ESTIMATION OF VEGETATIVE BIOMASS USING ON-THE-GO MOBILE SENSORS

J. J Pittman, T.J. Butler, S.M. Interrante, D B Arnall, C.A Moffet

Plant and Soil Science Department
Oklahoma State University
Stillwater, OK

Forage Improvement Division
Samuel Roberts Noble Foundation
Ardmore, OK

ABSTRACT

Non-destructive methods for estimation of vegetative biomass have been developed using several remote sensing strategies as well as physical measurement techniques. An effective method for estimating biomass must be at least as accurate as the accepted standard for destructive removal measurement techniques such as a forage harvester or quad harvest strategies. In large part vegetative biomass is considered a function of canopy or plant height. Subsequently, a method or piece of equipment which can estimate a height component is typically implemented for collecting measurements and from those measurements a relationship is created between height and mass. A number of sensing technologies have been examined for such applications. This study examined several types of ground-based sensing strategies for use in estimation of in-field forage biomass. A forage production trial consisting of multiple fertilizer treatments and mixed as well as monoculture species treatments was employed as an evaluation platform for the performance of the sensor estimation as compared to physical removal harvests. Predictive models were constructed and comparisons of sensor based estimates made to physically measured biomass harvested by hand from quad harvests as well as machine harvests using a forage harvester. Statistical analysis for both methods of harvest and sensor estimated harvests were performed as would normally be done according to treatment structure. Mean estimates were examined for evaluation of differences between biomass evaluation methods for each treatment. This strategy was employed in order to evaluate the difference if any on the overall research implications for data which was generated from physical collection techniques as well as sensor estimated data. Ultimately differences were minimal and did not contribute to disparity in implications for research aspects of the trial. Additionally, statistical analysis was performed on a subset of the data for repeatability. Paired identical plots were compared using Limits of agreement analysis to evaluate the repeatability of each technique. This analysis produced more narrow error bands for the sensing data as compared to the harvested data which suggests the sensing data is at least as stable as the physically harvested data. Subsequently, using ground-based mobile sensing for data collection which are incorporated into a biomass estimation model could prove to be effective in rapid accurate in field biomass estimation.

Keywords: Remote Sensing, Biomass Estimation, Mobile Sensors, Sensor System, Data Acquisition, High Through-Put

INTRODUCTION

An effective method for in-field estimation of biomass on a dry matter (DM) basis must be approximately as accurate as the accepted standard for destructive removal measurement. Non-destructive methods for estimating dry biomass have been developed using plant or canopy measurements (Tucker,1980; Fricke and Wachendorf, 2013). In large part, vegetative mass is considered a function of canopy or plant height (Machado et al., 2002; Lati et al., 2013). Devices such as the rising plate meter, capacitance meter, and meter stick are typically implemented for physical measurements of vegetation height (Tucker,1980; Sanderson et al., 2001; Fehmi and Stevens, 2009; Doughtery et al., 2013). The limitations associated with these techniques are labor and time needed to collect the measurements as well as variation due to vegetation growth characteristics and spatial variability. This may present difficulty in creating a robust estimation model, which is representative for a comprehensive range of dry biomass volumes that may be encountered. Alternatively, remote sensing strategies may overcome some of the limitations encountered with physical measurement strategies. Many more measurements can be taken in a considerably smaller amount of time and generally a much larger area can be sampled. This increased magnitude in data collection provides opportunity for development of a statistically robust estimation model as a more comprehensive representation of the area of interest (AOI) can be collected. Proximal optical sensors have been utilized for measuring height and estimating DM in pastures (Hutchings et al., 1990; Fricke et al., 2011; Fricke and Wachedorf, 2013) canopy characterization in orchards (Zaman and Salyani, 2004; Planas et al., 2011;), phyto-sanitary tissue in viticulture (Mazzetto et al., 2008), as well as crop production scenarios in wheat (*Triticum aestivum* L.) (Scotford and Miller, 2004), cotton (*Gossypium hirsutum* L.) (Sui, 2004), and corn (*Zea mays* L.) (Aziz et al., 2004). Spectral proximal sensors have been effectively used for height measurements in wheat (; Fumiki, 2009; Ehlert et al., 2010), corn (Selbeck et al., 2010) rape (*Brassica napus* L.), rye (*Secale cereale* L.), pasture (Ehlert et al., 2008), standing forests (Henning and Radtke, 2006), and miscellaneous vegetation (Hopkinson et al., 2006). Fricke and Wachendorf (2013) examined the combination of ultrasonic and active spectral reflectance for accuracy in white clover (Trifolium repens L.), red clover (Trifolium pratense L.), alfalfa (Medicago sativa L.) with perennial ryegrass (Lolium perenne L.) for dry biomass estimation. Fricke and Wachendorf (2013) reported R^2 = 0.99 in estimation of biomass for monoculture alfalfa and

0.90 in alfalfa perennial ryegrass mixtures. Scotford and Miller (2004) reported standard errors between 4.6 and 7.2 cm estimation of canopy height in wheat when combining ultrasonic and Normalized Difference Vegetation Index (NDVI). Similar examinations were made in corn by Freeman etal (2007) using NDVI and ultrasonic sensors where an R2 = 0.62 was reported for forage mass. Spectral strategies seek to base estimations on reflectance or absorption intensities of wavelengths from vegetation and/or soil (Hong et al., 2007; Jones et al., 2007; Erdle et al., 2011; Fricke and Wachendorf, 2013). This is an effective strategy but can become less accurate upon full canopy closure when a point of reflectance saturation may occur (Erdle et al., 2011; Gnyp et al., 2014;). Subsequently, canopy closure early in vegetative development, may limit spectral methods for biomass estimation. There is limited published research on the use of sensor system estimation models for forage measurement. Therefore, the objective of this research was to develop a sensor system and estimation model for forage mass measurement.

MATERIALS AND METHODS

Alfalfa and Bermudagrass Mixture Experiment

The alfalfa (*Medicago sativa* L. '600RR')-bermudagrass [*Cynodon dactylon* (L.) Pers. 'Midland 99'] mixture trial was conducted at the Noble Foundation Red River Research and Demonstration Ranch near Burneyville, OK (33.88^{o} N, 97.28^{o} W; elevation 234 m.). The soils are characterized as Slaughterville fine sandy loam (coarse-loamy, mixed, superactive, thermic Udic Haplustolls) with N-nitrate at less than 5 g kg^{-1} , soil test P value of 64 g kg^{-1}, K of 52 g kg^{-1} (amended 178.5 g kg^{-1} 0-0-60), B of 0.17 mg kg^{-1} (amended 74.5 mg kg^{-1}) and pH of 6.3. Alfalfa was inter-seeding alfalfa into an established bermudagrass sward in fall of 2012 and spring of 2013. Data was collected the following spring and summer of each establishment year. Additionally an adjacent experiment with eight replicates of 1.5 x 6 m bermudagrass only plots treated with seven different levels of N fertilizer ranging from 0 to 224 g kg^{-1} N was established and harvested concurrently with the alfalfa-bermudagrass mixture experiment. Measurements were taken from all plots using a meter stick and a 0.1-m^2 aluminum rising plate disk meter (NZ Agriworks LTD t/a Jenquip, Feilding, NZ) (Interrante et al., 2012). Plot biomass weights were recorded on a whole plot basis and converted to a dry matter basis. Active and passive spectral as well as proximal sensors were employed for data collection. A ground-based mobile platform in the form of an electric golf cart was utilized for moving sensors across the trial areas. The cart was custom-fitted with a mast extending from the front upon which all sensors were attached and power was routed through a common switch by which data acquisition could be initiated or terminated. The sensor array measured approximately 25 cm wide and 45 cm from front to back. Each plot was driven across at 3.2- 4.8 km hr^{-1} resulting in approximately 5 seconds of data acquisition per plot and approximately 25-30 averaged senor readings per plot resulting in 4-5 readings per linear m.

Wheat Experiments

Two wheat trials were also employed for sensor data collection. The first wheat experiment was initiated at the Noble Foundation Dupy farm near Gene Autry, OK (34.29^o N, 96.99^o W; elevation 220 m.). The soils are characterized as Dale silt loam with pH of 7.3 and N-nitrate, P, and K of 14, 31, and 132 g kg^{-1}, respectively. Approximately 1200 (1.5 x 3 m) plots of various wheat varieties were planted as part of variety selection trials. These were arranged in a two replication RCBD design. The second wheat experiment was initiated at the Noble Foundation Unit 3 farm in Ardmore, OK (34.17^o N, 97.08^o W; elevation 268 m.). The soils are characterized as Konsil loamy fine sandy with pH of 6.8 and N-nitrate P, and K of 28, 50, and 111 g kg^{-1}, respectively. This trial contained 136 (1.5 x 3 m) plots. Data were collected in the spring of 2014. Wheat dry matter was estimated by hand clipping a 0.16 m^2 quadrat which were dried in a forced draft oven at 50°C for 7 days prior to weighing and reported as kg ha^{-1} on DM basis. Sensor data was collected from the wheat trials using a gasoline-powered Spider high-clearance tractor (LeeAgra, Inc., Lubbock, TX). The factory installed spray mast attached to the front of the tractor was converted to a manifold configuration to accommodate the sensor array. All sensors were powered using the onboard factory installed 12 V power supply. The sensor array measured approximately 20 cm long by ten cm wide. Each plot was driven across at 1.6-3.2 km hr^{-1} resulting in approximately 3 seconds of data acquisition per plot. This amount of time provided approximately 25-30 sampled values per plot.

All Trials-Data Acquisition/Processing

Positional data was acquired during data collection for all trials using a GPS with OmniStar XP GNSS positioning at10 Hz such that multiple locations could be recorded within each plot. For all experiments, analog data were acquired by a laptop or notepad via USB connection to a data acquisition module (DAQ) or direct connection to the sensor. All data for all sensors was collected simultateously.For all experiments, all streams of data were captured real-time using Agri-logger and WinWedge Pro© software (TAL Technologies Inc., Philadelphia, PA). These software applications were not used simultaneously for concurrent data collection. Agri-logger is a proprietary software application was developed to accommodate multi sensor system data acquisition. WinWedge Pro was also used as a commercial comparison. Toggling of sensor power was necessary for plot delineation when acquiring data with WinWedge pro so as to insert skips in the data streams. This strategy required combining the data from all streams post-processing. Conversely, Agri-logger enabled the user to insert plot identifiers real-time as the data were acquired. Data from the passive radiometer was combined with other data post processing. Time intensive log file combination and plot delineation was necessary when data was acquired using WinWedge Pro. Data acquired using Agri-logger was manually edited to remove non-plot areas but due to the ability to mark the data as it was acquired this process was much less time intensive. Estimation models were generated by including all parameters measured for biomass and canopy height in partial least squares regression using SAS PROC PLS with cross validation as well as CVTEST and NOINT option for selection of simplest models (SAS, 2012; ; Chen

Table 1. Centered Scaled Parameter Estimates (CPSE) and Variable Importance Plot (VIP) scores for sensor parameters considered for model inclusion. Height Sensor 1 (H1) Height Sensor 2 (H2) Height Sensor 3 (H3).

Sensor Measurement	CPSE	VIP
	Dry Matter	
H1	0.33	1.37
H2	0.18	1.32
H3	0.02	1.11
NDVI	-0.07	1.10
690 nm	-0.26	0.90
650 nm	-0.09	0.83
590 nm	0.10	0.74
450 nm	-0.06	0.72
520 nm	0.08	0.71
570 nm	0.04	0.70
530 nm	0.07	0.69
	Canopy Height	
H1	0.25	1.08
H2	-0.40	1.01
H3	0.16	0.95

Statistical Analysis and Modeling

and Zhu, 2013; Luo et al.,2014; Wuerschum et al.,2014). The PLS procedure was also selected as cross validation and model training can be used to optimize estimation accuracy. Parameters included in biomass and canopy height estimation models were selected by evaluation of Variable Importance Plot (VIP) values and Centered Scaled Parameter Estimate (CSPE) values (Mehmood et al., 2012) (Table 1). This strategy was adopted in order to achieve an acceptable balance in estimate accuracy and model /sensor system complexity by excluding less contributive variables and equipment from the system. Approximately two-thirds of the total data (approximately 2300 samples) were used for construction of non-species specific ("ALL") estimation models for biomass, 1095 samples for sensor-based canopy height estimates. The remaining one-third was employed as validation data. Alternatively, smaller calibration/ validation data sets were used for by species modeling. Four sensor models, two physically-measured height models, and one plate meter model for biomass estimation as well as two models for canopy height estimation were generated for estimation performance evaluation (Table 2). Regression analyses were performed to evaluate relationships between measured and estimated values for biomass and canopy heightusing SAS PROC REG for samples from the validation data only (SAS, 2012). Additionally, accuracy of estimation models was evaluated on a percent basis by examining the mean of the percent difference from each sample measurement and its associated modeled estimate (Equation 1). Agreement of measured and estimated values and variation in repeatability were examined using limits of agreement analysis (LOA) for bermudagrass plots only (113 pairs of plots). Only bermudagrass plots were used in this analysis due to the fact that plots were homogenous and side by side such that an expectation of replication was appropriate and is a requirement for the LOA analysis (Bland and Altman,

Table 2. Dry biomass and canopy height estimation model label key for sensor and physical measures.

Model Number	Estimate	Species Specific	Number Of Sensors
1	Dry Biomass	Y	3
2	Dry Biomass	N	3
3	Dry Biomass	Y	2
4	Dry Biomass	N	1-2
5	Dry Biomass	Y	Meter Stick
6	Dry Biomass	N	Meter Stick
7	Dry Biomass	N	PlateMeter
8	Canopy Height	Y	2
9	Canopy Height	N	2

Equation 1. Calculation of Mean Percent Error

$$Mean\ Percent\ Error = Mean \sum_{n}^{1} \frac{|\text{Estimate} - \text{Measured}|}{Measured\ Dry\ Mass}$$

1995). To address competing indications of model performance, an Error, Consistency, and Mean Agreement (ECMA) score was calculated for ranking estimation effectiveness of each model. The score equally weighted the model error consistency (standard deviation of percent error), accuracy (mean of percent error), and the agreement of the mean of measured to estimated values (R^2 of estimate to measured, as well as difference in mean of estimate and measured) (Equation 2; Table 3).LSD mean estimate groupings were examined as a post hoc analysis ofaccuracy for biomass estimates as well as canopy height using validation samples only. This was done to illustrate the efficacy of using biomass or canopyheight estimations calculated from sensor readings in place of destructive harvesting methods or physical height measurements for research trial evaluations. Biomass comparisons groups were delineated based on destructively measured biomass in 1000 kg ha^{-1} increments from 0-6000 kg ha^{-1}. Canopy height comparisons were based on ten physically-measured canopy height classes at 10 cm increments. These comparisons were performed using PROC MIXED (SAS, 2012) in combination with the PDMIX800 macro (Saxton, 1998; Lauriault et al., 2013).

RESULTS AND DISCUSSION

All height sensor parameters were associated with VIP values greater than the exclusionary threshold of 0.8 for both biomass and canopy height. Normalized Difference Vegetation Index was selected as the spectral component for inclusion in biomass model construction based on greater Pearson coefficients and VIP values as compared to other spectral data. It must also be noted the CPSE associated with NDVI was not furthest from zero for all spectral data examined (Table 1).With the exception of alfalfa, sensor estimation models consistently offered higher percent DVV explanation for both biomass and canopy height than other forms of measure (Table 4). Limits of agreement analyses illustrated the variation in the standard method of destructively sampled measurement to be -1517 to1517 kg ha^{-1}. The variation of the two sensor model estimation was -1558

Equation 2. Calculation of Error, Consistency, and Mean Agreement (ECMA) Score

$$ECMA = \frac{\left(\frac{Coefficient\ of\ determination\ for\ estimate\ by\ measured}{|estimate\ mean - measured\ mean|}\right)}{mean\ percent\ error * standard\ deviation\ of\ percent\ error}$$

Table 3. Highest ranked sensor models based on Error, Consistency, and Mean Agreement Score (ECMA)

Forage Type	Model	ECMA Score
	Dry Matter ($kgha^{-1}$)	
ALL	4	0.057
Alfalfa	1	0.150
Bermuda	3	0.069
Wheat	1	0.013
MIX	4	0.174
	Canopy Height (cm)	
ALL	9	0.99
Alfalfa	9	0.04
Bermuda	8	4.05
MIX	9	0.88

to 1582 kg ha^{-1}. The combination sensor model produced the most repeatable results with a variation residual of 106. Subsequently, estimation models implemented for biomass based on destructively harvested values would likely not produce estimates with greater precision than that of the destructively harvested measures. Sensor models consistently overestimated low biomass values and underestimated high values. The LSD values for all estimation models were greater than those for the measured values. This indicated more variation within estimates which is most likely also influenced by the fact the classes were derived from sorted measured values. Subsequently, overlapping of mean estimate groups occurred due to greater LSD values for the estimated biomass as compared to measured. Additionally, sensor estimates for biomass had a larger range than that produced from measured height based models although neither modeling strategy duplicated measured biomass. Models were though effective in grouping biomass estimates for measured classes almost exactly the same as the measurements themselves dictated. The only exceptions to this occurred in the mixture and the ALL forage category, and occurred only at the highest biomass levels (Table 5).

CONCLUSION

Using mobile sensor systems for biomass estimation can enable a greater rate of data acquisition providing an appropriate software option for acquisition is employed. Results from this study illustrate modeling biomass from height sensor derived data alone can provide estimates accurate enough for most management and research applications. This is an important distinction as the cost associated with an approximately 1% increase in DVV explanation was facilitated by spectral components. This would come at a cost of US $4000in addition to the US$1500 cost for the basic system without spectral components. Time savings of

Table 4. DVV explaination for dry biomass and canopy height by sensor and measured estimation models and model equations.

Dry Matter (kgha^{-1})				
	Canopy Height	**Plate Meter**	**H2**	**H1**
Alfalfa	68.5%	18%	55%	64%
Bermuda	69%	23%	75%	78%
Wheat			72%	74%
MIX	67.8%	19%	73%	73%
ALL	64.4%	17%	62%	58%
	3 Sensor Model	**3 Sensor Equation**	**2 Sensor Model**	**2 Sensor Equation**
Alfalfa	65.7%	(46.22*H1+ 47.83(H2*NDVI)	65.5%	(46.9*H1)+ (43.13*H2)
Bermuda	80.5%	(65.3*H1)+ 58.3(H2*NDVI)	81%	(65.7*H1)+ (49*H2)
Wheat	75%	(118*H1)+ 108(H2*NDVI)	74%	231*H1
MIX	78.9%	70.5(H1*NDVI)+ 63.7(H2*NDVI)	78.5%	(61.3*H1)+ (53.9*H2)
ALL	65.8%	1.6(H1*H2)+ (2624*NDVI)	64.5%	(53.5*H1)+ (50*H2)
Canopy Height (cm)				
		Plate Meter	**H2**	**H1**
Alfalfa		<0%	57%	69%
Bermuda		<0%	67%	77%
MIX		<0%	54%	61%
ALL		6.1%	55%	64%
			2 Sensor Model	**2 Sensor Equation**
Alfalfa			70%	(0.46*H1)+ (0.42*H2)
Bermuda			77%	1.02*H1
MIX			64%	0.017(H1*H2)
ALL			65%	(0.74*H1)+ (0.2*H2)

a factor of 60 in the field and a factor of 10 for data processing were also observed when using this system. In order for the greatest level of precision to be obtained, it is likely necessary to implement specific models for predominant or monoculture species though a general estimation model can produce acceptable estimates. It may also be possible to stratify implementation of models based on height measurement. Enabling evaluation of biomass production without exerting influence on the system by vegetation removal would be useful in research scenarios where removal could negatively impact the longevity and homogeneity of trials. Ultimately real-world production management decisions could be made in a much more rapid manner such as stocking rate adjustments or forage harvesting intervals. Further examination of spectral data as model components will be necessary as there will likely be scenarios where these data will be more contributive than the observations made during this study. Future examination of additional species is necessary to develop an optimally robust collection of

Table 5. Mean estimates for destructively measured Dry Matter (DM), sensor estimates and measured height estimates derived from superior models indicated in table 3.

Forage Class	DM Class	Measured $kgha^{-1}$	Sensor Estimates	Measured Height Estimate
Alfalfa	1	780E	1170D	1074D
Alfalfa	2	1500D	1689C	1567C
Alfalfa	3	2474C	2420B	2170B
Alfalfa	4	3266B	2964A	2767A
Alfalfa	5	4432A	3460A	3185A
LSD		**202**	**401**	**425**
Bermuda	1	612F	1321E	1470E
Bermuda	2	1545E	1795E	2522D
Bermuda	3	2692D	2624D	3208C
Bermuda	4	3425C	3448C	4400B
Bermuda	5	4529B	4720B	5110AB
Bermuda	6	6332A	5617A	5850A
LSD		**489**	**686**	**881**
MIX	1	759G	1244F	2024F
MIX	2	1468F	1480E	2616E
MIX	3	2430E	2319D	2966D
MIX	4	3446D	2816C	3238C
MIX	5	4466C	4102B	4961B
MIX	6	5583B	4527A	5406A
MIX	7	6410A	4031B	4885AB
LSD		**145**	**227**	**328**
Wheat	1	709F	1376D	
Wheat	2	1425E	1631D	
Wheat	3	2505D	2553C	
Wheat	4	3494C	3934B	
Wheat	5	4441B	4520A	
Wheat	6	5676A	4977A	
LSD		**248**	**486**	
All	1	753G	1241E	1768F
All	2	1468F	1495D	2336E
All	3	2460E	2316C	2742D
All	4	3442D	2719B	3087C
All	5	4465C	3931A	4519B
All	6	5725B	4188A	4895A
All	7	6410A	4031A	4348B
LSD		**130**	**256**	**299**

models for estimating DM across different environments and for a variety of research and production systems.

REFERENCES

Aziz, S.A., Steward, B.L. Birrell, S.J., Shrestha, D.S. Kaspar, T.C. 2004. In *Ultrasonic sensing for corn plant canopy characterization*, ASAE/CSAE Annual International Meeting, Ottawa, Ontario, Canada. September 8, 2004; Ottawa, ON.

Bland, J.M., Altman, D.G. 1995. Comparing methods of measurement: Why plotting difference against standard method is misleading. The Lancet, 346, 1085-1087.

Chen, P., Zhu, Y. A. 2013.new method for winter wheat critical nitrogen curve determination. Agron. J. 105, 1839-1846.

Dougherty, M., Burger, J.A., Feldhake, C.M., AbdelGadir, A.H. 2013. Calibration and use of plate meter regressions for pasture mass estimation in an appalachian silvopasture. Archives of Agronomy and Soil Science. 59, 305-315.

Ehlert, D., Horn, H.J., Adamek, R. 2008. Measuring crop biomass density by laser triangulation. Comput Electron Agric. 61, 117-125.

Ehlert, D., Heisig, M., Adamek, R. 2010. Suitability of a laser rangefinder to characterize winter wheat. Precision Agric. 11, 650-663.

Erdle, K., Mistele, B., Schmidhalter, U. 2011. Comparison of active and passive spectral sensors in discriminating biomass parameters and nitrogen status in wheat cultivars. Field Crops Res. 124, 74-84.

Fehmi, J.S., Stevens, J.M. 2009. A plate meter inadequately estimated herbage mass in a semi-arid grassland. Grass Forage Sci. 64, 322-327.

Freeman, K.W., Girma, K., Arnall, D.B., Mullen, R.W., Martin, K.L., Teal, R.K., Raun, W.R. 2007. By-plant prediction of corn forage biomass and nitrogen uptake at various growth stages using remote sensing and plant height. Agron. J. 99, 530-536.

Fricke, T., Richter, F., Wachendorf, M. 2011. Assessment of forage mass from grassland swards by height measurement using an ultrasonic sensor. Comput Electron Agric. 79, 142-152.

Fricke, T. Wachendorf, M. 2013. Combining ultrasonic sward height and spectral signatures to assess the biomass of legume-grass swards. Comput Electron Agric. 99, 236-247.

Fumiki, H. Omasa, K. 2009. Estimating vertical plant area density profile and growth parameters of a wheat canopy at different growth stages using three-dimensional portable lidar imaging. ISPRS Journal of Photogrammetry and Remote Sensing. 64, 151-158.

Gnyp, M.L.; Miao, Y.; Yuan, F.; Ustin, S.L.; Yu, K.; Yao, Y.; Huang, S.; Bareth, G. 2014. Hyperspectral canopy sensing of paddy rice aboveground biomass at different growth stages. Field Crops Res. 155, 42-55.

Henning, J.G., Radtke, P.J. 2006. Detailed stem measurements of standing trees from ground-based scanning lidar. For Sci. 52, 67-80.

Hong, S.D. Schepers, J. Francis, D.D. Schlemmer, M.R. 2007. Comparison of ground-based remote sensors for evaluation of corn biomass affected by nitrogen stress. Commun. Soil Sci. Plant Anal. 38, 2209-2226.

Hopkinson, C., Chasmer, L., Lim, K., Treitz, P., Creed, I. 2006. Towards a universal lidar canopy height indicator. Can. J. Remote Sensing. 32, 139-152.

Hutchings, N.J., Phillips, A.H., Dobson, R.C. 1990. An ultrasonic rangefinder for measuring the undisturbed surface height of continuously grazed grass swards. Grass Forage Sci. 45, 119-127.

Interrante, S.M., Biermacher, J.T., Kering, M.K., Butler, T.J. 2012. Production and economics of steers grazing tall fescue with annual legumes or fertilized with nitrogen. Crop Sci. 52, 1940-1948.

Jones, C.L., Maness, N.O., Stone, M.L., Jayasekara, R. 2007. Chlorophyll estimation using multispectral reflectance and height sensing. Transactions of the ASABE. 50, 1867-1872.

Lati, R.N., Manevich, A., Filin, S. 2013. Three-dimensional image-based modelling of linear features for plant biomass estimation. Int. J. Remote Sensing. 34, 6135-6151.

Lauriault, L.M., VanLeeuwen, D.M., Turner, J.L. 2013. Irrigation and nitrogen treatments slightly affected teff yield and quality in the southwestern USA. Forage and Grazinglands. FG-2013-0326-2001-RS.

Luo, S., Wang, C., Xi, X., Pan, F. 2014. Estimating fpar of maize canopy using airborne discrete-return lidar data. Optics express. 22, 5106-5117.

Machado, S., Bynum, E.D., Archer, T.L., Lascano, R.J., Wilson, L.T., Bordovsky, J., Segarra, E., Bronson, K., Nesmith, D.M., Xu, W. 2002. Spatial and temporal variability of corn growth and grain yield: Implications for site-specific farming. Crop Sci. 42, 1564-1576.

Mazzetto, F., Calcante, A., Mena, A. 2008. Optical and analogical sensors for crop monitoring in precision viticulture. Agricultural and biosystems engineering for a sustainable world. International Conference on Agricultural Engineering, Hersonissos, Crete, Greece, 23-25 June. OP-815.

Mehmood, T., Liland, K.H., Snipen, L., Saebo, S. 2012. A review of variable selection methods in partial least squares regression. Chemometrics and Intelligent Laboratory Systems. 118, 62-69.

Planas de Martí, S., Rosell Polo, J.R., Pomar Gomà, J., Camp, F., Solanelles Batlle, F., Gràcia, F., Llorens Calveras, J., Gil Moya, E. 2011.Performance of an ultrasonic ranging sensor in apple tree canopies. Sensors. 11, 2459-2477.

Sanderson, M.A., Rotz, C.A., Fultz, S.W., Rayburn, E.B. 2001. Estimating forage mass with a commercial capacitance meter, rising plate meter, and pasture ruler. Agron. J. 93, 1281-1286.

SAS Institute. INC SAS/STAT users' guide release 9.3; STATS Publishing Inc.: Cary, NC, USA, 2012.

Saxton, A. 1998. A macro for converting mean separation output to letter groupings in proc mixed. Proceedings of the 23rd SAS users group international. 1243-1246.

Scotford, I., Miller, P. 2004. Combination of spectral reflectance and ultrasonic sensing to monitor the growth of winter wheat. Biosystems Engineering. 87, 27-38.

Selbeck, J., Dworak, V., Ehlert, D. 2010. Testing a vehicle-based scanning lidar sensor for crop detection. Can. J. Remote Sensing. 36, 24-35.

Sui, R., Thomasson, J. 2006. Ground-based sensing system for cotton nitrogen status determination. Transactions of the ASABE. 49, 1983-1991.

Tucker, C.J. 1980. A critical review of remote sensing and other methods for non-destructive estimation of standing crop biomass. Grass Forage Sci. 35, 177-182.

Wuerschum, T., Abel, S., Zhao, Y. 2014. Potential of genomic selection in rapeseed (brassica napus l.) breeding. Plant Breed. 133, 45-51.

Zaman, Q., Salyani, M. 2004. Effects of foliage density and ground speed on ultrasonic measurement of citrus tree volume. Appl Eng. Agri. 20, 173-178.