UAV-BASED HYPERSPECTRAL SENSING FOR YIELD PREDICTION IN WINTER BARLEY

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ABSTRACT

In this study we evaluated the potential of the hyperspectral sensor "Cubert UHD 185 Firefly" for yield prediction in 76 plots of a field trial with different varieties of winter barley at Königslutter (Lower-Saxony, Germany) in 2017. An UAV was used as carrier platform for the sensor. In 2017 we used 63 channels in a wavelength range of 450 to 700 nm. Predicted yield using PLSR and reference yield closely agreed with R^2=0.78. We also calculated the $NDVI_{RGB}$ and evaluated its suitability for yield prediction in the same field trial. $NDVI_{RGB}$ and reference yield were less well related to each other with R^2=0.46. The results show that using additional information from hyperspectral datasets allowed for a better yield prediction compared to RGB data alone. In 2018 a field trial with 76 plots of winter barley at Poppenburg (Lower- Saxony, Germany) was assessed on June 6, using the complete wavelength range of the sensor from 450 to 950 nm. In 2018, predicted yield using PLSR and reference yield agreed with R^2= 0,81.

Index Terms— UAV, hyperspectral, yield prediction, barley, phenotyping, phenomics, field experiment

1. INTRODUCTION

An adequate crop supply of the world population will be one of the biggest challenges for agriculture in 21st century, as experts estimate crop demand will nearly double in the first half of this century [1]. A sustainable intensification of agricultural production in terms of increasing yields will be required to satisfy the increasing demand [2;3]. Continuous agricultural research has advanced agricultural crop production in many of its different subareas like fertilization, irrigation, plant protection and the improvement of crop yield potential. In this context, agricultural field trials providing representative and statistically underpinned results have become a very important basis for research [4].
During the vegetation period, agricultural field trials are once or more often rated regarding different traits. The results of such ratings build an important part of the subsequent evaluation of field trials. Scoring traits like the number of germinated plants or the height of plants is quite easy but time-consuming. Rating of other traits (i.e. the extent of fungal infections or estimates of biomass) is more difficult and is highly experience based. In addition, scoring results of traits as obtained from different persons do in many cases not conform with each other and remain subjective. For these reasons, the availability of reliable aids supporting objective assessments in field trials would be an eminent gain for agriculture.

In this context, the usage of hyperspectral sensors as a remote sensing instrument has come to the fore. By providing images containing more information than common RGB cameras, hyperspectral sensors have increasingly gained attention for remote sensing, particularly also in agriculture. By and by, hyperspectral sensors have become continuously smaller, lighter and more resistant against environmental influences [5]. Hence, hyperspectral sensors are predestinated to be used in combination with Unmanned Aerial Vehicles (UAV's) [6]. Compared to systems used on the ground, UAV's are able to traverse comparatively large areas in a much shorter time independent of the traffic conditions. Thus, they have become more and more popular for usage in agriculture.

To analyze the suitability of hyperspectral sensors for yield prediction in agricultural field trials a hyperspectral sensor was used with an UAV as platform. In 2017 a field trial with different varieties of winter barley in Lower Saxony (Germany) was assessed. For yield prediction the spectral information was statistically analyzed based on linear regression or PLSR analysis and the predicted plot yields were correlated with the weighed plot yields. In addition, the spectral information was used to calculate the $NDVI_{RGB}$ as a simple frequently used index reflecting biomass and which was for this reason also correlated with the weighed plot yields to analyze whether hyperspectral data or the $NDVI_{RGB}$ as a vegetation index which can easily be obtained from a common RGB camera are more suitable for yield prediction [7].

2. MATERIALS AND METHODS

The rotary-wing UAV used was customized by the company Kopterzentrale (Hanover, Germany). Its weight including the hyperspectral sensor is about 5 kg. The flight time varies from 10 to 20 minutes, depending on the payload. The UAV and the hyperspectral sensor are linked via servo-gimbal. The hyperspectral sensor was obtained from Cubert (Ulm, Germany). We used the model "UHD 185 Firefly" which is a full-frame camera, capturing 138 spectral bands with a sampling interval of 4 nm. Cubert recommends the use of 125 bands between 450 and 950 nm (http://www.cubert-gmbh.de). For each band, the sensor captures a 50 by 50 pixel image with 12 bit precision [8]. At the same time a grayscale image with a resolution of 990 by 1000 pixel is created. Since the sensor was attached horizontally a mirror was used, guiding the ground image into the sensor. A mini pc (Pokini Z) was used to control the sensor. In 2017 a light intensity sensor could not be used because it did not properly work. For this reason the sensor was calibrated with a reference plate before each flight. Therefore, the UAV was placed on two boxes with the sensor aligned to avoid shadowing the plate. The distance from the lens to the plate during the calibration process was about 40 cm. Subsequent to the white reference panel calibration the software controlling the sensor proposed an integration time for the flight. In our case the proposed integration time of 1,2 ms was slightly increased. This was based on the manufacturer´s advice to adjust for different illumination conditions during the flight at given height compared to the comparatively short distance between the lens and the reference plate during the calibration process.

The field trial was planned with the software "MiniGIS" by Geo-Konzept (Adelschlag, Germany). The trial design included two blocks. One block was not treated with plant protectants while the other block was protected. After planning the trial was sown with a tractor equipped with a Trimble RTK guidance system to achieve a maximum precision. MiniGIS was also used to generate a flight plan considering the UAV's altitude, speed and the favored overlap of the hyperspectral images. In 2017, the UAV's speed was set to 3 m s^{-1} at an altitude of 80 meters. Overlapping of the images was set to 75 % in both directions. The analyzed field trial was assessed on June 8, 2017. At this time, the plants were in late milk ripeness (EC 77). During the flight the sensor generated 115 pictures. In the field, reference points were measured with a texxmo Kaleo RTK system. The generated images were processed with Agisoft Photoscan Professional (Agisoft LLC, St. Petersburg, Russia) due to positive experiences in several other studies [9;10]. Agisoft was used to create an orthomosaic which was then imported into MiniGIS. After the import, MiniGIS was used to excerpt the spectral information of the 125 channels for each of the 76 plots of the field trial. For further analysis the spectral information was exported by MiniGIS in a csv data sheet. This spectral raw data was also used for the calculation of the $NDVI_{RGB}$. The plot yields used as reference values were determined by a Mettler weighing system that was installed on a Haldrup C-85 plot combine at July 19, 2017. The yields were statistically predicted by calculating a Partial Least Square Regression (PLSR). We only used the information of the channels 1 to 64 which correspond to a spectrum of about 450 to about 700 nm. The $NDVI_{RGB}$ was calculated by picking the relevant information. In our case, the wavelengths 530 nm (green, channel 21), 460 nm (blue, channel 3) and 700 nm (red, channel 63) were used for the calculation.

2.1 Statistical analysis

The spectral raw data was edited with Microsoft Excel 2016 (Microsoft Corporation). Microsoft Excel was also used for linear regressions and for the calculation of the RGB vegetation indices. The PLSR was calculated with the software "The Unscrambler X 10.5 Client" (Camo Software AS).

Fig.1: The used rotary-wing UAV with gimbal and mounted hyperspectral sensor Cubert UHD 185 Firefly.

3. RESULTS

3.1 Yield prediction with hyperspectal data

Figure 2 shows the results of the correlation of the predicted yields and the reference yields of the 76 plots after a full cross validation. Previously, the spectrum was optimized via Gaussian filter transformation with a segment size of 7 and a standard normal variate. The PLSR was calculated with six factors. The predicted yields and the reference yields were related to each other with R^2= 0.78. The root mean square error was 6.42 dt/ha.

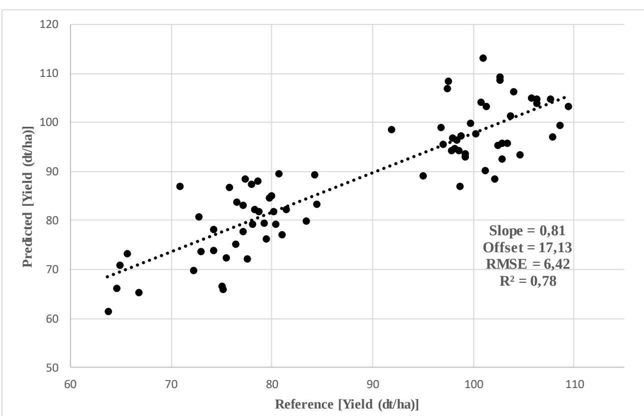

Fig. 2: Relationship of plot yields predicted by hyperspectral PLRS data analysis and weighed yields of 76 plots cultivated with different winter barley cultivars

3.2 Yield prediction by $NDVI_{RGB}$

Figure 3 shows the result of the correlation of the weighed plot yields and the calculated $NDVI_{RGB}$ for the 76 plots. The weighed yields and the $NDVI_{RGB}$ were related to each other with R^2=0,46.

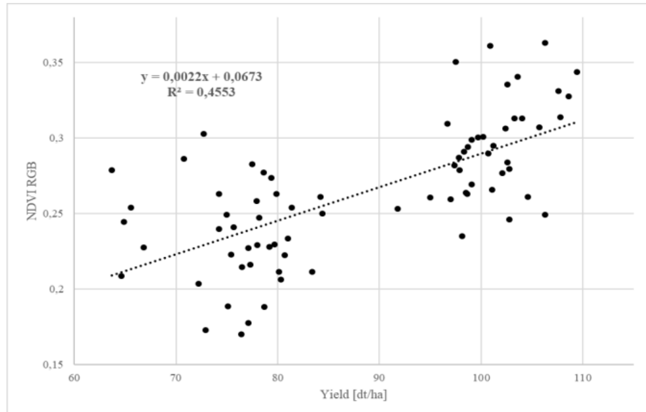

Fig. 3: Relationship of weighed plot yields and calculated $NDVI_{RGB}$

4. DISCUSSION

As indicated in the Materials and methods section the generated spectra were not completely evaluable. For this reason the potential influence on the quality of the hyperspectral material is previously discussed.

The hyperspectral sensor and the UAV were linked via servo-gimbal. In addition, the sensor was equipped with a mirror that guided the ground image to the sensor. Servo-gimbals are comparatively unfit to soften vibrations during the flight. This holds true for the mirror which constitutes a potential weakness for the quality assurance of the hyperspectral information. A transition from a servo-gimbal to a brushless-gimbal that softens vibrations more efficiently should be targeted. In addition, an omission of the mirror by vertical positioning of the sensor is advised for future studies. A refinement of the settings in the flight plan might also improve the quality of the material. Strictly speaking a reduction of the speed during the flight to 1 m/s might reduce vibrations and should therefore be targeted.

The integration time proposed after the calibration of the sensor was slightly increased before the flight. The weather at the day of the flight was characterized by sunny conditions with sparing clouds in the sky. Cloudy conditions during the calibration process and sunny conditions during the flight might in hindsight have caused an overexposure which is difficult to correct afterwards. This circumstance clarifies that weather conditions during the calibration process may have a marked influence on the generated imaging information. In future studies we will ascribe more importance to the weather conditions at the day of the flight. Ideally, days with not changing conditions such as a cloudless sky or overcast conditions should preferably be used for the calibration and the flight campaign. An ideal solution would be the usage of a light/imaging sensor that directly assesses the illumination and the reflected spectral information for high quality assurance.

Yield predicted by using hyperspectral data in a wavelength range from 450 to 700 nm and weighed plot yield agreed with $R^2= 0.78$. Barmeier et al. (2017) analyzed whether hyperspectral data can be used to predict grain yield in spring barley and achieved encouraging results [11]. Since we could only use information in the visible range of light we also analyzed the suitability of the $NDVI_{RGB}$ for yield prediction to allow for a comparison between common RGB cameras and hyperspectral data. Yield prediction by usage of a RGB camera would be a comparatively cheap solution. In addition, the collected amount of data would be comparatively small. In this case the results show that the hyperspectral dataset was better performing than the $NDVI_{RGB}$ to predict plot yields. In future studies we will focus more on the quality assurance of the material to be able to evaluate the complete spectrum and to explore the full potential of the hyperspectral data.

5. CONCLUSIONS AND OUTLOOK

Although the complete spectrum could not be evaluated the additional information of the hyperspectral dataset led to a better yield prediction compared to common RGB data in the visible range of light. An important future goal will be the improvement of the quality of the hyperspectral information to be able to assess the complete spectrum. The optimization of flight parameters such as the altitude and the flight speed and the usage of a brushless gimbal that offers the possibility to hold the sensor in a vertical position without using a mirror will possibly contribute to a significant improvement of the quality of the imaging information l and will therefore be used in future studies. This also applies for the usage of a light sensor that directly assesses the incident radiation and the reflected imaging information.

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