In-season estimation of barley biomass with plant height derived by terrestrial laser scanning

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Abstract: *The monitoring of plant development during the growing season is a fundamental base for site-specific crop management. In this regard, the amount of plant biomass at a specific phenological stage is an important parameter to evaluate the actual crop status. Since biomass is directly only determinable with destructive sampling, methods of recording other plant parameters, such as crop height or density, which are suitable for reliable estimations are increasingly researched. Over the past two decades the research interest has focused on non-destructive remote sensing approaches. They have the main benefit that plant parameters can be obtained without disturbing the plant growth. Terrestrial laser scanning (TLS) is known as promising tool for determining plant height at field scale and monitoring its development. In former studies, the usability of biomass regression models (BRMs) for estimating spring barley biomass based on TLS-derived plant height across-season was shown. However, from a field management perspective the in-season estimation of the actual biomass is more important. The herein presented study investigates the accuracy of these proven models for estimating the actual crop biomass at a specific date during the growing season. Overall the validity of all BRMs for across-season analyses is supported by high R^2 values of up to 0.73 and 0.85 between measured and estimated values for fresh and dry biomass, respectively. The R^2 values for the campaign-wise separated analyses are generally lower (ranging from 0.01 to 0.23). In contrast, strongly reduced root mean square error (RMSE) and relative RMSE values for these analyses underline the benefit of a campaign-wise separated investigation. In conclusion, the results verify that TLS-derived plant height is a suitable estimator for crop biomass at a specific date.*

Keywords*: terrestrial laser scanning; plant height; biomass; in-season; barley; field level*

Introduction

The growing world population demands a secure food supply, which increases the pressure on the conventional agricultural sector and requires an improvement of crop management methods. In this context, site-specific approaches increasingly gain interest to improve the productivity of crops and to minimize the environmental pollution (Whelan and Taylor 2013). Essential prerequisites for optimizing the field management are to assess the current state of the crops and to monitor changes. This current state can be evaluated by the actual biomass as an important parameter, which is however directly only determinable with destructive sampling. With the aim of avoiding destructive measurements, estimations based on remote sensing methods are widely investigated over the last several decades. These non-contact surveys prevent disturbing the plants by the taking of measurements (Liaghat and Balasundram 2010). Reviews of current approaches are given for example by Mulla (2012) and Liaghat and Balasundram (2010).

Even though the required temporal and spatial resolution is very case specific, timely flexible systems, which furthermore allow a high spatial resolution, are generally required for surveys at field scale, since influencing environmental factors are variable in time and space (Atzberger 2013). Measurements of the reflected radiation from plants are widely used to calculate vegetation indices (VIs), which allow the estimation of plant parameters such as leaf area index (LAI) or biomass (Casanova et al. 1998; Guyot et al. 1992; Haboudane et al. 2004). However, several studies show that VIs tend to saturate when high LAI or biomass values are reached (Heege et al. 2008; Thenkabail et al. 2000). Hence, other plant parameters, such as plant height, are investigated concerning the applicability as estimator for biomass. At the field scale, different sensors, such as light curtains (Montes et al. 2011), ultrasonic sensors (Reddersen et al. 2014), radar sensors (Kim et al. 2013), or terrestrial laser scanners (Ehlert et al. 2010) are investigated regarding their usability for measuring plant height as estimator for crop biomass.

In former studies, the herein used approach with terrestrial laser scanning (TLS) was demonstrated as promising method for determining plant height at field scale and monitoring its development (Hoffmeister et al. 2010; Tilly et al. 2014). The underlying concept thereby is the generation of crop surface models (CSMs) for the calculation of spatially resolved plant height, as shown in Fig. 1. At the beginning of the growing season a digital terrain model (DTM), representing the bare ground of the field is established from the TLS data as reference surface. In an almost biweekly rhythm across the growing season the crop canopy is then captured with the scanner and stored as a CSM. By subtracting the DTM from a CSM, plant heights are spatially measured.

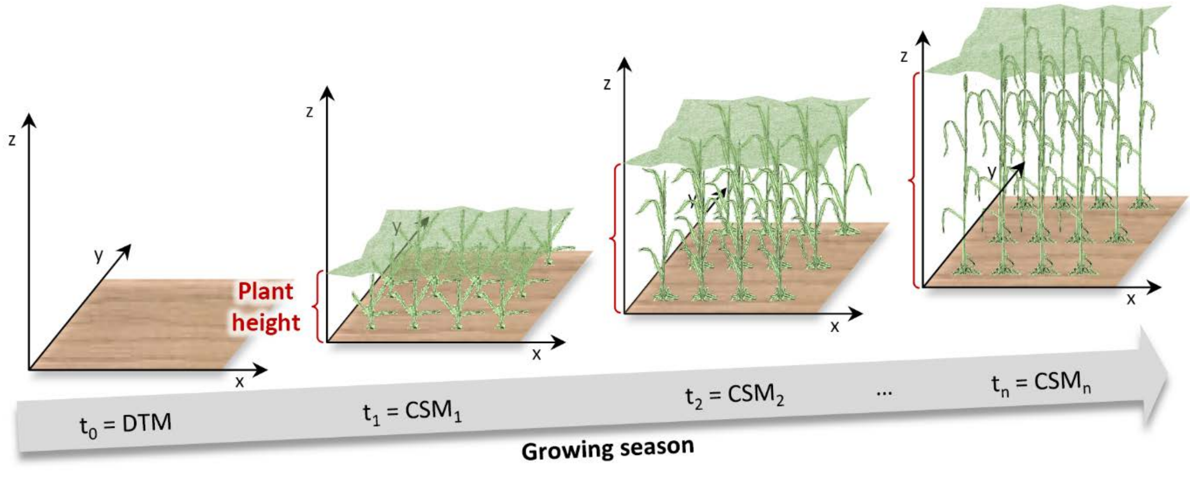

Fig. 1. Principle of crop surface models (CSMs). Figure taken from Tilly (2015).

This method of capturing plant height and monitoring its development across the growing season was successfully applied for a case study on spring barley (Tilly et al. 2015). In conjunction with destructive sampling, biomass regression models (BRMs) were empirically developed to estimate the crop biomass from the plant heights captured in this way. The high usability of BRMs based on the CSM-derived plant heights could be demonstrated for across-season biomass estimations in that study. Furthermore, the comparison to BRMs based on VIs showed the robustness of estimations based on plant height. However, due to the very different amounts of biomass between the respective campaign dates, the root mean square error (RMSE) is fairly high when calculated for the entire data set. Since, the accurate in-season estimation of the actual biomass is from a field management perspective more important, the herein presented study investigates the accuracy of these proven models for estimating the actual crop biomass at a specific date.

Methods

The measurements were carried out at a field experiment campus of the Faculty of Agriculture, University of Bonn (Germany), which is hosted in the nearby village Klein-Altendorf (50°37′ N, 6°59′ E). The area is situated on the main terrace of the lower River Rhine basin and is well suitable for crop cultivation due to the underlying clayey silt luvisol and good climatic conditions such as a yearly precipitation of about 600 mm and a daily average temperature of 9.3 °C (Uni Bonn 2010a, 2010b). Across the growing season of 2014 a field experiment was monitored where six cultivars of spring barley (*Barke*, *Beatrix*, *Eunova*, *Trumpf*, *Mauritia,* and *Sebastian*) were cultivated with two levels of N fertilization in 36 small-scale plots (3 × 7 m). The experiment and measurements were carried out within the interdisciplinary research network CROP.SENSe.net (www.cropsense.uni-bonn.de). This research project focused on non-destructive sensor-based methods for detecting crop status. A brief description of the measuring and data handling process is given in the following, however since the focus of this study lies on the accuracy of the proven models for estimating the actual crop biomass at a specific date, please see Tilly et al. (2015) for further detail.

Field measurements

In this study, remote sensing measurements from a TLS system and destructive measurements of biomass were used. The measurements from four campaigns during the pre-anthesis are regarded herein since an appropriate field management during these stages can mainly influence the plant development. The campaigns were carried out at approximately BBCH stage 29 (end of tillering), 31 (beginning of stem elongation), 49 (end of booting), and 56 (middle of heading). In an additional earlier campaign shortly after sowing, the bare ground of the field was captured with the scanner before the plants were visible.

For the TLS measurements a time-of-flight scanner was used. The basic concept of such scanners is that the travel time, or time-of-flight, from transmitting a signal until its return after the reflection on an object is measured. The range between the scanner and this reflection point is then calculated as half of the entire path from the measured time and the speed of light, which is known to be ~0.3 m/ns. The laser beam is generated in the bottom of the device and spatially distributed by a mirror or prism, which rotates around its horizontal axis, inside the scanner head, which rotates around the vertical axis. Main characteristics of the herein used Riegl LMS-Z420i (Riegl LMS GmbH 2010), which operates with a near-infrared laser beam, are that the beam divergence is 0.25 mrad and the measuring rate is 11,000 points/sec. Due to the scanning mechanism, the field of view is up to 80° in the vertical and 360° in the horizontal direction. In this study resolutions between 0.034° and 0.046° were used. Moreover, the digital camera Nikon D200 was mounted on the laser scanner. Point clouds gained from the laser scanner can thus be colorized from the recorded RGB-images. In addition, the system was mounted on the hydraulic platform of a tractor, raising the sensor to approximately 4 m above ground to achieve the best possible coverage of the crop surface (Fig. 2). This set-up also allowed a steep angle between scanner and the investigated area, which in return enabled the best possible homogenous penetration of the vegetation. The field was scanned from its four corners in each campaign to lower shadowing effects and to attain an almost uniform spatial coverage of the field. The coordinates of each scan position and an additional reference target were measured with the highly accurate RTK-DGPS system Topcon HiPer Pro (Topcon Positioning Systems 2006). These information were used for the georeferencing and co-registration of both the different positions of one campaign and the data sets of different campaigns in the post-processing.

At each campaign date, the above ground biomass of a 0.20 × 0.20 m area was destructively taken in a defined sampling area of each plot. This area was neglected for the remote sensing measurements. In the laboratory, the plants were cleaned and then the fresh weights were

Fig. 2. Instrumental set-up: (A) Tractor with hydraulic platform; (B) Terrestrial laser scanner Riegl LMS-Z420i with digital camera Nikon D200 and RTK-DGPS receiver on top.

measured. After drying the samples for 120 h at 70 °C, the dry biomass was also weighted. Finally both values were extrapolated to g/m².

Post-processing

In the scanner software RiSCAN Pro, the TLS data were merged, cleaned, and the area of interest was extracted per campaign. The point clouds were then filtered with a scheme for selecting minimum or maximum points to detect the bare ground or the crop surface, respectively (Fig. 3 (A)). After importing the final point clouds in Esri ArcGIS Desktop 10.2.1 the DTM representing the bare ground at the first campaign date and each CSM of the following campaigns were interpolated using the inverse distance weighting (IDW) algorithm. Since the exact, deterministic IDW algorithm retains measured values at their sample locations the accuracy of measurements with a high density is maintained (Johnston et al. 2001). The result of an interpolation was a raster data set with a spatial resolution of 1 cm. Based on the concept shown in Fig. 1, raster data sets of plant height were calculated from these CSMs with the DTM (Fig. 3 (B)). The plant heights were then averaged plot-wise, allowing a common spatial base with the destructive biomass measurements to be attained (Fig. 3 (C)). Previously, each plot was clipped with an inner buffer of 0.50 m to prevent border effects and the sampling area of the

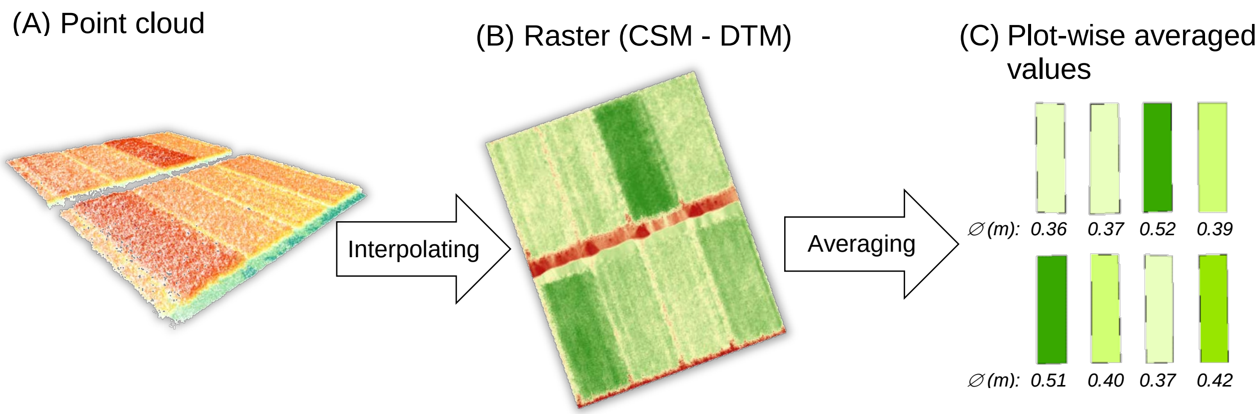

Fig. 3. Steps from TLS-derived point cloud to plot-wise averaged values: (A) Filtered point cloud representing the crop surface; (B) Raster data set of plant height, calculated from CSM minus DTM; (C) Plot-wise averaged plant heights.

destructive measurements was cut off.

Biomass regression models

The plot-wise averaged values of plant height and biomass were used to develop the BRMs for fresh and dry biomass, considering the values of all four campaigns for the model calibration (for each BRM n = 144). For both of them, the models were established with a linear function (1), an exponential function (2), and a power function (3). The coefficient of determination (R^2) between plant height and measured biomass across all campaigns was used to evaluate the model calibration.

$$biomass = a \cdot plant\ height + b \tag{1}$$

where a = slope, b = intercept

$$biomass = a \cdot e^{b \cdot plant\ height} \tag{2}$$

where a and b = factors, e = base of the natural logarithm

$$biomass = a \cdot plant\ height^{b} \tag{3}$$

where a and b = factors

These BRMs were then applied to estimate the biomass from the CSM-derived plant height. The results were evaluated by calculating the R^2 (measured *vs.* estimated biomass), the root mean square error (RMSE), and the relative RMSE (rRMSE). Since the aim of this study was to investigate the accuracy of the BRMs for in-season estimations at a specific date, the validation of the results was performed across all measurements, but moreover for each of the four campaigns separately.

Results

The TLS-derived point clouds were used to interpolate CSMs and spatially calculate plant height. Examples of the resulting raster data sets of plant height are presented in Tilly et al. (2015). In that study the CSM-derived plant height values were also validated against manual reference measurements. An R^2 of 0.98 between the CSM-derived and manual measured plant heights was reached (Tilly et al. 2015). The CSM-derived plant height can thus be regarded as reliable data source for the herein conducted analysis.

The spatially resolved plant height values were averaged plot-wise before establishing the BRMs to achieve a common spatial base with the biomass measurements. Table 1 shows the statistics of the CSM-derived plant height and the biomass for the four campaign dates (each n = 36) and for the across-season averaged values (n = 144).

Table 1. Statistics for the plot-wise averaged CSM-derived plant heights and destructively taken fresh and dry biomass ($\bar{x}$: mean value; min: minimum; max: maximum; SD: standard deviation). For each date n = 36.

		CSM-derived plant height (m)				Fresh biomass (g/m²)				Dry biomass (g/m²)			
	BBCH	$\bar{x}$	**min**	**max**	**SD**	$\bar{x}$	**min**	**max**	**SD**	$\bar{x}$	**min**	**max**	**SD**
1.	29	0.17	0.12	0.25	0.03	656.28	266.25	1116.50	202.07	89.01	33.00	155.25	27.66
2.	31	0.41	0.34	0.52	0.04	2227.08	1226.75	3236.50	531.72	289.83	165.75	417.75	66.03
3.	49	0.63	0.53	0.70	0.04	2825.48	1643.75	4162.00	603.19	465.49	276.62	706.65	97.89
4.	56	0.81	0.69	0.99	0.05	3185.13	2106.50	5433.25	687.74	777.23	486.35	1271.35	156.02
Mean		0.51	0.42	0.62	0.04	2223.49	1310.81	3487.06	506.18	405.39	240.43	637.75	86.90

The plot-wise averaged values were used to express the relation between plant height and fresh or dry biomass as BRMs. Fig. 4 shows this relation between plant height and the biomass values. Moreover, the resulting regression lines and equations are given for the linear, exponential, and power function. Generally, higher R^2 values and a better fit of the curves can be stated for the dry biomass models. A larger scattering occurs in the scatterplot for fresh biomass. The best R^2 values are achieved with the power function for fresh and dry biomass.

Each of the three BRMs was then used to estimate the biomass based on the averaged CSM-derived plant height. Fig. 5 shows the scatterplots of measured *vs.* estimated fresh and dry biomass. Generally a large scattering has to be stated again for the fresh biomass values. This is very likely caused by the data scattering during the model calibration. Nevertheless, the best results are attained with the linear and power function (both R^2 = 0.73). Moreover the estimated biomass from these two BRMs correspond well with the measured biomass (slopes are close to

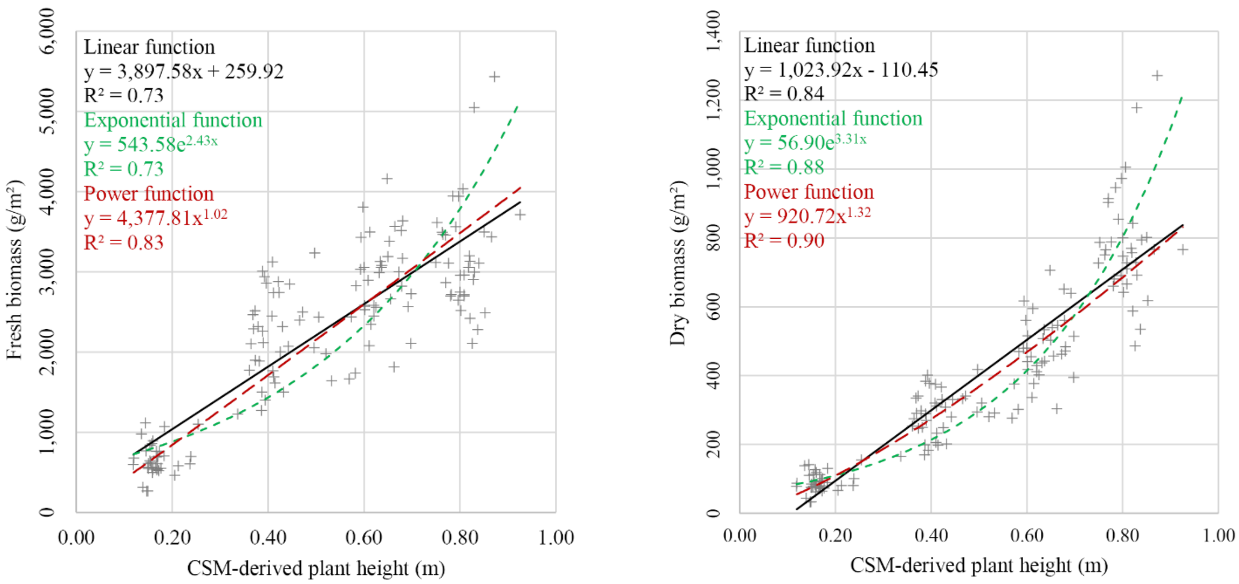

Fig. 4. Relation between CSM-derived plant height and fresh biomass (left) or dry biomass (right) (each n = 144) and the resulting BRM functions (linear: black solid line, exponential: green short-dashed line, and power: red long-dashed line).

the 1:1 line). The results of the dry biomass estimation are generally better, with a lower scattering and higher R^2 values of about 0.85 for all BRMs. The estimated biomass from all BRMs correspond well with the measured biomass (slopes are close to the 1:1 line).

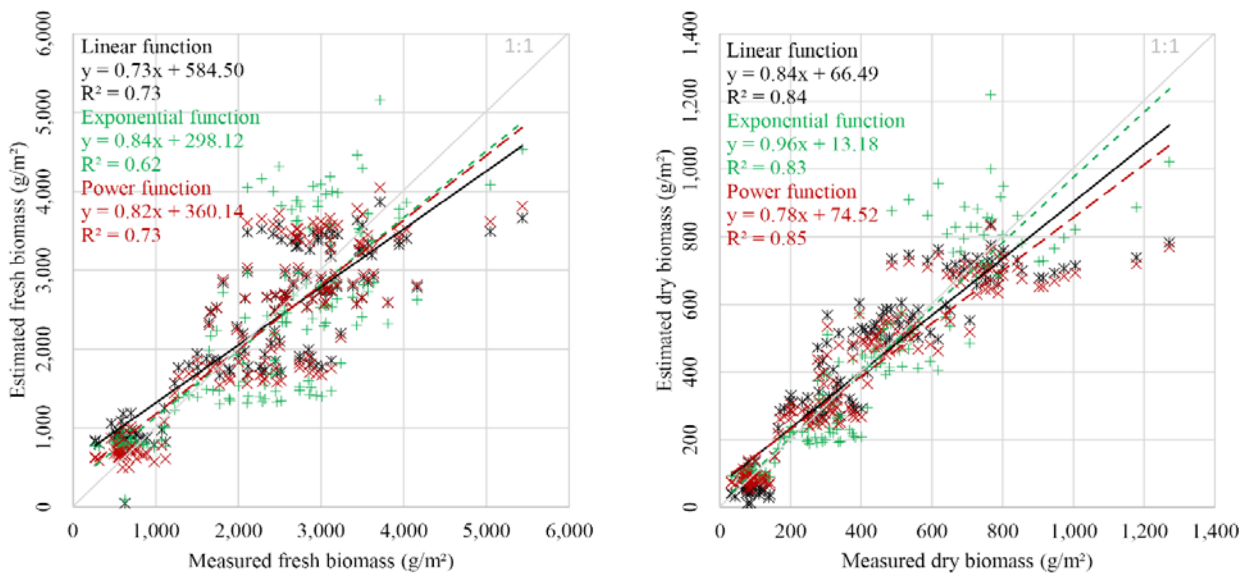

Fig. 5. Scatterplots of measured *vs.* estimated fresh biomass (left) or dry biomass (right) (each: n = 144) with the BRMs based on the linear (black solid line), exponential (green short-dashed line), and power (red long-dashed line) function.

Since the focus of this study was on the accuracy of the models for in-season estimations at a specific phenological stage, the R^2, RMSE, and rRMSE for fresh and dry biomass (measured *vs.* estimated values) were calculated across all measurements but moreover for each of the four campaign dates separately (Table 2). The across-season R^2 values are generally higher (R^2 ranging from 0.62 to 0.85) than the values for the campaign-wise separated analyses (R^2 ranging from 0.01 to 0.23). Even though the R^2 values for all campaigns show a poor performance, differences between the single dates can be observed. While the R^2 values for first and fourth campaign do not show any relation between the measures ($R^2 < 0.05$), values of 0.15 to 0.23 are reached for the second and third campaign.

The RMSE values of the across-season analyses are considerably high (fresh biomass: ~580 g/m² to ~760 g/m² and dry biomass: ~110 g/m² to ~120 g/m²) compared to the overall mean values of ~2,200 g/m² and ~400 g/m² for fresh and dry biomass, respectively (Table 1). These high values are very likely caused by the large value ranges between the first and last campaign from ~660 g/m² to ~3,200 g/m² and ~90 g/m² to ~780 g/m² for fresh and dry biomass, respectively.

Hence the campaign-wise separated analyses should be more suitable to evaluate the accuracy of the models for in-season estimations. The rRMSE as relative measure is thereby better suitable for a comparison between the campaigns than the absolute RMSE values, due to the large range of the absolute values. While the rRMSE values for the first two campaigns are similar or slightly weaker than the across-season values, the errors could be reduced for the third and fourth campaign. Regarding the different models, it is difficult to draw a general conclusion. However, the BRMs based on the power function thereby performed mostly slightly better than both of the others.

Table 2. Statistics for the BRM validation based on the linear, exponential, and power function. Values are given across-season and for each of the four campaigns separately (measured *vs.* estimated biomass). R^2: coefficient of determination; RMSE: root mean square error (g/m²); rRMSE: relative root mean square error (g/m²).

		Fresh biomass			Dry biomass		
		Linear	Exponential	Power	Linear	Exponential	Power
R^2	Across	0.73	0.62	0.73	0.84	0.83	0.85
	1	0.02	0.01	0.03	0.04	0.05	0.05
	2	0.16	0.15	0.16	0.15	0.15	0.15
	3	0.22	0.23	0.22	0.21	0.22	0.21
	4	0.03	0.03	0.03	0.02	0.02	0.02
RMSE	Across	579.98	756.98	594.05	109.87	116.60	107.76
	1	344.24	270.47	224.26	46.16	29.22	30.92
	2	626.39	898.59	685.05	71.36	91.28	66.36
	3	577.64	647.99	572.45	112.48	94.38	96.38
	4	707.78	995.79	751.19	168.55	190.48	178.33
rRMSE	Across	0.26	0.34	0.27	0.27	0.29	0.27
	1	0.52	0.41	0.34	0.52	0.33	0.35
	2	0.28	0.40	0.31	0.25	0.31	0.23
	3	0.20	0.23	0.20	0.24	0.20	0.21
	4	0.22	0.31	0.24	0.22	0.25	0.23

Discussion

Since biomass is an important parameter in agricultural science, several approaches aim at its non-destructive estimation. Recent studies showed that VIs, which have historically been widely applied, saturate beyond certain growth stages of plants and are then unsuitable for reliable estimations (Heege et al. 2008; Thenkabail et al. 2000). As an alternative, plant height, measured with different sensors (Busemeyer et al. 2013; Pittman et al. 2015; Reddersen et al. 2014) is used, but less investigated so far. The main benefits of the TLS-based approach applied in the herein presented study are the possibility to rapidly and easily measure plant height at field scale and the robustness against poor weather conditions. Even though the approach has previously been demonstrated as suitable for across-season estimations the question remained whether the established models are also applicable for in-season estimations. Hence, the aim of this study was to evaluate whether models which are proven for across-season estimations of spring barley biomass are usable for in-season estimations at a specific date.

Common measures for evaluating the quality of estimation models are the R^2 and the RMSE. It is commonly known that models based on multi-temporal data sets (Montes et al. 2011; Reddersen et al. 2014) reach higher R^2 values (> 0.60) than models based on the data of one campaign date, with R^2 values mostly not higher that 0.30 (Aasen et al. 2015). In comparison to those across-season studies the herein established models perform equally well with overall better results for dry biomass than for fresh biomass. Moreover, the campaign-wise separated analyses allowed an evaluation of the models regarding the performance for estimations at a specific phenological stages. However, limitations through the measuring process have to be taken into account. Since the plot-wise averaged values were used for all calculations, small-scale variations within the plots might have been obscured, which can produce errors during the model calibration. For test purposes established models based on the data of each individual campaign performed very poor, which can be attributed to this issue. For such models, initial data would be necessary in which plant height and biomass measurements can be directly linked with a higher spatial resolution, e.g. the x, y-coordinates of the destructively taken 0.20 × 0.20 m area should be measured and linked to CSM-derived plant heights only averaged across these small areas.

Regarding the varying performances of the models for fresh and dry biomass, the only difference between the used data sets is the presence of water in the fresh biomass. As shown in Fig. 4, the scatterplots of plant height *vs.* biomass show generally more noise for fresh biomass. It can therefore be assumed that the amount of water in the plants is not linked to plant height. This in return blurs the BRMs for fresh biomass and leads to less accurate estimations. However, further studies are required to investigate this topic.

As shown in this study, the RMSE, as a common error measure, is fairly high for across-season models when comparing it to the mean total biomass amounts, due to the large value range across the growing season. The campaign-wise separated calculation are consequently better suitable for evaluating the model fit, in particular for the early campaigns with the naturally lowest amounts of biomass. Owing to the large value range, the rRMSE was calculated as better comparable value. It can overall be summarized that a fairly wide range of values is worthwhile for the model calibration, since a certain degree of difference between the individual values is necessary. On the contrary, the large value range blurs the results of the model validation regarding the RMSE. Hence, it is recommendable to involve the across-season data set in the model calibration but validate the accuracy of the model for in-season estimations on campaign-wise separated data sets.

Conclusion & Outlook

The presented study investigated the accuracy of biomass regression models (BRMs) for the in-season estimation of spring barley biomass. These already existing BRMs are based on a multi-temporal data set and were proven to be suitable for across-season estimations. However, for site-specific crop management it is more important that the amount of biomass can be accurately estimated at specific phenological stages within the growing season. The root mean square error (RMSE), as usual error measure, is influenced by the value range. Since the amount of plant biomass strongly increases from the beginning to the end of the growing season the value range is large and hence the across-season RMSE is fairly high. However, herein it could be shown that the RMSE is much smaller in the campaign-wise separated analyses. The results overall suggest that it is recommendable to use multi-temporal, across-season data sets for calibrating the BRMs but for evaluating these models regarding an in-season estimation it is more advisable to campaign-wise calculate the RMSE or the relative RMSE, as better comparable measure. Nevertheless, this study was based on the data set of one year and further research is necessary with focus on the transferability of the models to independent data sets.

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