An automated method to quantify crop height and calibrate satellite-derived biomass using hypertemporal lidar

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Abstract

Crop biomass information is of great importance for a variety of applications, ranging from supporting farm management decisions to modeling the crop-environment system. Dimensionless spectral vegetation index values derived from satellite imagery are commonly used to derive crop biomass. However, the highly empirical nature of spectrally derived biomass estimates requires frequent and costly calibration with manually collected ground data. Recently, low cost, autonomously operating terrestrial laser scanners (ATLSs) have become available for near-surface applications. In contrast to the dimensionless nature of spectral index values, autonomous light detection and ranging (lidar) technology measures physical vegetation structure by recording the x, y, z coordinates of canopy components at very high

spatial (< 10 cm), and temporal (< 2 days) resolution. The objective of this study was to assess the suitability of an ATLS to i) monitor crop growth dynamics and ii) calibrate satellite imagery for estimating crop biomass. Wheat (*Triticum aestivum* spp.) growth was monitored by acquiring hypertemporal (every 28 hours for a full growing season) ATLS data at three different field sites across a range of experimentally manipulated crop growth conditions. The ATLS-derived crop height explained nearly three-quarters of the variability in destructively sampled wheat biomass ($r^2 = 0.74$, RMSE = 514.20 kg ha⁻¹), showing a slightly stronger correlation to crop biomass than did leaf area index (LAI) measurements collected in the field using a LAI-2000 Plant Canopy Analyzer ($r^2 = 0.71$, RMSE = 546 kg ha⁻¹). Satellite-based crop biomass estimates calibrated with ATLS data captured the variability in wheat biomass throughout a farm field with a biomass error of 730.96 and 727.60 kg ha⁻¹ (RMSE) during the jointing (Development stage: Zadoks 37) and heading (Development stage: Zadoks 50) growth stages, respectively. These findings suggest that the hypertemporal lidar information provided via ATLS technology could constitute a major step forward in operational monitoring and mapping of crop biomass.

Keywords: Autonomously operating terrestrial laser scanner (ATLS), Leaf area index (LAI), hypertemporal lidar, crop biomass, biomass scaling, error accounting, laser allometry

Introduction

Crop biomass information is of great importance for a variety of applications ranging from environmental modeling to supporting farm-based forecasting and management decisions. However, it remains difficult to obtain accurate and standardized information about crop biomass at the field to landscape scale due to a lack of automated and cost-effective technologies designed for such a purpose. Instead, crop biomass estimates still commonly rely on time- and cost-intensive manual ground measurements such as destructive biomass sampling or non-destructive optically based measurements of leaf area index (LAI) using optical devices (Norman and Campbell, 1989). In an attempt to more

efficiently estimate crop biomass information at the field scale and beyond, remote sensing approaches are commonly employed. Many of these remote sensing approaches rely on dimensionless spectral vegetation indices calculated using mathematical combinations of reflectance data in different wavebands (e.g., Bannari et al., 1995). To convert these dimensionless spectral index values into meaningful physical biomass metrics, simple calibration equations are commonly established between ground-measured biomass and the spectral indices (e.g., Nguy-Robertson et al., 2014). Though relatively easy to derive, such approaches rely on manual ground sampling and highly empirical calibration equations. However, spectral indices are not only affected by variations in biomass but by a multitude of other factors such as foliar biochemistry (e.g., foliar water and chlorophyll concentration), soil background, viewing and illumination geometry, and canopy architecture (Jasquemoud and Baret, 1990; Verhoef, 1984; Jackson and Huete, 1991; Eitel et al., 2009). Consequently, spectral index to biomass relationships are limited in their spatial and temporal transferability and require frequent and costly recalibration (Baret and Guyot, 1991; Verstraete et al., 1996; Foody et al., 2003; Vuolo et al., 2013). A less empirical approach that does not require costly ground sampling relies on the inversion of radiative transfer models (e.g., Haboudane et al., 2002; Eitel et al., 2007). However, several challenges limit the use of the radiative transfer based inversion approaches, including uncertainties in the model and reflectance measurements, violation of radiative transfer model assumptions, and the ill-posed problem where different model parameterizations result in similar spectra (Combal et al., 2002; Atzberger, 2004).

A viable alternative to passive remote sensing-based crop biomass estimates is the use of light detection and ranging (lidar) (Ehlert et al., 2009; Long and McCallum, 2013; Eitel et al., 2014; Hoffmeister et al., 2015). This laser-based technology provides physical biomass proxies such as plant height and has been successfully used for mapping biomass in many ecosystems, ranging from the Arctic (e.g., Greaves et al., 2015) to the Tropics (e.g., Asner et al., 2012). As opposed to passive remote sensing systems that rely on reflected solar radiation, lidar instruments utilize their own active light source to survey the x, y, z coordinates of object surfaces at a rate of up to one million survey points per second. To determine the x, y, z coordinates, lidar instruments measure the inclined distance and angle to each survey

point (Van Genechten et al., 2008; Eitel et al., 2013). Based on the distance and measured angles, the x , y , and z coordinates can be calculated for each point using trigonometric principles (Eitel et al., 2013). The x , y , z coordinates surveyed by lidar can then be used to derive physical proxies of plant biomass such as crop height, volume, and LAI (Zheng and Moskal, 2012; Eitel et al., 2014; Pittman et al., 2015; Hoffmeister et al., 2015). These physical proxies are relatively unaffected by factors such as foliar biochemistry, illumination geometry, and background reflectance that confound spectral index to biomass relationships. Hence, relationships between lidar-derived biomass proxies such as crop height and crop biomass are more analogous to field-based allometry and are thus relatively transferable across space and time. For example, Eitel and colleagues (2014) showed that a simple linear model could be spatially and temporally transferable in the prediction of dry biomass of wheat based on TLS height metrics. This is in agreement with findings by Tilly et al. (2015) who showed that a simple regression model for predicting dry biomass of paddy rice based on TLS derived crop height provided reliable estimates across space and time with R^2 values ranging between 0.60 to 0.90 and 0.56 to 0.85 for linear and exponential models, respectively. Importantly however, both of these examples suggest that relationships between lidar metrics and biomass are species-specific. For studies in structurally similar systems, the spatial and temporal transferability of crop height to biomass relationships constitutes a clear advantage when compared to spectral index based biomass estimates that require frequent and costly recalibration (e.g., Baret and Guyot, 1991; Verstraete et al., 1996; Foody et al., 2003; Eitel et al., 2014; Greaves et al., 2015; Tilly et al., 2015; Fekety et al., 2015).

Despite the great promise of lidar to provide accurate and physically based plant biomass information, airborne lidar data acquisition can be expensive and often lacks temporal resolution, limiting its use as a viable biomass monitoring approach (Wallace et al., 2012). However, recent technological advancements are now enabling automated hypertemporal lidar acquisition at a lower financial cost. For acquiring hypertemporal lidar datasets at the plot scale, autonomously operating terrestrial laser scanners (ATLS) have recently become available (Eitel et al., 2013; Portillo-Quintero et al., 2014; Culvenor et al., 2014; Griebel et al., 2015). After initial calibration, these instruments could replace manual and labor-

intensive biomass sampling by providing a novel solution for automated estimation of biomass (e.g., Eitel et al., 2014; Tilly et al., 2015) and plant structural characteristics. For example, Eitel et al. (2013) described a low-cost (< US\$12000) ATLS that proved suitable for capturing daily changes in plant structure throughout a period of 17 days during fall leaf drop in a mixed conifer/quaking aspen (*Populus tremuloides*) forest stand. Similarly, Portillo-Quintero et al. (2014) used an ATLS for mapping daily changes in Plant Area Index (PAI) for a period of 22 days during leaf drop in a boreal mixed forest.

Scaling plot-level biomass data to broader areas is of importance to many applications. To scale the plot-level plant biomass information derived with an ATLS to the landscape, passive spectral data could be used. This process requires that a simple calibration equation be established between dimensionless spectral indices for pixels within the ATLS footprint and biomass estimates derived from ATLS measurements (Rall and Knox, 2004; Portillo-Quintero et al., 2014; Hoffmeister et al., 2015). Establishing such a calibration based on ATLS data would not only allow replacing manual and labor-intensive ground validation measurements with automated plant structural measurements but would also alleviate difficulties in accurately obtaining field calibration/validation of biomass amounts for satellite pixels with a ground instantaneous field of view (GIFOV) commonly surpassing 20 m² in area (e.g., Verstraete et al., 1996; Ustin et al., 2004).

Despite the need, to date relatively little is known regarding the suitability of an ATLS for monitoring plant growth dynamics and calibrating satellite imagery to map crop biomass. To address this knowledge gap, the two specific objectives of this study were to assess the suitability of an ATLS to i) monitor crop growth dynamics and ii) calibrate satellite imagery for estimating and mapping crop biomass.

2. Methods

2.1 Study site

For testing the suitability of the ATLS for monitoring crop growth dynamics (Objective 1), soft white spring wheat (*Triticum aestivum* spp.) was grown in 2014 following soft white winter wheat in eighteen 100 m² (10 m x 10 m) plots with 19 cm row spacing at the Washington State University Cook Agronomy Farm (CAF) near Pullman, Washington, USA (N 46.7805, W 117.0855). The 18 research plots were divided into three fields (hereafter referred to as Field A, Field B, and Field C) to encompass a wide range of growth conditions and hence crop growth dynamics (see Magney et al., 2016a). Additionally, four "top-dressed" N application rates were applied at each of the three fields (0, 40, 80, and 120 kg ha⁻¹) using granular urea (46% N) three days post-seeding (similar to Eitel et al. 2014). Soil was sampled for inorganic N (NO₃ and NH₄) prior to N application; residual N in the soil did not significantly differ across the plots (p<0.05). The study site has silt loam soils developed in loess deposits with some ash (fine-silty, mixed, superactive, mesic Pachic Ultic Haploxerolls, Soil Survey Staff, 2013). CAF is a dryland site without irrigation, and soil permeability is moderate to high. Average annual precipitation ranges from 260 to 610 mm, and the average available water capacity through the entire soil profile is about 29 cm (Soil Survey Staff, 2013).

For testing the suitability of the ATLS for calibrating satellite-based biomass estimates (Objective 2), soft white spring wheat (*Triticum aestivum* L.) was grown in 2013 within one 36 ha commercial dryland wheat field located approximately 10 kilometers east of the research plots, near Moscow, Idaho (hereafter referred to "Moscow Farm"). Annual precipitation ranges between 580 to 730 mm and the soil type is Southwick silt loam (Soil Survey Staff, 2015).

2.2 ATLS instrumentation and data collection

The ATLS used in this study was a system described in detail by Eitel et al. (2013). The relatively low-cost (~ US\$12,000) ATLS consists of a time-of-flight laser rangefinder (optoNCDT ILR 1191, Micro-Epsilon Messtechnik GmbH & Co. KG, Ortenburg, Germany), circular level, electronic pan-tilt unit, tribrach, datalogger, and power supply (battery and 100 Watt solar panel) (Figure 1). The laser rangefinder employs a near infrared (905 nm) laser with 1.7 mrad beam divergence and has a maximum range of 150 m, 300 m, and 500 m for surfaces with reflectance at 905 nm of 6%, 10%, and 90%, respectively (Table 1).

Figure 1. Autonomously operating terrestrial laser scanner (ATLS) mounted on a tower structure. For more details on the design of the ATLS, please refer to Eitel et al. (2013).

Table 1. Technical specifications of time-of-flight laser rangefinder (optoNCDT ILR 1191, Micro-Epsilon Messtechnik GmbH & Co. KG, Ortenburg, Germany).

Laser wavelength	905 nm
Laser divergence	1.7 mrad
Light spot geometry	45x 41 mm at 10 m
Linearity	±20 mm (at measurement output 100 Hz) ±60 mm (at measurement output 2 kHz)
Repeatability	≤ 5 mm
Operating temperature	-40°C to +60°C

To monitor crop growth dynamics, one ATLS was installed at each of the three experimentally manipulated field sites (i.e., Field A, Field B, and Field C) and at the Moscow Farm. Each ATLS was installed on a tower structure about 3 meters above the ground. To obtain point clouds of the “bare earth”, measurements were initialized immediately after seeding in April. The vertical and horizontal angular step resolution of the pan-tilt unit was set to 2.27 mrad . The scan duration for each site was approximately 28 hours, resulting in unique lidar point cloud information of the crop canopy recorded almost daily between April and the conclusion of ATLS measurements in August.

2.3 Monitoring crop growth dynamics

At each of the 18 plots, the average of three crop height measurements taken with a meter stick on May 29th, June 4th, June 26th, and July 3rd was recorded. Regardless of growing stage, the distance between the highest point in the canopy and the ground were used for height measurements. Due to the relatively small size of the plots and locally homogeneous nature of wheat cropping systems, we assume that crop height variance within each plot was minimal. At the same locations as crop height measurements, three LAI measurements were taken on May 29th, June 4th, June 19th, June 26th, and July 3rd with a Li-Cor LAI-2000 Plant Canopy Analyzer (Li-Cor, Lincoln, NE, USA, following Magney et al., 2016). Directly following the crop height measurements, destructive biomass samples were collected. For

measuring crop biomass at each of the plot locations, plant material was harvested on each sampling date from a 1 m² subplot, dried, and weighed to determine crop dry mass.

To derive crop height of the sampled areas from ATLS data, 3x3 meter areas of interest (AOIs) were chosen that received the same N treatments and were exposed to the same environmental growth conditions as the harvested subplots. To identify an AOI in the ATLS point cloud, harvested subplots were visually identified in the post-sampling ATLS point cloud and the AOI was placed adjacent to it (Figure 2A).

Figure 2. Illustration of hypertemporal lidar data from an autonomously operating terrestrial laser scanner (ATLS) for studying crop growth dynamics at very high spatial and temporal resolution. Figure 2A shows an example of an ATLS point cloud, Figure 2B shows a cross section of the wheat canopy at location 1 (see Figure 2A for location labels) acquired during Julian day 150, Julian day 171, and Julian

day 190 and Figure 2C shows the wheat canopy height changes derived from ATLS data throughout the growing season at location 1, 2, and 3 (see Figure 2A for location labels).

Four of the 18 sampling plots could not be clearly identified from the point cloud and hence only 14 out of 18 sampling plots were considered for the analysis. The point clouds associated with each AOI and sampling date were then loaded into a program (available upon request from the authors) written in the Interactive Data Language (IDL) software package (Version 8.0, ITT Visual Information Solutions) to calculate crop height based on the surface differencing approach (e.g., Loudermilk et al., 2009; Eitel et al., 2014; Greaves et al., 2015). In surface differencing, a digital terrain model (DTM) is subtracted from a digital surface model (DSM) to calculate vegetation height. Here, the DTM was derived from a “bare earth” ATLS scan acquired directly after seeding (i.e. before the start of the growing season), and a DSM was derived from ATLS scans performed on each subsequent sampling date. To derive the DTM and the DSMs for each AOI and sampling date, the program grids each ATLS point cloud onto an arbitrarily subdivided $0.05\text{ m} \times 0.05\text{ m}$ surface. The z value assigned to each grid cell by the program is the minimum (for DTM) or maximum (for DSM) z value within a search radius from the center of the grid cell. If there is no z value within the search radius, the assigned z value is linearly interpolated based on surrounding z values. The search radius for both the DTM and DSM was optimized by varying the search radius between 1 and 30 cm in 1 cm intervals. Finally, the laser-derived crop height for the AOI is determined by calculating the mean of the height differences between the DSM and the DTM grid cells.

To assess the suitability of the ATLS for monitoring crop growth dynamics, we used R 2.3.2 (R Core Team, 2015) to fit both linear (using the ‘lm’ function) and nonlinear (using the ‘nls’ function) regression models between i) measured crop height and ATLS-derived crop height, ii) crop biomass and LAI and iii) crop biomass and ATLS-derived crop height. All models were fit with untransformed data and nonlinear regression models had the following general form:

$$y = a \cdot x^b \quad [1]$$

where y is the dependent variable (crop biomass), x the independent variable, and a and b are allometric constants. Goodness of fit was evaluated based on the coefficient of determination (r^2) and the root mean square error (RMSE).

2.4 Calibrating satellite imagery for estimating crop biomass

To assess the suitability of ATLS-derived structural metrics for calibrating satellite data, we used level 3A RapidEye images, which have already been radiometrically and geometrically corrected (RapidEye, AG 2013). The RapidEye satellite imagery of the Moscow Farm was acquired during the tillering (Zadoks 37) and heading (Zadoks 50) crop growth stage on June 15 and June 29, 2013, respectively (for more details on Zadoks scale, please refer to Zadoks et al., 1974). We calculated the Normalized Difference Vegetation Index (NDVI; Tucker, 1979) and the Normalized Difference Red-Edge index (NDRE; Gitelson and Merzlyak, 1994) as follows:

$$NDVI = (R_{band5} - R_{band3}) / (R_{band5} + R_{band3}) \quad [2]$$

$$NDRE = (R_{band5} - R_{band4}) / (R_{band5} + R_{band4}) \quad [3]$$

where band numbers refer to RapidEye band 3 (red: 630-685 nm), band 4 (red-edge: 690-730 nm), and band 5 (near-infrared: 760-850 nm). Both of these indices were selected due to their well-established sensitivity to variation in plant biomass (e.g., Tucker et al., 1979; Binnary et al., 1995; Torino et al., 2012; Tavakoli et al., 2014; Amaral et al., 2014; Kross et al., 2015), particularly for capturing variance in wheat for this particular study region from RapidEye (Magney et al., 2016b)

To calibrate the dimensionless spectral index values for estimating crop biomass at each of the two acquisition dates, spectral index values for a given pixel were linked to physically based measures of plant structure from the ATLS. For this, four geostationary reflector targets (Leica Geosystems Inc., Heerbrugg, Switzerland) with known geolocations were scanned by the ATLS and used in a translation

and rotation algorithm implemented within an R script to translate the ATLS coordinate system into a geographic coordinate system. This allowed the extraction of ATLS-derived crop height estimates (see section 2.3) associated with the geographic footprint of a pixel defined by its center coordinate and extent (5x5 meters for RapidEye pixels) (Figure 3).

Figure 3. Autonomously operating terrestrial laser scanner (ATLS) derived crop height estimates within the geographic footprint of RapidEye satellite pixels (pixels are shown as squares) defined by their center coordinate and extent (5x5 meters).

Based on the spectral vegetation index (SVI) values for pixels within the ATLS footprint and associated crop height estimates, a simple calibration equation was fit in R 2.3.2:

$$\text{Predicted crop height} = b_0 + b_1 * \text{SVI} \quad [4]$$

where b_0 is the intercept and b_1 is the slope. The calibration equation was then applied to the imagery to convert SVI values into crop height estimates. Next, crop height estimates were converted into biomass estimates using the regression model that was fit between crop dry weight and ATLS derived crop height (see section 2.3). To obtain an estimate of the error associated with the resulting satellite-derived biomass estimates, a bootstrap resampling procedure was developed (Efron and Tibshirani, 1993). In the bootstrap procedure, data were resampled from both the dataset used to fit equation 4, as well as from the dataset used to fit the crop dry weight-crop height linear model (section 2.3) so that the resulting distribution of RMSE values reflects the propagated error from both regression models.

3. Results and Discussion

3.1 Suitability of an ATLS to monitor crop growth dynamics

Manually measured biomass changed from a minimum of 153.33 kg ha⁻¹ to a maximum of 3820 kg ha⁻¹ throughout the growing season (1431.24±1013.90 kg ha⁻¹; mean ± standard deviation) (Figure 4). Similarly, manually measured crop height increased from a minimum of 0.14 m at the beginning of the growing season to a maximum of 0.93 m at the end of the growing season (0.47±0.27 m; mean ± standard deviation).

Manually measured crop biomass and manually measured crop height showed a strong ($r^2 = 0.88$, RMSE = 386.50 kg/ha, see Fig. 4A) statistically significant ($p < 0.0001$) correlation with each other, with the biomass and height values varying among the differently fertilized plots. For example, the crop height during the June 4th sampling campaign ranged between 0.08 m and 0.32 m. The ATLS captured this

manually measured spatial and temporal variability in crop growth, as illustrated in Fig. 2B and 2C. Figure 2B shows a cross-section through ATLS point clouds acquired during Julian Day 150, Julian Day 171, and Julian Day 190 with increasing point cloud heights at later growth stages. Similarly, Figure 2C shows ATLS-derived crop height changes over time for three different plot locations. Though crop heights at all three different plot locations show the same growth trend, spatially and temporally distinct crop growth patterns existed according to plot location. For example, the crop at location 2 (see Figure 2A for location labels) continued to grow from Julian day 184 to 186, in contrast to the crop at locations 1 and 3, which reached its maximum height on Julian day 184.

Figure 4. Relationships between A) crop dry weight and measured crop height, B) measured crop height and autonomously operating terrestrial laser scanner (ATLS) derived crop height, C) crop dry weight and ATLS derived crop height, and D) crop dry weight and leaf area index.

The degree to which the ATLS captured variations in crop growth was statistically quantified by linear regression models that related ATLS-derived biomass metrics to both manually measured crop height and manually measured crop biomass (Fig. 4B-C). ATLS-derived crop height was strongly correlated ($r^2 = 0.87$, and $RMSE = 0.10$ m) with manually measured crop height (Fig. 4B). These results are similar to findings by Hoffmeister et al. (2015) who showed an RMSE of 0.10 meters between manually measured and terrestrial lidar-derived canopy height of sugar beets. When compared to manual crop height measurements, the ATLS underestimated crop height (Fig. 4B). This could be explained by

the laser return integrating between the heights of different surfaces (e.g., top of canopy, flag leaf of wheat plant, and soil) that are within the ground instantaneous field of view of the laser beam. This results in a mixed edge return (also known as mixed pixel or air return) inherent in all laser-based ranging methods, where the recorded distance is neither the distance to the foreground object nor the background object, but rather the distance to a location (sometimes referred to as a “phantom object”) that lies somewhere between the objects (Hebert and Krotkov, 1992; Tuley et al., 2005).

The ATLS-derived crop height explained almost three-quarters of the variability in destructively sampled crop biomass ($r^2 = 0.74$, RMSE = 514.20 kg ha⁻¹) (Fig. 4C) and showed a slightly stronger correlation to crop biomass than did the LAI-2000 derived LAI values, which are widely used to non-destructively estimate crop biomass ($r^2 = 0.71$, RMSE = 546 kg ha⁻¹) (Fig. 4D). Some of the unexplained variability between dry biomass and ATLS-derived crop height might be explained by the relatively large beam divergence (1.7 mrad) of the ATLS, resulting in a beam diameter (i.e. ground instantaneous field of view) of > 45 mm at 10 m and > 155 mm at 75 m. This relatively large beam divergence does not allow small canopy components to be resolved, particularly at larger (> 10 m) distances between the ATLS and the surveyed crop. However, even though in this study the distance between the ATLS and surveyed plots varied between 5 – 40 m (associated beam diameter: 37 mm – 96 mm), this variable had a minimal effect on the regression model as shown by a non-significant (p-value > 0.05) effect of “distance” when included as a covariate in the regression model.

The strength of the relationship between biomass and ATLS-derived crop height weakened with increasing biomass as shown by the heteroscedastic behavior of the regression model (Figure 4C). One explanation for the heteroscedastic model behavior could be that ATLS derived crop height does not account for differential crop density. In other words, although the crop height might be the same between different plots, crop density might differ. This explanation appears to be unsatisfactory, however, because the relationship between crop biomass and LAI shows the same heteroscedastic behavior even though LAI measurements account for variations in crop density.

Another explanation for the heteroscedastic behavior might be phenotypic variations between different fields and treatments that become more pronounced during later growth stages. Even though crop height, LAI, and crop density might be similar between plots, differences in environmental growth conditions such as water availability, nutrient availability, and air temperature might result in phenotypic variation (e.g., in plant tissue density) that cannot be detected using either the ATLS or the LAI-2000.

The strength of the relationship between crop biomass and ATLS-derived crop height was unaffected by the upper and lower search radius used to identify the minimum and maximum z values to calculate the DTM and DSM, respectively (Fig. 5). This finding differs from previous work that showed that the search radius had strong effects on terrestrial lidar derived biomass estimates of different types of plant canopies (Eitel et al., 2014; Greaves et al., 2015). A likely cause for this discrepancy is that in contrast to previous studies, there is no vegetation in the “bare-earth” ATLS scans to confound the identification of ground points. Furthermore, because the canopy is relatively uniform, this optimization procedure is likely unnecessary.

Figure 5. Search radii for fitting the digital terrain model (lower search radius) and digital surface model (upper search radius) and resulting coefficient of determination (r^2) for the regression model fit between the observed crop dry weight and autonomously operating terrestrial laser scanner (ATLS) derived crop height.

3.2 Suitability of an ATLS to calibrate satellite-based crop biomass estimates

The ATLS-derived crop height provided reliable biomass estimates of the wheat crop (Figure 4C). While the spatial extent of ATLS measurements is confined to the plot scale (< 50x50 meters), this extent does allow for physically based ATLS crop height estimates to be directly compared with passive satellite data to estimate and then map crop biomass at broader scales. Our results showed that satellite-derived NDRE and NDVI values were correlated ($r^2 \geq 0.63$, $RMSE \leq 0.06$ m) with ATLS-derived crop height estimates on both June 15th, 2013 and June 29, 2013 (Fig. 6). These relationships are considerably stronger than previously observed relationships between NDVI and terrestrial lidar derived crop height during similar crop growth stages in winter barley and winter wheat ($r^2 < 0.26$) (Hoffmeister et al., 2015).

Figure 6. Relationships between autonomously operating terrestrial laser scanner (ATLS)- derived crop height and spectral vegetation indices during the jointing (Zadoks 37; June 15, 2013) and heading (Zadoks 50; June 29, 2013) growth stage.

The reason for this discrepancy could be differences in the range of height values within the farm fields. The wider the range of crop height values throughout a field for a given acquisition date, the more likely it is to detect and model a trend in the relationship between spectral vegetation indices (e.g., NDVI and NDRE) and crop height. Some of the data variance could be explained by minor positional inaccuracies in both the satellite and ATLS data, which may not allow perfect co-registration of satellite pixels with ATLS-derived crop height estimates.

The NDRE showed stronger relationships to crop biomass than did NDVI, confirming previous findings showing that NDRE is more sensitive to variations in biomass and less prone to saturation at higher biomass values than NDVI (Viña and Gitelson, 2005; Torino et al. 2012; Amaral et al., 2014). The need to frequently re-calibrate spectral index values for estimating crop biomass is illustrated by the

regression models that show different slopes and intercepts for each acquisition date. For example, the slope and intercept for the regression model between ATLS-derived crop height and NDVI on June 15th is -0.06 and 0.54, respectively, and on June 29th it is -0.56 and 1.83, respectively. This result further confirms the inconsistent nature of relationships between spectral index values and crop properties highlighted in other works (e.g., Kross et al., 2015; Fitzgerald et al., 2010; Eitel et al., 2008, Hatfield et al., 2008).

This strongly empirical relationship between spectral index values and crop biomass indicates that innovative methods are needed to effectively calibrate satellite-based biomass estimates. The relationships between crop biomass and ATLS-derived crop height (Fig. 3C) and between spectral index values and ATLS-derived crop height (Fig. 6) suggest that the ATLS could be used for such a purpose. For the commercial farm field near Moscow, NDVI-based biomass estimates calibrated with ATLS data showed a biomass error of 796.18 and 745.11 kg ha⁻¹ (RMSE) during the wheat jointing (Zadoks 37) and heading (Zadoks 50) growth stages, respectively. The biomass error decreased to 730.96 and 727.60 kg ha⁻¹ (RMSE), respectively, when NDRE was used instead of NDVI. Figure 7 shows biomass estimates throughout the commercial farm field near Moscow during the heading growth stage, where biomass estimates are based on NDRE calibrated with ATLS data.

Figure 7. True color RapidEye image of a commercial dryland wheat field near Moscow, Idaho acquired on June 29, 2013 during the heading (Zadoks 50) growth stage of soft white spring wheat and associated crop biomass estimates calibrated with ATLS data (biomass error is 727.60 kg ha⁻¹ (RMSE)).

3.3 Limitations, research needs, and opportunities

The relationship between crop biomass and ATLS derived crop height might be species and even variety specific. For example, Pittman et al. (2015) showed different regression models for predicting dry biomass in alfalfa, Bermuda grass, and wheat based on laser- and ultrasonic-derived crop height. The relationships between ATLS-derived crop height and dry biomass might also change with crop density,

which can vary due to row spacing or fine scale variation in edaphic conditions and nutrient availability. Yet, given that crop density in this study varied widely due to nutrient and water availability (see Magney et al., 2016a) and that ATLS-derived crop height estimates showed slightly better relationships to crop biomass than LAI measurements that take variations in crop density into account, variations in crop density seem to be a lesser concern. Nevertheless, further investigations are needed to explicitly examine the effects of crop density, plant tissue density, crop species, and crop varieties on the accuracy and reliability of the relationships between ATLS-derived crop height and dry biomass. Further, this study only focuses on crop height as a lidar proxy for crop biomass. Though beyond the scope of this study, other metrics could be derived from ATLS data to obtain potentially more accurate proxies for crop biomass such as fractional crop cover and canopy gap fraction, particularly where the ATLS views the crops at relatively low view zenith angles (Zheng et al. 2012). Further, recent research suggests that the laser return intensity recorded by lidar instruments for one or more wavelengths might further increase the suitability of ATLS for crop monitoring, be useful (Eitel et al., 2010, Eitel et al., 2011, Gaulton et al., 2013; Danson et al., 2014; Eitel et al., 2014; Magney et al., 2014, Eitel et al., 2016). Of particular interest for agricultural applications might be the laser return intensity of a green scanning lidar, which has been shown to provide information about foliar chlorophyll concentration (Eitel et al., 2010), foliar nitrogen (Eitel et al., 2011; Eitel et al., 2014), and even plant photoprotective capacity (Magney et al., 2014). Hence, even though this might decrease the range, replacing the near-infrared (905 nm) laser used in this study with a green (532 nm) laser might allow monitoring of not only crop structure, but also foliar biochemistry and crop physiological function.

The results of this study provide initial evidence of the suitability of the ATLS for calibrating satellite-based biomass estimates. With further development, web-enabled ATLS monitoring networks across growing regions could make it feasible to deliver biomass estimates in near real time that are suitable for calibrating satellite imagery. This development would allow the creation of physically based

biomass maps for agricultural decision makers, representing a major technological step forward since such information is currently difficult to obtain at scales relevant for agricultural decision making.

4. Summary and conclusion

The objectives of this study were twofold – to first assess the suitability of an ATLS to monitor crop growth dynamics, and then to calibrate satellite imagery using these physically-based relationships to better scale and map crop biomass. The results suggest that an ATLS is suitable for monitoring crop growth dynamics. Crop height information derived from a total of three ATLSs reliably tracked changes in dry biomass ($r^2 = 0.74$, RMSE = 514.20 kg/ha) both throughout the growing season and across a wide range of experimentally manipulated crop growth conditions. These findings, combined with the spatial and temporal transferability of crop height-to-biomass relationships shown in previous studies (Eitel et al., 2014; Tilly et al., 2015) suggests that after initial calibration, ATLS technology could enable automated biomass sampling and reduce the need for traditional labor-intensive manual biomass sampling approaches. ATLS data were also suitable for calibrating satellite-based crop biomass estimates. Satellite-based biomass estimates calibrated with ATLS data captured variability in crop dry biomass throughout a commercial farm field with a biomass error of 730.96 and 727.60 kg ha⁻¹ (RMSE) during the wheat jointing (Zadoks 37) and heading (Zadoks 50) growth stages, respectively. The physically based biomass estimates derived from hypertemporal ATLS data and ATLS-calibrated satellite data constitute important progress in obtaining reliable crop biomass estimates for both agricultural decision-making and research applications. Additional research is needed to further test the robustness of the ATLS for monitoring crop growth dynamics and calibrating satellite-based biomass estimates across different crops, fields, growing seasons, and satellite sensors.

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749

750 **Figure captions:**

751

752 **Figure 1.** Autonomously operating terrestrial laser scanner (ATLS) mounted on a tower structure. For
753 more details on the design of the ATLS, please refer to Eitel et al. (2013).

754 **Figure 2.** Illustration of hypertemporal lidar data from an autonomously operating terrestrial laser
755 scanner (ATLS) for studying crop growth dynamics at very high spatial and temporal resolution. Figure
756 2A shows an example of an ATLS point cloud, Figure 2B shows a cross section of the wheat canopy at
757 location 1 (see Figure 2A for location labels) acquired during Julian day 150, Julian day 171, and Julian
758 day 190 and Figure 2C shows the wheat canopy height changes derived from ATLS data throughout the
759 growing season at location 1, 2, and 3 (see Figure 2A for location labels).

760 **Figure 3.** Autonomously operating terrestrial laser scanner (ATLS) derived crop height estimates within
761 the geographic footprint of RapidEye satellite pixels (pixels are shown as squares) defined by their center
762 coordinate and extent (5x5 meters).

763 **Figure 4.** Relationships between A) crop dry weight and measured crop height, B) measured crop height
764 and autonomously operating terrestrial laser scanner (ATLS) derived crop height, C) crop dry weight and
765 ATLS derived crop height, and D) crop dry weight and leaf area index.

766 **Figure 5.** Search radii for fitting the digital terrain model (lower search radius) and digital surface model
767 (upper search radius) and resulting coefficient of determination (r^2) for the regression model fit between
768 the observed crop dry weight and autonomously operating terrestrial laser scanner (ATLS) derived crop
769 height.

Figure 6. Relationships between autonomously operating terrestrial laser scanner (ATLS) derived crop height and spectral vegetation indices during the jointing (Zadoks 37; June 15, 2013) and heading (Zadoks 50; June 29, 2013) growth stage.

Figure 7. True color RapidEye image of a commercial dryland wheat field near Moscow, Idaho acquired on June 29, 2013 during the heading (Zadoks 50) growth stage of soft white spring wheat and associated crop biomass estimates calibrated with ATLS data (biomass error is $697.50 \text{ kg ha}^{-1}$ (RMSE)).