 2019; Gago et al., 2015; Liebisch et al., 2015; Perich et al., 2020).

However, the relationship between transpiration and canopy temperature is very complex since it depends on the (micro-) environmental conditions around the plant, for example, ambient temperature, wind and vapour pressure (Costa et al., 2013; Maes and Steppe, 2012). This poses significant challenges to translate measurements of canopy temperature to physiologically meaningful results, particularly in areas with potentially fluctuating environmental conditions (e.g. temperate zone countries such as Switzerland). Several approaches to normalizing this effect and establishing a relationship between canopy temperature and transpiration have been proposed. Experimental approaches include wet and dry reference surfaces situated within the image, which is challenging to achieve in UAV remote sensing (Jones, 1999; Maes and Steppe, 2012). Other approaches normalize canopy temperature with air temperature or model reference values based on meteorological data (Berni et al., 2009, 2009; Idso et al., 1981; Jackson et al., 1981; Maes and Steppe, 2012; Zarco-Tejada et al., 2013, 2018). While these existing approaches have been shown to work with airborne and UAV observations in arid and semi-arid regions, to the authors' knowledge they have not been validated for crop genotype screening in temperate climates. In environments where environmental conditions fluctuate sometimes within minutes, the temporal offset between image acquisitions may introduce bias

In cases where the canopy is not fully closed (e.g. wheat), a pixel often does not contain a pure signal from the foliage, but rather an integrated signal from both soil and vegetation, when the canopy is measured by a UAV sensor at a right angle to that surface (NADIR). The soil background interferes with the signal from the foliage (Deery and Jones, 2021). The degree to which it does so depends on shoot biomass, phenology, morphology and structural parameters of the canopy, such as plant height, LAI, ground cover and leaf and spike orientation [reviewed by Prashar and Jones (2014)]. A study by Hund et al. (unpublished) showed that in breeding experiments where genotypes with different heights are placed next to each other, canopy height is the most important driver for canopy temperature. This finding has significant implications for thermal field phenotyping. In such settings, the interpretation of canopy temperature should be handled with care until this effect can be normalized by means of statistical approaches or experimental designs.

4 Conclusion and future trends

The adaption of remote sensing tools by plant scientists has opened up new perspectives and provided the base for high-throughput field phenotyping. Some kind of remote sensing technology, method or philosophy is now part of almost any field phenotyping programme – whether using proximal handheld, robotic or flying platforms [or a combination of those (Pretto et al., 2021)] or the adaption of sophisticated machine learning approaches to make sense of the big data that results from applying remote sensing systems.

However, the rapid adaption of these tools needs to be followed by a deeper understanding of the data captured and the information gathered to be able to truly interpret the information about the extracted traits. This chapter has reviewed recent trends in high-throughput field phenotyping from the perspective of remote sensing. In doing so we have not only highlighted promising approaches but provided some background on remote sensing theory to cast light into the shadows that hide potential pitfalls.

But we should not stop here. The remote sensing community is becoming increasingly aware of the needs of plant scientists and more and more remote sensing researchers are discovering the plant to plot scale as a fruitful field (Machwitz et al., 2021). Fostering this development and bringing plant scientists, remote sensing specialists, ecologists and breeders to the same (dinner) table to exchange ideas and initiate collaborations would allow us to unlock the full potential of current remote sensing technologies by identifying common interests and enabling transfer of knowledge. Moreover, this would also allow the transfer of insights gained by applying remote sensing technology to the plant to plot scale back to the landscape scale by improving satellite remote sensing approaches. Finally, in the whole field phenotyping community, there is a risk that research is driven by technology rather than applications. This exchange should therefore go both ways: we call for plant scientists to help guide the research of remote sensing specialists and the whole field phenotyping community into directions that yield improvements towards a more sustainable agriculture.

5 Authors' contributions

H. A. conceived and wrote major parts of the text. L. R. contributed partially to the text, revised the text and created Fig. 3.

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