ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume IV-2/W5, 2019
ISPRS Geospatial Week 2019, 10–14 June 2019, Enschede, The Netherlands

ON THE DERIVATION OF CROP HEIGHTS FROM MULTITEMPORAL UAV BASED IMAGERY

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KEY WORDS: RGB UAV imagery, 3D crop structure, point cloud, crop height raster, crop growth

ABSTRACT:

In this paper, we investigate the usage of unmanned aerial vehicles (UAV) to assess the crop geometry with special focus on the crop height extraction. Crop height is classified as a reliable trait in crop phenotyping and recognized as a good indicator for biomass, expected yield, lodging or crop stress. The current industrial standard for crop height measurement is a manual procedure using a ruler, but this method is considered as time consuming, labour intensive and subjective. This study investigates methods for reliable and rapid deriving of the crop height from high spatial, spectral and time resolution UAV data considering the influences of the reference surface and the selected crop height generation method to the final calculation. To do this, we performed UAV missions during two winter wheat growing seasons and generate point clouds from areal images using photogrammetric methods. For the accuracy assessment we compare UAV based crop height with ruler based crop height as current industrial standard and terrestrial laser scanner (TLS) based crop height as a reliable validation method. The high correlation between UAV based and ruler based crop height and especially the correlation with TLS data shows that the UAV based crop height extraction method can provide reliable winter wheat height information in a non-invasive and rapid way. Along with crop height as a single value per area of interest, 3D UAV crop data should provide some additional information like lodging area, which can also be of interest in the plant breeding community.

1. INTRODUCTION

1.1 Challenges of sustainable crop production

It became more and more obvious, sustainable crop production is one of the key challenges for our and upcoming generations. Current crop production cannot support future yield demands which are predicted to increase by 2.40% annually (Ray et al., 2013). Rapid population growth, limited arable land, negative environmental footprint in combination with climate changes give us enough reasons for a change. Producing more with fewer resources, with less negative impact on the environment and in a sustainable manner is a huge challenge in the future.

Better understanding of the connection between a crop genetic mark up (genotype) and its observable characteristics (phenotype) in a real world growing system should allow the selection of a high-yield stress and tolerant crop and improve current agriculture production.

The possibility of observing crop characteristics, i.e. crop traits, should be reliable, efficient and multifunctional. A novel technology should support this. Creating autonomous or semi-autonomous, affordable phenotyping platforms on the one hand and developing reliable and effective workflows for crop phenotyping on the other hand should allow plant scientist to understand plants better and to create new standards for crop phenotyping.

Unmanned Arial Vehicles (UAV) as versatile and affordable phenotyping platforms fit to this paradigm. Using different sensors like RGB, multispectral or thermal cameras or even a LIDAR mounted to UAV can provide lots of useful crop related data, which can be further transferred into useful crop traits.

1.2 UAV field based phenotyping

Crop phenotyping in controlled environments like greenhouses using fully automated platforms became a standard in the recent years. Phenotyping platforms used in greenhouses are able to collect crop related data in a non-invasive way during the whole crop development cycle (Yang et al., 2017).

The crop traits from controlled systems are different than the ones from real growing systems with location specific environmental influences (Poorter, H. at all., 2016) .Field based phenotyping is increasingly recognized as the only approach capable to deliver crop traits from real-world growing system. The performance of breeding programs should be evaluated under natural conditions (Gonzalez-Dugo et al., 2014).

Looking from a field perspective, there is still a lot of space for developing ground wheeled field – based phenotyping platforms deployed with different sensors. Thus far field phenotyping is still time – consuming on the big field scale. (Yang et al., 2017) give an example, more than 40 hours were required to cover the 20,000 plots with a single vehicle traveling at 2 km/h to measure traits on single row. Using more vehicles could increase the performance, but the cost as well. Some of these limitations can be addressed using satellite or plane based remote sensing techniques. However, their major limitations are usually a lower spatial and temporal resolution, and weather influences, such as clouds.

Automated aerial and close-range photogrammetry has become a powerful and widely used tool for three-dimensional modelling. 'Structure-from-Motion' (SfM) photogrammetry is often described as a revolutionary, low-cost and user-friendly photogrammetric technique for obtaining high-resolution data sets (Westoby et al., 2012). Furthermore, UAVs become flexible and affordable therefore important crop phenotyping tools (Berni et al., 2008). UAVs can meet the requirements on spatial, spectral and temporal level. On a spatial level, sub centimetre resolution is achievable and with deploying multispectral, hyperspectral or thermal sensors many relevant traits can be derived. Above all, it is possible to use UAVs almost any time and exactly within a specific time interval during the crop growing season.

1.3 Multi-temporal crop height measurements

Crop height is defined as shortest distance between ground level and the upper boundary of the main photosynthetic tissues on a plant (Perez-Harguindeguy et al., 2013). It is classified as a reliable trait in crop phenotyping and recognized as a good indicator for biomass, expected yield, lodging or crop stress (Madec et al., 2017).

The current industrial standard for crop height measurement is a manual measurement using a ruler. This data sampling method is time consuming, labour intensive and subjective due to specific approaches of the observer in the field. Looking back into the challenges of sustainable crop production, replacing manual field work with technology-supported methods is necessary to reach the demanded reliability and effectivity of the phenotyping process.

When multi-temporal data are used, crop height time series and growth rate curves can be calculated. In this way monitoring of the plants growth over the whole growing season can become a reliable source of location specific information to the breeders.

The generation of high resolution 3D crop models offers more potentially useful information than a simple plant height per plot.

1.4 Contribution of this paper

The derivation of the crop height from multitemporal UAV based images has been presented in several publications (Bendig et al., 2014; Holman et al., 2016). The workflow usually consists of (a) the generation of reference surface, representing the zero values of plant height, (b) the derivation of the 3D model at later growth stages in the same coordinate system, (c) the distance calculation between the models at later stages and the reference model to get absolute plant heights and finally (d) the extraction of a useful height value for a certain area of interest, such as a plot. Mostly, the reference and crop surface models are represented as Digital Elevation Models (DEM), which are directly provided by the Structure from motion software packages like Agisoft PhotoScan (Agisoft LLC, Russia). However, it is also possible to represent the models as 3D point clouds and derive heights from comparing these clouds. Although this method seems to be computationally more demanding, it does not apply any unknown assumptions or models as in the DEM generation step of the commercial software. In this contribution, we compare different ways of representing the reference and crop surfaces and of building differences between them. We also compare different points in time for performing the reference surface measurement, that are (i) shortly after seeding, (ii) shortly after plant emergence, where still a sufficient amount of soil is visible in the images and (iii) shortly after harvest. We investigate the general quality of the UAV derived point cloud in the context of height estimation by comparing it with a terrestrial laser scan (TLS) and we compare the derived heights with manual measurements, representing the industry standard. Finally, we present results from a winter wheat breeding experiment with 12 genotypes, two management systems at two locations. As additional information from crop height data we identify lodging areas within a part of breeding experiment. Lodging has been a problem in cereal production with whole fields often flattened after summer storm (Crook and Ennos, 1994) and its rapid identification is also important for breeding community.

2. MATERIALS AND METHODS

2.1 Field experiments

Most of the data in this study have been taken in a winter wheat breeding experiment, which was set up for the research project CropWatch (Honecker et all., 2018). The comparison between UAV, Laser Scanning and ruler measurement have been performed in a FACE experiment (Free-Air Carbon Dioxide Enrichment – FACE), called BeedFACE.

CropWatch Breeding Experiment. The main goal of the project Crop Watch is to develop an information system for seamless process control and analysis in crop production, testing the impact of different location and fertilization related influents to different winter wheat genotypes. Various crop phenotyping data for winter wheat were collected during a two growing seasons at two different locations near Bonn. Location of the first experimental field was in University Bonn Campus Klein Altendorf and the second in Bornheim near the river Rhine. The two different locations a have different soil structure and different weather conditions but the same experiment set up. Figure 1 shows part of an experimental field structure in Klein Altendorf, consisting of 96 plots, 10 m x 1.5 m in size, with 12 winter wheat genotypes in two management treatments with four repetitions per system. The intensive management treatment consists of 300 seeds/m² and 200 kg/ha N. On the other hand, extensive management treatment consists of 165 seeds/m² and 100 kg/ha N. Bolded numbers represent 12 different genotypes codes explained in Table 1.

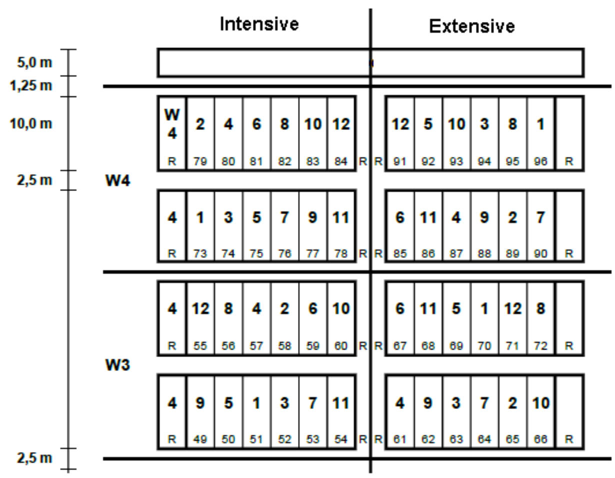

Figure 1. Experimental field set up in Klein Altendorf

Genotype Code	Genotype Name
1	Julius
2	Dichter
3	Tobak
4	KWS Ferrum
5	Erixer
6	Hyvento
7	Hyfi
8	LG Alpha
9	Midas
10	RGT Reform
11	Diplomat
12	Caribo

Table 1. Genotypes within Experiment field

BreedFACE Experiment. The experiment represents the infrastructure to phenotype novel varieties under free air CO_2 enrichment (Kimball, 2016).BreedFAce consists of three rings with 59 plots in each ring (plot size 1.5 x 3 m) under elevated CO_2 treatment and the same set-up in the three control rings of the experiment. We use a breeder's panel of several barley varieties, organised by the Plant Science Group from Forschungszentrum Jülich, for a quality analysis using different types of crop height measurements: TLS, UAV and a ruler.

2.2 Data Capturing

Within the CropWatch project the UAV flights were performed every two weeks from March to July 2017 and 2018 plus two additional reference flights shortly after seeding.
Terrestrial laser scanning of the crop surface combined with field ruler crop height measurement and UAV measurements were performed at the 15 of May 2018 in the Breed FACE experiment.

UAV images. During the whole CropWatch experiment two different UAVs were used. During the first season a DJI Matrice 100, equipped with DJI Zenmuse X5 camera with 3-Axis Gimbal and 15 mm f/1.7 lens was used. During the second season a DJI Phantom 4 Pro with integrated 20MP camera, FOV 84˚, 24 mm f/2.8 - f/11 lens was used. In both seasons the same flight plan settings were deployed (Table 2) to minimize flight planning influence on the end result. Flight missions were performed during eleven dates in 2016/2017 season with two unsuccessful missions and during ten dates in 2017/2018 with all successful missions. It is worth to mention, that each mission was realized using a cross flight pattern at two different heights and flight directions, to achieve a better 3D data quality. The UAV flight in the Breed FACE experiment, was done with the DJI Phantom 4 Pro and the same settings as above.

Flight planning parameters	
Flight height 1	30 m
Flight height 2	25 m
Forward overlap	80 %
Side overlap	75 %
Camera Angle	90˚
Ground Sample Distance	0.8 - 1 cm
ISO	100
White Balance	auto
Shutter Speed	auto

Table 2. Flight planning parameters

Each of the flights in the CropWatch experiment took around ten minutes covering approximately 0.35 hectare. For the accuracy assessment within the BreedFACE project a flight took less than five minutes.

Georeferencing. The data georeferencing was realized with ground control points (GCPs) which have been previously deployed and measured with a Leica GNSS receiver (11 GCPs for each of CropWatch fields and 5 for BreedFACE experiment). Homogeneous distribution of GCPs over the area and their stability over the growing season is strongly important for the geometrical accuracy of the data reconstruction. In addition, having accurately georeferenced data is a crucial argument for further multi-temporal analysis and data comparisons. RMSE of GCPs used for georeferencing UAV data during the all the flight used in this study is in the range of 0.007 m to 0.020 m.

Manual height measurements. The ruler based measurement process was performed in a standardised way, measuring five randomly selected samples per plot (1.5 x 3 m) using 2 m ruler. We measured up to the highest point of the selected plant as it was suggested from plant breeders.

Terrestrial Laser Scans: Along with the ruler measurements, a terrestrial laser scanner (TLS) (Leica ScanStation P20) was used to collect crop surface data for the same 40 plots. The scanner measures 3D crop data from five different stations. The stations have been equipped with tilt & turn targets and georeferenced using RTK GNSS. The point clouds from the five stations were then registered and georeferenced using the software Leica Cyclone (Leica Geosystems Holdings AG, Switzerland). In this way, we created a single absolutely georeferenced 3D point cloud, with a resolution of about 5 mm and an accuracy in the order of a few mm. We consider this 3D information as more accurate than the 3D information generated from the images, as it does not need any reconstruction algorithm, which usually needs assumptions and approximations. Each point is a truly measured point, calculated from two angles and an electronic distance measurement. We therefor expect the TLS to provide accurate samples of the canopy structure, measuring points from between the plants and on their tips.

2.3 Data Processing

Point cloud and DEM generation: Unlike the TLS measurement, the image - based point cloud is not the result of direct 3D measurements, but the result of data reconstruction based on overlapping 2D images. The Structure from Motion (SfM) algorithm uses multiple overlapping images of an object or feature to create a three-dimensional set of points corresponding to the surface of the feature. Images are taken from numerous positions focusing on the same object. The overlap ensures finding matching points in multiple images that belong to the same spot on the ground but from a different perspective. Then these matched features from multiple images are used to estimate relative camera positions, which are extrapolated to create a 3D point cloud of the scene.

For creating 3D point clouds from overlapping images, collected during two flying patterns, Agisoft PhotoScan was used with 'high' Alignment Accuracy, 'medium' Dense Point Quality and 'moderate' Depth Filtering.

We assume that 'medium' dense point cloud quality with 'moderate' depth filtering mode should provide a reasonable point cloud representation of the crop surface. 'Aggressive'

Depth Filtering could probably cut some upper crop parts and contrarily 'mild' filtering mode could give rise to data noise.
Figure 2 shows crop development stages observing 3D point clouds from different epochs. A side cut of four plots, each around 1.2 m wide, is visible here. Each layer represents UAV point cloud data for a specific flight date.

Figure 2. Multi temporal UAV point cloud. Side view

Although SfM software packages provide height raster data as Digital Elevation Models (DEM) very easily it is not specified by the authors of the software how it works. Using a self-created Matlab (MathWorks, USA) script for point cloud rasterization we could understand what is happening with the data and define most suitable parameters for point cloud rasterization. We select 3 cm cell size as a suitable size for the crop point cloud rasterization with maximum cell value and N8 neighbourhood interpolation to fill the empty cells within the area of interest.

2.4 Reference surface generation

In order to extract the crop heights from 3D data it is necessary to calculate the difference between crop surface and reference surface, which is usually the bare soil without any plants. The reference surface can be reconstructed the same way as the actual crop surface. For our investigation, we used UAV missions at three different points in time and created three different reference surfaces.

After seeding reference surface. From our perspective, the reference surface should be created shortly before the plants emerge and then assume that the surface does not significantly change during the growing season. It is recommended here to choose 'aggressive' Depth Filtering mode instead of 'moderate' filtering, as this smooths the soil surface which can have bigger soil chunks after plugging and seeding.

Early season reference surface. However, it may be the case that a flight before plant emergence is not possible and therefore an alternative has to be found. One alternative option is to use an early season flight with sufficiently visible ground segments between the plants. Then, the plant points can be automatically removed from the resulting point cloud, while the remaining ground points are used to create a 3D representation of the reference surface, e.g. by interpolation. For the classification into the two classes, soil and plants, we used a threshold on the Excess Green Index (ExG, Meyer & Neto, 2008), which can be calculated from standard RGB images. A detailed description of this method is beyond the scope of this paper.

Post-harvest reference surface. Another alternative is to use a flight after harvesting. This option may be useful in specific cases, where a flight was not possible at all before canopy closure. However, we expect leftover materials from straws to add some bias to the soil surface estimation. Also, an automatic segmentation of this material, as described in the option before, is more challenging, as it is not green anymore.

The reference surface may be also derived from a dense GNSS point survey with an additional surface estimation step or an official DEM could be used. However, we do not consider these options in this study.

2.5 Distance calculation

Point cloud based methods: In this section, we briefly describe three possibilities of calculating distance directly using the point clouds, often used for deformation analysis. The *Cloud to cloud distance (C2C)* is based on the distance between two point clouds using a 'nearest neighbourhood' approach. For each point of the compared cloud, the algorithm searches the nearest point in the reference cloud and computes their Euclidean distance. If the reference point cloud is dense enough, approximating the distance from the compared cloud to the underlying surface, represented by the reference cloud, is acceptable. If the reference cloud is not dense enough, the nearest neighbour distance is not precise enough (Figure 3a, left). Often, a local model is fitted to the reference surface close to the point of interest in order to reduce this error (Figure 3a, right). The *Cloud to mesh distance (C2M)* calculates the distance between the point cloud and a reference surface represented as a mesh. If the reference point cloud is triangulated to a mesh, then the C2M algorithm calculates the distance of a point to the closest triangle of the mesh. In *Multiscale model to model cloud (M3C2)* comparisons, the number of points of one epoch is reduced by building core points that should represent the geometry of their neighbourhood of size D (Figure 3b). These core points are gained by filtering. The difference to the other point cloud is calculated along each core point's normal vector regarding its neighbourhood D. Hence, two neighbourhoods of size D and d need to be specified for this point cloud comparison. For a more detailed explanation, see Barnhart and Crosby (2013). All the calculations using point cloud methods were done using an open source software called 'CloudCompare v.2.9.1.' (Daniel Girardeau-Montaut, 2003).

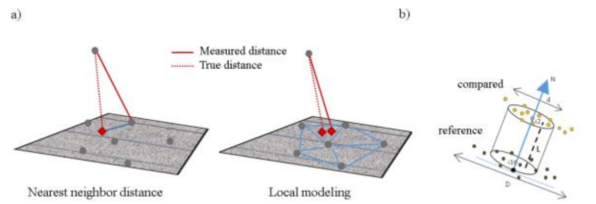

Figure 3. a) Cloud to cloud distance concept and b) M3C2 distance concept

Raster based methods: Since crop surfaces are mainly horizontal structures and the parameter of interest is the vertical distance between these surfaces, the rasterization of the surfaces and a simple distance calculation between the raster data is also a possibility to calculate plant height values. The processing steps are (a) calculate heights raster from reference surface point cloud, (b) calculate heights raster from crop surface point cloud, (c) subtract the reference surface raster from the crop surface raster. As we present in chapter 2.3 for the heights raster the exported digital surface model from PhotoScan of own created heights raster can be used.

2.6 Plot height calculation

As written before, the crop height is defined as the shortest distance between ground level and upper boundary of the main photosynthetic tissues of a plant. In the contest of crop height extraction from 3D data, it can be defined as a vertical distance between crop surface and reference surface. In order to derive the crop height in a certain plot at a certain time (which is in most cases the actual phenotypic trait of interest), we first calculate this distance using one of the methods described in section 2.5, and then rasterize the results using a grid size of 3 cm. For each epoch and each location, we generate a plant height raster file for further statistical processing using own created Matlab script.

Plots in each field experiment were created manually within QGIS (Open source Geographic Information System) as polygonal vector layer with a unique plot IDs, genotype and management system. As a base map for creating plots layer georeferenced Digital Ortomosaic from UAV flight in April was used (as shown in Figure 1 and Figure 6). Based on previously created plot layer, we are now able to derive statistical values about the plant height for each plot and then filter it by genotype and management system.

Nevertheless, for crop height calculation we decided to use the mean of the 90th percentile of the height values within one plot rather than the whole mean. This takes into account, that the 3D reconstruction also shows lower canopy points or even soil, especially during the early season, which are not necessarily plant parts. We also removed a buffer zone of 25 cm to avoid boarder effects.

3. RESULTS AND DISCUSSION

3.1 UAV Point Cloud Quality and Rasterization

To evaluate the general quality of the point clouds generated from UAV imagery we compared them with point clouds from a TLS. We performed UAV and TLS data acquisition at the same day (15th of May 2018) within the FACE experiment as described in section 2.6. For this experiment RMSE of georeferencing TLS data, using four targets mounted on tripods, is 0.0026 m. On the other hand, RMSE of georeferencing UAV data using ground control points (GCPs) is here 0.0152 m.

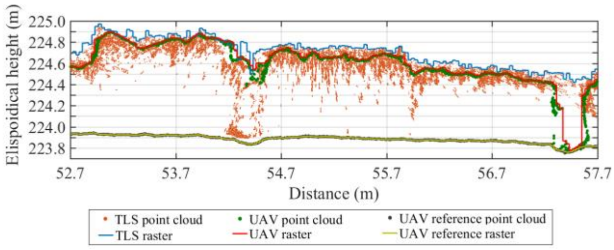

Figure 4. Example of a cross section of canopy height measures derived from UAV and TLS point clouds. The orange points represent TLS measurements, green points show SfM results from UAV and the brown points are reference soil points (dereived from SfM from UAV images)

It is apparent that the UAV point cloud is systematically lower than the TLS point cloud (Figure 4). This is in agreement with our expectations, since SfM algorithm tend to smooth the data by considering smaller structures (e.g. plant tips or ears) as noise, while the TLS is able to capture them due to its measurement principle. The generated raster values (maximum cell size in this case) in the plot show this bias even more clearly.

The effect of the rasterization process, which extracts a single height value from the number of points laying within the cell boundaries (we chose a cell size of 3 cm here to ensure a minimum number of 1-2 points per cell). In this cross section, we compare the result of using mean, maximum or median as cell statistic with the PhotoScan DEM (Figure 5). It is obvious, that the maximum values within a cell seem to be the best representation of the actual plant height. The reconstruction algorithm of SfM software tends to smooth the surface and the building of a mean of heights within one cell would even increase this effect, leading to an underestimation of the plant height. It is necessary to remove outliers in the point cloud, as they appear directly in the cell, if they show higher height values. The DEM from PhotoScan seems to be based on the mean or median statistic, sacrificing some crop surface points to remove outliers.

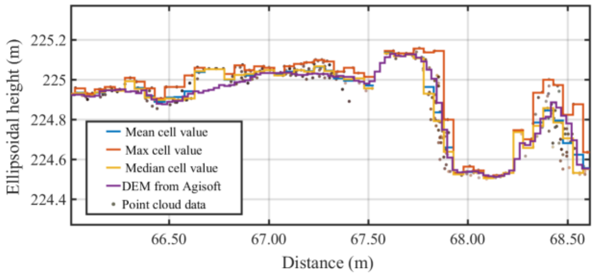

Figure 5. Rasterization of the crop surface. Cross section

Based on these results we recommend using the maximum height value within one cell, assuming no significant outliers in the point cloud. In the case of the rasterization of the reference surface, we recommend to use the median.

3.2 Difference calculation

For the comparison of the difference calculation methods, we used an area of around 60 m^2 from the CropWatch experiment in Klein Altendorf on 8th of June 2017 to calculated plant heights (Figure 6) .

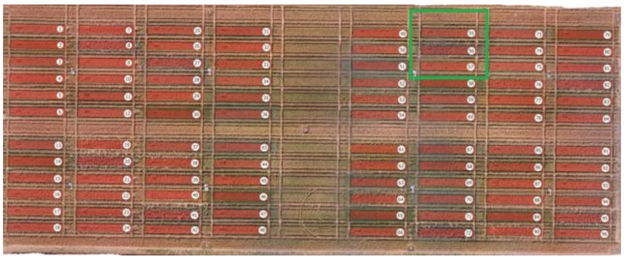

Figure 6. Field experiment. Test area in green

The point cloud has been calculated with Agisoft PhotoScan using a previously defined processing parameters. Based on these point clouds we calculated the crop heights using the methods described in 2.5. In order to compare the results, we show the histogram of heights (Figure 7) for each of the methods, but limited to the test area.

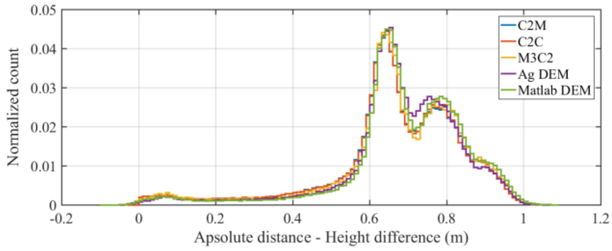

Figure 7. Crop height of test area calculated from different methods

It can be seen that all methods have almost the same behaviour and crop heights have the same distribution with three peaks. The Agisoft DEM (Ag DEM) based results seem to have a tendency towards lower values, which confirms our conclusion about smoothing the surface and building of a mean of heights sacrificing some crop surface points. However, it can be concluded, that the distribution of measured heights using the different methods do not differ more than a few centimetres. Therefore, we suggest the most efficient method, which is based on a rasterization of the point cloud described in section 2.5 to be used in the future. As demonstrated in section 3.1, we also suggest to use the maximum height value within this rasterization routine, as it represents a more realistic estimation of the plant height than the standard mean or median operation.

3.3 Reference surface generation

The generation of a reference surface marking the plants zero height is a crucial part of the height estimation procedure. Errors in the reference surface generation directly influence the estimation of the plant height. We compared the three options, described in section 2.4, where the surface have been generated from flights directly after seeding, in an early growth stage and shortly after harvest.

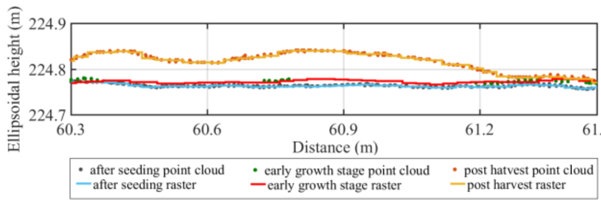

Figure 8: Example of a cross section of the reference surface rasterization. The points are point cloud data derived from after seeding (grey), early growth stage (green) and post-harvest (orange). The lines represent derived raster from each point cloud data using median value per cell with 3 cm size.

While the surface after seeding (blue) and the surface from segmented soil patches in an early growth stage (red) show similar values, the surface after harvest is 5-10 cm higher than other two (Figure 8). This can be explained by the leftover materials from the harvest.

Assuming that the after seeding flight to be the best option, as it resembles bare soil, we compared this option with the other two in the form of a distribution of height differences. Figure 9 confirms, that a surface from interpolated bare soil patches is a valid option, if an after seeding flight is not possible. However, an after harvest flight leads to a negative plant height offset in the order of several centimetres, which needs to be considered in the analysis.

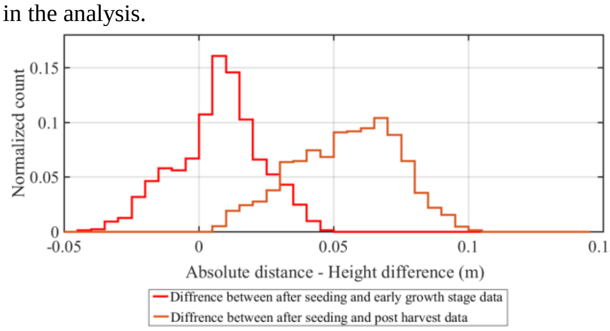

Figure 9. Height differences between after seeding reference and two alternatives

3.4 Accuracy evaluation

In section 3.1 we showed the quality of the UAV imagery based point cloud by a visual comparison with the TLS point cloud in a close up area. The actual variable of interest is the plant height per plot, we calculate this as described before for 40 plots of the BreedFACE experiment, based on the TLS and the UAV data. We compared this with the ruler-based measurement, which have been performed at the same day. At Figure 10 the correlation between the UAV results and the ruler results and the correlation between the TLS measurement and the ruler is shown.

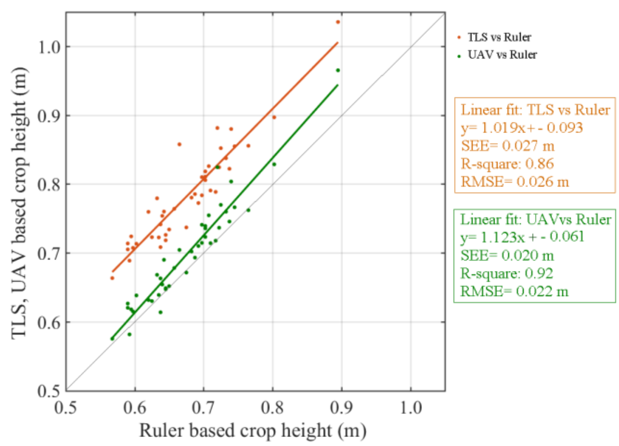

Figure 10. Linear correlation between UAV, TLS and ruler crop height

UAV heights and TLS show a good correlation with the ruler measurements, where the TLS seems to overestimate the height systematically by about 8cm. Since we consider the TLS as the most accurate method measuring the upper tip of the plants, we state, that the ruler and the UAV based method generally underestimate the real height values by a few centimetres. At least for the UAV method this is expected, as we discussed in section 3.1. The resulting noise (RMSE) is in the order of a few centimetres, although it is not possible to say, if it comes from the TLS, the UAV methods or the ruler measurements.

3.5 Growth curves in the breeding experiment

Taking all results described so far into account we generated plant height time series for each plot of the CropWatch breeding experiments in 2017 and 2018. As described in section 2.1, 12 winter wheat genotypes have been planted at two different locations in two different years with 4 repetitions. We used a reference surface from an after seeding flight, represented as a raster with 3 cm cell size and the median value for cell calculation. From the crop surface point clouds, we generated raster data using the maximum value per cell. We calculated the plant height as the difference between the rasters and used the mean of the 90th percentile to generate one height value for each plot. The four plot repetitions per cultivar were simply averaged.

Plant height serves plant breeders as an early-on selection criteria. Very short plants will be removed from the breeding process due to minor yield potential. Also, high growing plants will be dismissed from the breeding process due to the serious risk of buckling of the plants in later developmental stages (Whan et al., 1981).

Here, we selected two genotypes, KWS Ferrum (new cultivar, short, Figure 11 bottom) and Caribo (old cultivar, long, Figure 11 top) to determine the influence of the location (BO = Bornheim and KA = Klein-Altendorf), the management system (int = intensive and ext = extensive) and the growing season (17 = 2016/2017 and 18 = 2017/2018) on the height curve, derived automatically using the measurement and analysis pipeline described above, to demonstrate its general capability.
Klein-Altendorf and Bornheim were selected as testing sites because of their differing potential of plant growth and yield production. Both cultivars show bigger heights in Klein-Altendorf, supporting the assumption of a higher yield potential in KA due to the better soils. Due to the strong drought during 2018 we expected an additional gap in height between both testing sites. Our data proves our hypothesis since we can observe considerably lower heights of both cultivars in BO 2018.

Furthermore, we observed higher longitudinal growth with higher levels of nitrogen fertilization, proving the influence of nitrogen fertilization on plant growth (Hussain et al., 2006).

Between the two cultivars the expected clear differences in plant height could be detected, indicating the new height measuring system as useful for the selection / phenotyping procedure in the breeding process. Although statistical analysis or deep agronomical discussions are far beyond the scope of this paper, we can already state that in terms of plant breeding, automated measurement of plant heights could serve as a highly precise and objective phenotyping system for selecting potential new genotypes in a more cost and time effective manner than the manual system with rulers.

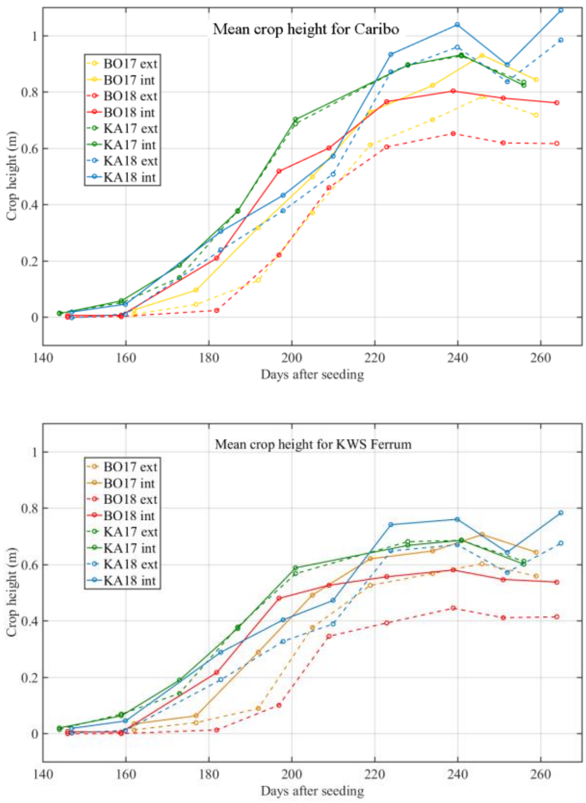

Figure 11. Seasonal crop height for two selected genotypes at different location, different systems and different growing season

3.6 Lodging of crop stands

So far, we presented the crop height of a plot (or any other area of interest) and its evolution over time as the parameter of interest resulting from the processing pipeline. However, due to the high spatial resolution of the crop height raster data it is possible to derive other potentially useful other traits, such as crop surface variability or roughness. As an example, we present the possibility to detect lodging. The so called lodging is described as the permanent buckling of the plants stem, induced by environmental factors such as rain, hail or excessive fertilization (Pinthus, 1974). The quantification of lodging area within a field could serve farmers as a valuable information in terms of decision making and could therefore lead to a more sustainable agriculture.

Figure 12 shows a section of the Orthophoto of the breeding experiment, overlapped with green or red colours. Automatically identified potential lodging areas in marked red. We only use a very simple approach here, where areas with a crop height of less than 1/3 of the expected crop height are classified. We did no effort here in separating lodging and inter-plot areas and we did not use any advanced methods to automatically derive the thresholds. Both would be necessary in order to derived an automated process. However, we can clearly see the potential as the detected lodging area within the plot is visible also in the Orthophoto and its area can be calculated very accurately due to the high spatial resolution. More investigations regarding UAV based lodging detection on defining proper thresholds, which also allow the assessment of the lodging severity is subject of current research and will be published soon.

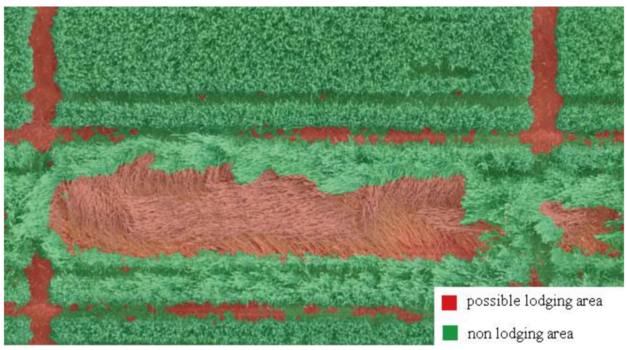

Figure 12. Lodging area detection from the UAV height data

4. CONCLUSION

In this paper we presented a pipeline on deriving wheat crop heights from multi temporal imagery taken with a UAV. In contrast to previous publications, we started with the dense point clouds, generated from SfM and MVS, and focussed on the comparison of different processing options within this pipeline. The goal was to select a number of options and parameters, which allow an automatic extraction of crop height curves from areas of interests, such as plots in a breeding experiment, in an efficient way.

We showed that the calculation of the crop height as the difference between crop surface and some reference surface, representing the soil (height = 0), can be efficiently realized by subtracting two rasters (‘elevation models’). The result is very similar to the computational more demanding options based on point clouds, which we have used for comparison. However, we recommend to use a custom rasterization routine, based on the maximum values within one cell, rather than the standard DEM output provided by the SfM software.

We recommend generating the reference surface from images at a point in time before any plants emerged. However, it is also possible to use later flights and filter out plant point, while interpolating remaining soil points. A flight after harvest will lead to an underestimation of the heights in the order of several centimetres, as leftover material from the crops will change the surface estimation.
Comparison with a terrestrial laser scan, which is considered to be the geometrically most accurate 3D measurement method, the UAV based heights appears to be up to 10 cm lower due to a smoothing effect during the photogrammetric reconstruction of the point cloud. However, they are consistent with ruler based methods representing the industry standard.

We applied the presented pipeline to a breeding experiment by calculating height values per plot and per measurement day by building the 90% percentile of all height values in the plot. In this way, we were able to generate growth curves for different winter wheat varieties and compare them in different conditions, which are the location, the management system and the season. Without any detailed statistical analysis, we showed visually that differences between the curves provide very useful information to breeders.

ACKNOWLEDGEMENTS

This work was funded by the German Federal Office for Agriculture and Food (project identification number: 2815702315). Part of this work (BreedFACE experiment) was supported within the German-Plant-Phenotyping Network which is funded by the German Federal Ministry of Education and Research (project identification number: 031A053).

We thank to the students A. Berghaus, P.C. Busch, N. Kirch, D. Lovric, S. Schmetz and Norman Wilke for support during the measurements in the FACE experiment and experiment supervisor Onno Müller for useful support.

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