1 Predicting Cover Crop Biomass by Lightweight UAS-
2 Based RGB and NIR Photography: An Applied
3 Photogrammetric Approach

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Abstract

Easy-to-capture and robust plant status indicators are important factors when implementing precision agriculture techniques on fields. In this study, aerial red, green and blue color space (RGB) photography and near-infrared (NIR) photography was performed on an experimental field site with nine different cover crops. A lightweight unmanned aerial system (UAS) served as platform, consumer cameras as sensors. Photos were photogrammetrically processed to orthophotos and digital surface models (DSMs). In a first validation step, the spatial precision of RGB orthophotos (x and y, ± 0.1 m) and DSMs (z, ± 0.1 m) was determined. Then, canopy cover (CC), plant height (PH), normalized differenced vegetation index (NDVI), red edge inflection point (REIP), and green red vegetation index (GRVI) were extracted. In a second validation step, the PHs derived from the DSMs were compared with ground truth ruler measurements. A strong linear relationship was observed ($R^2 = 0.80\text{--}0.84$). Finally, destructive biomass samples were taken and compared with the remotely-sensed characteristics. Biomass correlated best with plant height (PH), and good approximations with linear regressions were found ($R^2 = 0.74$ for four selected species, $R^2 = 0.58$ for all nine species). CC and the vegetation indices (VIs) showed less significant and less strong overall correlations, but performed well for certain species. It is therefore evident that the use of DSM-based PHs provides a feasible approach to a species-independent non-destructive biomass determination, where the performance of VIs is more species-dependent.

Keywords

biomass, plant height, cover crop, precision agriculture, UAS

Introduction

At present, precision agriculture is a widely discussed concept, but its implementation is rather fragmentary (Pierpaoli et al. 2013). This situation might change soon: recent developments in unmanned aerial systems (UASs) have improved the availability of affordable hardware and software for remote sensing purposes (see Colomina and Molina (2014) for a general review and Shahbazi et al. (2014) for specific applications in natural resources management). At the same time, research has been done in the field of crop phenotyping in defining traits for plant performance (White et al. 2012; Walter et al. 2012, 2015).

Part of the discussed trait indices for precision agriculture are the normalized differenced vegetation index (NDVI) and the red edge inflection point (REIP), both generally derived from spectral data in the visible and near-infrared (NIR) range (Thenkabail et al. 2000; Tilly et al. 2015). Also under discussion are red, green and blue color space (RGB) based vegetation indices (VIs) such as the red green blue vegetation index (RGBVI) (Tilly et al. 2015). Significant, but weak correlations between NDVI and plant biomass, leaf biomass and crop yield are indicated in several studies, e.g. for wheat by Jensen et al. (2007), for winter cover crops by Hunt et al. (2011) and for corn by Liebisch et al. (2015). In barley, Tilly et al. (2015) found weak correlations between NDVI, RGBVI and biomass and good correlations between REIP and biomass in pre-flowering stages.

Plant height (PH) represents another indicator potentially useful for precision agriculture (Yin et al. 2011). Studies in corn have shown a good relationship between crop yield and PH (Freeman et al. 2007; Machado et al. 2002; Yin et al. 2011), and studies in other crops have presented correlations between PH and biomass for rice (Tilly et al. 2014), oilseed rape, winter rye, winter wheat and grassland (Ehlert et al. 2008) and barley (Tilly et al. 2015).

To remotely sense PHs by extracting them from digital surface models (DSMs), photogrammetry is a possible option (Wolf and Dewitt 2000). Structure from Motion (SfM)

algorithms enable such extractions to be performed on photos captured by UASs (Dandois and Ellis 2010). Turner et al. (2012) showed that SfM algorithms are able to produce mosaics with less than 0.15 m error in X and Y directions; the Z error remained unevaluated. Sona et al. (2014) evaluated different SfM software packages and assessed the package Agisoft PhotoScan (Agisoft LLC, St. Petersburg, Russia), which we used in this study, as producing a high quality photogrammetry product.

Nevertheless, PH derived from aerial photography has rarely been used in agronomic studies: Murakami et al. (2012) examined the lodging tendency of buckwheat, and Gillan et al. (2014) modeled the vegetation height of grassland. To calculate PHs, both a digital terrain model (DTM) and a digital surface model (DSM) are necessary. The two mentioned studies used interpolation to estimate a DTM. They were able to demonstrate good correlations between PHs measured by hand (e.g. with a ruler) and PHs derived from a crop surface model (CSM) (PH_{CSM}). Subsequent studies have not interpolated the DTM but rather used photos from an additional flight over bare soil to generate the DTM. Good correlations between PH measured by hand and PH_{CSM} and between biomass and PH_{CSM} is given by Bendig et al. (2014) for barley. Geipel et al. (2014) found good correlations between PH_{CSM} and yield for corn, and Bendig et al. (2015) between PH_{CSM} and dry biomass for barley.

Predicting crop yield is one step towards precision agriculture. However, to prevent fertilizer waste, ensure quality of yield, protect the soil, and for other environmental issues, it is even more important to analyze inhomogeneity in between subplots of a field. In a production system such as conservation agriculture including cover crops (Lal 2015), the cover crop stage offers a possibility to analyze the (potentially differing) soil condition and to pro-actively prevent an inhomogeneous starting condition for the following crop.

Common used cover crops vary widely as regards color, surface properties, shape, canopy cover (CC), and as a consequence spectral reflectance. It is still unclear whether using lightweight UAS-based photos captured with consumer cameras and subsequently produced orthophotos and DSMs are suitable for estimating cover crop biomass. Furthermore, the influence of growth stage and of species-specific physiological characteristics represent additional sources of uncertainty. In this study, UAS-based data from a small-scale, no-till/cover crop field experiment were used to test the following hypotheses: (1) the method of capturing and processing photos with an UAS is sufficient to produce spatially precise DSMs and RGB/NIR orthophotos, (2) the resulting PH_{CSM} is a species- and growth-stage-independent representation of ground truth, (3) depending on plant species, the PH, CC, or different VIs correlate with plant biomass.

Methods

To test the above-mentioned hypotheses, the cover crop biomass was compared with different remotely-sensed characteristics: PH derived from DSMs (PH_{CSM}), CC based on NIR and RGB photography, and three different VIs, NDVI and REIP based on NIR photography, and green red vegetation index (GRVI) based on RGB photography. Data acquisition campaigns were realized at three different timings: One at bare soil stage (Campaign 0), one 35 days after sowing (Campaign 1) and one at the end of the cover crop cycle (Campaign 2), shortly before sowing winter wheat (Table 1). Before finally correlating the destructively harvested biomass samples with the VIs, CC and PH, several steps were performed (Fig. 1): The acquired photos were photogrammetrically processed and the resulting orthophotos compared with ground truth references captured with global position system (GPS) equipment (Trimble GeoExplorer 2008 Series DGPS, Trimble Ltd., Sunnyvale, U.S.A.). VIs, CC and PH_{CSM} were calculated, and the latter validated against ground truth PH ruler measurements (PH_{ground truth}).

Experimental Setup

The experimental field was located in Leuzigen, Switzerland (1°22'33.5" N, 2°6'1'8.30" E). The area used was part of an established conservation agriculture management system including cover crops and regular crop rotation. The preceding crop was winter wheat, as was the following crop. The cover crops analyzed in this study represent a selection of common available legumes (Experiment 1) and some other, rarer dicots (Experiment 2). The legume selection included: *Pisum sativum arvense* L. 'Arvika' (field pea), *Vicia faba* L. 'Hiverna' (field bean), *Trifolium alexandrinum* L. 'Tigri' (Egyptian clover), *Trifolium resupinatum* L. 'Lightning' (Persian clover), *Vicia sativa* L. 'Berninova' (garden vetch), *Lupinus albus* L. 'Amiga' (white lupin) and *Lens culinaris* MEDIK. 'Anicia' (lentil). The dicot selection included: *Linum usitatissimum* L. 'Duchess' (flax), *Cannabis sativa* L. 'Fedora17' (hemp) and additionally *P. sativum arvense* as reference to Experiment 1.

The experimental setup was organized as Latin square design with four replications (Experiment 1) and three replications (Experiment 2) (Fig. 3). The plot size was 3 x 8 meters (Fig. 2b). Four control plots without cover crops in Experiment 1 as well as three control plots without cover crops in Experiment 2 were excluded from analysis. Another four plots with poorly growing cover crop species in Experiment 2 (*Phacelia tanacetifolia* BENTH. 'Julia' and *Onobrychis viciifolia* SCOP. 'Visnovsky'), caused by overgrowing weeds, became excluded too. Four ground control points (GCPs) (Set 2) were defined at the corners of Experiment 1, four additional GCPs (Set 1) at the corners of the whole field.

Cover crops were sown on July 21, 2015 with a Gaspardo DP 300 no-till drill with single disc openers modified for small plot experiments (Maschio Gaspardo S.p.A., Pordenone, Italy). Experimental plots were kept weed-free by regular hand weeding. On August 11, 2015, 0.5 l ha⁻¹ of the grass herbicide Select (240 g a.i. l⁻¹ Clethodim, Stähler Suisse SA, Zofingen, Switzerland) was applied. Twice (August 6 and August 10, 2015), local application of Zwei, 4 - D Dicopur (496 g a.i. l⁻¹ 2,4-D, Leu+Gygax AG, Birmenstorf, Switzerland) was required to prevent spreading of *Cirsium arvense* (L.) SCOP. (field thistle). The task was performed with a spot sprayer (Birchmeier Sprühtechnik AG, Stetten, Switzerland).

Ground Truth Measurements

Eight GCPs and 74 altitude reference points (Fig. 3a) were captured using a Trimble GeoExplorer 2008 Series DGPS (Differential Global Positioning System) with swipos-GIS/GEO RTK (Real Time Kinematic) correction (Federal Office of Topography swisstopo, Wabern, Switzerland) with an overall horizontal and vertical precision of 0.1 m. PH_{ground truth} ruler measurements were carried out for Campaign 1 (Experiment 1) and Campaign 2 (Experiment 1 and 2) using a meter stick. Average height was taken four times per plot at one-meter distance from each corner (Fig. 3b). Dry weight biomass determination was performed for Campaign 2 by destructively harvesting an area of 0.5 x 0.5 m in the center of each plot. Samples were processed in a drying oven at 105 °C for 48 h and later weighed. For analysis, weights were extrapolated to g m⁻².

Image Acquisition

An ARF Mikrokopter Okto XL in combination with the autopilot system Mikrokopter tool 2.10c (HiSystems GmbH, Moormerland, Germany) was used as UAS (Fig. 2a). Flight parameter differed for RGB and NIR campaign by means of flight height, distance between exposure stations and spacing between flight lines (Table 2). The sensors were exposed by use

of an external camera trigger cable connected to a Mikrokopter output channel. Depending on the flight speed, the autopilot system Mikrokopter tool sent a signal to the camera trigger in the appropriate time interval, resulting in the intended distance between exposure stations.

A Canon EOS 100D (Canon, Tokyo, Japan) with a Voigtländer SL II - N 20 mm / F 3,5 Color Skopar lens (Voigtländer, Braunschweig, Germany) served as RGB sensor (aerial photo sample: Fig. 2c). Focus was set to infinity. Aperture was set to automatic mode. For each campaign, shutter speed was fixed either to 1/1000 or 1/800 s, depending on lighting condition. This resulted in the following configurations – Campaign 0: ISO 100, 1/1000 s, f/4.6; Campaign 1: ISO 100, 1/1000 s, f/3.5, Campaign 2: ISO 100, 1/800 s, f/3.5.

As NIR sensor a Tetracam Mini-MCA (Tetracam Inc., Chatsworth, U.S.A.) with center wavelengths/bandwidths 670-10, 700-10, 740-10, 780-10 and 970-10 nm, fixed aperture (f/3.2) and fixed lens was used (aerial photo sample: Fig. 2d). Shutter speed was set to automatic mode (Auto EXP Method Average). The camera was decoupled to the Mikrokopter frame in two different ways: By use of the gimbal itself and also through the use of rubber sockets to fix the camera on the gimbal. A rolling shutter effect caused by the rotor vibrations could thus be successfully avoided.

The NIR sensor was supplied with an integrated incident light sensor, gathering downwelling radiation at the same wavelengths as those captured by the camera. The recorded RAW files became processed with PixelWrench2 1.0.8.5 (Tetracam Inc., Chatsworth, U.S.A.). This process included vignetting correction based on standard configuration files provided with the camera as well as radiometric calibration based on the data from the integrated incident light sensor. Finally, the photos were exported as multipage TIFF files including the calculated reflectance values of all five bands.

First results indicated that the flight height of 75 m for NIR photo capturing had been incorrectly calculated, resulting in a too low resolution of the orthophoto. For validation purpose, flight height was retained at 75 m to ensure comparability. For Campaign 2 an additional flight at 30 m was carried out to enhance resolution and to improve validity for final correlation analysis (Table 2).

Image Processing

Aerial photos were mosaiced with the SfM-based software Agisoft PhotoScan Profession 1.1.6. One set of photos was referenced using GCP Set 1, covering the whole farm field. The resulting orthophoto and DSMs were used to check the position accuracy of the photogrammetric product. Another set of photos was referenced using GCP Set 2, covering only the examined area. This set was used to validate PH_{CSM} and for correlation analysis. For each set, GCPs were imported to Agisoft PhotoScan and manually placed on each photo. Uniform settings were used for the subsequent processing steps (Table 4). After processing, DSM, RGB and NIR orthophoto were exported in GeoTIFF format. Pixel size was reduced at same time to the final resolution (see Table 2 for resulting pixel size). The coordinate reference system used in this study was EPSG:2056 (CH1903+ LV95).

All further processing was performed using GRASS 7.0.2 (GRASS Development Team 2015), scripted in R 3.2.2 (R Core Team 2015) by the use of package rgrass7 (Bivand 2015). For the validation of spatial accuracy of the photogrammetric product, orthophoto coordinates and DSM altitudes were extracted by manually identifying the corresponding GCP and altitude marks, exporting their position and re-importing to R. For PH_{CSM} validation and correlation analysis, PH_{CSM} and VIs were calculated in GRASS (Table 3) and imported to R using package rgrass7 for further analysis.

For NDVI calculation, instead of the more commonly used 670 nm band (Tilly et al. 2014; Jensen et al. 2007; Hunt et al. 2011) we used the 700 nm band. This decision was due to the

fact that the selection of the 700 nm band led to more reasonable NDVI scaling. The reason for the better performance of NDVI(700 nm) is most probably a saturation effect of the NDVI(670 nm), as shown in Fig. 9, caused by an undersaturation of the 670 nm band in advanced growth stages (Tilly et al. 2015).

For the purpose of segmenting plant and soil, a concept proposed by Liebisch et al. (2015) was used: A first segmentation mask was produced by masking parts with $NDVI < 0.2$ as soil, all other parts as plant. A second segmentation mask was produced using a monochrome raster representing the reflection intensity of RGB photos to filter out highly shaded areas ($DN < 125$) and mask them as soil, while other parts were masked as plant. Optimal thresholds for both segmentation masks were determined by visually comparing NIR and RGB orthophotos and the resulting segmentation mask. Finally, a raster map representing plant parts was produced by multiplying the two segmentation masks and therefore only mark pixels as plant if they had a high NDVI, but were not part of a highly shaded area. This mask served as mask for CC (Table 3), $NDVI_{plant}$, $REIP_{plant}$ and $GRVI_{plant}$ calculation.

To extract remotely-sensed characteristic values, a circle with radius 0.5 m was drawn around points of interest (corner or middle of plots). A zonal statistic feature was applied, summarizing the underlying raster values as statistical report, grouped by points of interest.

Data Validation and Analysis

Data validation and analysis was done in R 3.2.2 (R Core Team 2015). To validate the spatial precision of the orthophotos, the delta between reference point position in orthophoto and ground truth was calculated and summarized in mean, standard deviation and absolute maximum. To validate DSM precision, the delta between reference altitude in DSM and ground truth was calculated and summarized in mean, standard deviation and absolute maximum. Position accuracy validation of orthophotos was done for all three campaigns, validation of DSM only for Campaign 0 due to growing crops covering the reference points in following campaigns.

To evaluate PH_{CSM} precision, a Pearson product moment correlation for several aggregated statistical values (average, first quantile, median, third quantile, 90th percentile) was performed. As the 90th percentile correlated highest to the measured plant height ($PH_{ground\ truth}$), this percentile was used for following correlation and linear regression analysis.

Coefficients of correlation between the dry biomass and all remotely-sensed characteristics (PH_{CSM} , CC and VIs) were calculated by the Pearson product moment correlation. This calculation was performed at the level of the experiments as well as at the level of species. In a second step, to take into account the constant heterogeneity among species influencing the dry biomass, a mixed effects model was performed using R package lme4 (Bates et al. 2015). Species was set as random effect and the examined remotely-sensed characteristics as fixed effect. As a consequence, the species-independent performance of the remotely-sensed characteristics became visible.

For the remotely-sensed characteristics significantly affecting the dry biomass in the mixed effects model, a linear regression was performed to test their suitability as species-independent biomass predictor. All species were included in this first regression analysis. As some species showed higher correlations between biomass and remotely-sensed characteristics than others, a selection was performed based on the arbitrary decision to consider only species with correlations > 0.6 . This selection was then used for a second linear regression analysis, resulting in a semi-species-independent biomass prediction model.

Fig. 1 Overview of method, divided into procedures (image acquisition of near-infrared (NIR) and red, green and blue color space (RGB) photos; image processing including digital surface model (DSM) extraction; ground truth measurements including ground control point (GCP) capturing with global position system (GPS); data validation and data analyses including normalized differenced vegetation index (NDVI), red edge inflection point (REIP), green red vegetation index (GRVI), canopy cover (CC) and crop surface model (CSM) calculation) and resources (photo sequences; orthophotos; index raster; manual measurements and plot statistics) (All icons used (except UAS) created by Freepik from <http://www.flaticon.com>)

Fig. 2 Overview of field experiment and equipment. **(a)** ARF Mikrokopter Okto XL used as unmanned aerial system (UAS) with red, green and blue color space (RGB) sensor mounted on gimbal (source: Nicole Berger). **(b)** Experimental field. **(c)** Single RGB photo from Campaign 2. **(d)** Single near-infrared (NIR) photo from Campaign 2

Fig. 3 Experimental setup. **(a)** Experimental design for digital surface model (DSM) and orthophoto validation. Ground control points (GCPs) used for photogrammetry (orange boxes), reference points for position (red circles) and altitude (blue circles) validation. **(b)** Experimental design for plant height (PH) validation and biomass analysis. GCP used for photogrammetry (red circles), reference points used for PH validation (white crosses), biomass sampling points (white circles with crosses) and replications (blue boxes). Plots (white boxes) with species (Experiment 1, 1: *P. sativum arvense*, 2: *V. faba*, 3: *T. alexandrinum*, 4: *T. resupinatum*, 5: *V. sativa*, 6: *L. albus*, 7: *L. culinaris*, Experiment 2, 1: *P. sativum arvense*, 2: *L. usitatissimum*, 3: *C. sativa*)

Table 1 Timing of measurement campaigns; the date and days after sowing (DAS) is given for each task

Campaign	Timing of performed measurements (DAS)		
	Image acquisition	Plant height	Biomass
0: bare soil	2015-08-07 (17)		
1: crop growing	2015-08-25 (35)	2015-08-26 (36)	
2: final crop stage	2015-10-05 (76)	2015-10-08 (79)	2015-10-13 (84)

Table 2 Resolution of red, green and blue color space (RGB) and near-infrared (NIR) orthophotos and digital surface model (DSM), affected by sensor attributes and flight parameters

Type	Focal length	Sensor size	Parameter	
	mm	Pixel (mm)		
RGB	20	5184 × 3456 (22.3 × 14.9)	Flight height	50 m
			IFoV	0.011 m
			FoV	55 × 37 m
			AoV	58.3° × 40.9°
			W, B	16 m, 5 m
			PE, PS	87 %, 70 %
			RGB pixel size	0.02 m
			DSM pixel size	0.10 m
NIR	9.6	1280 × 1024 (6.66 × 5.32)	Flight height	75 m
			IFoV	0.054 m
			FoV	69 × 55 m
			AoV	38.3° × 31.0°
			W, B	16 m, 6 m
			PE, PS	89 %, 77 %
			NIR pixel size	0.06 m
			Flight height	30 m
			IFoV	0.016 m
			FoV	17 × 21 m
			AoV	38.3° × 31.0°
			W, B	6 m, 5 m
			PE, PS	76 %, 65 %
			NIR pixel size	0.04 m

IFoV = Instantaneous FoV = ((sensor dimension) × flight height) /
focal length (Liebisch et al. 2015)

FoV = Field of View = IFoV × sensor resolution

AoV = Angle of View = $2 \times \arctan(\text{sensor dimension} / (2 \times \text{focal length}))$

B = distance between exposure stations, W = spacing between flight lines

PE = Percent end lap = $(\text{FoV}_y - B) / \text{FoV}_y \times 100$ (Wolf and Dewitt 2000, p. 460)

PS = Percent side lap = $(\text{FoV}_x - W) / \text{FoV}_x \times 100$ (Wolf and Dewitt 2000, p. 461)

Table 3 Vegetation indices (VIs), canopy cover (CC) and plant height (PH) applied on red, green and blue color space (RGB) and near-infrared (NIR) orthophotos and on digital surface models (DSMs)

Index	Formula	
PH _{CSM}	$DSM_{Crop} - DSM_{Ground}$	(Bendig et al. 2014)
NDVI	$\frac{NIR_{780} - NIR_{700}}{NIR_{780} + NIR_{700}}$	
REIP	$700 + 40 \times \frac{NIR_{670}^{1/2} + NIR_{780}^{1/2} - NIR_{700}}{NIR_{740} - NIR_{700}}$	(Vincini and Frazzi 2011)
GRVI	$\frac{RGB_{green} - RGB_{red}}{RGB_{green} + RGB_{red}}$	(Tucker 1979)
CC	$\frac{Segmentation_{Plant}}{Segmentation_{Plant} + Segmentation_{Soil}}$	

Table 4 Parameters used in Agisoft PhotoScan Profession

Step	Parameter
Align photos	Accuracy: High Pair pre-selection: Disabled Key point limit: 40,000; Tie point limit: 1,000
Build Dense Cloud	Quality: High Depth filtering: Mild
Build Mesh	Surface type: Height field Face count: Medium Interpolation: Enabled
Build Texture	Mapping mode: Orthophoto Blending mode: Mosaic

Results

Spatial Precision of Orthophotos and Digital Surface Models

The first aim of this study was to produce precise RGB/NIR orthophotos and DSMs and to verify their spatial accuracy. The necessary flight campaigns were performed under constant lighting conditions. No photos had to be excluded for the subsequent photogrammetrical approach. GCPs were clearly visible on the photos, and the photogrammetric process succeeded in all cases. DSM heights of the bare soil (Campaign 0) had a range of 1.2 m and a standard deviation of 0.3 m.

Subsequent orthophoto and DSM validation showed a high spatial accuracy of photogrammetric products for RGB orthophotos and DSMs (Table 5) – for RGB orthophotos, differences were within GPS measurement tolerance (mean difference of <0.1 m with a standard deviation of 0.1 m, maximum at 0.2 m, 95 %-confidence interval of ± 0.1 m), as it was for DSM orthophotos (mean difference of <0.1 m with a standard deviation of 0.1 m, maximum at 0.2 m, 95 %-confidence interval of ± 0.1 m). NIR orthophotos showed a higher spread (standard deviation of 0.3 m with maximum at 0.7 m, 95 %-confidence interval of ± 0.4 m), but the mean difference was still acceptable (<0.1 m). However, maximum errors were quite high, which led to the decision to perform an additional flight at 30 m height for the last NIR campaign (compare with chapter Image Acquisition).

Precision of Plant Heights Derived from Digital Surface Models

The second aim of this study was to analyze whether the resulting PH_{CSM} represents a plant-stage-independent image of ground truth or not. Therefore, manual PH ruler measurements were carried out with a scale accuracy of 0.05 m for Campaign 1 and 0.1 m for Campaign 2. The scale accuracy for Campaign 2 was lower due to inhomogeneity in canopy height, requiring rougher estimations by the examiner. For Campaign 1, all species were in a vegetative stage, whereas for Campaign 2, *P. sativum arvense*, *V. faba*, *L. albus* and *L. usitatissimum* were in full flowering stage, while *P. sativum arvense* was lodging at same time, *T. alexandrinum* and *T. resupinatum* were partially flowering and *C. sativa* was in senescence (Table 7).

A strong and significant overall correlation for PH_{CSM} to PH_{ground truth} was found (Table 6), despite the different vegetative stages. Strongest correlation existed when using the 90th percentile to summarize the areas of interest in PH_{CSM}. Further analyses were performed by dividing the data by campaign, experiment and species. By applying a linear regression, an adjusted R^2 of 0.803–0.839 was found, whereby Campaign 2 had a slightly higher R^2 for both experiments (Fig. 4). PH was consequently underestimated for higher values for both campaigns, but was appropriate for smaller values for Campaign 2, in contrast to Campaign 1.

At species level, strong and significant correlations were found for several species and stages (Table 7). No obvious trend in growth stage having influence on correlation coefficients was found. In Experiment 1, some species had lower correlations and weaker significance, especially *L. culinaris* in Campaign 1, and *T. resupinatum* and *P. sativum arvense* in Campaign 2.

Relationship of Remotely-Sensed Characteristics to Cover Crop Biomass

The third aim of this study was to analyze the relationships among dry biomass, PH, CC, and different VIs. Therefore, destructive biomass sampling was carried out. Dry biomass differed

largely between species and samples (Fig. 5). Due to smaller sample sizes for Experiment 2 (n=3), deviations of *C. sativa* and *L. usitatissimum* were more pronounced than those of other species. However, *C. sativa* and *L. usitatissimum* represented, together with *P. sativum arvense*, the species with the highest dry biomass weights.

The scatter plots of the VIs versus dry biomass indicate that the NDVI showed saturation (Fig. 6c and d), as the mean values of most plots were within 0.7 ± 0.1 . The REIP was less prone to saturation (Fig. 6e and f). The GRVI seemed to saturate within particular species, but clearly distinguishes between species (Fig. 6a and b). Senescence led to lower values for all VIs, an obvious effect of flowering was not visible. CC showed no obvious trend compared to dry biomass (Fig. 7).

At the level of experiments, for Experiment 1 a highly significant positive correlation was found between dry biomass and PH_{CSM} , and a highly significant negative correlation between dry biomass and CC (Table 9). REIP and $REIP_{plant}$ had weak significant positive and significant positive correlations to biomass, respectively. For Experiment 2, a significant positive correlation was found between dry biomass and PH_{CSM} . All VIs had non-significant positive coefficients. For CC, the coefficient was negative. The best correlation for both experiments was given by PH_{CSM} . At the level of species, PH was significantly negatively correlated for *P. sativum arvense*, and weakly positively correlated for *C. sativa*. The different VIs performed well for *L. albus* with highly significant values for $NDVI_{plant}$ and significant values for NDVI, GRVI and $GRVI_{plant}$. Selecting the best correlation per species led to a mixed list of different remotely-sensed characteristics, where only NDVI and PH_{CSM} had significant coefficients.

The linear mixed effects model showed that dry biomass was affected by the CC slightly significantly by factor -1065.6 ($\chi^2 = 5.837$, $p = 0.0157$), PH_{CSM} affected dry biomass significantly by factor 450.4 ($\chi^2 = 29.475$, $p < 0.0001$), no VI had a significant influence on dry biomass (Table 8). The segmentation in plant and soil had a highly positive impact on the GRVI (for the linear mixed model, $p = 0.4348$ for GRVI; $p = 0.2330$ for $GRVI_{plant}$), but no remarkable impact on any other VI.

A linear regression between PH_{CSM} and dry biomass showed a good approximation with an R^2 of 0.579 (Fig. 8a). An additional analysis was done by adding an arbitrary threshold of 0.6 to the correlation coefficients of PH_{CSM} for all species. A linear regression on the thus selected species *C. sativa*, *L. albus*, *L. culinaris*, *L. usitatissimum* and *T. alexandrinum* found an adjusted R^2 of 0.742 (Fig. 8b).

Fig. 4 Scatter plot of plant height (PH) derived from crop surface model (CSM) (PH_{CSM}) versus ground truth ruler measurements ($PH_{ground\ truth}$). The solid line represents the regression line, the dotted line an implied 1:1 relationship

Fig. 5 Boxplot of destructive dry biomass samples per species. The boxes show the 25 and 75 % percentile, the solid line represents the median, the whiskers the 5 and 95 % percentile

Fig. 6 Scatter plot of dry biomass versus vegetation indices (VIs). **(a)** green red vegetation index (GRVI), **(b)** GRVI segmented by canopy cover (CC) ($GRVI_{Plant}$), **(c)** normalized differenced vegetation index (NDVI), **(d)** NDVI segmented by CC ($NDVI_{Plant}$), **(e)** red edge inflection point (REIP), **(f)** REIP segmented by CC ($REIP_{Plant}$)

Fig. 7 Scatter plot of biomass versus canopy cover (CC)

Fig. 8 Scatter plot and regression of plant height (PH) derived from crop surface model (CSM) (PH_{CSM}) versus dry biomass. **(a)** All species of Experiment 1 and 2. **(b)** Selected species with a correlation coefficient >0.6

Table 5 Spatial accuracy of orthophotos for red, green and blue color space (RGB) sensor and near-infrared (NIR) sensor and of digital surface model (DSM)

Campaign		Variable	Difference to ground truth measurements			
			Mean (m)	SD (m)	Maximum (m)	n
RGB	0	X, Y	<0.1	0.1	0.1	8
	1	X, Y	<0.1	0.1	0.1	8
	2	X, Y	-0.1	0.1	0.2	8
	All	X, Y	<0.1	0.1	0.2	24
NIR	0	X, Y	-0.1	0.2	0.3	8
	1	X, Y	<0.1	0.4	0.7	8
	2	X, Y	<0.1	0.1	0.3	8
	all	X, Y	<0.1	0.3	0.7	24
DSM	0	Z	<0.05	0.06	0.16	74

Table 6 Coefficients of correlation between statistically aggregated plant height (PH) derived from crop surface model (CSM) (PH_{CSM}) and ground truth ruler measurements ($PH_{ground\ truth}$) (n=260)

Statistical function used (to summarize PH_{CSM})	Correlation to $PH_{ground\ truth}$
Average	0.97***
First quantile	0.95***
Median	0.97***
Third quantile	0.97***
90th percentile	0.98***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

1 **Table 7** Coefficients of correlation between plant height (PH) derived from crop surface model (CSM) (PH_{CSM}) and ground truth ruler
2 measurements (PH_{ground truth}), divided by campaign, experiment and species. Additionally the growth stage is given

Experiment	Cover crop	Campaign 1		Campaign 2		n
		Correlation	Stage	Correlation	Stage	
Experiment 1	<i>L. culinaris</i>	0.42 ns	vegetative	0.50 **	vegetative	16
	<i>L. albus</i>	0.77 ***	vegetative	0.92 ***	flowering	16
	<i>V. sativa</i>	0.90 ***	vegetative	0.70 ***	vegetative	16
	<i>T. resupinatum</i>	0.70 ***	vegetative	0.48 *	partially flowering	16
	<i>T. alexandrinum</i>	0.56 **	vegetative	0.61 **	partially flowering	16
	<i>V. faba</i>	0.72 ***	vegetative	0.80 ***	flowering	16
	<i>P. sativum arvense</i>	0.64 ***	vegetative	0.47 *	flowering (lodging)	16
Experiment 2	<i>C. sativa</i>			0.95 ***	senescence	12
	<i>L. usitatissimum</i>			0.97 ***	flowering	12
	<i>P. sativum arvense</i>			0.86 ***	flowering (lodging)	12

ns = p $\geq$ 0.1; * p<0.1; ** p<0.05; *** p<0.01

1 **Table 8** Linear mixed model factors and intercepts for the vegetation indices (VIs), plant
2 height (PH) and canopy cover (CC)

Index	Fixed effect factor	Fixed effect intercept	χ^2	p
PH	450.4	107.0	29.475	<0.0001
CC	−1065.6	1385.7	5.837	0.0157
GRVI	989.4	262.7	0.610	0.4348
GRVI _{Plant}	1529.6	200.3	1.422	0.2330
NDVI	−229.3	527.5	0.301	0.5834
NDVI _{Plant}	−224.2	524.4	0.273	0.6012
REIP	7.525	−5048.5	0.251	0.6161
REIP _{Plant}	8.1	−5463.6	0.270	0.6033

3

1 **Table 9** Correlation biomass to remotely-sensed characteristics per cover crop, including canopy cover (CC), plant height (PH) derived from crop
2 surface model (CSM) (PH_{CSM}), green red vegetation index (GRVI), GRVI segmented by CC (GRVI_{Plant}), normalized differenced vegetation
3 index (NDVI), NDVI segmented by CC (NDVI_{Plant}), red edge inflection point (REIP) and REIP segmented by CC (REIP_{Plant})

Cover crop	Correlation biomass to ...								Best performance
	CC	PH _{CSM}	GRVI	GRVI _{Plant}	NDVI	NDVI _{Plant}	REIP	REIP _{Plant}	
Experiment 1									
All	-0.49 ^{***}	0.53 ^{***}	0.12	0.17	0.30	0.31	0.37 [*]	0.40 ^{**}	PH _{CSM} ^{***}
<i>L. albus</i>	0.87	0.67	0.96 ^{**}	0.97 ^{**}	0.99 ^{**}	0.99 ^{***}	0.88	0.91 [*]	NDVI _{Plant} ^{**}
<i>L. culinaris</i>	-0.26	0.64	0.61	0.63	0.74	0.79	0.17	0.31	NDVI _{Plant}
<i>P. sativum</i> arv.	-0.25	-0.97 ^{**}	0.57	0.68	-0.61	-0.60	-0.64	-0.57	PH _{CSM} ^{**}
<i>T. alexandrinum</i>	0.37	0.81	0.31	0.31	0.84	0.83	0.82	0.81	NDVI
<i>T. resupinatum</i>	-0.35	0.35	-0.27	-0.25	-0.08	-0.07	-0.12	-0.06	PH _{CSM} /CC
<i>V. faba</i>	-0.66	0.50	0.08	0.45	0.12	0.11	0.03	0.08	CC
<i>V. sativa</i>	0.87	0.03	0.21	0.13	-0.60	-0.61	-0.06	-0.12	CC
Experiment 2									
All	-0.25	0.75 ^{**}	0.20	0.22	0.03	0.03	0.03	0.01	PH _{CSM} ^{**}
<i>C. sativa</i>	-0.25	0.99 [*]	0.50	0.57	0.31	0.29	0.30	0.17	PH _{CSM} ^{**}
<i>L. usitatissimum</i>	-0.05	0.99	0.92	0.92	0.77	0.82	0.96	0.99	PH _{CSM} /REIP _{Plant}
<i>P. sativum</i> arv.	0.29	-0.83	0.93	0.89	-0.90	-0.58	-0.99	-0.97	REIP

* p<0.1; ** p<0.05; *** p<0.01

Discussion

This study confirms the hypothesis that lightweight UAS-based aerial photos are suitable for producing spatial precise orthophotos and DSMs. Measured standard deviations indicate a 95 %-confidence interval of ± 0.1 m for DSMs and ± 0.1 m for RGBs. These degrees of accuracy are in accordance with those indicated by Turner et al. (2012), Bendig et al. (2013) and Sona et al. (2014). The NIR orthophotos of the first two campaigns in this study were of lower quality than the RGB orthophotos. The subsequently performed flight campaign with lower flight heights led to a higher resolution of the resulting orthophoto, and according to the internal statistics of the photogrammetrical software, to better alignment accuracy and therefore spatial precision.

It should be emphasized that the GCPs were distributed at the field edges and not in between the examined plots. As it is likely that the CSM quality is influenced by the distribution of GCPs, this offers room for further improvements. One option would be for example to double the number of GCPs and distribute four of them in between plots and four at the edges. On the other hand, placing GCPs inside the experimental field itself increases the maintenance effort, as regular cutting of the surrounding area becomes necessary.

PH_{CSM} extracted from the corresponding DSMs were highly and significantly correlated with ground truth data for all examined cover crops (except *L. culinaris* in Campaign 1). This is in accordance with studies performed for grassland (Gillan et al. 2014), buckwheat (Murakami et al. 2012) and barley (Bendig et al. 2014, 2015). Underestimation of PH was reported by all these studies, in accordance with our study. The mentioned studies averaged PH_{CSM} and had not calculated the 90th percentile as was done in this study. The superior performance of correlations based on the 90th percentile is most probably due to an overestimation effect when measuring PHs manually with a ruler, as already mentioned in Bendig et al. (2014). However, the differences in significance between the statistical functions remained low. Nevertheless, to be consistent with manual ruler measurements, it may be advantageous to use the 90th percentile for PH_{CSM} in subsequent studies.

Murakami et al. (2012) mentioned a lower correlation between biomass and PH_{CSM} for buckwheat in flowering and senescence stage. In our study, although *C. sativa* was in senescence stage and several species were flowering, the correlation between PH_{CSM} and PH_{ground truth} remained high. The data indicates that flowering has no remarkable effect in PH_{CSM} determination.

When comparing the calculated remotely-sensed characteristics for their suitability as biomass predictor, PH_{CSM} was a robust growth-stage-independent indicator according to the linear mixed model ($p < 0.0001$). This is in accordance with results for barley (Bendig et al. 2014, 2015; Tilly et al. 2015). However, restrictions of the PH were clearly observed: For species with a tendency to grow low but widely spread, the correlations remained low (*V. faba*, *V. sativa* and *T. resupinatum*) or even became negative when plant stands were lodging (*P. sativum arvense*). The mentioned species are clearly visible as outlier in Fig. 8a and had a strong influence on the performed linear regression ($R^2 = 0.579$). By excluding them from the linear regression, we were able to present a much more reliable model (Fig. 8b, $R^2 = 0.742$), to the restriction that it is no longer species-independent.

Surprisingly, the linear mixed model indicates that the CC could serve as an overall biomass indicator with negative correlation ($p = 0.0157$), which is not in accordance with e.g. Liebisch et al. (2015), where a positive correlation between CC and total biomass of corn is mentioned. Keeping in mind that quite different species were evaluated, these contradictions at species level

are explicable: High-growing plants tend to have high biomass but low CC, and *vice versa*. As a consequence, correlations at species level were not high and for some species even negative. The same argument may be applied to the effect of negative correlations at species level as at inter-species level: Weakly developed individual plants with less biomass tend to grow in loose layers, whereas stronger individuals able to accumulate more biomass may tend to grow more upright in dense layers.

Comparing the VIs, the GRVI performed best in the linear mixed model. A clear advantage of using GRVI_{plant} instead of GRVI was observed (GRVI: $p = 0.4348$; GRVI_{plant}: $p = 0.2330$). The performance of the GRVI seems to be very species-specific: While for *L. albus* the biomass correlated highly significantly with the GRVI and GRVI_{plant}, species of a second group showed less pronounced correlations (*L. culinaris*, *P. sativum arvense*, *C. sativa* and *L. usitatissimum*) and a third group very weak correlations (*T. alexandrinum*, *T. resupinatum*, *V. sativa*). The latter group consisted only of low-growing plants, indicating that the physiological characteristics had a strong influence on the GRVI.

It should be emphasized that the GRVI extraction was based on uncalibrated RGB photography. Small changes in radiation during the flight campaigns might have resulted in varying values for the color bands. No radiometric correction was performed due to the lack of a known reference. This source of uncertainty must be taken into account when relying on the GRVI values presented in this study, but it does not apply for the NDVI and REIP values, where a radiometric correction was performed based on the incident light sensor data.

The performance of the NDVI and REIP was varied. For *L. albus* the NDVI and REIP correlated highly significantly and weakly significantly with the biomass, respectively. For *L. usitatissimum*, both NDVI and REIP performed well, whereas for *L. culinaris* only the NDVI performed well. For *P. sativum arvense* correlations became negative, most probably due to lodging. For *T. alexandrinum* the correlations were rather distinct, whereas for the close relative *T. resupinatum* the correlations were close to zero. *T. alexandrinum* and *T. resupinatum* can be clearly distinguished by their leaf colors, and plant color might have had an influence for other species too. Another reason for the varying performance were saturation effects of the VIs as mentioned in Tilly et al. (2015) and Thenkabail et al. (2000). Saturation effects for the NDVI can be seen in Fig. 6c and d, less obvious saturation effects for the REIP in Fig. 6e and f.

No obvious advantages of using VI_{plant} instead of VI were observed. As cover crops are destined to suppress weeds, their canopy should be to a high degree closed, and segmentation in plant and soil is rather superfluous.

Conclusion

For precision agriculture, the need for a method to estimate plant biomass is obvious. Lightweight UASs combined with consumer cameras offer an affordable platform to perform the necessary remote sensing activities, followed by photogrammetrically processing the photos. The spatial accuracy of the resulting orthophotos is suitable to extract VI values for specific locations in the field. To extract PH from DSMs offers an additional source of information, comparable with manual ruler measurements when considering the 90th percentile.

Two tendencies were observed in our study: For cover crops reaching senescence at the end of their crop cycle, VIs are not suitable for biomass prediction, whereas PH_{CSM} remained suitable. If lodging occurs, all examined remotely-sensed characteristics lose their suitability as biomass predictor. Despite these two restrictions, VIs are a feasible approach for non-destructive biomass prediction for selected species, while the PH can serve as a more general biomass indicator.

Expanding the knowledge of the relationships among PH, VIs and biomass will presumably lead to speedy progress in precision agriculture. The hypotheses on which this study was based have been confirmed. However, further research is needed: It is conceivable that a robust plant status indicator should include more than one component, and should be based on different domains such as spatial, spectral, thermal, and other electromagnetic radiation measurements.

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Author Contributions

LR designed and maintained the experiment, designed and implemented the method and performed the analyses, figures and tables. The manuscript was drafted by LR with help and contributions from BS. Both authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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1 **Appendix**

- 2 **Fig. 9** Scatter plot of biomass versus normalized differenced vegetation index (NDVI). **(a)**
3 NDVI based on 700 nm band. **(b)** NDVI based on 670 nm band

Figure1

(a) Figure2

(c)

(b)

(d)

○ <i>C. sativa</i>	× <i>L. usitatissimum</i>	⊠ <i>T. resupinatum</i>
△ <i>L. albus</i>	◇ <i>P. sativum arvense</i>	* <i>V. faba</i>
+ <i>L. culinaris</i>	▽ <i>T. alexandrinum</i>	⋄ <i>V. sativa</i>

Figure5

Figure7

$\circ$ *C. sativa* $+$ *L. culinaris* $\diamond$ *P. sativum arvense* $\boxtimes$ *T. resupinatum* $\diamondplus$ *V. sativa*
 $\triangle$ *L. albus* $\times$ *L. usitatissimum* ∇ *T. alexandrinum* $*$ *V. faba*

Figure8

(a)

(b)

○ <i>C. sativa</i>	× <i>L. usitatissimum</i>	⊠ <i>T. resupinatum</i>
△ <i>L. albus</i>	◇ <i>P. sativum arvense</i>	* <i>V. faba</i>
+ <i>L. culinaris</i>	▽ <i>T. alexandrinum</i>	⊞ <i>V. sativa</i>

Figure9 (a)

(b)

○ *C. sativa* + *L. culinaris* ◇ *P. sativum arvense* ⊠ *T. resupinatum* ⋈ *V. sativa*
 △ *L. albus* × *L. usitatissimum* ▽ *T. alexandrinum* * *V. faba*