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

Remote sensing on the plant scientists' playground – recent trends and future perspectives for high-throughput field phenotyping with UAVs

1. Introduction

Many scientific disciplines use UAVs (Aasen et al., 2018; Adão et al., 2017; Colomina and Molina, 2014; Maes and Steppe, 2019; Pádua et al., 2017; Pajares, 2015, 2015; Sanchez-Azofeifa et al., 2017; Warner and Cracknell, 2017; Zarco-Tejada, 2008; Zhang and Kovacs, 2012) and some have even said they revolutionize disciplines (Anderson and Gaston, 2013; McCabe et al., 2017; Sanchez-Azofeifa et al., 2017). Already more than 10 years ago, unmanned aerial vehicles (UAVs) were envisioned to bring about a new era in Agriculture (Zarco-Tejada, 2008). Seen from today's perspective, the biggest impact can be seen in the application of UAVs in high-throughput field phenotyping. Field phenotyping refers to a quantitative description of a plant's phenotype - i.e. 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 performance, high-throughput field phenotyping allows the timely and rapid screening of multiple traits in early breeding stages, with 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 sensing systems have matured as remote sensing platforms (Aasen et al., 2018), almost all "big players" (research groups, companies, organizations, …) in the area of field phenotyping have started to use UAVs for their measurements (see reviews of (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 an adaption of remote sensing technologies by agronomists, which is also reflected by an exponential increase of publications (Figure 2) and have greatly helped to relieve the phenotyping bottleneck.

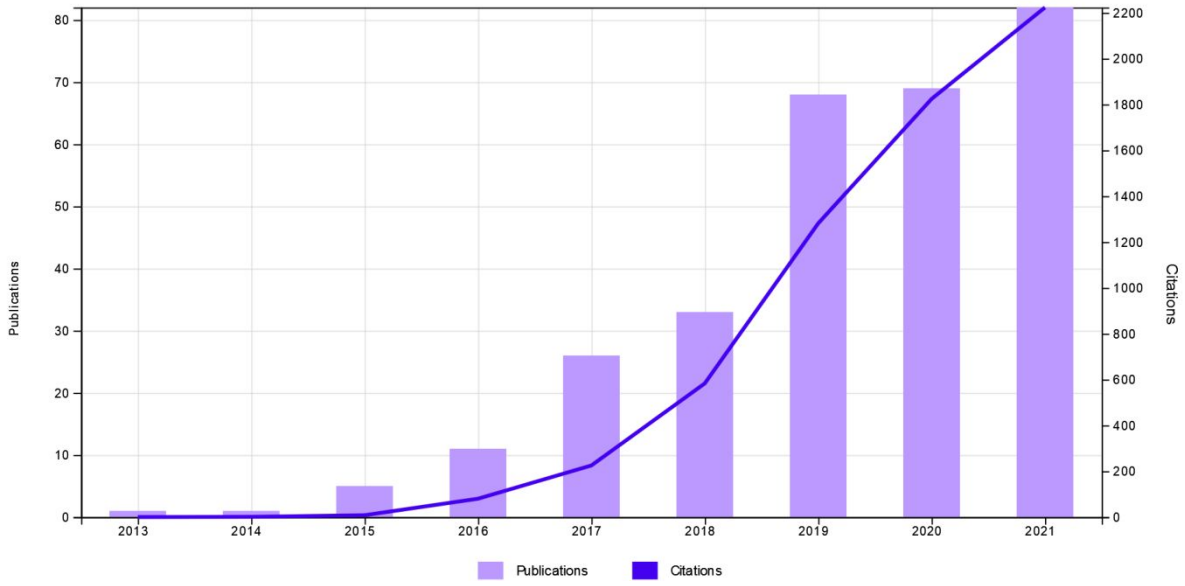

Figure 1 Number of publications and citations with the topics field phenotyping and UAVs[1]

This trend can be seen as a welcomed development, since the large toolbox of remote sensing has long been underexplored in agricultural sciences. Unfortunately, applying UAV technologies also comes with some hurdles, since not every agronomist embarking on that journey has a background in remote sensing or image processing. Additionally, some have been deceived by promises put forward by the marketing of companies shading the challenges that one has to face from the step of being able to fly a certain sensor to reliable trait extraction. In the following we will reflect on UAV remote sensing along with data analysis approaches in the toolbox for high-throughput field phenotyping and ecophysiological research.

2. Remote sensing tools for the plant scientists' playground

2.1. UAVs

In a typical field phenotyping scenario, a couple of hundred to thousand plots (patches of crop canopies with uniform conditions, ranging in size from single plants/rows to machine harvestable yield plots of a few meters) situated on a few hectares need to be screened. UAV remote sensing combines the potential of capturing highly spatially resolved data with high throughput and a great choice of sensors. On the other extreme to UAVs, handheld measurements have a very attractive setup cost, are easy to setup and are highly flexible (Aasen et al., 2020; Perich et al., 2020). Along with phenotyping stations

[1] 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)

such as the 'Field Phenotyping Platform' (FIP) at ETH Zürich (Kirchgessner et al., 2017), the 'Field Scanalyzer' in Rothamsted (Virlet et al., 2017) and similar stations described in (Hund et al., 2019b), handheld measurements arguably have the highest GSDs available. However, sampling large field experiments with such devices is in most cases unfeasible due to the high running costs and the long time needed to sample a whole experiment with potentially hundreds of plots: Changes in environmental conditions during the sample time might bias the results, i.e., in case of thermal and spectral measurements (Deery et al., 2016a; Perich et al., 2020; Sagan et al., 2019).

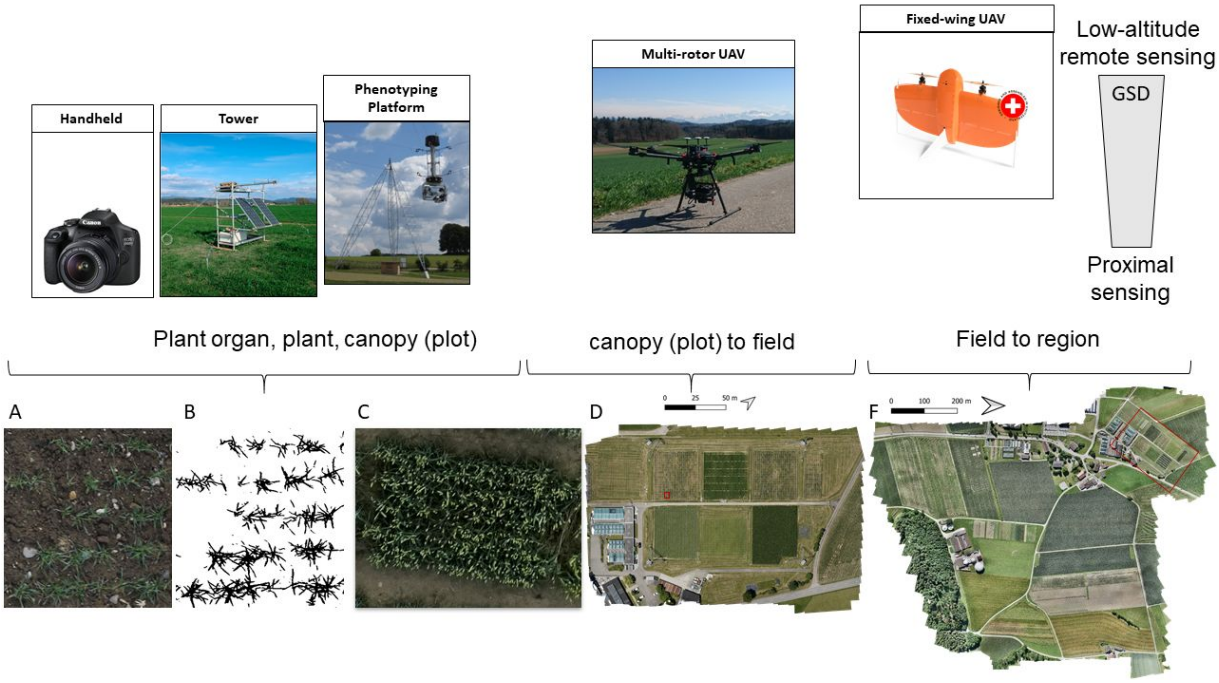

Figure 2 UAVs sensing systems in comparison with other field phenotyping approaches regarding coverage and ground sampling distance (GSD). A and B are a image taken with the Field Phenotyping Platform (FIP) with 0.0005 m GSD and a segmentation of leaves using the method of (Zenkl et al., "in review"). C is the area of a plot extracted from a multi-rotor UAV flying at 30 m AGA with 0.003 m GSD. D is an orthomosaic with an extend of 2 ha and a GSD of 0.008 m generated from a multi-rotor UAV flying at 80 m above ground altitude (AGA). The red rectangle marks the area of C. E is an orthomosaic with an extend of approximately 60 h and a GSD of 0.013 m generated from with a fixed-wing UAV flown at 110 m AGA. The red rectangle marks the area of D.

In contrast to phenotyping stations, UAVs have the advantage of low setup and running costs of the measurement system. Additionally, the size of the coverable area is only limited by the flight time of the carrier system but can be extended by combining imagery from multiple flights (Perich et al., 2020) or by adjusting the flight height by the cost of lowering the ground sampling distance (GSD). While multi-rotor systems are more flexible when it comes to flight trajectory, fixed wing UAVs are more efficient when it comes to areal coverage. Besides, multi-rotor UAVs have greater payload potential then fixed wing UAVs. The latter allows to mount a wide range of spectral, thermal, RGB or LiDAR sensors (Aasen et al., 2018; Lucieer et al., "in preparation"; Yang et al., 2017).

Overall, UAVs can measure traits of interest with relatively little effort across several ha in a couple of minutes. The exact coverage per time depends on the ground sampling distance necessary to extract the trait of interest. Additionally, due to the low manual effort, measures can be carried out in a high temporal frequency, with no disturbance of the soil or plants, and potentially by non-experts, since the flight path and data capturing procedure can be programmed. Finally, UAVs allow to carry out the same measurements at multiple places. However, key to a repeatable and reliable trait extraction are well established flight (c.f. subsection 2.2) and trait extraction protocols (c.f. section 3).

2.2. **Flight protocols**

Defining UAV measurement protocols can be complex. It requires good knowledge and experience not only about the sensing system, but also about the data processing workflow and the analysis methods (Aasen et al., 2018). Moreover, to harvest the full potential and reduce the effort for each flight, the area of interest should be equipped with auxiliary 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 the data, focal length, image resolution, exposure time) need to match the requirements given for the trait of interest (ground sampling distance and motion blur). Luckily, several tools are available to help with configuring the flight parameters and equipping area of interest (Roth et al., 2018b).

3. A flight through major plant traits that can be extracted with UAV remote sensing

In the following, we will go through some important traits for field phenotyping. The objective of this chapter is to align the definitions of the agronomic community with terminology of the remote sensing community and give hints of where remote sensing methods could be used in the context of field phenotyping. Then, some examples approaches are highlighted.

3.1. **Canopy cover and leaf area index**

Different terms exist to describe the foliage of plant canopies. While the canopy cover describes how well a plant canopy covers the soil, a physiologically more relevant term is the leaf area index (LAI) that describes the total leaf area per ground area. The LAI can reach up to values far 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 ground area. Unfortunately, it is challenging to measure the LAI nondestructively as soon as multiple leaf layers overlap. Even in the early season where overlaps are sparse it is not straight forward to estimate LAI: Leaves are often not planar and growth at a certain inclination angle, leading to a complex 3D geometry, which makes it difficult to estimate a correct leaf area, and oblique viewing geometries (e.g.,

towards the edge of an image) may introduce biases due to perspective distortion[2]. Keeping these constrains in mind, two major approaches are used to estimate the leaf area, namely i) image-based leaf from soil segmentation and ii) absorption-based proxy measurements.

3.1.1. Leaf area estimation by image segmentation

Image segmentation-based leaf area estimation is based on the differentiation of "green" leaf pixels and "brown" soil pixels by some kind of classification. Then, the apparent ratio of "green" to total pixels is expressed as the canopy cover. Sometimes, the resulting quantities are also referred to as fractional cover or green cover. Besides of the constrains mentioned above, the precision of this method relies on the possibility to differentiate "green" from "brown" pixels on the image. Consequently, the ground sampling distance and motion blur need to be tuned such that the necessary precision can be reached (Hu et al., 2019; Roth et al., 2018b) – which is relative to the organ (leaf) size and thus, crop specific (c.f. Figure 3). Moreover, shadows and overexposure of reflecting leaf parts might compromise the precision of classification.

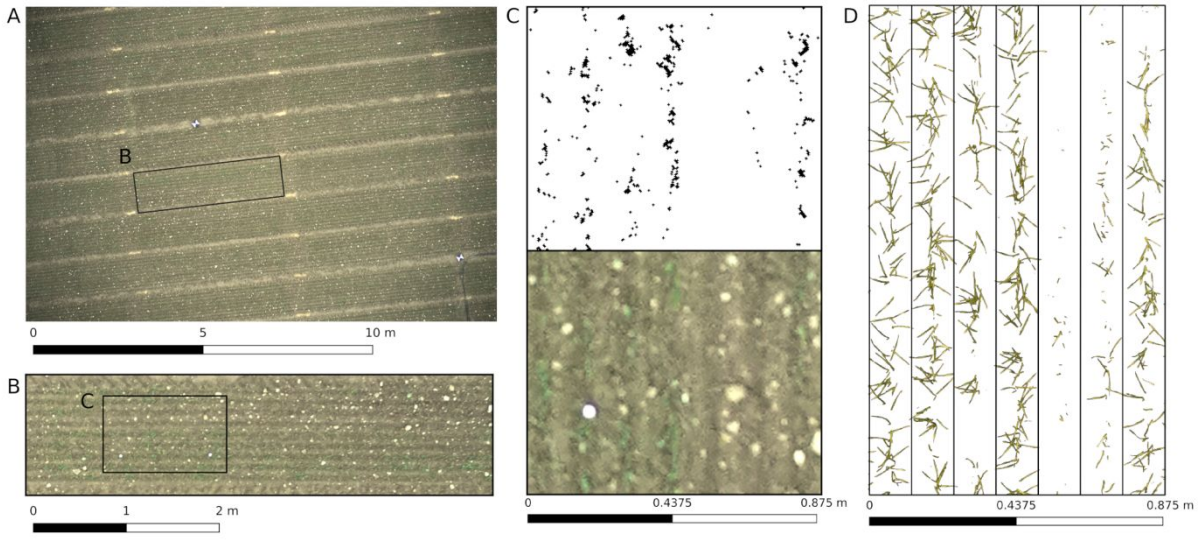

Figure 3: Example of UAV image of wheat (A, B, C) with a ground sampling distance of 3 mm per pixel that covers an area of approximately 13 x 9 m in comparison to an image captured with the field phenotyping platform (FIP) of ETH Zurich with a ground sampling distance of 0.3 mm per pixel that covers an area of approximately 0.9 x 1.2 m (D), both taken at 2018-11-12 a 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).

Today decision tree based segmentation (e.g. Random Forest) classifiers (in their simplest form as an Otsu thresholding, e.g. (Torres-Sánchez et al., 2014)), often in combination with different color space transformations to make the classification more robust (Roth et al., 2020, 2018a) are often used to

[2] 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 meters aside from it.

segment “green” from “brown”. The most recent segmentation approaches also include the information of neighboring pixels for the classification. A recent study by Zenkle et al. (“in review”) compared different segmentation approaches for very-high resolution RGB images (0.003 m) of the “*Eschikon Wheat Segmentation Dataset”* (Zenkl et al., “in review”) and concluded that a deep learning based approach outperformed other machine learning methods which use Support Vector Machines and/or Random Forrest. Most methods are able to assign uncertainties to the prediction (Figure 2), which allows carrying-forward these uncertainties to subsequent processing steps. However, to perform such studies, well annotated datasets such as the “*Eschikon Wheat Segmentation Dataset”* (Zenkl et al., “in review”) are necessary (c.f. other chapter). The last “trick” to be mentioned for leaf area estimation by image segmentation is to use the full information of multiple overlapping images captured from different angles. This so called “multiview imaging” combines the complementary information included in these images to improve the prediction of leaf area (Roth et al., 2020, 2018a). Still, all segmentation-based methods reach their limit 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 (respectively the change in reflection from a surface covered by vegetation) to approximate the plant material in an area of interest. This approach is particularly useful when the ground sampling distance is not sufficient to discriminate plants from soil background.

Consequently, 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, the most well-known one being 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 squares 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., 2019, 2015).

The general advantage of spectral data-based approaches is, that they can increase the throughput significantly since absorption-based approximation of plant traits are not depending on very-high

ground sampling distances to segment objects. Consequently, they allow to fly higher and faster. Also, they can discriminate 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 should be used (for a review on the current state of the art in UAV spectral remote sensing please refer to (Aasen et al., 2018)). When only relative differences at one location are needed, uncalibrated systems may also be suitable as long as the image capturing settings and conditions remain constant (Rasmussen et al., 2016).

Besides, structural properties of the canopy such as leaf angle 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). Consequently, empirical relationship of spectral reflectance indices and plant traits are not always stable across years and phenological stages (Aasen et al., 2014; Gnyp et al., 2013). To the authors knowledge, the robustness across different genotypes has not yet been assessed. Still, one may also exercise caution when using empirical models for plant trait retrieval from spectral data – in particular in the context of breeding, where structural properties of new varieties are unknown. Inverting physically based radiative transfer model may be a way forward, since it builds on mechanistical relationships between the spectral formation and biophysical and structural plant traits (Verrelst et al., 2015).

3.2. **Plant emergence, density and tillering**

Important drivers of yield are the number of shoots that bear harvestable organs. This number is determined by two parameters: (1) The number of plants per area (which itself is the product of the 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 allows determining the germination rate, the tillering rate, and related dynamics' parameters. Consequently, corresponding high-throughput approaches are of high interest for UAV based field phenotyping.

Monitoring the development of plants and tillers is usually done early in the season when canopies establish. Two types of approaches have been assessed for this early growth phase, namely coverage-based approaches and counting approaches. 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 (c.f. section 2.2). Consequently, they measure the totality of the canopy and are unable to distinguish tillers from main shoots. Therefore, they can only estimate number of tillers and not 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 specific variances that are unrelated to the tiller density. On the positive side, coverage-based approaches demand for a relatively low ground sampling distance. To overcome

the limitations of pure coverage-based approaches while still working with low ground sampling distances, Roth et al. (2020) used a multi-view 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, e.g., leaves. Consequently, those approaches require ground sampling distances that allow to clearly separate tiny plant organs in early growth stages from the soil and from each other. For wheat, this typically demands for ground sampling distances < 0.5 mm per pixel (Roth et al., 2020). With such data, both hand-crafted feature extraction as well as machine learning approaches proofed 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), which significantly decreases their suitability in large breeding experiments.

3.3. **Plant height, growth and lodging**

Plant height has become a standard trait to be extracted by UAV remote sensing. In 2010, Hoffmeister et al. (2010) introduced the concept of crop surface models (CSMs) that was later refined by Tilly et al. (2014) to track plant growth and adapted to UAV remote sensing by Bendig et al. (2015, 2014, 2013). With plant height also lodging – as a depression in plant height – can be detected. Plant growth information can then be used to e.g. investigate the interaction of environmental variables, genetic information and stem elongation (Kronenberg et al., 2021, 2017).

For UAV sensing systems, laser scanning and image-based approaches are available to extract plant height. Practically, image-based approaches have become most popular since they require 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 mathematical model of central projection imaging (Luhmann et al., 2014). Particularly important for UAV remote sensing was 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 of the latter in image matching (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 (Figure 4). Practically, SfM thus can barely penetrate the canopy (Harwin and Lucieer, 2012). Since the structural traits gain increasing attention, UAV laser scanning based approaches hold great potential for field phenotyping applications.

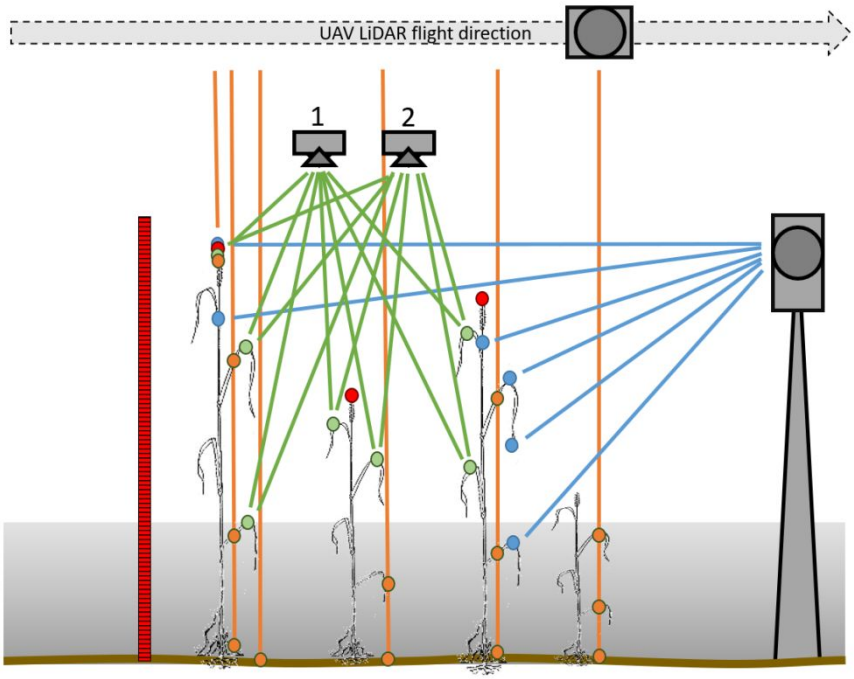

Figure 4 Schematics of plant height estimated with a ruler (red), terrestrial laser scanner (blue), UAV (multi-return) laser scanning moving across the area (orange) and structure from motion with two camera positions (green). The active laser scanning systems can penetrate the shade (grey area) (figure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

With the availability of 2D spectral images, spectral and 3D data could be captured at the same time (Aasen et al., 2015).

3.4. **Biomass**

Biomass can be estimated based on structural and spectral approaches. Structural approaches are mainly based on empirical relationships of biomass and plant height. It has shown great potential to estimate biomass increase of crops throughout the season (Aasen and Bareth, 2018; Bendig et al., 2015; Tilly et al., 2015). Still, seen from a theoretical perspective, one can be skeptical when it comes to 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 source. Approaches that include other canopy-related information, e.g., 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 also frequently applied in field phenotyping applications. Mostly, 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, Martin Leon 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 (c.f. subsection 3.1.2) and thus,

this approach is also from a theoretical point of few more robust than the relationship of plant height to biomass. Still, similar as with LAI, the retrieval of biomass based on empirical relationships with spectral data may not be robust across genotypes, phenological stages and years – and similar to LAI also here inversion of physiological based radiative transfer models in combination with non-parametric machine learning may be a way forward (c.f. subsection 3.1.2).

3.5. **Flowering and 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. Overall, two approaches can be used to determine flowering and fruiting. An indirect method is to monitor the change in colorization of the canopy that indicates that reproduction organs are appearing. A direct approach is to directly detect these organs with image processing techniques. Several attempts have been published in this regard that use 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., "in review") and wheat ears (David et al., 2020). The publications by David et al. (2021, 2020) are particularly interesting, since they represent a worldwide effort 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.

Still, for the direct detection approach the ground sampling distance needs to be appropriate which may bring down the 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 able to ease this issue (Lucieer et al., "in preparation").

Besides the detection aspect, differences in flowering between genotypes can happen within only a few days and thus require a very high revisit frequency of the sensing approach. While this might be feasible for permanently manned research stations, for more remote research fields solutions such as PhenoCams might be a more applicable approach (Aasen et al., 2020).

3.6. **Senescence**

Senescence is a developmental process which in annual crop plants overlaps with the reproductive phase. Senescence might reduce crop yield when it is induced prematurely under adverse environmental conditions. On the other hand, a number of studies found that for 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 with the decolorization of leaf tissue, traditional it is rated as the ratio of decolorized of individual leaves (e.g. flag leaf in wheat) or the whole canopy (Pask et al., 2012). Consequently, also digital methods follow that approach and quantify canopy color. Burkart et al. (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 transferred to flying platforms.

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 proxy for the water status of plants and associated traits, e.g. 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., 2016b), 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, increasing repeatability as compared to manual plot-by-plot measurements (Deery et al., 2019, 2016a; 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, e.g. 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 physiological meaningful quantities – in particular in areas with potentially fluctuating environmental conditions (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 into the image, which is challenging to be achieved 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., 2018, 2013). 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.

Further, in cases where the canopy is not fully closed (e.g. wheat), most often a pixel 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). Thus, the soil background confounds 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, leaf area index, ground cover and leaf and spike orientation (reviewed by (Prashar and Jones, 2014)). A study by Hund et al. ("in-preparation") 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 great implications for thermal field-phenotyping and 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 outlook

The adaption of remote sensing tools by plant scientists has opened new perspectives and provided the base for high-throughput field phenotyping. Today, some remote sensing technology, method or philosophy is part of almost any field phenotyping – may it be by applying 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 understand of the data captured and the information gathered to be able to truly interpret the information carried within the extracted traits. With this text we reviewed recent trends in high-throughput field phenotyping from the perspective of remote sensing – and by that not only highlighted the promising approaches but also gave some background from the remote sensing theory to casting light into the shadows that hide potential pitfalls.

But we should not stop here. The remote sensing community is increasing getting aware off 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., "accepted"). Fostering this development and bringing plant scientist, remote sensing specialist, ecologist, and breeders to the same (dinner) table to exchange ideas and initiate collaborations would allow to unlock the full potential of current remote sensing technologies by faster identifying intersections and enabling the transfer of knowledge. Moreover, this would also allow transferring the 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. Thus, this exchange should go in both ways and we call for plant scientist to help guiding the research activities of remote sensing specialists and the whole field phenotyping community into directions that yield improvements towards a more sustainable agriculture.

5. Authors contribution

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

6. Acknowledgements

We acknowledge Quirina Merz for providing the Orthomosaic of the fixed-wing UAV in Figure 2. We acknowledge the funding of the Swiss Science Foundation for the projects “PhenomEn” (grant number IZCOZ0_198091), “PhotoInd” (grant number CRSK-3_195591) and “Trait spotting” (grant number KTI P-Nr 27059.2 PFLS-LS) and the Swiss National Science Foundation (SNSF), within the framework of the National Research Programme “Sustainable Economy: resource-friendly, future-oriented, innovative” (NRP 73), in the InnoFarm project, Grant-N° 407340_172433. Also, we thank Radek Zenkl for his contributions to Figure 2 and the whole Crop Science Group of ETH Zürich with Professor Achim Walter and the Remote Sensing and GIS Group at the University of Cologne with Professor Georg Bareth without whom this research would not have been possible.

7. Literature

Aasen, H., 2016. The acquisition of hyperspectral digital surface models of crops from UAV snapshot cameras (Dissertation). University of Cologne, Cologne, Germany.

Aasen, H., Bareth, G., 2018. Ground and UAV sensing approaches for spectral and 3D crop trait estimation, in: Thenkabail, P., Lyon, J.G., Huete, A. (Eds.), Hyperspectral Remote Sensing of Vegetation - Volume II: Biophysical and Biochemical Characterization and Plant Species Studies. Chapman and Hall/CRC, Milton.

Aasen, H., Burkart, A., Bolten, A., Bareth, G., 2015. Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance. ISPRS J. Photogramm. Remote Sens. 108, 245–259. https://doi.org/10.1016/j.isprsjprs.2015.08.002

Aasen, H., Gnyp, M.L., Miao, Y., Bareth, G., 2014. Automated Hyperspectral Vegetation Index Retrieval from Multiple Correlation Matrices with HyperCor. Photogramm. Eng. Remote Sens. 80, 785–795. https://doi.org/10.14358/PERS.80.8.785

Aasen, H., Honkavaara, E., Lucieer, A., Zarco-Tejada, P., 2018. Quantitative Remote Sensing at Ultra-High Resolution with UAV Spectroscopy: A Review of Sensor Technology, Measurement Procedures, and Data Correction Workflows. Remote Sens. 10, 1091. https://doi.org/10.3390/rs10071091

Aasen, H., Kirchgessner, N., Walter, A., Liebisch, F., 2020. PhenoCams for Field Phenotyping: Using Very High Temporal Resolution Digital Repeated Photography to Investigate Interactions of Growth, Phenology, and Harvest Traits. Front. Plant Sci. 11, 593. https://doi.org/10.3389/fpls.2020.00593

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., Sousa, J., 2017. Hyperspectral Imaging: A Review on UAV-Based Sensors, Data Processing and Applications for Agriculture and Forestry. Remote Sens. 9, 1110. https://doi.org/10.3390/rs9111110

Anderegg, J., Yu, K., Aasen, H., Walter, A., Liebisch, F., Hund, A., 2020. Spectral Vegetation Indices to Track Senescence Dynamics in Diverse Wheat Germplasm. Front. Plant Sci. 10, 1749. https://doi.org/10.3389/fpls.2019.01749

Anderson, K., Gaston, K.J., 2013. Lightweight unmanned aerial vehicles will revolutionize spatial ecology. Front. Ecol. Environ. 11, 138–146. https://doi.org/10.1890/120150

393 Araus, J.L., Cairns, J.E., 2014. Field high-throughput phenotyping: the new crop breeding frontier.
394 Trends Plant Sci. 19, 52–61. https://doi.org/10.1016/j.tplants.2013.09.008
395 Araus, J.L., Kefauver, S.C., Zaman-Allah, M., Olsen, M.S., Cairns, J.E., 2018. Translating High-Throughput
396 Phenotyping into Genetic Gain. Trends Plant Sci. 23, 451–466.
397 https://doi.org/10.1016/j.tplants.2018.02.001
398 Atzberger, C., Guérif, M., Baret, F., Werner, W., 2010. Comparative analysis of three chemometric
399 techniques for the spectroradiometric assessment of canopy chlorophyll content in winter
400 wheat. Comput. Electron. Agric. 73, 165–173. https://doi.org/10.1016/j.compag.2010.05.006
401 Bendig, J., Bolten, A., Bareth, G., 2013. UAV-based Imaging for Multi-Temporal, very high Resolution
402 Crop Surface Models to monitor Crop Growth Variability. Photogramm. - Fernerkund. -
403 Geoinformation 2013, 551–562. https://doi.org/10.1127/1432-8364/2013/0200
404 Bendig, J., Bolten, A., Bennertz, S., Broscheit, J., Eichfuss, S., Bareth, G., 2014. Estimating Biomass of
405 Barley Using Crop Surface Models (CSMs) Derived from UAV-Based RGB Imaging. Remote Sens.
406 6, 10395–10412. https://doi.org/10.3390/rs61110395
407 Bendig, J., Yu, K., Aasen, H., Bolten, A., Bennertz, S., Broscheit, J., Gnyp, M.L., Bareth, G., 2015.
408 Combining UAV-based plant height from crop surface models, visible, and near infrared
409 vegetation indices for biomass monitoring in barley. Int. J. Appl. Earth Obs. Geoinformation
410 39, 79–87. https://doi.org/10.1016/j.jag.2015.02.012
411 Berni, J.A.J., Zarco-Tejada, P.J., Sepulcre-Cantó, G., Fereres, E., Villalobos, F., 2009. Mapping canopy
412 conductance and CWSI in olive orchards using high resolution thermal remote sensing
413 imagery. Remote Sens. Environ. 113, 2380–2388. https://doi.org/10.1016/j.rse.2009.06.018
414 Burkart, A., Hecht, V.L., Kraska, T., Rascher, U., 2018. Phenological analysis of unmanned aerial vehicle
415 based time series of barley imagery with high temporal resolution. Precis. Agric. 19, 134–146.
416 https://doi.org/10.1007/s11119-017-9504-y
417 Cendrero-Mateo, M.P., Muller, O., Albrecht, H., Burkart, A., Gatzke, S., Janssen, B., Keller, B., Körber,
418 N., Kraska, T., Matsubara, S., Jinquan, L., Müller-Linow, M., Pieruschka, R., Pinto, F., Rischbeck,
419 P., Schickling, A., Steier, A., Watt, M., Schurr, U., Rascher, U., 2017. Field phenotyping: concepts
420 and examples to quantify dynamic plant traits across scales in the field, in: Chabbi, A.,
421 Loescher, H.W. (Eds.), Terrestrial Ecosystem Research Infrastructures: Challenges and
422 Opportunities, Abad Chabbi. Abad Chabbi, Henry W. Loescher; CRC Press, Boca Raton, pp. 53–
423 80.
424 Colomina, I., Molina, P., 2014. Unmanned aerial systems for photogrammetry and remote sensing: A
425 review. ISPRS J. Photogramm. Remote Sens. 92, 79–97.
426 https://doi.org/10.1016/j.isprsjprs.2014.02.013
427 Costa, J.M., Grant, O.M., Chaves, M.M., 2013. Thermography to explore plant-environment
428 interactions. J. Exp. Bot. 64, 3937–3949. https://doi.org/10.1093/jxb/ert029
429 David, E., Madec, S., Sadeghi-Tehran, P., Aasen, H., Zheng, B., Liu, S., Kirchgessner, N., Ishikawa, G.,
430 Nagasawa, K., Badhon, M.A., Pozniak, C., de Solan, B., Hund, A., Chapman, S.C., Baret, F.,
431 Stavness, I., Guo, W., 2020. Global Wheat Head Detection (GWHD) Dataset: A Large and
432 Diverse Dataset of High-Resolution RGB-Labelled Images to Develop and Benchmark Wheat
433 Head Detection Methods. Plant Phenomics 2020, 1–12.
434 https://doi.org/10.34133/2020/3521852
435 David, E., Serouart, M., Smith, D., Madec, S., Velumani, K., Liu, S., Wang, X., Espinosa, F.P., Shafiee, S.,
436 Tahir, I.S.A., Tsujimoto, H., Nasuda, S., Zheng, B., Kichgessner, N., Aasen, H., Hund, A., Sadhegi-
437 Tehran, P., Nagasawa, K., Ishikawa, G., Dandrifosse, S., Carlier, A., Mercatoris, B., Kuroki, K.,
438 Wang, H., Ishii, M., Badhon, M.A., Pozniak, C., LeBauer, D.S., Lilimo, M., Poland, J., Chapman,
439 S., de Solan, B., Baret, F., Stavness, I., Guo, W., 2021. Global Wheat Head Dataset 2021: more
440 diversity to improve the benchmarking of wheat head localization methods. ArXiv210507660
441 Cs.
442 Deery, D.M., Jones, H.G., 2021. Field Phenomics: Will It Enable Crop Improvement? Plant Phenomics
443 2021, 1–16. https://doi.org/10.34133/2021/9871989
444 Deery, D.M., Rebetzke, G.J., Jimenez-Berni, J.A., Bovill, W.D., James, R.A., Condon, A.G., Furbank, R.T.,
445 Chapman, S.C., Fischer, R.A., 2019. Evaluation of the Phenotypic Repeatability of Canopy

Temperature in Wheat Using Continuous-Terrestrial and Airborne Measurements. Front. Plant Sci. 10, 875. https://doi.org/10.3389/fpls.2019.00875
Deery, D.M., Rebetzke, G.J., Jimenez-Berni, J.A., James, R.A., Condon, A.G., Bovill, W.D., Hutchinson, P., Scarrow, J., Davy, R., Furbank, R.T., 2016a. Methodology for High-Throughput Field Phenotyping of Canopy Temperature Using Airborne Thermography. Front. Plant Sci. 7. https://doi.org/10.3389/fpls.2016.01808
Deery, D.M., Rebetzke, G.J., Jimenez-Berni, J.A., James, R.A., Condon, A.G., Bovill, W.D., Hutchinson, P., Scarrow, J., Davy, R., Furbank, R.T., 2016b. Methodology for High-Throughput Field Phenotyping of Canopy Temperature Using Airborne Thermography. Front. Plant Sci. 7. https://doi.org/10.3389/fpls.2016.01808
Eltner, A., Schneider, D., 2015. Analysis of Different Methods for 3D Reconstruction of Natural Surfaces from Parallel-Axes UAV Images. Photogramm. Rec. 30, 279–299. https://doi.org/10.1111/phor.12115
Erdle, K., Mistele, B., Schmidhalter, U., 2013. Spectral high-throughput assessments of phenotypic differences in biomass and nitrogen partitioning during grain filling of wheat under high yielding Western European conditions. Field Crops Res. 141, 16–26. https://doi.org/10.1016/j.fcr.2012.10.018
Fu, Y., Yang, G., Wang, J., Song, X., Feng, H., 2014. Winter wheat biomass estimation based on spectral indices, band depth analysis and partial least squares regression using hyperspectral measurements. Comput. Electron. Agric. 100, 51–59. https://doi.org/10.1016/j.compag.2013.10.010
Furbank, R.T., Tester, M., 2011. Phenomics – technologies to relieve the phenotyping bottleneck. Trends Plant Sci. 16, 635–644. https://doi.org/10.1016/j.tplants.2011.09.005
Gago, J., Douthe, C., Coopman, R.E., Gallego, P.P., Ribas-Carbo, M., Flexas, J., Escalona, J., Medrano, H., 2015. UAVs challenge to assess water stress for sustainable agriculture. Agric. Water Manag. 153, 9–19. https://doi.org/10.1016/j.agwat.2015.01.020
Gallmann, J., Schüpbach, B., Jacot, K., Albrecht, M., Winizki, J., Aasen, H., "in review." Flower Mapping in Grasslands with Drones and Deep Learning.
Gnyp, Martin Leon, Miao, Yuxin, Yuan, Fei, Yu, Kang, Yao, Yinkun, Huang, S., Bareth, Georg, 2014. Derivative analysis to improve rice biomass estimation at early growth stages. https://doi.org/10.5880/TR32DB.KGA94.7
Gnyp, M.L., Yu, K., Aasen, H., Yao, Y., Huang, S., Miao, Y., Bareth, G., 2013. Analysis of Crop Reflectance for Estimating Biomass in Rice Canopies at Different Phenological Stages. Photogramm. - Fernerkund. - Geoinformation 2013, 351–365. https://doi.org/10.1127/1432-8364/2013/0182
Gregersen, P.L., Culetic, A., Boschian, L., Krupinska, K., 2013. Plant senescence and crop productivity. Plant Mol. Biol. 82, 603–622. https://doi.org/10.1007/s11103-013-0013-8
Gruen, A., 2012. Development and Status of Image Matching in Photogrammetry: Development and status of image matching in photogrammetry. Photogramm. Rec. 27, 36–57. https://doi.org/10.1111/j.1477-9730.2011.00671.x
Guo, W., Fukatsu, T., Ninomiya, S., 2015. Automated characterization of flowering dynamics in rice using field-acquired time-series RGB images. Plant Methods 11, 7. https://doi.org/10.1186/s13007-015-0047-9
Haala, N., 2013. The Landscape of Dense Image Matching Algorithms. Presented at the Photogrammetric Week'13, pp. 271–284.
Hansen, P.M., Schjoerring, J.K., 2003. Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. Remote Sens. Environ. 86, 542–553. https://doi.org/10.1016/S0034-4257(03)00131-7
Harwin, S., Lucieer, A., 2012. Assessing the Accuracy of Georeferenced Point Clouds Produced via Multi-View Stereopsis from Unmanned Aerial Vehicle (UAV) Imagery. Remote Sens. 4, 1573–1599. https://doi.org/10.3390/rs4061573

Herrero-Huerta, M., Bucksch, A., Puttonen, E., Rainey, K.M., 2020. Canopy Roughness: A New Phenotypic Trait to Estimate Aboveground Biomass from Unmanned Aerial System. Plant Phenomics 2020, 1–10. https://doi.org/10.34133/2020/6735967

Hoffmeister, D., Bolten, A., Curdt, C., Waldhoff, G., Bareth, G., 2010. High-resolution Crop Surface Models (CSM) and Crop Volume Models (CVM) on field level by terrestrial laser scanning, in: The Sixth International Symposium on Digital Earth. International Society for Optics and Photonics, p. 6.

Hu, P., Guo, W., Chapman, S.C., Guo, Y., Zheng, B., 2019. Pixel size of aerial imagery constrains the applications of unmanned aerial vehicle in crop breeding. ISPRS J. Photogramm. Remote Sens. 154, 1–9. https://doi.org/10.1016/j.isprsjprs.2019.05.008

Hund, A., Kislinger, F., Aasen, H., "in-preparation." Plant height drives canopy temperature in breeding experiments.

Hund, A., Kronenberg, L., Anderegg, J., Yu, K., Walter, A., 2019a. Non-invasive phenotyping of cereal growth and development characteristics in the field, in: Ordon, F., Friedt, W. (Eds.), Advances in Crop Breeding Techniques. Burleigh Dodds.

Hund, A., Kronenberg, L., Anderegg, J., Yu, K., Walter, A., 2019b. Non-invasive field phenotyping of cereal development 249–292. https://doi.org/10.19103/as.2019.0051.13

Idso, S.B., Jackson, R.D., Pinter, P.J., Reginato, R.J., Hatfield, J.L., 1981. Normalizing the stress-degree-day parameter for environmental variability. Agric. Meteorol. 24, 45–55. https://doi.org/10.1016/0002-1571(81)90032-7

Jackson, R.D., Idso, S.B., Reginato, R.J., Pinter, P.J., 1981. Canopy temperature as a crop water stress indicator. Water Resour. Res. 17, 1133–1138. https://doi.org/10.1029/WR017i004p01133

Jin, X., Liu, S., Baret, F., Hemerlé, M., Comar, A., 2017. Estimates of plant density of wheat crops at emergence from very low altitude UAV imagery. Remote Sens. Environ. 198, 105–114. https://doi.org/10.1016/j.rse.2017.06.007

Jones, H.G., 1999. Use of thermography for quantitative studies of spatial and temporal variation of stomatal conductance over leaf surfaces. Plant Cell Environ. 22, 1043–1055. https://doi.org/10.1046/j.1365-3040.1999.00468.x

Kirchgessner, N., Liebisch, F., Yu, K., Pfeifer, J., Friedli, M., Hund, A., Walter, A., 2017. The ETH field phenotyping platform FIP: A cable-suspended multi-sensor system. Funct. Plant Biol. 44, 154–168. https://doi.org/10.1071/FP16165

Kronenberg, L., Yates, S., Boer, M.P., Kirchgessner, N., Walter, A., Hund, A., 2021. Temperature response of wheat affects final height and the timing of stem elongation under field conditions. J. Exp. Bot. 72, 700–717. https://doi.org/10.1093/jxb/eraa471

Kronenberg, L., Yu, K., Walter, A., Hund, A., 2017. Monitoring the dynamics of wheat stem elongation: genotypes differ at critical stages. Euphytica 213. https://doi.org/10.1007/s10681-017-1940-2

Li, X., Ingvordsen, C.H., Weiss, M., Rebetzke, G.J., Condon, A.G., James, R.A., Richards, R.A., 2019. Deeper roots associated with cooler canopies, higher normalized difference vegetation index, and greater yield in three wheat populations grown on stored soil water. J. Exp. Bot. 70, 4963–4974. https://doi.org/10.1093/jxb/erz232

Liebisch, F., Kirchgessner, N., Schneider, D., Walter, A., Hund, A., 2015. Remote, aerial phenotyping of maize traits with a mobile multi-sensor approach. Plant Methods 11, 9. https://doi.org/10.1186/s13007-015-0048-8

Liu, S., Baret, F., Andrieu, B., Burger, P., Hemmerlé, M., 2017. Estimation of Wheat Plant Density at Early Stages Using High Resolution Imagery. Front. Plant Sci. 8, 739. https://doi.org/10.3389/fpls.2017.00739

Liu, T., Yang, T., Li, C., Li, R., Wu, W., Zhong, X., Sun, C., Guo, W., 2018. A method to calculate the number of wheat seedlings in the 1st to the 3rd leaf growth stages. Plant Methods 14, 101. https://doi.org/10.1186/s13007-018-0369-5

Lopes, M.S., Reynolds, M.P., 2010. Partitioning of assimilates to deeper roots is associated with cooler canopies and increased yield under drought in wheat. Funct. Plant Biol. 37, 147. https://doi.org/10.1071/FP09121

549 Lucieer, A., ..., Aasen, H., ..., “in preparation.” Advances in remote sensing of vegetation with drones –
550 review and outlook.
551 Machwitz, M., Pieruschka, R., Berger, K., Schlerf, M., Aasen, H., Fahrner, S., Jimenez-Berni, J.A., Baret,
552 F., Rascher, U., “accepted.” Bridging the gap between remote sensing and plant phenotyping
553 - challenges and opportunities for the next generation of sustainable agriculture. Front. Plant
554 Sci.
555 Maes, W.H., Steppe, K., 2019. Perspectives for Remote Sensing with Unmanned Aerial Vehicles in
556 Precision Agriculture. Trends Plant Sci. 24, 152–164.
557 https://doi.org/10.1016/j.tplants.2018.11.007
558 Maes, W.H., Steppe, K., 2012. Estimating evapotranspiration and drought stress with ground-based
559 thermal remote sensing in agriculture: a review. J. Exp. Bot. 63, 4671–4712.
560 https://doi.org/10.1093/jxb/ers165
561 McCabe, M.F., Rodell, M., Alsdorf, D.E., Miralles, D.G., Uijlenhoet, R., Wagner, W., Lucieer, A., Houborg,
562 R., Verhoest, N.E.C., Franz, T.E., Shi, J., Gao, H., Wood, E.F., 2017. The future of Earth
563 observation in hydrology. Hydrol. Earth Syst. Sci. 21, 3879–3914.
564 https://doi.org/10.5194/hess-21-3879-2017
565 Pádua, L., Vanko, J., Hruška, J., Adão, T., Sousa, J.J., Peres, E., Morais, R., 2017. UAS, sensors, and data
566 processing in agroforestry: a review towards practical applications. Int. J. Remote Sens. 1–43.
567 https://doi.org/10.1080/01431161.2017.1297548
568 Pajares, G., 2015. Overview and Current Status of Remote Sensing Applications Based on Unmanned
569 Aerial Vehicles (UAVs). Photogramm. Eng. Remote Sens. 81, 281–330.
570 https://doi.org/10.14358/PERS.81.4.281
571 Pask, A., Pietragalla, J., Mullan, D., Raynolds, M. (Eds.), 2012. Physiological breeding II : a field guide to
572 wheat phenotyping. CIMMYT, Mexico.
573 Perich, G., Hund, A., Anderegg, J., Roth, L., Boer, M.P., Walter, A., Liebisch, F., Aasen, H., 2020.
574 Assessment of Multi-Image Unmanned Aerial Vehicle Based High-Throughput Field
575 Phenotyping of Canopy Temperature. Front. Plant Sci. 11, 150.
576 https://doi.org/10.3389/fpls.2020.00150
577 Phillips, S.B., Keahey, D.A., Warren, J.G., Mullins, G.L., 2004. Estimating Winter Wheat Tiller Density
578 Using Spectral Reflectance Sensors for Early-Spring, Variable-Rate Nitrogen Applications.
579 Agron. J. 96, 1. https://doi.org/10.2134/agronj2004.0591
580 Prabhakara, K., Hively, W.D., McCarty, G.W., 2015. Evaluating the relationship between biomass,
581 percent groundcover and remote sensing indices across six winter cover crop fields in
582 Maryland, United States. Int. J. Appl. Earth Obs. Geoinformation 39, 88–102.
583 https://doi.org/10.1016/j.jag.2015.03.002
584 Prashar, A., Jones, H., 2014. Infra-Red Thermography as a High-Throughput Tool for Field Phenotyping.
585 Agronomy 4, 397–417. https://doi.org/10.3390/agronomy4030397
586 Pretto, A., Aravecchia, S., Burgard, W., Chebrolu, N., Dornhege, C., Falck, T., Fleckenstein, F.V.,
587 Fontenla, A., Imperoli, M., Khanna, R., Liebisch, F., Lottes, P., Milioto, A., Nardi, D., Nardi, S.,
588 Pfeifer, J., Popovic, M., Potena, C., Pradalier, C., Rothacker-Feder, E., Sa, I., Schaefer, A.,
589 Siegwart, R., Stachniss, C., Walter, A., Winterhalter, W., Wu, X., Nieto, J., 2021. Building an
590 Aerial–Ground Robotics System for Precision Farming: An Adaptable Solution. IEEE Robot.
591 Autom. Mag. 28, 29–49. https://doi.org/10.1109/MRA.2020.3012492
592 Rasmussen, J., Ntakos, G., Nielsen, J., Svensgaard, J., Poulsen, R.N., Christensen, S., 2016. Are
593 vegetation indices derived from consumer-grade cameras mounted on UAVs sufficiently
594 reliable for assessing experimental plots? Eur. J. Agron. 74, 75–92.
595 https://doi.org/10.1016/j.eja.2015.11.026
596 Rebetzke, G.J., Jimenez-Berni, J., Fischer, R.A., Deery, D.M., Smith, D.J., 2019. Review: High-throughput
597 phenotyping to enhance the use of crop genetic resources. Plant Sci. 282, 40–48.
598 https://doi.org/10.1016/j.plantsci.2018.06.017
599 Rebetzke, G.J., Rattey, A.R., Farquhar, G.D., Richards, R.A., Condon, A.T.G., 2013. Genomic regions for
600 canopy temperature and their genetic association with stomatal conductance and grain yield
601 in wheat. Funct. Plant Biol. 40, 14–33. https://doi.org/10.1071/FP12184

Remondino, F., Del Pizzo, S., Kersten, T.P., Troisi, S., 2012. Low-Cost and Open-Source Solutions for Automated Image Orientation – A Critical Overview, in: Ioannides, M., Fritsch, D., Leissner, J., Davies, R., Remondino, F., Caffo, R. (Eds.), Progress in Cultural Heritage Preservation. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 40–54.

Reynolds, M., Balota, M., Delgado, M., Amani, I., Fischer, R., 1994. Physiological and Morphological Traits Associated With Spring Wheat Yield Under Hot, Irrigated Conditions. Funct. Plant Biol. 21, 717. https://doi.org/10.1071/PP9940717

Roth, L., Aasen, H., Walter, A., Liebisch, F., 2018a. Extracting leaf area index using viewing geometry effects—A new perspective on high-resolution unmanned aerial system photography. ISPRS J. Photogramm. Remote Sens. 141, 161–175. https://doi.org/10.1016/j.isprsjprs.2018.04.012

Roth, L., Camenzind, M., Aasen, H., Kronenberg, L., Barendregt, C., Camp, K.-H., Walter, A., Kirchgessner, N., Hund, A., 2020. Repeated Multiview Imaging for Estimating Seedling Tiller Counts of Wheat Genotypes Using Drones. Plant Phenomics 2020, 1–20. https://doi.org/10.34133/2020/3729715

Roth, L., Hund, A., Aasen, H., 2018b. PhenoFly Planning Tool: flight planning for high-resolution optical remote sensing with unmanned areal systems. Plant Methods 14. https://doi.org/10.1186/s13007-018-0376-6

Rouse, Jr., J.W., Haas, R.H., Schell, J.A., Deering, D.W., 1974. Monitoring Vegetation Systems in the Great Plains with Erts, in: Third Earth Resources Technology Satellite-1 Symposium- Volume I: Technical Presentations. NASA, Washington, D.C., pp. 309–317.

Sagan, V., Maimaitijiang, M., Sidike, P., Eblimit, K., Peterson, K.T., Hartling, S., Esposito, F., Khanal, K., Newcomb, M., Pauli, D., Ward, R., Fritschi, F., Shakoor, N., Mockler, T., 2019. UAV-based high resolution thermal imaging for vegetation monitoring, and plant phenotyping using ICI 8640 P, FLIR Vue Pro R 640, and thermomap cameras. Remote Sens. 11. https://doi.org/10.3390/rs11030330

Sanchez-Azofeifa, A., Antonio Guzmán, J., Campos, C.A., Castro, S., Garcia-Millan, V., Nightingale, J., Rankine, C., 2017. Twenty-first century remote sensing technologies are revolutionizing the study of tropical forests. Biotropica 49, 604–619. https://doi.org/10.1111/btp.12454

Scotford, I.M., Miller, P.C.H., 2004. Estimating Tiller Density and Leaf Area Index of Winter Wheat using Spectral Reflectance and Ultrasonic Sensing Techniques. Biosyst. Eng. 89, 395–408. https://doi.org/10.1016/j.biosystemseng.2004.08.019

Tardieu, F., Cabrera-Bosquet, L., Pridmore, T., Bennett, M., 2017. Plant Phenomics, From Sensors to Knowledge. Curr. Biol. 27, R770–R783. https://doi.org/10.1016/j.cub.2017.05.055

Tilly, N., Aasen, H., Bareth, G., 2015. Fusion of Plant Height and Vegetation Indices for the Estimation of Barley Biomass. Remote Sens. 7, 11449–11480. https://doi.org/10.3390/rs70911449

Tilly, N., Hoffmeister, D., Cao, Q., Huang, S., Lenz-Wiedemann, V., Miao, Y., Bareth, G., 2014. Multitemporal crop surface models: accurate plant height measurement and biomass estimation with terrestrial laser scanning in paddy rice. J. Appl. Remote Sens. 8, 083671. https://doi.org/10.1117/1.JRS.8.083671

Torres-Sánchez, J., Peña, J.M., de Castro, A.I., López-Granados, F., 2014. Multi-temporal mapping of the vegetation fraction in early-season wheat fields using images from UAV. Comput. Electron. Agric. 103, 104–113. https://doi.org/10.1016/j.compag.2014.02.009

Verrelst, J., Camps-Valls, G., Muñoz-Marí, J., Rivera, J.P., Veroustraete, F., Clevers, J.G.P.W., Moreno, J., 2015. Optical remote sensing and the retrieval of terrestrial vegetation bio-geophysical properties – A review. ISPRS J. Photogramm. Remote Sens. 108, 273–290. https://doi.org/10.1016/j.isprsjprs.2015.05.005

Verrelst, J., Malenovský, Z., Van der Tol, C., Camps-Valls, G., Gastellu-Etchegorry, J.-P., Lewis, P., North, P., Moreno, J., 2019. Quantifying Vegetation Biophysical Variables from Imaging Spectroscopy Data: A Review on Retrieval Methods. Surv. Geophys. 40, 589–629. https://doi.org/10.1007/s10712-018-9478-y

Virlet, N., Sabermanesh, K., Sadeghi-Tehran, P., Hawkesford, M.J., 2017. Field Scanalyzer: An automated robotic field phenotyping platform for detailed crop monitoring. Funct. Plant Biol. 44, 143–153. https://doi.org/10.1071/FP16163

Walter, A., Liebisch, F., Hund, A., 2015. Plant phenotyping: from bean weighing to image analysis. Plant Methods 11, 14. https://doi.org/10.1186/s13007-015-0056-8

Wan, L., Zhu, J., Du, X., Zhang, J., Han, X., Zhou, W., Li, X., Liu, J., Liang, F., He, Y., Cen, H., 2021. A model for phenotyping crop fractional vegetation cover using imagery from unmanned aerial vehicles. J. Exp. Bot. 72, 4691–4707. https://doi.org/10.1093/jxb/erab194

Warner, T.A., Cracknell, A.P., 2017. Unmanned aerial vehicles for environmental applications. Int. J. Remote Sens. 1–8. https://doi.org/10.1080/01431161.2017.1301705

Yang, G., Liu, J., Zhao, C., Li, Zhenhong, Huang, Y., Yu, H., Xu, B., Yang, X., Zhu, D., Zhang, X., Zhang, R., Feng, H., Zhao, X., Li, Zhenhai, Li, H., Yang, H., 2017. Unmanned Aerial Vehicle Remote Sensing for Field-Based Crop Phenotyping: Current Status and Perspectives. Front. Plant Sci. 8. https://doi.org/10.3389/fpls.2017.01111

Zarco-Tejada, P.J., 2008. A new era in remote sensing of crops with unmanned robots. SPIE Newsroom. https://doi.org/10.1117/2.1200812.1438

Zarco-Tejada, P.J., Camino, C., Beck, P.S.A., Calderon, R., Hornero, A., Hernández-Clemente, R., Kattenborn, T., Montes-Borrego, M., Susca, L., Morelli, M., Gonzalez-Dugo, V., North, P.R.J., Landa, B.B., Boscia, D., Saponari, M., Navas-Cortes, J.A., 2018. Previsual symptoms of Xylella fastidiosa infection revealed in spectral plant-trait alterations. Nat. Plants 4, 432–439. https://doi.org/10.1038/s41477-018-0189-7

Zarco-Tejada, P.J., González-Dugo, V., Williams, L.E., Suárez, L., Berni, J.A.J., Goldhamer, D., Fereres, E., 2013. A PRI-based water stress index combining structural and chlorophyll effects: Assessment using diurnal narrow-band airborne imagery and the CWSI thermal index. Remote Sens. Environ. 138, 38–50. https://doi.org/10.1016/j.rse.2013.07.024

Zenkl, R., Timofte, R., Kirchgessner, N., van Gool, L., Walter, A., Aasen, H., “in review.” Outdoor Wheat Segmentation with Deep Learning.

Zhang, C., Kovacs, J.M., 2012. The application of small unmanned aerial systems for precision agriculture: a review. Precis. Agric. 13, 693–712. https://doi.org/10.1007/s11119-012-9274-5

Zou, X., Haikarainen, Iina, Haikarainen, Iikka, Mäkelä, P., Mõttus, M., Pellikka, P., 2018. Effects of Crop Leaf Angle on LAI-Sensitive Narrow-Band Vegetation Indices Derived from Imaging Spectroscopy. Appl. Sci. 8, 1435. https://doi.org/10.3390/app8091435

Zou, X., Mõttus, M., 2015. Retrieving crop leaf tilt angle from imaging spectroscopy data. Agric. For. Meteorol. 205, 73–82. https://doi.org/10.1016/j.agrformet.2015.02.016