3D Data Acquisition to Monitor Cropping Systems: Sensors and Methods

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ABSTRACT

In the last 5 years, a significant trend characterizes sensor development: miniaturization. The latter also accounts for TLS and UAV sensors. In combination with the developments in low-weight unmanned airborne vehicles (UAVs) or RPAS, new research opportunities arise. Especially, the generation of 3D point clouds from TLS or UAV-based imaging campaigns enables a new era in remote sensing applications in terms of spatial and temporal resolutions. Especially in precision agriculture, the demand of non-destructive sensing methods which provide within-field variabilities in space and time is given to improve crop management. Consequently, the new 3D sensing methods implicate a significant potential to improve crop monitoring. In this contribution, the focus will be on (i) 3D data analysis using multi-temporal Crop Surface Models (CSM), (ii) understanding the 3D information of crop surfaces derived by different sensors, and (iii) applying an established GIS method for resampling plant height data .

1. INTRODUCTION

In the last decade, the trend to minimize electronic devices also accounts for sensing and sensor technologies as well as for Remotely Piloted Aerial Systems (RPAS) also named UAV. These developments result in multisensor platforms for laser scanning, stereo imaging, multispectral, hyperspectral and thermal sensing (Jaakkola et al. 2010). In precision agriculture, sensing methods are of key importance to improve nutrient, pest, and stress management (Mulla 2013). Therefore, the acquisition of non-destructive sensor data has to be carried out in dependence of important phenological growing stages. In this context, the nitrogen nutrition index (NNI) was introduced as a sensing-based management approach (Mistele und Schmidthalter 2008). In short, the NNI is calculated by dividing the actual (spectrally) measured N content (N_{act}) by the critical N content (N_c). For the calculation of both parameters, dry biomass data is needed. Biomass is also a key parameter for calculating the harvest index which is used for yield simulations (Kemanian et al. 2007). A typical approach to estimate biomass non-destructively is proximal or remote sensing (Gnyp et al. 2014; Koppe et al. 2012; Koppe et al. 2013). Besides these approaches, it is known that plant height is a strong predictor for biomass (Fricke and Wachendorf 2013). Therefore, the concept of multi-temporal Crop Surface Models (CSMs) was introduced by Hoffmeister et al. (2011) to derive plant height from terrestrial laser scanning (TLS). This concept of multi-temporal CSMs was transferred on an UAV approach using RGB imaging and Structure from Motion (SfM) data analysis (Bendig et al. 2013). In this contribution, the focus will be on (i) 3D data analysis using multi-temporal Crop Surface Models (CSM), (ii) understanding the 3D information of crop surfaces derived by different sensors, and (iii) suggesting an established GIS method for resampling plant height data.

2. METHODS

In several publications, it is shown that the approach of multi-temporal CSMs is very suitable to derive crop plant height and crop biomass by using terrestrial laser scanning (TLS) or UAV-based RGB imaging (Bendig et al. 2014, Geipel et al. 2014, Hoffmeister et al. 2010, Tilly et al. 2014, Bareth et al. 2015). The idea of the CSM approach is shown in Fig. 1. After sowing and before plant emergence, a first Digital Elevation Model (DEM) is captured. Afterwards and in dependence of the phenological important growing stages, additional Digital Surface Models, in the crop context named CSM, are produced. By raster data calculations, the crop height for each raster cell is calculated for each phenological stage. The data for the DEM and the CSMs can be generated either by TLS or UAV campaigns as shown in Fig. 2 and Fig. 3.

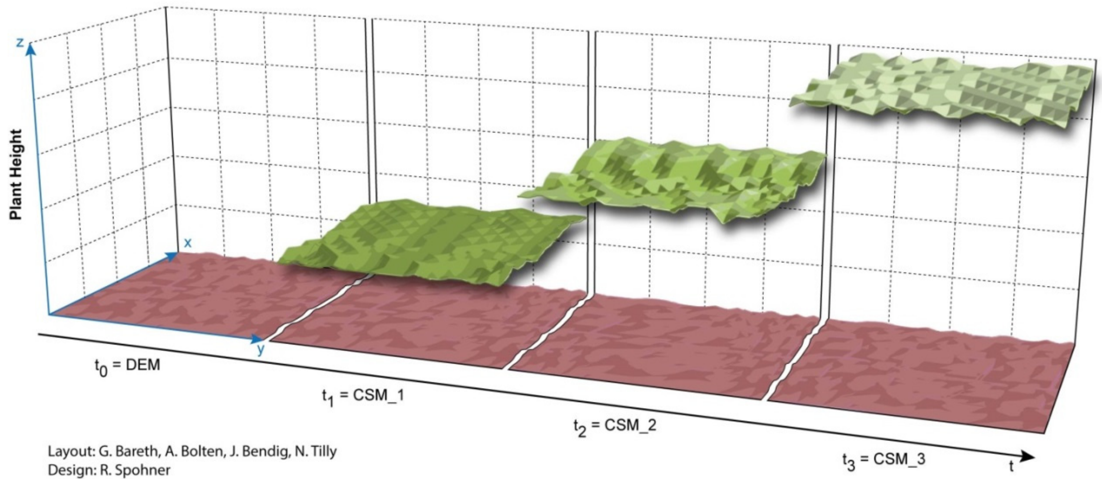

Figure 1: Multi-temporal Crop Surface Models (CSMs) (Bendig et al. 2014).

Figure 2: TLS data campaign.

Figure 3: UAV data campaign.

3. RESULTS

The CSM derived plant height data is suitable to estimate biomass with a high R^2. The latter is proofed and investigated in several investigations (Bendig et al. 2014, Tilly et al. 2014, Bareth et al. 2015). In Fig. 4, UAV-derived plant height data for barley are validated against manual measurements resulting in a R^2 of 0.92. As shown is Fig. 5, similar results are produced with TLS-derived plant height for rice (R^2 = 0.91). Finally, the approach is also working for grasslands. In Fig. 6, UAV-derived plant height is plotted against compressed sward height which was measured with a rising plate meter. The latter is used in grasslands for determining biomass increase. Also in this example a very high R^2 of 0.89 is produced.

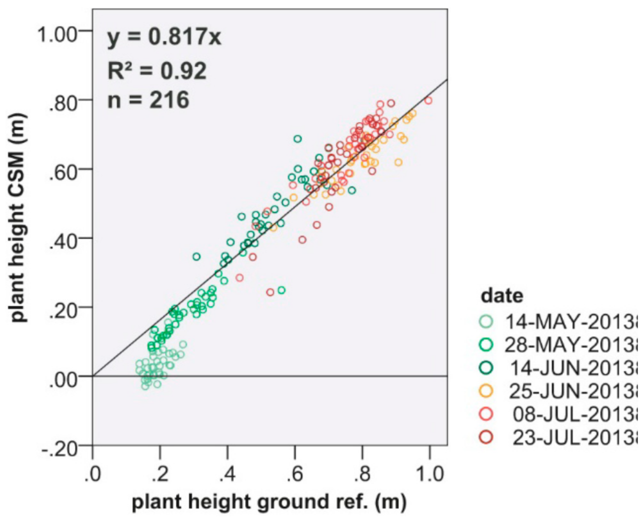

Figure 4: UAV-derived CSM-plant height evaluated against manual plant height measurements in barley (Bendig et al. 2014).

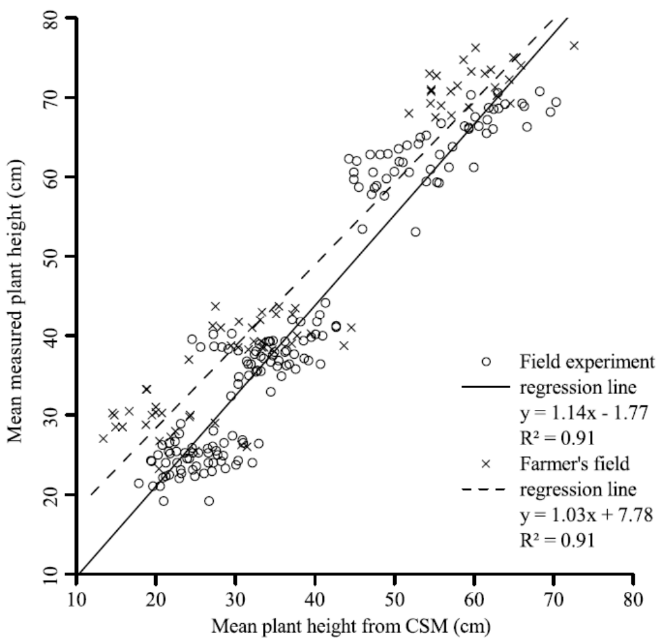

Figure 5: TLS derived CSM-plant height evaluated against manual plant height measurements in rice (Tilly et al. 2014).

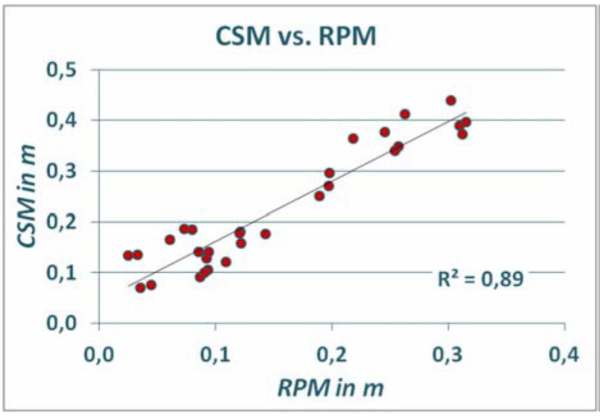

Figure 6: UAV derived CSM-plant height evaluated against manual rising plate measurements in grassland (Bareth et al. 2015).

4. WYSIWYG

"What you see is what you get" (WYSIWYG) seems to be generally true in RGB imaging. But from the experiences working with TLS- and UAV-derived CSMs, an essential research question developed: What do we actually "see" from nadir imaging and from oblique laser scanning in the CSMs? The data acquisition situations are shown in Fig. 7 and Fig. 8. In Fig. 7, the nadir imaging with UAVs is visualized for different crop densities. Even so the single plant height is equal in both densities, the average plot plant height differs according to the plant cover density. This density information is not included in the oblique data acquisition shown in Fig. 8. Here, the average plant is similar to the one of the higher density because less low plant height values are recorded.

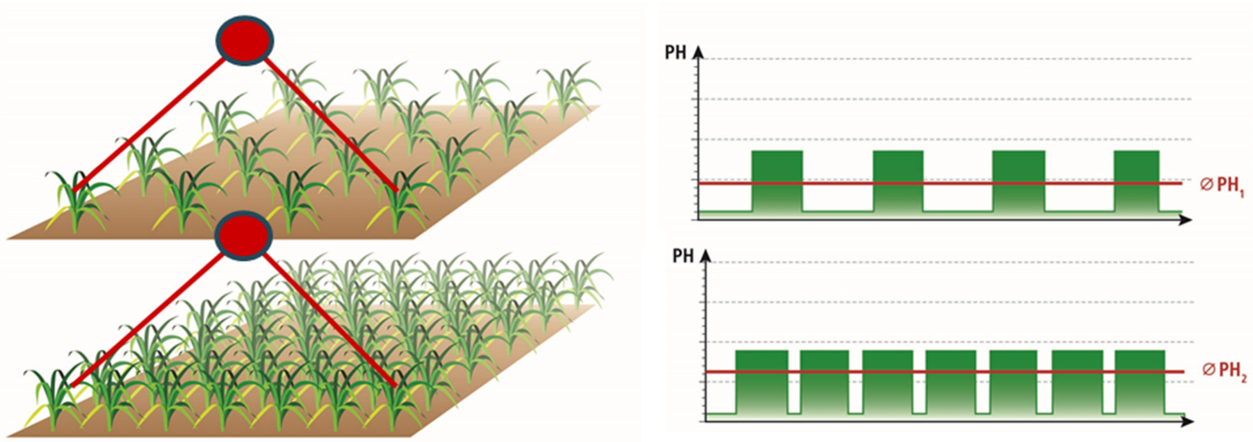

Figure 7: Nadir view: equal plant height but different plant densities result in different mean plant height.

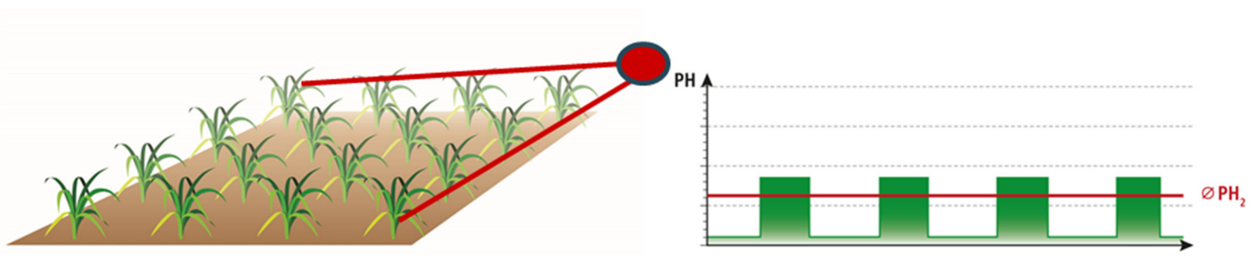

Figure 8: Oblique view: equal plant height and plant density but different plant density than in nadir view.

5. ZONAL STATISTICS

As shown in Fig. 7 and Fig. 8, the very high spatial resolution of TLS- and UAV-derived CSMs (< 3 cm) on field level contains additional useful plant height information which could be described as surface roughness. On the one hand, homogenous plant height of crops within a field results in a smooth CSM without a high variance of plant height. On the other hand, a large inhomogeneity of crop plant height within a field produces a rough CSM. Usually, a spatial resolution of < 3 cm is not needed in precision agriculture. More applicable are spatial resolutions in dm or m. For such a processing step standard resampling methods like nearest neighbor are usually applied resulting again in one value class of the raster data set. But the spatial variance in plant height also contains valuable information. Therefore, it is of research interest to keep some of this information to explore its potential for crop monitoring. Hence, I suggest to use a vector grid for "resampling" the very high resolution into a coarser one. The method is known as zonal statistics and provides a data set of descriptive statistics for each vector cell.
As an example, results of such a zonal statistic approach are shown in Fig. 9 and Fig. 10. The CSM presented in Fig. 9 has a spatial resolution of 0.2 m while the original input CSM was generated in a spatial resolution of 0.01 cm. The cells with the black outline are the cells of the vector grid which was used to compute the zonal statistics for each cell. In Fig. 9 the mean plant height is visualized for each cell which was computed from all 400 input raster cells. To show the potential of the zonal statistics for a vector grid, the standard deviation of the resampled CSM shown is Fig. 9 is presented in Fig. 10. Interestingly, a very different spatial pattern for the different plots can be identified.

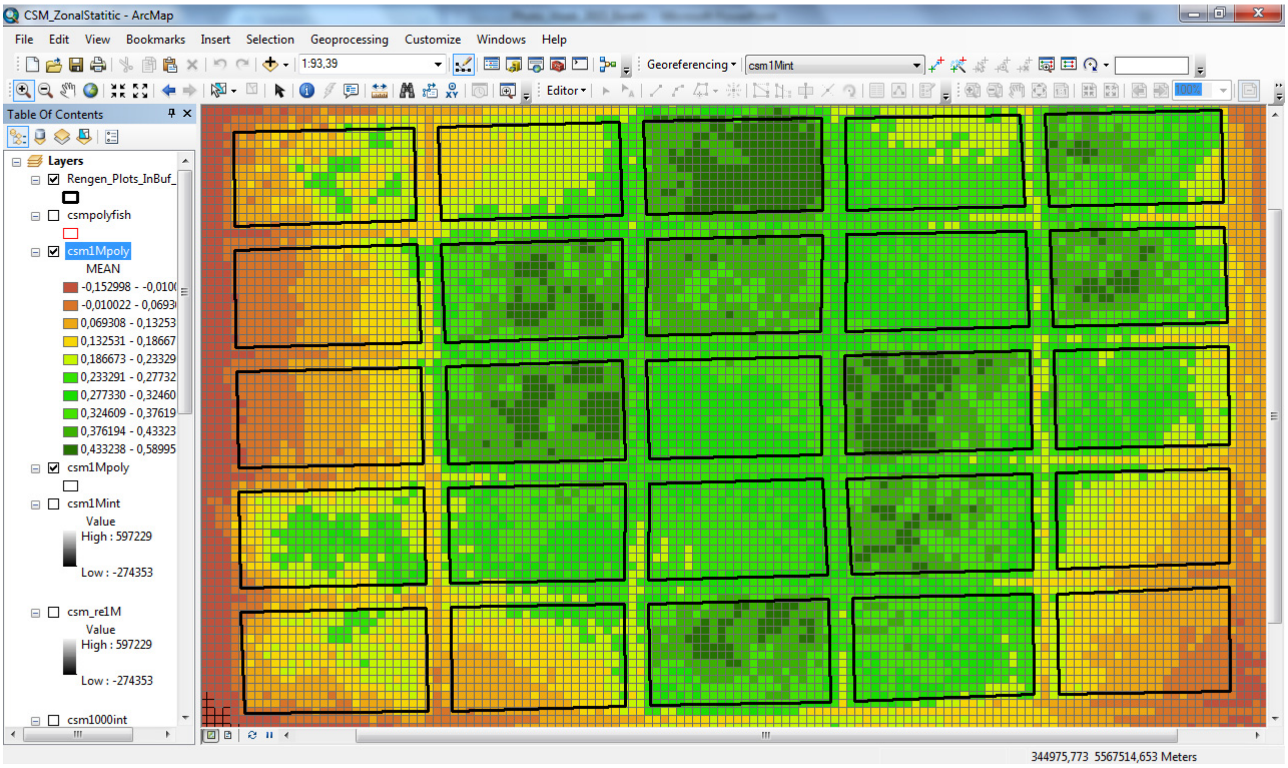

Figure 9: CSM containing mean plant height computed with zonal statistics.

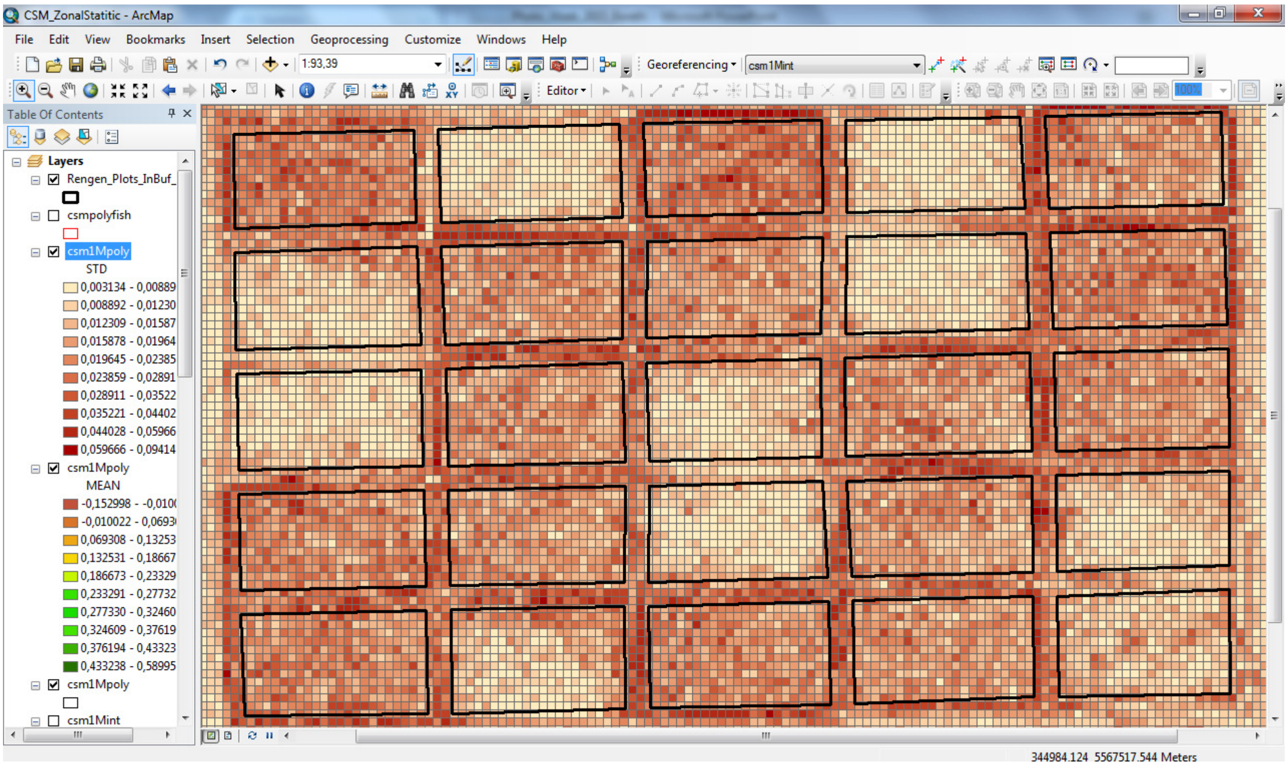

Figure 10: Oblique view: equal plant height and plant density but different plant density.

6. CONCLUSIONS

In numerous studies it is proofed that crop growth and corresponding biomass can be reliable monitored with 3D data capturing approaches. TLS- and UAV-derived multi-temporal CSMs are good predictors for crop biomass. As expected, there is a difference in nadir- or oblique-derived plant height information which has to be considered in future studies. Finally, the use of vector grids in combination of zonal statistics might have the potential to improve biomass monitoring.

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8. REFERENCES

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